# HOW RISKY IS IT?

## An assessment of the relative risk of engaging in potentially unsafe driving behaviors

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# EXECUTIVE SUMMARY

This report presents the results of a research project funded by the AAA Foundation for Traffic Safety. The primary aim of the study was to increase the understanding of the relative risks associated with particular driving behaviors. The results of the current study are intended to inform future studies, policies, and technologies directed at reducing driving behaviors that pose the most risk, thereby reducing crashes and their associated injuries and fatalities.

## Background

Many drivers choose to drive and behave in ways that increase their risk of crashing; for example: Elvik, Christensen, and Amundsen (2004) concluded that a relationship exists between mean traffic speed and the number and severity of crashes that occur on a road. In fact, the authors suggest that speed is likely to be the single most important determinant in the frequency of traffic fatalities; they report that a 10% reduction in the mean speed of traffic is likely to reduce fatal traffic crashes by 34% and have a greater impact on traffic fatalities than a 10% reduction in traffic volume.

Safety-belt non-use has been associated with increased risk of injury and death in a crash. The National Highway Traffic Safety Administration (NHTSA) estimates that safety belts saved 195,382 lives between 1975 and 2004, including 15,434 lives in 2004 alone (NHTSA 2005b). Furthermore, according to NHTSA, more than half of passenger-vehicle occupants fatally injured in crashes in 2004 were unrestrained, and an estimated 5,839 of them would have survived if they had been wearing safety belts (NHTSA 2005b). Nevertheless, NHTSA estimates that nationwide roughly one in five drivers still does not use a safety belt (Glassbrenner 2004).

Driving a vehicle is a psychomotor task, and continually monitoring the roadway and anticipating the actions of other drivers are critical for safely operating a motor vehicle. A distracted or inattentive driver is likely to have delayed recognition or no recognition of information necessary for safe driving (Stutts et al. 2003). Driver distraction and inattention have been cited frequently as contributing factors in crashes; for example: the Indiana Tri-Level Study (Treat et al. 1979) and the Hendricks, Fell, and Freedman (1999) crash-causation study both found that driver inattention contributed to at least 20% of the crashes studied. A more recent study suggests that visual inattention and engagement in secondary tasks contributed to nearly 60% of crashes (Klauer, Dingus, Neale, Sudweeks, and Ramsey 2006). Driver distraction and inattention is a contributing factor in 8% to 12% of tow-away crashes (Stutts, Reinfurt, and Rodgman 2001; Wang, Knipling, and Goodman 1996), and according to recent data from NHTSA's Fatality Analysis Reporting System (FARS), a census of all fatal motor vehicle crashes occurring on public roadways in the United States, police indicate that driver inattention is a contributing factor in roughly 10% of all fatal crashes annually.

Drowsy driving is another risky behavior; drowsiness is a general term commonly used to describe the experience of being "sleepy," "tired," or "exhausted." Drowsiness contributes to an estimated 76,000 to 100,000 crashes each year in the United States, resulting in an estimated 1,500 deaths and thousands of injuries (Knipling and Wang 1995; Wang, Knipling and Goodman 1996). Most crash database statistics based on police-reported crashes suggest that 2% to 4% of vehicle crashes nationwide involve a drowsy driver. These statistics, however, likely underestimate the role of drowsiness in crashes because it is difficult to identify and because drivers are unlikely to admit they were drowsy after being involved in a crash. A recent in-depth naturalistic study found that drowsiness affected crashes in which the study sample was involved at much higher rates than would have been predicted based on existing databases. That study found drowsiness to be a contributing factor in 20% of all crashes and 16% of near-crashes in the study sample (Klauer, Dingus, Neale, Sudweeks, and Ramsey 2006).

## Methods

The data used for the analyses in this report were collected during the 100-Car Naturalistic Driving Study, or the 100-Car Study (Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. 2006). The 100-Car Study collected naturalistic, continuous, real-time data over a 12- to 13-month period from a sample of 109 primary drivers and 132 secondary drivers in the Northern Virginia/Washington, DC area. The dataset included five channels of video and electronic data from sensors in the car to detect several driving behaviors (e.g., speeding, safety belt use, and so forth). Thus, the data acquisition system provided both video and quantitative kinematic data for analysis.

The driving performance data were used as post-hoc triggers to identify moments in the video where a crash, near-crash, or incident, as defined herein, had occurred. Post-hoc triggers are values of a single driving performance variable (e.g., 0.6 *g* lateral acceleration) or combinations of performance variables (e.g., speeds greater than 20 mph and forward range of 100 ft) used to identify moments when the driver may be involved in an unsafe situation. These triggers were used to flag specific video segments for more in-depth examination. Trained data reductionists reviewed the video and driving performance data surrounding these post-hoc triggers to determine whether a crash, near-crash, or incident had actually occurred. If so, they recorded a battery of variables for that driving epoch (typically 30 s), which included the sequence of events surrounding the crash, near-crash, or incident (collectively referred to hereafter as "events"); the driver behavior just prior to and during the event; environmental conditions; and road and traffic-related conditions. After data reduction was complete, 82 crashes, 761 near-crashes, and 8,295 incidents were identified (13 of the 82 crashes were excluded from analyses due to incomplete data; only the remaining 69 crashes with complete data are discussed hereafter). The operational definitions of each are as follows:

- **Crash:** Any contact with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. This includes contact with other vehicles; roadside barriers; and objects on or off of the roadway, including pedestrians, cyclists, or animals.
- **Near-Crash:** Any circumstance requiring 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 a steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle's capabilities.
- **Incident:** Any circumstance requiring a crash avoidance response by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal that is less severe than a rapid evasive maneuver (as defined previously), but more severe than a "normal" maneuver to avoid a crash. A crash-avoidance response can include braking, steering, accelerating, or any combination of control inputs. Incidents were judged to be highly irregular for the same driver.

Also, 20,000 normal, uneventful driving segments or “epochs” (i.e., segments of driving performance data that did not contain triggered events) were reviewed and reduced to provide a baseline comparison to those driving behaviors observed just prior to crashes, near-crashes, and incidents.

Note that one powerful aspect of the 100-Car database is that detailed driving behavior data were collected just prior to crashes and near-crashes. This level of detail has never before been captured in either epidemiological databases or empirical studies. Twelve of the 69 crashes were police-reported; thus, 57 were not police-reported and would almost certainly not have been observed using these other methods. Data gathered from these types of crashes and near-crashes provide unique insight into the precipitating and potentially risky driving behaviors associated with these events.

There were two phases of data analysis for this report. In Phase I, data collected in the original 100-Car Study were used to (a) assess the frequency of crashes, near-crashes, and incidents in which drivers were engaging in particular driving behaviors; and (b) determine which data would be used for the modeling effort in Phase II.

For the Phase II analysis, logistic regression was used to compare and contrast the behaviors associated with crashes and near-crashes to the behaviors associated with “normal” driving, by computing odds ratios. Odds ratios, as applied in this study, estimate the relative risk of observing a given driver state or driving behavior in a crash or near-crash, relative to in an epoch, while controlling for all other driver states and driving behaviors included in the regression model. This analysis provides unique insight regarding which driving behaviors are riskier than others.

Additionally, analyses in Phase II assessed whether differences existed between those drivers who were operationally defined as high- or low-risk drivers based on their observed rates of involvement in crashes, near-crashes, and incidents.

## Conclusions

The results indicate that four driving states/behaviors are associated with an increased risk of being involved in a crash or near-crash. First, driving at inappropriate speeds was associated with nearly tripling the odds of being involved in a crash or near-crash (OR = 2.9, 95% CI = 1.7 – 4.8) relative to driving at appropriate speeds.

Second, driving while drowsy was associated with a similar increase in the odds of being involved in a crash or near-crash, relative to driving while not drowsy (OR = 2.9, 95% CI = 2.0 – 4.3). Third, when a driver's eyes were off the forward roadway for greater than 2 s, the odds of a crash or near-crash occurring were nearly double those when the driver was paying attention to the forward roadway (OR = 1.9, 95% CI = 1.4 – 2.5). Finally, the odds of a crash or near-crash more than doubled when a driver was exhibiting aggressive driving behaviors (OR = 2.1, 95% CI = 1.3 – 3.4).

When comparing high-risk drivers (defined as 12.5% of the study sample with the highest rate of crashes, near-crashes, and incidents per mile driven) to low-risk drivers (defined as the 12.5% of the study sample with the lowest rate of crashes, near-crashes, and incidents), the high-risk drivers were less likely to wear a safety belt and more likely to drive while drowsy than the low-risk drivers. In addition, the high-risk drivers' average rate of crashes, near-crashes, and incidents (219.5 per 10,000 miles driven) was more than 100 times that of the low-risk drivers (2.1 crashes per 10,000 miles driven).

In summary, driving faster than surrounding traffic, driving while drowsy, looking away from the forward roadway for longer than 2 s, and aggressive driving are associated with increased risk of being involved in crashes and near-crashes. Note that Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) showed that near-crashes were kinematically similar to crashes (i.e., involved comparable levels of braking and swerving). The primary difference between a crash and a near-crash is a successful evasive maneuver. Thus, crashes lead to property damage, injury, and possibly death, but near-crashes do not, even though they have similar properties. Including both near-crash and crash events in the calculation of odds ratios greatly improves statistical precision of the estimates, and appears to be a promising technique for use in future research.

These results can be used to educate the public on the dangers of looking away from the forward roadway, driving while drowsy, driving faster than surrounding traffic, and driving aggressively. They also have implications for collision avoidance warning systems; for example: a collision warning or collision avoidance system that can determine whether the driver's eyes are closed or directed away from the forward roadway could potentially be more efficient and accurate. In general, this research highlights driving behaviors that produce the greatest driving risk, which, if avoided, could greatly reduce near-crash and crash events.

# INTRODUCTION

This report presents the results of a two-phased project funded by the AAA Foundation for Traffic Safety. The data used for the analyses in this report were collected during the 100-Car Naturalistic Driving Study, or the 100-Car Study, (Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. 2006), conducted by the Virginia Tech Transportation Institute (VTTI), under sponsorship from the National Highway Traffic Safety Administration (NHTSA), Virginia Department of Transportation (VDOT), and Virginia Tech. The primary aim of the current study was to increase the understanding of the relationship between potentially unsafe driving behaviors as well as crashes, near-crashes, and incidents (collectively referred to hereafter as "events"). The results of this study are intended to inform future studies, policies, and technologies directed at reducing driving behaviors found to be associated with increased risk of involvement in a crash or near-crash, thereby reducing crashes and their associated injuries and fatalities. The results in the current study, for example: could initiate new traffic enforcement policies, educate drivers about the relationship between their personal driving habits and the risk associated with those habits, and indicate potential uses of countermeasure technologies (e.g., lane-departure and rear-end crash avoidance).

## Background and Significance

Unintentional injury is responsible for more years of potential life lost before the age of 65 than cancer and heart disease combined (National Center for Health Statistics 2004). Motor vehicle crashes are the single largest cause of unintentional injury for ages 1 to 65, accounting for a total of 42,643 deaths in 2003 when motor vehicle fatalities killed 14.66 out of every 100,000 Americans (NHTSA 2005). Societal costs associated with these crashes include lost wages, medical expenses, insurance claims, production delays, property damage, and indirect costs (National Safety Council 1995). In 2000, the total economic cost of traffic fatalities was approximately $230.6 billion, including $61 billion in lost productivity, $59 billion in property damage, and $32.6 billion in travel delays (Blincoe et al. 2002).

One of the most significant studies on the factors contributing to motor vehicle crashes was the Indiana Tri-Level Study (Treat et al. 1979). Using epidemiological methods, this study investigated how frequently various factors contributed to traffic crashes. Researchers assessed causal factors as definite, probable, or possible. The study determined the following:

- 90.3%[1] of crashes involved human error, such as risky driving behavior, inadvertent errors, and impaired states.
- 34.9% of crashes involved environmental factors, such as wet or slick road conditions and poor weather.
- 9.1% of crashes involved vehicle factors, such as brake failure and worn tires.

The two most frequent human behaviors found in all the crashes investigated at the three different levels were driver inattention/distraction (20.3% of the crashes) and speeding (14.7% of the crashes).

A more recent study by Hendricks, Fell, and Freedman (1999) tried to replicate the epidemiological method employed in the Indiana Tri-Level Study. More specifically, the researchers assessed the specific driver behaviors and unsafe driving acts that led to crashes, and the situational, driver, and vehicle characteristics associated with these behaviors. Similar to the Indiana Tri-Level Study, Hendricks, Fell, and Freedman found human error was the most frequently cited contributing factor in these crashes (99.2%), followed by environmental (5.4%) and vehicle factors (0.5%). Thus, crashes and their associated injuries and fatalities are related to unsafe driving behaviors.

Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) recently completed the *100-Car Naturalistic Driving Study,* the primary purpose of which was to assess

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1 Note the percentages above do not total to 100% because some events were coded as involving more than a single factor.

crash causation. Continuous driving data were collected from 109 primary drivers and 132 secondary drivers in the Northern Virginia/Washington, DC, area over 12 to 13 months. The data included five channels of video, including the driver's face and over-the-shoulder views, and many sensors measuring various driving performance variables, such as longitudinal deceleration, vehicle speed, distance to lead vehicle, and Global Positioning System (GPS) coordinates. Using the driving performance and video data, trained data reductionists identified 82 crashes, 761 near-crashes, and 8,295 incidents, and recorded driving behaviors occurring just prior to these events. (Note that 13 of the 82 crashes were excluded from analyses due to incomplete data; only the remaining 69 crashes with complete data are discussed hereafter.) Results from this study indicated driver drowsiness and engaging in secondary tasks were frequent contributors to crashes, near-crashes, and incidents and were shown to increase crash risk. While various potentially risky driving behaviors were recorded in the original 100-Car Study, no in-depth analyses of these behaviors have been conducted to date. The study reported here used data from the 100-Car Study to assess the relationship between these behaviors and the risk of occurrence of crashes and near-crashes.

## Driving Behaviors

Motor vehicle crashes and their associated injuries and fatalities are often associated with potentially risky or unsafe driving behaviors. Yet many drivers choose to drive and behave in ways that increase their risk of crash involvement and serious injury.

### *Excessive speed*

The estimated annual savings of 2,000 to 4,000 lives as a result of implementing the National Maximum Speed Limit of 55 mph in 1974 (Waller 1987) illustrates the dramatic risk associated with vehicle speed. When the National Maximum Speed Limit was later raised to 65 mph on rural interstate highways in 1987, vehicle crashes showed a marked increase (Evans 1991). A recent analysis of repealing the National Maximum Speed Limit in late 1995 found that 23 states had raised their rural interstate speed limits to 70 or 75 mph in December 1995 or during 1996. The researchers analyzed fatality rates on rural interstates from 1992 through 1999 in states that either did not change their rural interstate speed limits, raised the speed limits to 70 mph, or raised their speed limits to 75 mph; and found that fatality rates in both groups of states that had raised their speed limits were higher than expected based on fatality rates in states that did not change their speed limits (Patterson, Frith, Povey, and Keall 2002).

Similarly, Elvik, Christensen, and Amundsen (2004) conducted a rigorous meta-analysis that included 97 different studies totaling 460 estimates of the relationship between changes in speed and changes in the frequency of crashes or associated injuries and fatalities. The study concluded that a relationship exists between mean speed and the number and severity of crashes on a road. Furthermore, the authors suggest that speed is likely to be the single most important determinant in the frequency of traffic fatalities; they report that a 10% reduction in the mean speed of traffic is likely to reduce fatal traffic crashes by 34% and have a greater impact on traffic fatalities than a 10% reduction in traffic volume.

While increases in posted speed limits increase crash risk and severity, research also suggests that speeding decreases time to respond to an event and increases speed differential at the time of impact. As cited by NHTSA in *Traffic Safety Facts 2004:* "Speeding reduces a driver's ability to steer safely around curves or objects in the roadway, extends the distance necessary to stop a vehicle, and increases the distance a vehicle travels while the driver reacts to a dangerous situation" (NHTSA 2005c). Furthermore, impact force during a vehicle crash varies with the square of the vehicle speed, so even small increases in speed have large and potentially lethal effects on the force at impact (Road and Traffic Authority 2005).

### *Safety belt use*

NHTSA estimates that safety belts saved 195,382 lives between 1975 and 2004, including 15,434 lives in 2004 alone (NHTSA 2005b). Furthermore, according to NHTSA, more than half of passenger-vehicle occupants fatally injured in crashes in 2004 were unrestrained, and an estimated 5,839 would have survived if they had been wearing safety belts (NHTSA 2005b). Nevertheless, nationwide, an estimated one in five front-seat occupants still do not wear safety belts (Glassbrenner 2004).

### *Driver distraction/inattention*

Driver distraction/inattention was the most frequently citied contributing factor in the Indiana Tri-Level Study (20.3% of the crashes) and the Hendricks, Fell, and Freedman crash-causation study (23% of the crashes). A more recent study suggested that visual inattention and engaging in secondary tasks contributed to nearly 60% of crashes observed in the study (Klauer, Dingus, Neale, Sudweeks, and Ramsey 2006). Driving a vehicle is a psychomotor task, and continually monitoring the roadway and anticipating the actions of other drivers are critical for operating a motor vehicle safely. A distracted or inattentive driver is likely to have delayed recognition or no recognition of information necessary for safe driving (Stutts et al. 2003). Driver distraction/inattention was estimated to be a contributing factor in 8% to 12% of tow-away crashes (Stutts, Reinfurt, and Rodgman 2001; Wang, Knipling, and Goodman 1996). According to recent data from NHTSA's Fatality Analysis Reporting System (FARS), a census of all fatal motor vehicle crashes occurring on public roadways in the United States, police indicate driver inattention as a contributing factor in roughly 10% of all fatal crashes annually.

### *Driver drowsiness*

Drowsiness is a general term commonly used to describe the experience of being "sleepy," "tired," or "exhausted." Drowsiness is both a physiological and a psychological experience (Institute for Road Safety Research 2004). Drowsiness affects physical and mental alertness, decreasing an individual's ability to safely operate a vehicle and increasing the risk of human error that could lead to crashes. As with drugs and alcohol, drowsiness slows reaction time, decreases awareness, and impairs judgment (Lyznicki et al. 1998; Leger 1995). Drowsy driving is a key factor in an estimated 76,000 to 100,000 crashes occurring each year in the United States, resulting in 1,500 deaths and thousands of injuries (Knipling and Wang 1995; Wang, Knipling, and Goodman 1996). Most crash database statistics indicate 2% to 4% of vehicle crashes involve a drowsy driver. These statistics, however, likely underestimate the role of drowsiness in crashes, because it is difficult to identify and because drivers are unlikely to admit they were drowsy while driving. The 100-Car Study found that drowsiness affected crashes at much higher rates than recorded in existing crash databases. Drowsiness was found to be a contributing factor in 20% of all crashes and 16% of near-crashes that were documented in the 100-Car Study (Klauer, Dingus, Neale, Sudweeks and Ramsey 2006).

## Interrelationships of Driving Behaviors

NHTSA's annual *Traffic Safety Facts* publications present statistics illustrating associations between several specific risky behaviors. Speeding and alcohol impairment, for example, have been shown to be associated: 40% of drivers with illegal blood alcohol concentrations who were involved in fatal crashes were also speeding, as compared to only 15% of drivers with blood alcohol concentrations of 0.00 (2005c). Speeding and lack of safety belt use also appear to be associated with one another. Fewer than half

(44%) of all drivers 21 and older who were involved in speeding-related fatal crashes were wearing safety belts, as compared to 72% of non-speeding drivers 21 and older who were involved in fatal crashes (NHTSA 2005c).

One line of research suggests that people who engage in one potentially unsafe driving behavior are also likely to engage in several others (e.g., Ludwig and Geller 1997). In a monograph describing more than 15 years of research with pizza delivery drivers, Ludwig and Geller (2000) found that drivers who learned to perform one safe driving behavior were likely to perform several others. Ludwig and Geller (1991), for example, used a combination of education and awareness meetings, prompts, and commitment cards to significantly increase safety belt use among pizza delivery drivers. They also observed significant increases in turn-signal use (a behavior not directly targeted by the intervention) compared to a control group that did not receive any of the intervention materials. Similarly, in the same setting, an intervention using goal setting and feedback techniques to increase full stops at intersections was found to be effective, and also significantly increased both turn signal and safety belt use (Ludwig and Geller 1997; 1999).

Since many observed driving behaviors were correlated, the authors speculated that they fall under the same response class, which is a constellation of behaviors that produce the same consequence (e.g., driving attentively and following at a safe distance result in "safe" operation of a motor vehicle). Behaviors that share some type of functional attribute, such as safety-related driving behaviors, are more likely to be correlated than unrelated combinations of behaviors, such as typing and traveling above the posted speed limit. Driving behaviors, for example, are typically shaped through similar processes and are, therefore, likely to operate under similar contingencies or rules in the environment (Ludwig and Geller 2000). Most people learn to drive a vehicle though a similar process, such as parental instruction or driver education and training programs. As these driving behaviors operate under the same contingencies and environmental rules, such as traffic enforcement polices, behaviors that correlate are more likely to generalize than novel combinations of behaviors (Ludwig 2001).

If safe driving practices correlate in a consistent fashion, then intervening to increase one desired safe driving behavior may have indirect effects on others within the same response class. This behavioral correlation can result in changes in other safety-related behaviors besides the behavior targeted by the intervention. Thus, safety-related driving behaviors may be conceived not as individual responses, but as groups of functionally related behaviors (e.g., the response class of safe driving practices). This is called “response generalization” (Carr 1988). Response generalization occurs when multiple behaviors clustered in a functional response class, such as safety-related behaviors, increase as a result of intervention aimed at one of the behaviors within that response class (Russo, Cataldo, and Cushing 1981). Unfortunately, a rather narrow and piecemeal approach is taken in intervention research when assessing intervention effectiveness. In other words, most scientists have intervened upon, measured, and reported their findings on a single target response, without considering that a variety of responses may correlate as a function of similar response classes and reinforcement histories (Geller 2001; Ludwig and Geller 1991, 1997, 2001).

## Limitations of Prior Research

Knowledge of how risky driving behaviors relate to crashes is limited. First, the populations studied have not always been representative of the driving population; for example: while pizza delivery drivers are typically drivers aged 16 to 24, and young drivers clearly need intervention, pizza drivers operate under external contingencies, such as being paid per delivery, a factor not present in the population at large.

Second, the data collected in most studies used spot checks, which only represent a small fraction of the participants’ on-road driving behavior, making it more difficult to generalize these findings to the broader driving population.

Third, most of the data from national crash statistics are obtained from police accident reports. While these reports provide general insight into a crash, they have limitations: (1) witnesses and crash participants can be biased and report conflicting stories; (2) police officers, while sometimes experienced, generally do not receive extensive training in crash reconstruction; and (3) witnesses or those who were severely injured in a crash are unlikely to be able to effectively persuade the police officer with their opinions of the crash.

Finally, the few studies that have examined the relationship of multiple risky behaviors have done so under one or more of these limitations. A naturalistic study approach, in which many drivers are studied over an extended period of time, provides considerable advantages.

## Advantages of the Naturalistic Approach

Naturalistic driving studies involve the real-world collection of driving data over protracted portions of time, such as 1 year, using sophisticated but unobtrusive data collection systems, without an on-board experimenter. This type of data collection enables detailed driving behavior to be recorded while drivers are commuting to work, running errands, or driving in other common scenarios. Most importantly, the drivers are under no experimenter-induced time restrictions and are dealing with daily traffic conditions as well as all the pressures associated with real-world driving. These data are then reviewed and reduced into a rich database that can be mined for multiple research purposes.

The 100-Car Study collected naturalistic, continuous, real-time data over a 12- to 13-month period from a sample of 109 primary drivers in the Northern Virginia/Washington, DC area. An on-board apparatus captured five channels of video and electronic data from sensors that detected a variety of driving behaviors, such as speeding and safety belt use. Thus, the data provided both video and quantitative data for analysis. Note that the original 100-Car Study captured data from an additional 132 secondary drivers who also operated the 109 study vehicles at some point during the study period. Data collected from all drivers were analyzed in the first phase of the current study; however, only data from primary drivers were used in the second phase.

The driving performance data were used as post-hoc triggers to identify moments in the video where an event occurred. Trained data reductionists reviewed the video and driving performance data surrounding these post-hoc triggers to determine whether the event was valid, and if so, recorded a battery of variables. These variables included the sequence of events surrounding the crash, near-crash, or incident; the driver behavior just prior to and during the event; and environmental-, road-, and traffic-related conditions. After data reduction was complete, 69 crashes, 761 near crashes, and 8,295 incidents were identified. The operational definitions of each type of event were as follows:

- **Crash:** Any contact with an object, either moving or fixed, at any speed in which kinetic energy is transferred or dissipated. Includes other vehicles, roadside barriers, and objects on or off of the roadway, including pedestrians, cyclists, or animals.

- **Near-Crash:** Any circumstance requiring 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 a steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle's capabilities.

- **Incident:** Any circumstance requiring a crash avoidance response by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal that is less severe than a rapid evasive maneuver (as defined previously), but more severe than a "normal" maneuver to avoid a crash. A crash-avoidance response can include braking, steering, accelerating, or any combination of control inputs. Incidents were judged to be highly irregular for the same driver.

Also, 20,000 normal, uneventful driving segments or "epochs" were reviewed and reduced to provide a baseline for comparison to the driving behavior observed in association to the events.

One powerful aspect of the 100-Car database is that data were collected on crashes that have never before been captured in either epidemiological databases or empirical studies. Only 12 of the 69 crashes were police-reported; 57 were not. These types of crashes provide unique insight into the following analyses of risky driving behaviors. Using crash database statistics, researchers hypothesized prior to the 100-Car Study that data would be collected on approximately 12 to 14 police-reported crashes and perhaps 24 total crashes. The 100-Car Study database contained roughly five times as many non-police-reported crashes as had been expected.

The primary advantage to the naturalistic approach is the video and dynamic sensor data that allows experimenters to review all pre-event and event parameters, such as distraction, drowsiness, and error. This detailed and accurate information regarding the driver's behavior leading up to and during a crash, near-crash, or incident is severely limited or utterly absent using other data collection approaches. The naturalistic approach also permits the accurate calculation of parameters such as vehicle speed, vehicle headway, time-to-collision (TTC), and driver reaction time. These variables are all included in an event database similar to an epidemiological crash database, but with video, driver, and vehicle data appended. The video and electronic data can be replayed at varying frame rates in order to fully understand the nature of each event. Additionally, unlike an epidemiological crash database, this database also provides data pertaining to the behavior and performance of drivers during ordinary driving.

The data collection approach used in the 100-Car Study provides a unique tool that augments other data collection methods, such as epidemiological and empirical data collection. Traditional epidemiological or empirical methods lack sufficient detail for studying the relationship between driving behaviors and crashes and do not always capture the complexities of the driving environment or of natural driving behavior. Thus, naturalistic driving data collection, such as in the 100-Car Study, provides sufficient detail to examine the relationship between human behavior and crashes, near-crashes, and incidents (Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. 2006).

Precise analysis of the events leading up to a crash, near-crash, or incident is possible with the 100-Car Study dataset since both video and electronic sensor data are available for all such events. The study of near-crashes has two important advantages over the study of crashes alone: (1) near-crashes occur much more frequently than crashes, and thus increase the sample size of events from which useful information can be collected, and (2) every near-crash involves a driver performing a successful evasive maneuver. Capturing data on near-crashes will likely provide additional insight into effective defensive driving techniques and potential countermeasures for these driving situations. Assessment of successful avoidance maneuvers for different near-crash scenarios, for example, could initiate driver training course material on appropriate responses for a driver encountering these situations as well as crash countermeasure technologies. Furthermore, the absence of an on-board experimenter greatly reduces the likelihood of the driver artificially conforming his or her behaviors to perceived expectations. Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) reported evidence suggesting that drivers tended to drive more carefully during the first few hours of the 100-Car Study, but that they quickly adapted to the presence of the in-vehicle instrumentation and resumed normal driving behavior.

# METHODS

This section provides a brief summary of that data collection effort, followed by a description of additional methods specific to the current analyses.

There were two phases of data analysis for this report. In Phase I, data from the original 100-Car Study were used to assess (1) the frequency of crashes, near-crashes, and incidents where all 241 drivers were engaging in potentially risky driving behaviors; and (2) whether a subset of events (e.g., only crashes, or crashes and near-crashes) or all events (i.e., crashes, near-crashes, and incidents) would be used for the modeling effort in Phase II.

Logistic regression was used for Phase II analyses to compute odds ratios to estimate the relative risk of involvement in a crash or near-crash, associated with specific driving behaviors. Additionally, Phase II analyses assessed the impact of demographic variables (such as age and gender) on crash risk, and also assessed whether differences existed between those drivers that were operationally defined as high- or low-risk drivers. In Phase II, only data from the primary drivers were analyzed.

## Participants and Setting

One hundred participants who commute to and from the Washington, DC metropolitan area were recruited as drivers in the 100-Car Study (Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. 2006). As the study progressed, some participants had to be replaced for various reasons (e.g., moved from the area), so the final number of participants was 109. Driver age and annual mileage were used as screening criteria to select the subject population. As explained in Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006), one of the primary goals of the original 100-Car Study was to examine factors associated with rear-end crashes. Thus drivers aged 18 to 25 and male drivers were recruited heavily, because such drivers are over-represented in rear-end collisions (Knipling, Wang, and Yin 1993). Additionally, higher-mileage drivers were sought to increase the expected number of crashes, near-crashes, and incidents observed during the study. The annual mileage criteria, however, were only used for part of the subject-recruiting process, as identifying high-mileage drivers became increasingly difficult. The number of miles driven during the 100-Car Study is shown in Table 1. Table 2 displays the age and gender distribution of participants.

**Table 1.** **Miles driven during the 100-Car Study.**

| Actual Miles Driven | Number of Drivers | Percentage of Drivers |
|---|---|---|
| 0–9,000 | 29 | 26.6% |
| 9,001–12,000 | 22 | 20.2% |
| 12,001–15,000 | 26 | 23.9% |
| 15,001–18,000 | 11 | 10.1% |
| 18,001–21,000 | 8 | 7.3% |
| More than 21,000 | 13 | 11.9% |

**Table 2.** **Participant age and gender distributions for the 100-Car Study.**

<table>
<tr><th rowspan="2">Age</th><th colspan="2">Gender<br>(N and % of Total)</th><th rowspan="2">Total</th></tr>
<tr><th>Female</th><th>Male</th></tr>
<tr><td rowspan="2">18-20</td><td>9</td><td>7</td><td>16</td></tr>
<tr><td>8.3%</td><td>6.4%</td><td>14.7%</td></tr>
<tr><td rowspan="2">21-24</td><td>11</td><td>10</td><td>21</td></tr>
<tr><td>10.1%</td><td>9.2%</td><td>19.3%</td></tr>
<tr><td rowspan="2">25-34</td><td>7</td><td>12</td><td>19</td></tr>
<tr><td>6.4%</td><td>11.0%</td><td>17.4%</td></tr>
<tr><td rowspan="2">35-44</td><td>4</td><td>16</td><td>20</td></tr>
<tr><td>3.7%</td><td>14.7%</td><td>18.4%</td></tr>
<tr><td rowspan="2">45-54</td><td>7</td><td>13</td><td>20</td></tr>
<tr><td>6.4%</td><td>11.9%</td><td>18.3%</td></tr>
<tr><td rowspan="2">55+</td><td>5</td><td>8</td><td>13</td></tr>
<tr><td>4.6%</td><td>7.3%</td><td>11.9%</td></tr>
<tr><td>Total N</td><td>43</td><td>66</td><td>109</td></tr>
<tr><td>Total Percentage</td><td>39.4%</td><td>60.6%</td><td>100.0%</td></tr>
</table>

Note that the oldest participant was 68 years old.

Note that driver demographic data and questionnaire data were only collected on the 109 primary drivers, but not any of the secondary drivers. Also note that the sample of drivers in these analyses included a mix of drivers between the ages of 18 and 68, but did not include any younger "novice drivers" or older "senior drivers."

## Light Vehicle Types

The data collected in the 100-Car Study came from six vehicle models, including Toyota Camry (1997-2001), Toyota Corolla (1993-2002), Ford Explorer (1995-2000), Ford Taurus (2000-2002), Chevrolet Malibu (2002), and Chevrolet Cavalier (2002). Six vehicle models were selected a priori to reduce the number of custom bracket types required to instrument the vehicles without causing permanent damage. Figures 1 and 2 show examples of the vehicles used in the 100-Car Study.

**Figure 1. Toyota Camry and Toyota Corolla used in 100-Car Study.**

**Figure 2. Ford Explorer and Ford Taurus used in 100-Car Study.**

A total of 22 Chevrolet vehicles (12 Malibus and 10 Cavaliers) were leased from the Virginia Tech Motor Pool and instrumented with data collection equipment. These leased vehicles were used to help recruit younger drivers because finding younger drivers who actually drove one of the six vehicle models was difficult. Twenty-two younger participants were given leased vehicles to drive for 1 year. These drivers received free use of the vehicle, including standard maintenance, and a bonus at the end of the study. The additional 78 vehicles (comprised of the aforementioned Toyota, Ford, or GM models) were the participants' personal vehicles and instrumented with the same type of data collection systems as the leased vehicles. For allowing their vehicles to be instrumented, these participants received $125.00 per month and the same bonus as the leased-vehicle participants at the end of the study.

## Data Collection in the 100-Car Study

The 100-Car Study instrumentation package was engineered by VTTI to be rugged, durable, expandable, and unobtrusive. The system consisted of a Pentium-based computer that received and stored data from a network of sensors distributed around the vehicle. Several weeks of data could be stored on the system's hard drive before space limitations made retrieving the data necessary.

Each sensing subsystem within a vehicle was independent, so any failures were constrained to a single sensor type. Sensors included a box to obtain data from the vehicle network, an accelerometer box for longitudinal and lateral acceleration, a system to provide information on distance to lead and following vehicles, a system to detect conflicts with vehicles to either side of the subject vehicle, an incident box to allow drivers to flag incidents for the research team, a video-based lane-tracking system to measure lane-keeping behavior, and video to validate any sensor-based findings. The video subsystem provided a continuous window into the happenings in and around the vehicle. Five camera views monitored the driver's face and driver's side view of the road, the forward road view, the rear road view, the passenger-side road view, and the over-the-shoulder view of the driver's hands and surrounding areas. The video system was digital, with software-controllable video compression capability, allowing synchronization, simultaneous display, and efficient archival and retrieval of 100-Car Study data.

Other capabilities of the 100-Car Study's Data Acquisition System (DAS) provided the research team with additional information. These capabilities included automatic notification to inform the research team of possible collisions, cellular communications to determine system status and vehicle position, initialization equipment to automatically control system status, and a GPS subsystem to collect information on vehicle position. This subsystem was one of 10 used in conjunction with the cellular communication subsystems to track and locate vehicles for repair and data downloading.

The main DAS unit (Figure 3) was mounted under the package shelf (Figure 4). Doppler radar antennas were mounted behind specially acquired plastic license plates on the front and rear of the vehicle (Figure 5). Table 3 shows a list of all the network and VTTI sensor variables that the DAS recorded.

**Figure 3.**
**The 100-Car DAS main unit shown without the top cover.**

**Figure 4.**
**The main DAS unit mounted under the trunk "package shelf."**

**Figure 5.** **Doppler radar antenna mounted on the front of a vehicle, covered by a plastic license plate.**

**Table 3. Network and VTTI sensor variables recorded by the DAS.**

| Sensor Subsystem | Description |
|---|---|
| Lateral acceleration | Records the rate of acceleration as vehicle moves to the left or right (measure in g-force). |
| Longitudinal acceleration | Records the rate of acceleration/deceleration as the driver applies the accelerator/brake (measured in g-force). |
| Yaw rate | Records the rate of side movement (measured in deg/s). |
| Forward radar | Records the distance and TTC to vehicles in front of the instrumented vehicle. Used to calculate forward range (ft), range-rate (ft/s), TTC (s). |
| Rear radar | Records the distance and TTC to vehicles behind the instrumented vehicle. Used to calculate forward range (ft), range-rate (ft/s), TTC (s). |
| Side radar range | Records the presence of a vehicle beside the instrumented vehicle as well as closing speed of a vehicle in adjacent lane. |
| Lane position | Records the vehicle position between the two lane markings on the roadway using digital imaging techniques (measured in inches from center of lane). |
| Radio Frequency sensor | Records the presence of an RF signal that is transmitted when a cell phone is in use. |
| GPS antenna | Records the vehicle's latitude, longitude, elevation, as well as horizontal and vertical speed. |
| In-vehicle network | Records the vehicle speed (mph), brake activation (on/off), accelerator pressure (% depression), and turn-signal use (left, right, hazards, off). |
| Incident pushbutton | Manual sensor initiated when the driver presses a button. The computer will record an audio message from the driver as well as insert a flag in the data stream. |

Other major components were mounted above and in front of the center rearview mirror (Figure 6), including an incident pushbutton box containing a button a participant could press whenever an unusual driving event occurred; an unobtrusive miniature camera for the driver face view, which was mounted behind a smoked plexiglass cover and, therefore, invisible to the driver; and a forward-view camera and glare sensor, which were mounted behind the rearview mirror (Figure 7) so as not to occlude the driver's normal field of view.

**Figure 6.** **The incident pushbutton box mounted above the rearview mirror. The right-hand portion contains the driver-face/left-road view camera hidden behind a smoked plexiglas cover.**

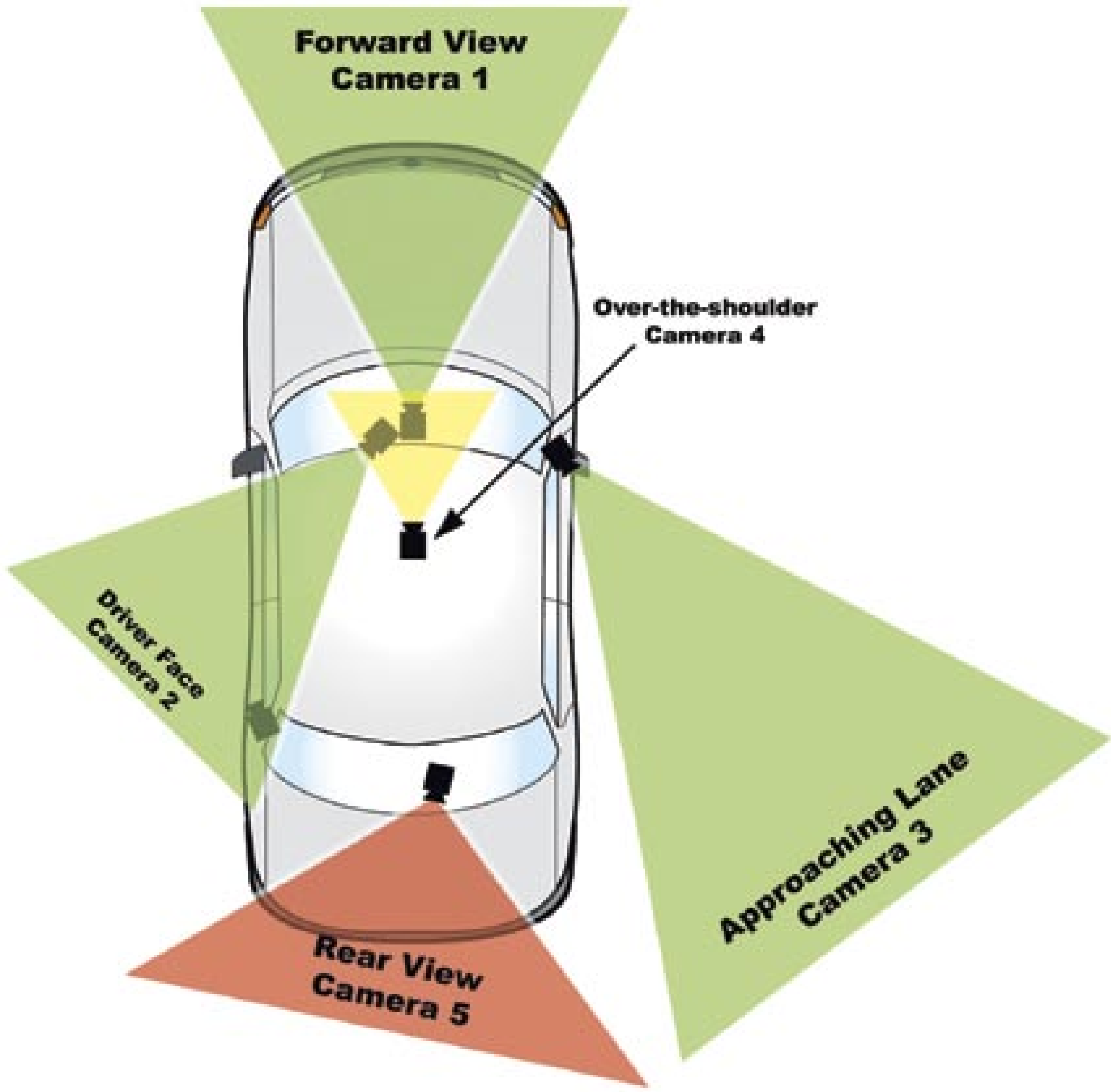
**Figure 7.** **The mounting for the glare sensor behind the rearview mirror. The forward-view camera was part of the same mounting assembly.**

## Video Camera Systems

As shown in Figure 8, five video cameras were used in the video recording system: (1) a forward-looking camera that captured the forward roadway scene, traffic situation, and possible incidents; (2) a driver's face camera that recorded facial expressions, eyelid closure, glance position, and head turns; (3) a right-side camera, mounted on the A-pillar of the passenger side to capture the rear-passenger side; (4) a dome camera mounted from inside the vehicle that captured data over the driver's shoulder toward the steering wheel, hands, and feet; and (5) a rear camera, mounted near the center-high-mounted stop lamp, that captured the situation behind the vehicle. Infrared

(IR) lighting illuminated the vehicle cab so the driver's face and hands could be viewed by the camera during nighttime driving, without creating glare or distracting the driver (i.e., infrared light is not detectable to the human visual system).

**Figure 8. The five camera views recorded in the instrumented vehicle (top view).**




The video camera arrangement shown in Figure 8 captured several important piecesThe video camera arrangement shown in Figure 8 captured several important pieces of data: incidents around the vehicle as they developed; the driver's facial expression, approximate glance direction, and approximate level of eye closure; and the pertinent visual scene, whether moving forward or backward. The five camera images were multiplexed into a single image as shown in Figures 9 and 10. Note that the right-side camera and the rear camera were presented in the lower right quadrant in a split arrangement.

**Figure 9.** **Diagram of the multiplexed camera views.**

<table>
<tr><td>Driver Face and Left-Side View</td><td>Forward View<br>(68º Horizontal)</td></tr>
<tr><td rowspan="2">Over-the-Shoulder View<br>(Pinhole, 70º Diagonal)</td><td>Right-Side View<br>(55º Horizontal)</td></tr>
<tr><td>Rear View<br>(68º Horizontal)</td></tr>
</table>

**Figure 10.** **A compressed video image from the 100-Car data. The driver's face (upper left quadrant) is distorted to protect the driver's identity. The lower right quadrant is split with the left-side (top) and the rear (bottom) views.**

Digital video recording was tied to the booting/powering system and began to operate 2 min after the ignition was on. The video then continuously recorded, thereby allowing laboratory review and selection of scenes with minimal losses. The video time-stamp was used to access the corresponding digital driving performance data and plot in a synchronized manner. Data reductionists were able to access and observe both the video and associated driving performance data simultaneously, such as lateral acceleration and vehicle speed, which greatly assisted their ability to assess and record driving behaviors.

## Data Collection and Storage

To collect the data from the experimental vehicles, “chase vehicles” were used to track the vehicle, go to the location, and download data. The chase vehicle drivers called the DAS onboard the instrumented vehicle using a cellular telephone and laptop configuration, downloaded the GPS coordinates using in-house software, and then displayed a map showing icons indicating the locations of the chase and experimental vehicles. The chase vehicle driver then drove to the location of the instrumented vehicle and downloaded its data, using a data transfer cable connected to an outlet near the instrumented vehicle’s rear license plate, which was connected to a data storage device. Each chase vehicle had a laptop computer with a large hard drive to store all vehicle data. After each download from the experimental vehicles, the duplication procedure and data integrity were verified. Data were again duplicated in Northern Virginia onto DVDs. One copy was sent to VTTI, and another copy was kept in Northern Virginia.

As the data arrived at VTTI, they were downloaded to the company’s network attached storage (NAS) and saved. Afterward, quality checks were performed, and the data were then remotely deleted from the experimental vehicle’s hard drive.

Data were downloaded from each experimental vehicle once every 2 to 3 weeks. Some vehicles were more difficult to locate and were, therefore, downloaded less frequently. No vehicle operated longer than 5 weeks without someone downloading data. Given that the chase-vehicle drivers were able to access GPS coordinates via the DAS, instrumented vehicle drivers were frequently unaware that their vehicle’s data had been downloaded. Chase vehicle drivers sometimes contacted instrumented vehicle drivers who were difficult to locate to obtain the location and optimal time for downloading data. Contacting the drivers was done infrequently and only as a last resort to ensure the drivers were not reminded regularly of their participation in a driving study.

## Post-Hoc Triggering Method

A crash, near-crash, or incident involves an unexpected event requiring rapid action, such as an evasive maneuver, on the part of a driver to avoid a crash. Using the entire dataset, crashes, near-crashes, and incidents were detected by one or more of the following three methods:

### *Triggering method #1*

The first method involved flagging events in which the car's sensor information exceeded a specified value. As stated in Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006), data were collected continuously onboard the instrumented vehicles. As project resources did not allow for the review of all the data, a sensitivity analysis was conducted to establish post-hoc "triggers," which use either a single signature (e.g., any longitudinal acceleration value greater than ±0.6 g) or multiple signatures (e.g., forward TTC value ≤ 4.0 s plus a longitudinal acceleration magnitude > 0.5 g) in the driving performance data stream to identify those points in time when a driver was likely to have been involved in a crash, near-crash, or incident. See Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) for complete discussion of the sensitivity analysis. The resulting trigger criteria used are shown in Table 4.

**Table 4. Dependent variables used as event triggers.**

| Trigger Type | Description |
|---|---|
| 1. Lateral acceleration | • Lateral acceleration of magnitude 0.7 *g* or greater. |
| 2. Longitudinal acceleration | • Acceleration or deceleration of magnitude 0.6 *g* or greater<br>• Acceleration or deceleration of magnitude 0.5 *g* or greater coupled with a forward TTC of 4 s or less.<br>• All longitudinal decelerations between 0.4 *g* and 0.5 *g* coupled with a forward TTC value of 4 s or less and that the corresponding forward range value at the minimum TTC is not greater than 100 ft. |
| 3. Event button | • Activated by the driver by pressing a button located on the dashboard when an event occurred that he/she deemed critical. |
| 4. Forward Time-to-collision (TTC) | • Acceleration or deceleration of magnitude 0.5 *g* or greater coupled with a forward TTC of 4 s or less.<br>• All longitudinal decelerations between 0.4 *g* and 0.5 *g* coupled with a forward TTC value of 4 s or less and that the corresponding forward range value at the minimum TTC is not greater than 100 ft. |
| 5. Rear Time-to-collision (TTC) | • Any rear TTC trigger value of 2 s or less that also has a corresponding rear range distance of 50 ft or less and any rear TTC trigger value in which the absolute acceleration of the following vehicle is greater than 0.3 *g.* |
| 6. Yaw rate | • Any value greater than or equal to a plus and minus 4° change in heading (i.e., vehicle must return to the same general direction of travel) within a 3-second window of time. |

### *Triggering method #2*

The second method occurred when the driver pressed the incident pushbutton above the rearview mirror. Drivers were instructed to depress this button if they witnessed a safety-related traffic conflict or were involved in an accident. They were instructed to press the button after the event, not during the event.

### *Triggering method #3*

The third method transpired through data reductionists' judgment when reviewing the video events identified via triggering methods #1 and #2. Note that the video systems were operational as long as the ignition was on. In identifying events, data reductionists looked through epochs flagged from either of the first two methods and flagged additional events within the epoch if an incident was detected visually.

As expected, these three methods proved to have varying success. More than 95% of all the events were initially identified using triggering method 1 with an additional 5% identified with triggering method 2. Fewer than 1% of all events were identified using triggering method 3, which was to be expected as reductionists viewed a very small total percentage of the video collected over the course of data collection. Also, more than 50% of the events where the driver pressed the critical incident button were also triggered by method 1.

## Data Reduction

Fourteen data reductionists were hired and trained to reduce the triggered data. A data reduction manager gave each data reductionist a manual to guide him or her in learning the software and reduction procedures. All trainees practiced data reduction with another trained reductionist prior to performing the work independently. After each trainee felt comfortable with the process, he or she worked alone under the supervision of the data reduction manager. Once the trainee and manager felt confident in the new data reductionist's abilities, he or she began working independently, with "spot check" monitoring from the project leader and other reductionists. The data reductionists were responsible for analyzing a minimum number of events per week and required to attend weekly meetings to discuss lessons learned during the prior week. These meetings provided iterative and ongoing training throughout the entire process.

The validity of all triggered events was determined through video review. A crash, near-crash, or incident consistent with the definitions provided previously was considered a valid event. An invalid event was a flagged epoch in which there was no crash, near-crash, or incident. Data reductionists watched 90-second epochs for each event (60 s prior to and 30 s after) and assessed the validity of the trigger. Examples of valid events included hard braking in response to a specific crash threat, swerving around an obstacle in the roadway, or driving off the roadway. Examples of invalid events included TTC values for an object on the side of the roadway, such as a bridge abutment, as well as high lateral acceleration on curves not resulting in any loss of control, lane departure, close proximity to other vehicles, or an intentional sharp lane change into a turn lane.

To ascertain the severity of an event, data reductionists used the operational definitions of each, defined previously, as well as training with expert reductionists. Only crashes, near-crashes, and incidents were included in the current analyses. No reduction was completed on any event that was deemed to be invalid by the trained reductionists.

### *Data reduction inter- and intra-rater reliability (Phase I)*

Some of the data in the 100-Car Study included subjective judgments of video and dynamic sensor data by data reductionists. Since these data were based on subjective judgments from several different data reductionists, inter- and intra-rater reliability was a concern in this study as it has been in similar studies (e.g., Stutts et al. 2003). Inter-rater reliability refers to the degree a data reductionist's subjective judgments agreed with another data reductionist's subjective judgments on the same event; in other words, the consistency between data reductionists to score the event the same way. Intra-rater reliability refers to the degree a data reductionist's judgment for an event agreed with his or her judgment on the same event at a later time; in other words, the consistency of a data reductionist to score the event the same way each time. Generally speaking, higher reliability provides greater confidence that the data are free of errors.

Inter- and intra-rater reliability tests were conducted during the last 3 months of data reduction. Data reduction was conducted over 12 months. The following, adapted from Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006), describes the assessment of data reduction inter- and intra-rater reliability.

Three reliability tests were developed, each containing 24 events, for which each data reductionist was required to determine whether the event valid or invalid. If the reductionist determined the event was indeed valid, the event was fully reduced. Events the reductionist determined were invalid were not reduced and only included in the reliability analyses as a means of evaluating raters' judgment of event severity.

During the first reliability test, two events were also fully reduced, including severity level (i.e., crash, near-crash, or incident), driving behaviors, distractions, environmental variables, etc. Three of the test events in Test 1 were repeated in Test 2, and three other events were duplicated between Tests 2 and 3 to obtain a measure of intra-rater reliability. Based upon the judgment of the data reductionist managers, one epoch in the first test and one in the third were removed from the reliability assessment. Therefore, the first and third tests provided reductionists with 20 events for inter-rater assessment and 3 events for intra-rater assessment, and the second test provided reductionists with 18 events for inter-rater assessment and 6 for intra-rater assessment.

Using the data reductionist managers' evaluations of each epoch as a "gold standard," the proportion of agreement between the expert data reductionists and each data reductionist (also called rater) was calculated for each test. The measures for each rater for each testing period, along with a composite measure, can be found in Table 5. The average across all tests was 88.4%; in other words, 88.4% of the total scores from data reductionists agreed with the expert data reductionist. Thus, data reductionists were coding the events consistently as compared to expert data reductionists.

**Table 5. Percentage agreement with expert data reductionists for event validity judgment task.**

| Rater | Test 1 Percentage (n = 23) | Test 2 Percentage (n = 24 ) | Test 3 Percentage (n = 23 ) |
|---|---|---|---|
| 1 | 78.3 | 87.5 | 91.3 |
| 2 | 65.2 | 70.8 | 78.3 |
| 3 | 100.0 | 91.7 | 95.7 |
| 4 | 100.0 | 91.7 | 87.0 |
| 5 | 100.0 | 83.3 | 87.0 |
| 6 | 95.7 | 87.5 | 91.3 |
| 7 | 91.3 | 87.5 | 91.3 |
| 8 | 91.3 | 91.7 | 91.3 |
| 9 | 95.7 | 70.8 | 91.3 |
| 10 | 95.7 | 91.7 | 87.0 |
| 11 | 95.7 | 87.5 | 100.0 |
| 12 | 78.3 | 87.5 | 87.0 |
| 13 | 87.0 | 83.3 | 96.0 |
| 14 | 78.3 | 83.3 | 91.3 |
| **Average (across all tests)** | | | 88.4 |

The percentage agreement across raters for the full data reduction also showed acceptable reliability. During the first intra-rater reliability test (Test 2), the mean percentage agreement across raters was 67.7%, while the second intra-rater reliability test (Test 3) had a mean percentage agreement across raters of 90.5%. Overall, the mean percentage agreement across raters during the two intra-rater reliability tests was 79.1%. The low mean percentage agreement across raters during the first intra-rater reliability test was due to three raters who coded the event invalid. An event coded invalid was not reduced, and these three raters thus received 0% agreement when compared with the expert rater.

### *Data reduction inter- and intra-rater reliability (Phase II)*

For Phase II, additional data were reduced. As these data were based on subjective judgments from several different data reductionists, inter- and intra-rater reliability was a potential concern. The training method used in Phase II was identical to the training method in Phase I (previously described). The inter- and intra-rater reliability procedures during Phase II were identical to Phase I, with three tests given to the reductionists. The only difference was that each of the three reliability tests in Phase II contained 30 events as compared to 24 events in Phase I.

Again, using the data reductionist managers' evaluations of each epoch as a "gold standard," the proportion of agreement between the expert data reductionists and each data reductionist was calculated for each test. The inter-rater reliability for Tests 1, 2, and 3 were 95%, 95%, and 93%, respectively. The average across all inter-rater reliability tests was 94%. Thus, data reductionists coded events consistently as compared to expert data reductionists. The percentage agreement across raters for the full data reduction also showed acceptable reliability across two intra-rater reliability tests at 94%.

### *Data summary*

Table 6 provides a summary of the number of crashes, near-crashes, and incidents identified by the trained data reductionists. As defined previously, an event was recorded as a crash if there was physical contact with another object causing kinetic energy to be transferred or dissipated. This could include striking another vehicle resulting in airbag deployment or a high-speed tire strike, such as hitting a curb at a speed of over 30 mph.

Note that data were not collected on 13 of the total crashes for several reasons. The majority of these crashes occurred prior to system initialization (e.g., the driver backed into another vehicle just after leaving a parking spot). The next most common cause of data loss resulted from drivers tampering with cameras. There were very few sensor failures that resulted in loss of driving data.

**Table 6. The total number of events reduced for each severity level.**

| Event Severity | Total Number |
|---|---|
| Crashes | 69<br>(Plus 13 without complete data) |
| Near-Crashes | 761 |
| Incidents | 8,295 |

Given the high degree in variability among crashes, the 69 crashes were reviewed and placed into one of the following four categories:

- Category I: Police-reported, or involved air-bag deployment or injury.
- Category II: Police-reported, property damage only.
- Category III: Non-police-reported, property damage only.
- Category IV: Non-police-reported, low-g physical contact or tire strike (greater than 10 mph), no property damage.

The breakdown of crashes in each of these four categories, by crash type, is shown in Table 7.

Note that 75% of the single-vehicle crashes were low g-force physical contact or tire strikes. These types of crashes, while indicating loss of vehicular control, are not currently present in any crash database. While many researchers have hypothesized how many non-police-reported collisions occur (e.g., Knipling and Wang 1995), the 100-Car Study actually collected data on these types of crashes and included them in the following analyses. This is another powerful component to naturalistic driving data and to the 100-Car database.

**Table 7. Crash type by crash severity category.**

| Category 1 | | Category 2 | |
|---|---|---|---|
| Left Turn Against Path | 1 | Lane Change | 1 |
| Rear-End Struck | 2 | Left Turn Against Path | 1 |
| Run-Off-Road | 2 | Rear-End Struck | 2 |
| | | Rear-End Strike | 3 |
| ***Subtotal*** | ***5*** | ***Subtotal*** | ***7*** |
| **Category 3** | | **Category 4** | |
| Backing | 2 | Animal | 2 |
| Object | 3 | Backing | 2 |
| Rear-End Strike | 5 | Object | 5 |
| Rear-End Struck | 5 | Rear-End Strike | 6 |
| Run-Off-Road | 5 | Rear-End Struck | 3 |
| Sideswipe | 1 | Run-Off-Road | 18 |
| ***Subtotal*** | ***21*** | ***Subtotal*** | ***36*** |
| ***TOTAL 69*** | | | |

### *Event database for Phase I*

All crashes, near-crashes, and incidents that contained values for all driver behavior variables and driver state variables were used in Phase I. Both primary and secondary drivers were included. Driver behavior variables, such as following too closely, and driver state variables, such as driver impairment, were recorded if they occurred 5 s prior to and 1 s after the onset of an event. Reductionists recorded up to three driver behavior variables and as many driver state variables appropriate for each event.

Driving behaviors were recorded differently than driving state variables due to their inherent characteristics. Driving behaviors tend to occur in sequence; for example, excessive speed occurs first and braking hard occurs second. Driver states, such as drowsiness, for example: are either present or not. Only one driving behavior, therefore, was used, as this was primarily the first behavior in a sequence that led to a crash or near-crash. Driver state was recorded as either present or not present. Note that all driver state variables, but only the first driver behavior recorded, were considered in the Phase I analysis. A complete list of the driver behavior variables and driver state variables recorded and included in the Phase I analysis is provided in Appendix A.

### *Event database for Phase II*

All crashes and near-crashes for primary drivers that contained values for all driver behavior variables or driver state variables were used in the Phase II analysis. Only the primary drivers were included since age and gender information were only collected for primary drivers.

### *Baseline database for Phase II*

The baseline database was comprised of 20,000 6-second segments in which the vehicle maintained a velocity greater than 5 mph (referred to as an epoch). Kinematic triggers on driving performance data were not used to select these baseline epochs. Rather, they were selected at random throughout the 12- to 13-month data collection period for each vehicle. Variables such as time of day or type of roadway were not used in selecting epochs. Also, selecting by driver was not possible, so baseline epochs were randomly selected based upon vehicle identification, not driver. A supplemental analysis was conducted to determine the percentage of baseline epochs for which the primary driver was present versus a secondary driver. This analysis indicated that the primary driver was present for 88.2% of all baseline epochs.

As previously stated, driver behavior data were reduced in detail if they occurred 5 s prior to a conflict and 1 s after the onset of an event; for example: a driver had to have been speeding within 5 s prior to or 1 s after the onset of the event for speeding to have been considered a contributing factor to the event. Baseline epochs, therefore, were also 6 s in duration. Again reductionists recorded up to three driver behavior variables and all driver state variables applicable for each baseline epoch. For these analyses, only the most pertinent driver behavior was used (e.g., one driver behavior per baseline epoch), whereas each driver state variable was coded as observed or not observed.

While each baseline epoch was randomly selected, the number of baseline epochs per vehicle was proportional based upon vehicle involvement in events. This proportional sample was conducted to create a case-control dataset in which multiple baseline epochs were compared to each event. Each of these elements was analyzed as if it was completely independent.

Case-control designs are optimal for calculating odds ratios, which provide good approximations of relative risks when the probability of event occurrence is low, due to the increased power a case-control dataset possesses. Greenberg, Daniels, Flanders, Eley, and Boring (2001) argue that using a case-control design is an efficient means to study rare events, such as automobile crashes. The causal relationships that exist for these events can also be evaluated using relatively smaller sample sizes than are used in typical crash database analyses where thousands of crashes may be used.

Four vehicles were not involved in any events, and were, therefore, eliminated from the baseline database. The reasons that the four vehicles did not contain any of these events included very low mileage due to driver attrition (2 vehicles), frequent mechanical malfunctions (1 vehicle), and a possibility of excellent driver performance (1 vehicle). Future efforts are required to determine whether excellent driving performance or an unknown mechanical failure resulted in no triggered events in the last of these four vehicles.

After the baseline epochs were selected, data reductionists were trained to identify each driving behavior. This training included operational definitions of each driving behavior to use as a guide, video examples of each risky driving behavior, and common mistakes to avoid when coding the driving behaviors. While many of these behaviors, such as cutting in too closely, require subjective judgment, the reductionists worked with each other to ensure that all of them made similar judgments. After training, data reductionists began to reduce the 6-second baseline epochs and were instructed to code all of the driving behaviors that occurred during that epoch. Thus, more than one driving behavior could be coded for each baseline epoch (identical to the procedures used in Phase I).

## Analyses

All data analyses in this report are based on reduced data resulting from the data reduction process. These data were copied, created, or edited into a MySQL™ database and linked using identification codes, such as vehicle or epoch identification numbers. This database made it possible to investigate the relationship between various driving behaviors and crashes, near-crashes, incidents, and baseline epochs.

# RESULTS

The primary goals of this project included:

1. Determining the frequency with which drivers engage in potentially risky driving behaviors;
2. Determining the relationship between specific driving behaviors and crashes, near-crashes, and incidents;
3. Determining the relationship among the driving behaviors; and
4. Determining the differences between high- and low-risk drivers.

## Phase I Results

The following analyses were conducted in Phase I:

1. The frequency of driving behaviors was determined in the Phase I dataset.
2. Chi-Square analyses were conducted on the frequency data between the severity levels as follows: crashes and near-crashes vs. incidents, and incidents versus baseline epochs.

### *Frequency of driving behaviors (Phase I)*

The master list of behaviors considered for these analyses is shown in Appendix A, and includes operational definitions for each. Given that all behaviors were determined based upon review of driver videos, the master list of behaviors was broadly categorized into two groups: driver state, such as drowsy or aggressive driving, and driver behavior. Driving states are behaviors that are more ubiquitous in nature. Driver behaviors are risky behaviors that occur at particular moments in time. These categorizations are summarized here.

The driver state risk categories refer to a driver's emotional, perceptual, or mental state, which may adversely affect driving performance, reaction time, and general safety, including:

- Driver Impairment: included all the mental and emotional variables such as drowsiness or anger.

- Willful behavior: included all the variables that described repeated intentional driving behaviors performed by the driver, such as aggressive driving or intimidation and purposeful violation of traffic laws.

- Total Time Eyes Off the Forward Roadway (EOR): operationally defined as EOR time in which the length of one single glance or the sum of multiple glances within 6 s is equal to the Total Time EOR. This variable was used as an indicator to replace each individual distraction type, such as talking on the cell phone, reaching for an object, and combing or fixing hair. This technique prevents the data from being diluted while maintaining statistical power. In other words, all distraction-related tasks were grouped under the category of total time EOR. In a separate analysis of 100-Car data, Klauer, Dingus, Neale, Sudweeks, and Ramsey (2006) found that if the total time EOR was greater than 2 s, relative crash risk increased to greater than two times that of normal driving. This should not be interpreted as implying that some secondary tasks are not more dangerous than others, only that for the purposes of this study, secondary tasks were grouped according to the amount of time for which the driver's visual attention was diverted from the forward roadway.

Table 8 shows the frequency of events in the Phase I dataset by severity levels for the Driver State risk categories.

**Table 8. Frequency of events where Impairment, Willful Behavior, and EOR Driver State were observed.**

| Driver State Risk Category | Specific Driving Behavior | Crashes and Near-crashes N = 476 (% of Total) | Incidents N = 5,796 (% of Total) |
|---|---|---|---|
| Impairment | Fatigue | 85 (17.9%) | 517 (8.9%) |
| | Angry | 12 (2.5%) | 31 (0.5%) |
| | Other emotional state | 4 (0.08%) | 16 (0.2%) |
| | Drugs/alcohol | 0 (0%) | 2 (0.03%) |
| | No impairment | 375 (78.8%) | 5,230 (90.2%) |
| Willful Behavior | Aggressive driving/ intimidation | 91 (19.1%) | 687 (11.9%) |
| | No willful behavior | 385 (80.1%) | 5,109 (88.1%) |
| Total Time EOR | Total time eyes are off the forward roadway >2 s | 138 (29.0%) | 1,318 (22.7%) |
| | Total time eyes are off the forward roadway ≤2 s | 338 (71.0%) | 4,478 (77.3) |

Figure 11 displays the percentage of crashes or near-crashes and incidents where one of these driving state behaviors was a contributing factor. Note that each of these driver states is more prevalent in crashes and near-crashes than in incidents. This finding will be discussed more fully in subsequent analyses.

Table 9 displays the frequency of events by severity level for the Driving Behavior risk categories, which refer to observable driving behaviors while driving an instrumented vehicle. The Driving Behavior categories include specific behaviors such as exceeding the speed limit, passing on the right, and not wearing a safety belt.

As shown in Table 9, many Driving Behavior risk categories were similar and grouped accordingly.

**Figure 11.** **Percentage of crashes or near-crashes (N = 476) and incidents (N = 5,796) where Driver States were present.**

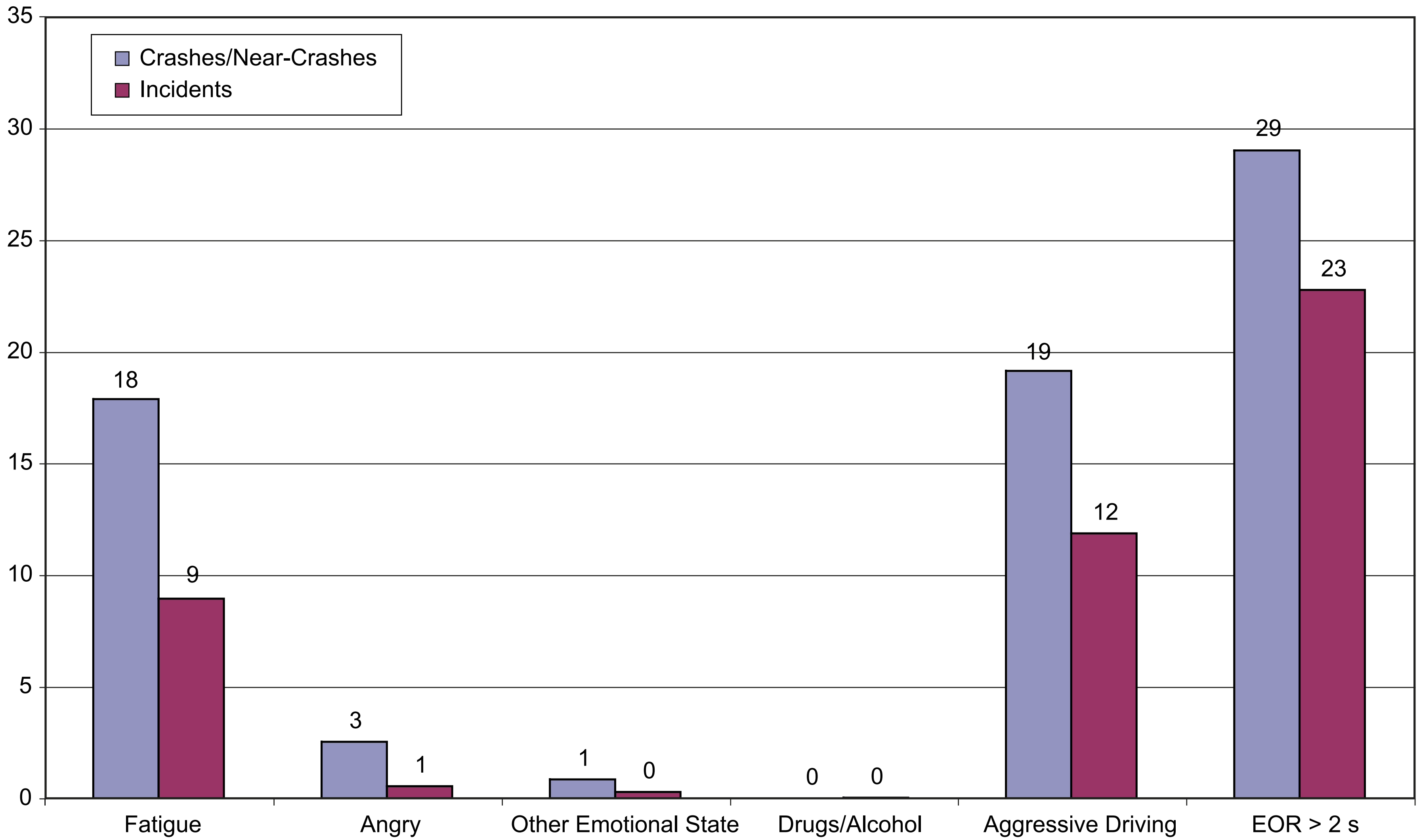


**Table 9. Frequency of events where Driving Behaviors were present.**

| General Driving Behavior | Specific Driving Behavior | Crashes/ Near Crashes | Inci-dents | Crashes/ Near crashes N = 476 (% of Total) | Incidents N = 5,796 (% of Total) |
|---|---|---|---|---|---|
| Inappropriate Avoidance Maneuver | Avoiding animal | 5 | 22 | 58 (12.2%) | 432 (7.5%) |
| | Avoiding other vehicle | 50 | 382 | | |
| | Avoiding pedestrian | 3 | 28 | | |
| Inappropriate speed | Driving slowly in relation to other traffic not below speed limit | 0 | 2 | 35 (7.4%) | 256 (4.4%) |
| | Driving slowly below speed limit | 1 | 3 | | |
| | Exceeded safe speed but not speed limit | 16 | 154 | | |
| | Exceeded speed limit | 17 | 95 | | |
| | Speeding or other unsafe actions in work zone | 1 | 2 | | |
| Improper passing/ Lane Change | Passing on right | 9 | 54 | 57 (12.0%) | 352 (6.1%) |
| | Other improper or unsafe passing | 10 | 127 | | |
| | Illegal passing | 2 | 86 | | |
| | Did not see other vehicle during lane change or merge | 35 | 59 | | |
| | Driving in other vehicle's blind spot | 1 | 1 | | |
| | Wrong Side of Road, Overtaking | 0 | 25 | | |
| Traffic control device violation | Right-of-way error decision failure | 3 | 6 | 8 (1.7%) | 34 (0.6%) |
| | Right-of-way error recognition failure | 1 | 6 | | |
| | Right-of-way error unknown cause | 0 | 4 | | |
| | Signal violation did not see | 1 | 2 | | |
| | Signal violation intentional | 1 | 3 | | |
| | Signal violation tried to beat signal change | 1 | 2 | | |
| | Stop sign violation did not see | 0 | 1 | | |
| | Stop sign violation intentional and at speed | 0 | 3 | | |
| | Stop sign violation rolling stop | 1 | 4 | | |
| | Other sign violation did not see | 0 | 1 | | |
| | Other sign violation intentional | 0 | 2 | | |
| | Other sign violation | 0 | 0 | | |
| Improper braking | Sudden or improper braking | 188 | 2,776 | 233 (48.9%) | 3,226 (55.7%) |
| | Sudden or improper stopping on roadway | 45 | 450 | | |
| | Cruise control contributed to late braking | 0 | 0 | | |
| Close Proximity to Vehicle | Following too close | 24 | 372 | 49 (10.3%) | 706 (12.2%) |
| | Cutting in too close behind other vehicle | 10 | 82 | | |
| | Cutting in too close in front of other vehicle | 15 | 252 | | |
| No driving behavior | No Behavior | 36 | 790 | 36 (7.6%) | 790 (13.6%) |
| Safety Belt | None Used | 104 | 956 | 104 (21.8%) | 956 (16.5%) |
| | Lap/shoulder belt, lap only | 372 | 4,840 | 372 (78.2%) | 4,840 (83.5%) |

The three specific driving behaviors of avoiding an animal, other vehicle, or pedestrian, for example: all refer to the driver performing an inappropriate maneuver to avoid something in the roadway, and were, therefore, grouped into "inappropriate avoidance maneuver." Examples of this include a driver swerving into oncoming traffic to avoid an obstacle in the roadway. The appropriate maneuver would be to either slow or stop until traffic had cleared before maneuvering around the object.

Some events could not be coded accurately and, therefore, had to be eliminated from the analysis. Safety belt use, for example, could not always be detected via video due to lighting issues or camera angles. Similarly, assessing whether a driver was under the influence of drugs or alcohol was difficult unless the driver was actually observed consuming alcohol or using drugs on-camera during video reduction, thus, this and other such infrequently-observed behavior types (e.g., other emotional state) were eliminated due to low statistical power. Thus by eliminating those events that could not be coded accurately or were very infrequent reduced the number of crashes and near-crashes to 660 (170 crashes and near-crashes were removed) and incidents to 6,870 (1,425 incidents were removed).

Figure 12 displays the percentage of driving behaviors that occurred during crashes or near-crashes and during incidents.

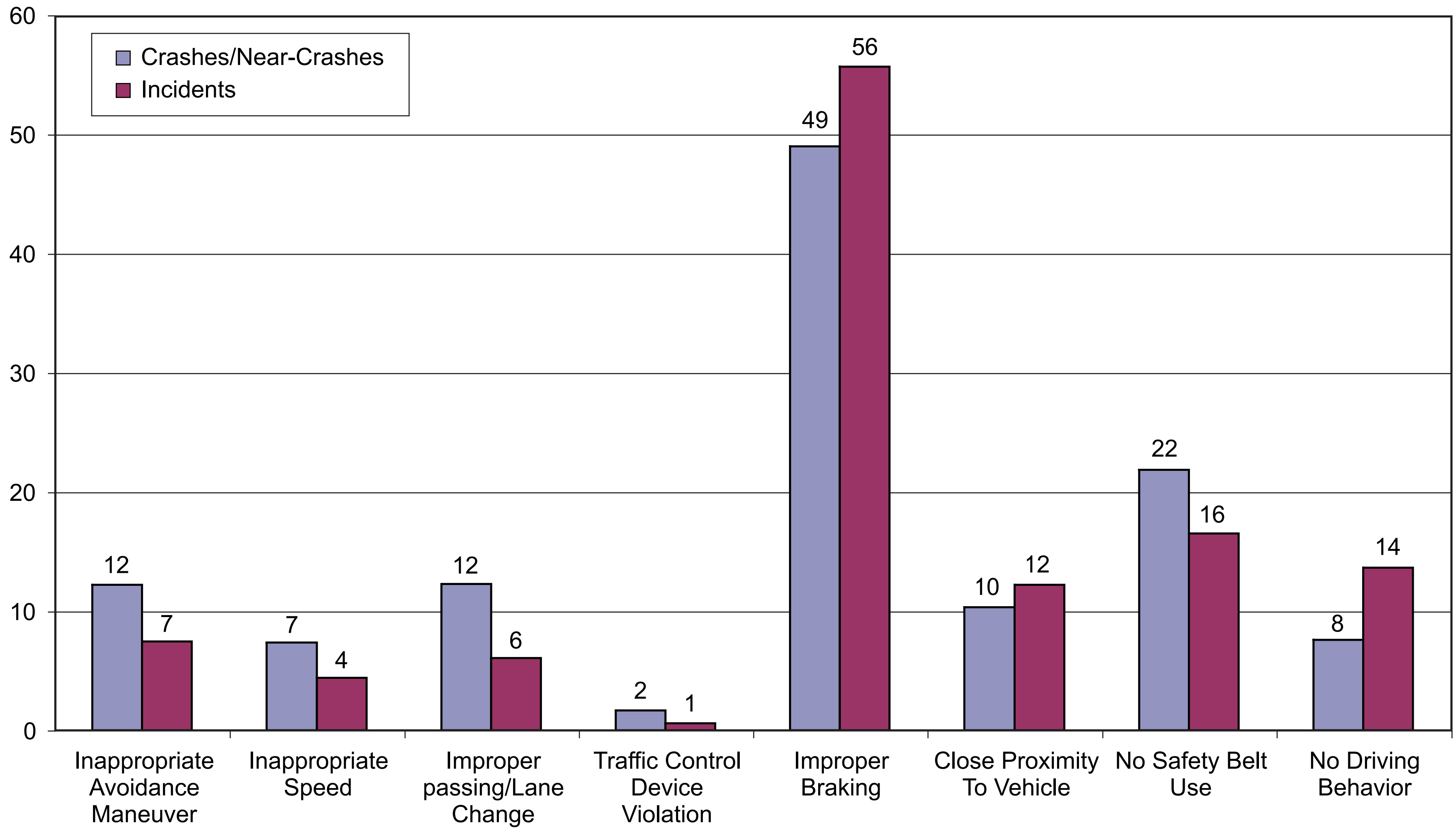
Note that most of the driving behaviors are present in a higher percentage of crashes and near-crashes than incidents except for Close Proximity to other Vehicle. This result will be discussed in more depth in the following analyses.

## Event Definition

Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) found that crashes and near-crashes are kinematically similar to one another, but kinematically different from incidents. In other words, crashes and near-crashes contained similar levels of hard braking and swerving whereas the incident data did not reach those same levels. Given this result and the need to increase statistical power, the data from both crashes and near-crashes were combined to estimate relative risk in Phase II analyses.

The current analyses investigated the relationship between potentially risky driving behaviors and crashes, near-crashes, and incidents. For this reason, determining

**Figure 12.** **Percentage of crashes and near-crashes (N = 476) and incidents (N = 5,796) where Driving Behaviors were present.**



whether these behaviors occur at the same frequency for crashes and near-crashes as for incidents and baseline epochs was necessary. If a difference is shown between the three categories, incidents cannot be considered predictive of crashes or be used in the Phase II analyses.

## Crash/Near-Crash vs. Incident Chi-Square Analyses

Evaluating both Driver State and Overt Driving Behavior risk categories, analyses were performed to determine whether differences existed between the frequency of individual behaviors occurring during crashes or near-crashes versus incidents.

### *Impairment risk category*

A Fisher's Exact Test found significant differences in the frequency of specific driving behaviors between crashes and near-crashes and incidents in the Impairment risk category ($p < 0.0001$). This test does not allow inferences to be made about which specific driving behaviors in the Impairment risk category were different. Adjusted standardized residuals, derived from a Chi-Square test, allow such inferences to be made. To interpret, adjusted standardized residual values ≥ 2 or ≤ -2 indicate that a certain event is more or less likely than expected.

As drowsiness was of particular interest, a Chi-Square test was performed. The test found a significant difference in the frequency of crashes and near-crashes versus incidents where driver drowsiness was a contributing factor ($X^2_{(1)} = 24.35$, $p < 0.0001$). The adjusted standardized residuals indicated drivers were more likely to be driving drowsy during a crash or near-crash than during an incident.

### *Willful Behavior/Aggressive Driving risk category*

The Chi-Square test found a significant difference in the frequency of willful behaviors contributing to crashes and near-crashes versus incidents ($X^2_{(1)} = 6.43$, $p < 0.05$). The adjusted standardized residuals indicated that drivers were more likely to be driving aggressively during a crash or near-crash than during an incident.

### *Total Time EOR risk category*

The Chi-Square test did not find a significant difference for total time EOR greater than 2 s prior to crashes or near-crashes as compared to incidents.

### *Driving Behavior risk category*

For the Driver Behavior risk category, safety belt use was analyzed separately, since it does not reflect an actual behavior with respect to the vehicle. It may reflect general attitudes toward safe driving, however.

For the driver behaviors excluding safety belt use, the Chi-Square test found a significant difference between frequency of occurrence during crashes and near-crashes as compared to incidents ($X^2_{(6)} = 51.0$, $p < 0.0001$). The adjusted standardized residuals indicated that drivers were more likely to engage in inappropriate avoidance maneuvers, drive at inappropriate speeds, commit traffic-signal violations, and brake inappropriately prior to crashes and near-crashes than prior to incidents. Conversely, drivers were more likely to be following too closely just prior to an incident than just prior to a crash or near-crash.

The Chi-Square test did not find a significant difference in the frequency of safety belt use during crashes and near-crashes relative to during incidents ($X^2_{(1)} = 2.31$, $p > 0.05$).

## Summary of Crash/Near-Crash vs. Incident Chi-Square Analyses

The results of the Chi-Square tests showed that many of the driving behaviors were more likely to occur during crashes and near-crashes than during incidents. Drivers involved in a crash or near-crash, for example: were more likely to be drowsy, drive aggressively, engage in inappropriate avoidance maneuvers, drive at inappropriate speeds, commit traffic-signal violations, or brake inappropriately than when involved in an incident. Drivers involved in a crash or near-crash, were less likely, however, to be following too closely (proximity conflict) during a crash or near-crash than during an incident. Although this result may seem counterintuitive, this is most likely an artifact of the heavily congested traffic conditions in and around the Washington, DC area. While following too closely should not be advocated as a safe driving behavior, drivers learning to be more alert and responsive to these dynamic traffic environments may have contributed to this result. Other possible explanations for this unlikely finding are discussed in the Summary of Phase II Results.

These results indicate that crashes and near-crashes should be viewed separately from incidents. Events in Phase II thus consist of crashes and near-crashes, but not incidents; however, incidents and baseline epochs may not significantly differ from each other.

Rather than excluding incidents from further analyses, they were compared to baseline epochs. If the behaviors associated with incidents were found not to differ from those associated with baseline epochs, then incidents could be combined with baseline epochs in Phase II analyses. If the behaviors associated with incidents and baseline epochs were found to be significantly different, however, incidents would be excluded from further analyses.

## Incident vs. Baseline Epoch Chi-Square Analyses

Because several variables are being considered for modeling, EOR time was used as a surrogate to replace each individual distraction type. This technique prevents the data from being diluted while maintaining statistical power. In other words, all distraction-related tasks were grouped according to the amount of time for which the driver's eyes were directed away from the forward roadway. To assess EOR, trained reductionists performed eye-glance analysis on 4,977 randomly selected baseline epochs, primarily because project resources permitted eye-glance reduction, a highly time-intensive process, for only 4,977 of the baseline epochs. Table 10 shows the frequency of specific driving behaviors in the Driver State risk categories during incidents and the 4,977 baseline epochs.

**Table 10. Frequency of incidents and baseline epochs where Impairment, Willful Behavior, and EOR Driver State were observed.**

| Driver State Risk Category | Specific Driving Behavior | Incidents (N = 2,538) N (% of Total) | Baseline Epochs (N = 4,033) N (% of Total) |
|---|---|---|---|
| Impairment | Fatigue | 239 (9.4%) | 174 (4.3%) |
| | No impairment | 2,299 (90.6%) | 3,859 (95.7%) |
| Willful Behavior | Aggressive driving/intimidation | 551 (21.7%) | 120 (3.0%) |
| | No willful behavior | 1,987 (78.3%) | 3,913 (97.0%) |
| Total Time EOR | Total time EOR > 2 s | 878 (34.6%) | 569 (14.1%) |
| | Total time EOR ≤2 s | 1,660 (65.4%) | 3,464 (85.9%) |

It was determined during the review of events that Improper Braking could not be used as a variable in the model. Braking is usually an appropriate behavior based on a driver's response to his or her driving environment, and while the brake force may have been high, the end result was avoiding a collision. Improper Braking was, therefore, removed from the analysis. Furthermore, Angry, Other Emotional State, and Drugs/Alcohol in the Impairment risk category were not assessed because they were not observed during baseline epochs. Note that drivers may have been impaired by alcohol or drugs during baseline epochs, incidents, near-crashes, or crashes; however, the study design employed here would not have allowed such impairment to be determined unless the driver was actually observed, via the in-vehicle camera, consuming alcohol or using drugs. Removing these variables reduced the total frequency of incidents to 3,611 and baseline epochs to 4,033. Figure 13 displays the percentage of incidents and baseline epochs during which each of the driver states were observed. Note again that each of these driver states is present in a higher percentage of incidents than in baseline epochs.

**Figure 13. Percentage of incidents (N = 2,538) and baseline epochs (N = 4,033) where Driver States were present.**

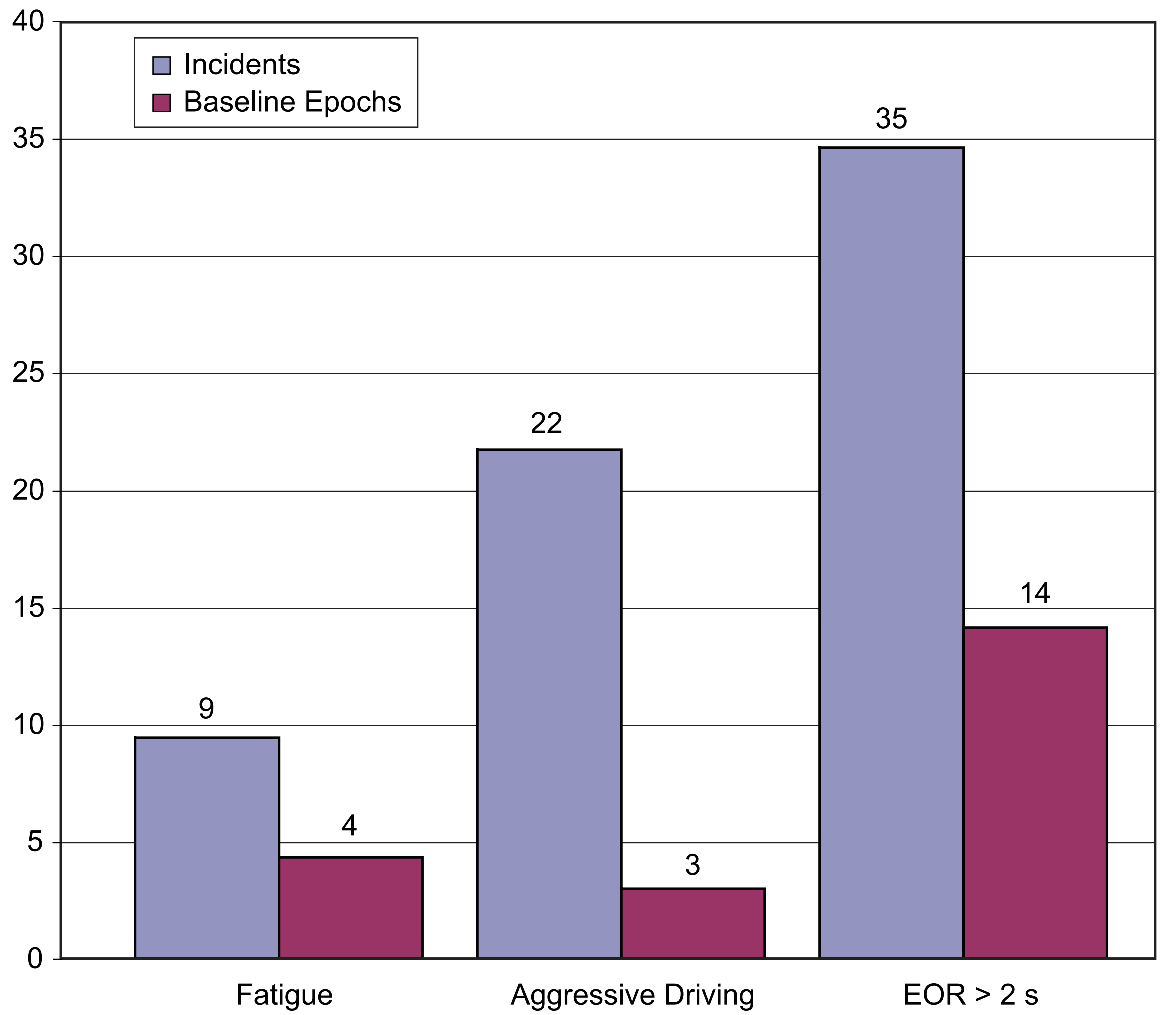


Table 11 shows the frequency of general driving behaviors in the Driving Behavior risk categories during the incidents and baseline epochs.

**Table 11. Frequency of incidents and baseline epochs where Driving Behaviors were present.**

| General Driving Behavior | Specific Driving Behavior | Inci-dents | Baseline Epochs | Incidents (N=2,538) N (% of Total) | Baseline Epochs (N=4,033) N (% of Total) |
|---|---|---|---|---|---|
| Inappropriate Avoidance Maneuver | Avoiding animal | 22 | 0 | 426 (16.8%) | 4 (0.1%) |
| | Avoiding other vehicle | 377 | 2 | | |
| | Avoiding pedestrian | 27 | 2 | | |
| Inappropriate speed | Driving slowly in relation to other traffic not below speed limit | 2 | 1 | 252 (9.9%) | 105 (2.6%) |
| | Driving slowly below speed limit | 3 | 0 | | |
| | Exceeded safe speed but not speed limit | 151 | 50 | | |
| | Exceeded speed limit | 94 | 54 | | |
| | Speeding or other unsafe actions in work zone | 2 | 0 | | |
| Improper passing | Passing on right | 53 | 2 | 346 (13.6%) | 5 (0.1%) |
| | Other improper or unsafe passing | 124 | 1 | | |
| | Illegal passing | 85 | 1 | | |
| | Did not see other vehicle during lane change or merge | 58 | 0 | | |
| | Driving in other vehicle’s blind spot | 1 | 0 | | |
| | Wrong side of road, not overtaking | 25 | 1 | | |

| | | | | | |
|---|---|---|---|---|---|
| Traffic control device violation | Right-of-way error decision failure | 6 | 0 | 31 (1.2%) | 52 (1.3%) |
| | Right-of-way error recognition failure | 5 | 0 | | |
| | Right-of-way error unknown cause | 4 | 0 | | |
| | Signal violation did not see | 2 | 0 | | |
| | Signal violation intentional | 3 | 0 | | |
| | Signal violation tried to beat signal change | 2 | 0 | | |
| | Stop-sign violation did not see | 1 | 1 | | |
| | Stop-sign violation intentional and at speed | 2 | 14 | | |
| | Stop-sign violation rolling stop | 3 | 37 | | |
| | Other sign violation did not see | 1 | 0 | | |
| | Other sign violation intentional | 2 | 0 | | |
| | Other sign violation | 0 | | | |
| Close proximity to Vehicle | Following too close | 366 | 781 | 696 (27.4%) | 786 (19.5%) |
| | Cutting in too close behind other vehicle | 81 | 5 | | |
| | Cutting in too close in front of other vehicle | 249 | 0 | | |
| No driving behavior | None Used | 787 | 3,081 | 787 (31.0%) | 3,081 (76.4%) |
| Safety Belt | Lap/shoulder belt, lap only | 545 | 493 | 545 (21.5%) | 493 (12.0%) |
| | No Belt Used | 3,066 | 3,540 | 1,993 (78.5%) | 3,540 (88.0%) |

**Figure 14.** Percentage of incidents (N = 2,538) and baseline epochs (N = 4,033) where Driving Behaviors were present.

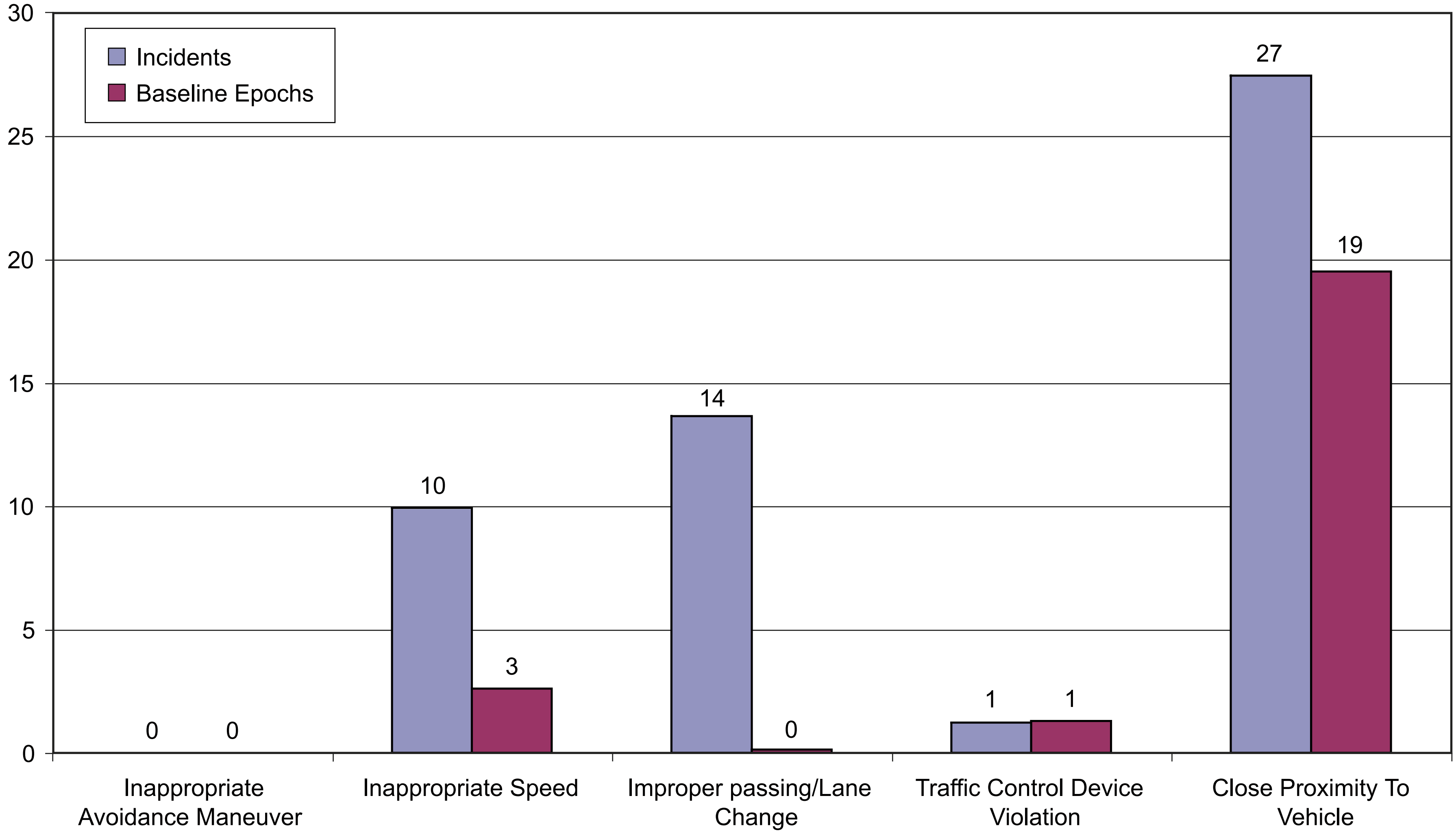


Figure 14 displays the percentage of driving behaviors that occurred during incidents and baseline epochs.

Evaluating both Driver State and Driver Behavior risk variables, Chi-Square analyses were performed to determine whether a difference exists in the frequency of occurrence of individual behaviors during incidents and baseline epochs. The results of these tests are described herein.

### *Impairment risk category*

The Chi-Square test found a significant difference in the frequency of impaired driving between incidents and baseline epochs ($X^2_{(1)} = 19.8$, $p < 0.0001$). The adjusted standardized residuals indicated that drivers were more likely to be driving while drowsy during an incident than during a baseline epoch.

### *Willful Behavior risk category*

The Chi-Square test found a significant difference in the frequency of drivers engaging in willful behaviors between incidents and baseline epochs ($X^2_{(1)} = 358.9$, $p < 0.0001$). The adjusted standardized residuals indicated drivers were more likely to be driving aggressively during an incident than during a baseline epoch.

### *Total Time EOR risk category*

The Chi-Square test found a significant difference in the frequency of drivers' total time EOR between incidents and baseline epochs ($X^2_{(1)} = 129.3$, $p < 0.0001$). The adjusted standardized residuals indicated that drivers were more likely to be looking away from the forward roadway for >2 s prior to an incident than during a baseline epoch.

### *Driving Behavior risk category*

The Chi-Square test found a significant difference in the frequency of specific driving behaviors, again excluding safety belt use, between crashes and near-crashes and baseline epochs ($X^2_{(5)} = 1{,}559.0$, $p < 0.0001$). The adjusted standardized residuals indicated five differences in the frequency of general driving behaviors between incidents and baseline epochs. Drivers were more likely to be engaging in inappropriate avoidance maneuvers, driving at inappropriate speeds, and engaging in improper passing maneuvers during an incident than during a baseline epoch. Drivers were less likely to be following too closely during an incident than during a baseline epoch.

### *Safety Belt risk category*

The Chi-Square test found a significant difference in the frequency of safety belt use for drivers involved in incidents versus drivers' baseline epochs ($X^2_{(1)} = 13.4$, $p < 0.0003$). The adjusted standardized residuals indicated that drivers were more likely to be driving without their safety belts when involved in an incident than during normal, baseline driving.

## Summary of Incident vs. Baseline Epoch Chi-Square Analyses

The results of these Chi-Square tests clearly show that incidents were significantly different from baseline epochs. Drivers involved in an incident were more likely to be drowsy, drive aggressively, look away from the forward roadway for >2 s, avoid an object, speed, perform improper passing maneuvers, and not wear their safety belts. Interestingly, Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) was unable to differentiate incidents from baseline epochs using kinematic signatures (i.e., lateral/longitudinal accelerometers, TTC, etc.). Nonetheless, the present analysis was able to distinguish between incidents and baseline epochs by assessing observable driver behavior.

Drivers were more likely to be following too closely during normal, baseline driving than prior to incidents, which once again seems counterintuitive. Nonetheless, this provides more evidence for the earlier hypothesis that following too closely occurs frequently during normal, baseline driving because of the normally heavy traffic conditions in and around the Washington, DC area.

While incidents were significantly different from crashes and near-crashes, they were also significantly different from baseline epochs. While this is certainly an interesting result that may lend itself to future study, it indicates that incidents are not predictive of crashes. This result is congruent with those reported in Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006). Thus, incidents were not included as events or non-events in Phase II and will be excluded from subsequent analyses.

## Phase II Results

Phase II results are provided for the following four separate analyses:

1. Comparison of the frequency of behaviors in crashes and near-crashes to that in the baseline epochs
2. Identification of main effects of specific driving behaviors via logistic regression modeling
3. Identification of interactions between different driving behaviors via logistic regression modeling
4. Comparison of risky driving behavior engagement by high- vs. low-risk drivers

### *Frequency of driving behaviors (Phase II)*

For Phase II, risky driving behaviors were grouped in the same manner as for Phase I.

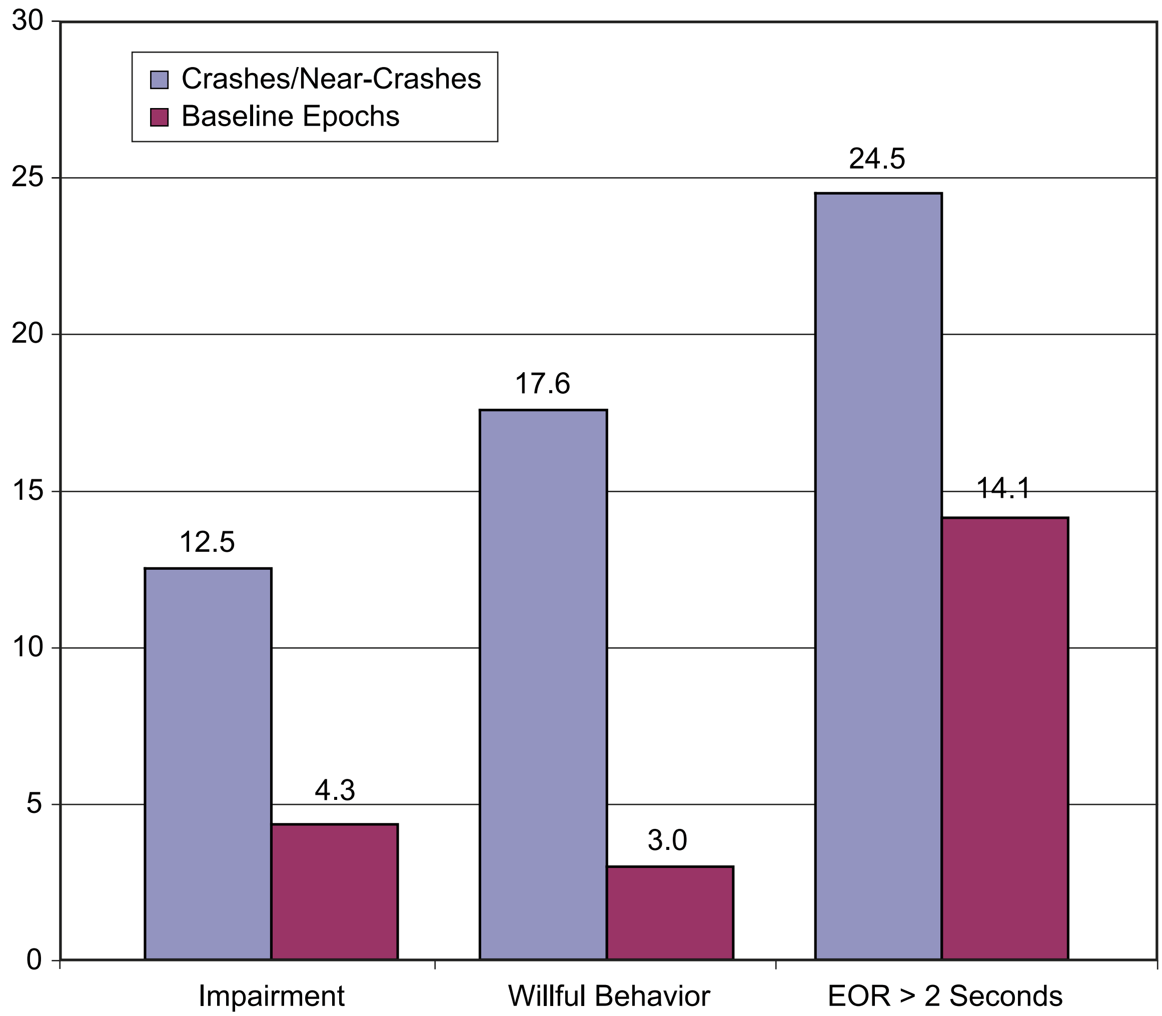
Table 12 displays the frequency of crashes and near-crashes and baseline epochs in the Driver State categories of Impairment, Willful Behavior, and Total Time EOR.

**Table 12. Frequency of crashes/near-crashes and baseline epochs where Impairment, Willful Behavior, and EOR > 2 seconds were present.**

| Driver State Category | Specific Driving Behavior | Crashes and Near-Crashes (N = 376) N (% of Total) | Baseline Epochs (N = 4,033) N (% of Total) |
|---|---|---|---|
| Impairment | Drowsiness | 47 (12.5%) | 174 (4.3%) |
| | No impairment | 329 (87.5%) | 3,859 (95.7%) |
| Willful Behavior | Aggressive driving/intimidation | 66 (17.6%) | 120 (3.0%) |
| | No willful behavior | 310 (82.4%) | 3,913 (97.0%) |
| Total Time EOR | Total time EOR > 2 s | 92 (24.5%) | 569 (14.1%) |
| | Total time EOR ≤ 2 s | 284 (75.5%) | 3,464 (85.9%) |

Figure 15 shows the percentage of baseline epochs, and crashes and near-crashes, in which the various driver states were observed, in the Phase II dataset.

**Figure 15. Percentage of crashes and near-crashes (N = 376) and baseline epochs (N = 4,033) where Driver States were present.**




Note that drowsiness, aggressive driving, and total time EOR are all present in a higher percentage of crashes and near-crashes than in baseline epochs. These relationships will be discussed more in-depth in the odds ratio discussion.

Table 13 displays the frequency of crashes and near-crashes and baseline epochs in which specific behaviors were observed.

As in Phase I, Improper Braking could not be used as a variable in the model because braking is usually an appropriate behavior based on a driver's response to his or her driving environment, and while the brake force may have been high, the end result was avoiding a collision. “Improper Braking,” therefore, was removed from the analysis.

**Table 13. Frequency of crashes/near-crashes and baseline epochs where Driving Behaviors were present.**

<table>
<tr><th>General Driving Behavior</th><th>Specific Driving Behavior</th><th>Crashes/ Near crashes (N = 376) N (% of Total)</th><th>Baseline Epoch (N = 4,033) N (% of Total)</th></tr>
<tr><td rowspan="3">Inappropriate Avoidance</td><td>Avoiding animal</td><td rowspan="3">13 (3.5%)</td><td rowspan="3">4 (0.10%)</td></tr>
<tr><td>Avoiding other vehicle</td></tr>
<tr><td>Avoiding pedestrian</td></tr>
<tr><td rowspan="5">Inappropriate speed</td><td>Driving slowly in relation to other traffic not below speed limit</td><td rowspan="5">33 (8.8%)</td><td rowspan="5">105 (2.6%)</td></tr>
<tr><td>Driving slowly below speed limit</td></tr>
<tr><td>Exceeded safe speed but not speed limit</td></tr>
<tr><td>Exceeded speed limit</td></tr>
<tr><td>Speeding or other unsafe actions in work zone</td></tr>
<tr><td rowspan="3">Improper passing</td><td>Passing on right</td><td rowspan="3">70 (18.6%)</td><td rowspan="3">10 (0.25%)</td></tr>
<tr><td>Other improper or unsafe passing</td></tr>
<tr><td>Illegal passing</td></tr>
<tr><td rowspan="12">Traffic control device violation</td><td>Right-of-way error decision failure</td><td rowspan="12">8 (2.1%)</td><td rowspan="12">52 (1.3%)</td></tr>
<tr><td>Right-of-way error recognition failure</td></tr>
<tr><td>Right-of-way error unknown cause</td></tr>
<tr><td>Signal violation did not see</td></tr>
<tr><td>Signal violation intentional</td></tr>
<tr><td>Signal violation tried to beat signal change</td></tr>
<tr><td>Stop sign violation did not see</td></tr>
<tr><td>Stop sign violation intentional and at speed</td></tr>
<tr><td>Stop sign violation rolling stop</td></tr>
<tr><td>Other sign violation did not see</td></tr>
<tr><td>Other sign violation intentional</td></tr>
<tr><td>Other sign violation</td></tr>
<tr><td rowspan="3">Close proximity to other vehicle</td><td>Cutting in too close behind other vehicle</td><td rowspan="3">22 (5.9%)</td><td rowspan="3">781 (19.4%)</td></tr>
<tr><td>Cutting in too close in front of other vehicle</td></tr>
<tr><td>Following too close</td></tr>
<tr><td>No Seat Belt Use</td><td></td><td>58 (15.4%)</td><td>493 (12.2%)</td></tr>
<tr><td>No driving behavior</td><td></td><td>172 (45.7%)</td><td>2,588 (64.2%)</td></tr>
</table>

**Figure 16. Percentage of crashes and near-crashes (N = 376) and baseline epochs (N = 4,033) where Driving Behaviors were present.**

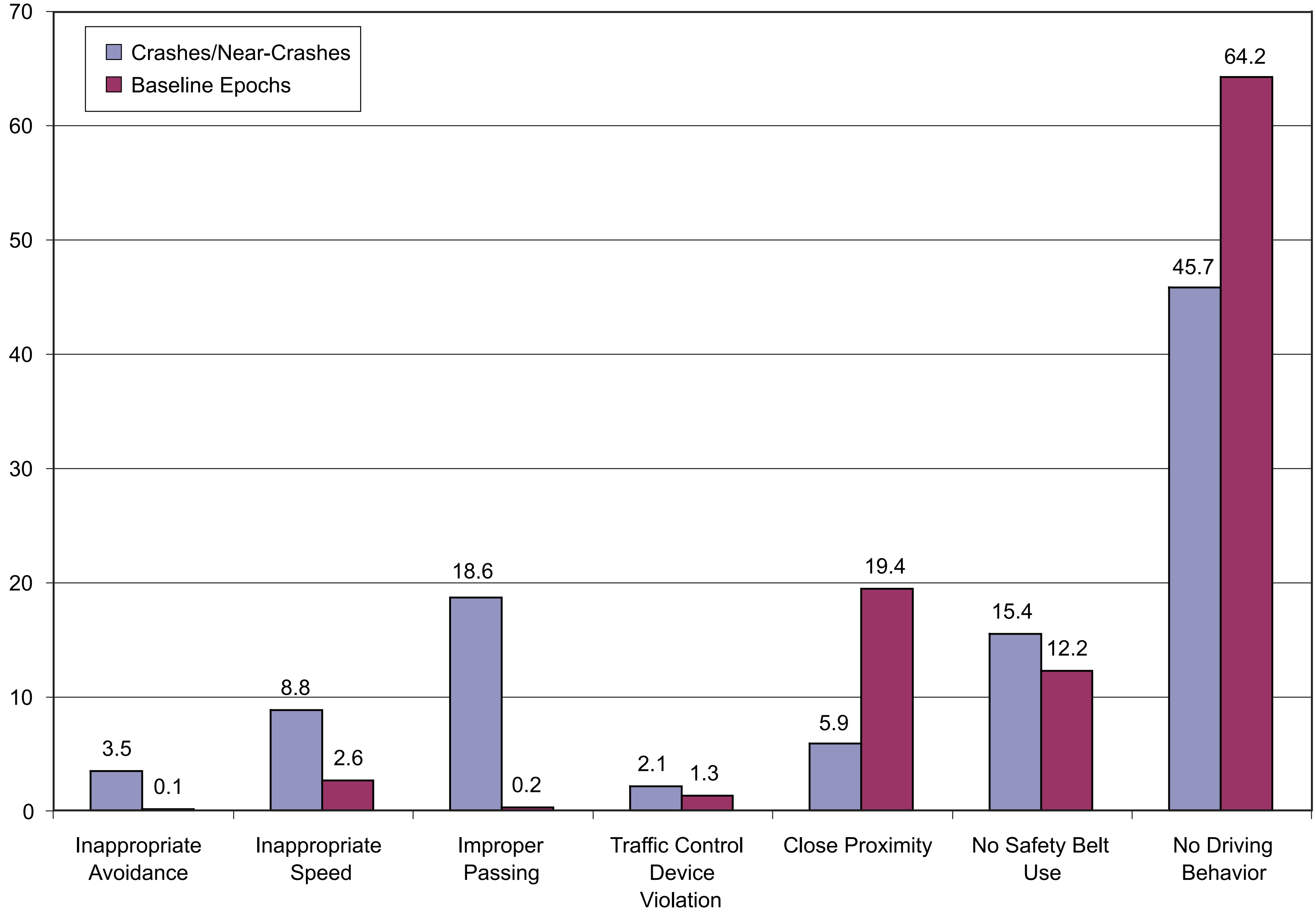


Figure 16 shows the percentage of crashes and near crashes, and baseline epochs, during which specific driving behaviors were observed, in the Phase II dataset.

Note that each driving behavior was present in a higher percentage of crashes and near-crashes than in baseline epochs except for close proximity to other vehicles. Again, these relationships will be discussed in more detail in the odds ratio section of this report.

### *Modeling strategy (Phase II)*

The primary goal of this analysis was to determine whether engaging in specific driving behavior could predict crashes and near-crashes. There was also interest in investigating interactions between various behaviors and the impacts on crash risk of these interactions. The goal of the modeling process was to arrive at a parsimonious model that adequately fit the data.

Several attempts were made to model the interactions present. While some efforts were more successful than others, several limitations continually produced insurmountable problems. First, several behavioral categories did not have enough data present for both crashes and near-crashes or for baseline epochs to statistically model (e.g., inappropriate avoidance). Second, the modeling strategy used required complete data for each crash, near-crash, and baseline epoch included in the model. In other words, if a given crash contained a missing value for one or more of the variables present in the model (e.g., safety belt use), then that crash was excluded by necessity. Thus, using multiple types of behaviors in the model ultimately led to the removal of 46% of the crashes and near-crashes due to variables with missing values, and the analysis was conducted using only the remaining 54% of the available data from crashes and near-crashes. Given this severe reduction in data, a stable interaction model could not be produced. Odds ratios, therefore, were estimated using only the main effects model.

The revised analysis strategy for Phase II used a forward selection logistic regression modeling approach. The dependent variable was a binary indicator of whether a given segment was an event (crash or near-crash, coded as “1”) or a baseline epoch (coded as “0”). Specific driving behaviors and driver states served as the covariates of interest.

The general modeling strategy consisted of evaluating each covariate in a univariate analysis. Given the exploratory nature of these analyses, less conservative alpha levels were used to assess statistical significance. Thus, variables demonstrating statistical significance at the level of $\alpha = 0.25$ were included in simultaneous evaluations. Various factors were taken into consideration when removing or retaining a term in the simultaneous evaluations. The behaviors of Traffic Control Device Violation and Gender were both removed, as these terms were not statistically significant. The simultaneous evaluations began with estimating main effect parameters, and then attempted to estimate parameters for relevant interactions. A traditional statistical significance level of $\alpha = 0.10$ was used in the simultaneous evaluations. The logistic regression parameter values were then used to calculate odds ratio estimates of the relative risk that given driver states or driving behaviors were associated with the occurrence of crashes or near-crashes.

The resulting main effects model includes Driver Impairment, Safety Belt Use, Willful Behavior, Total Time EOR, Inappropriate Avoidance, Close Proximity to Other Vehicle, Inappropriate Speed, Improper Passing, and Age.

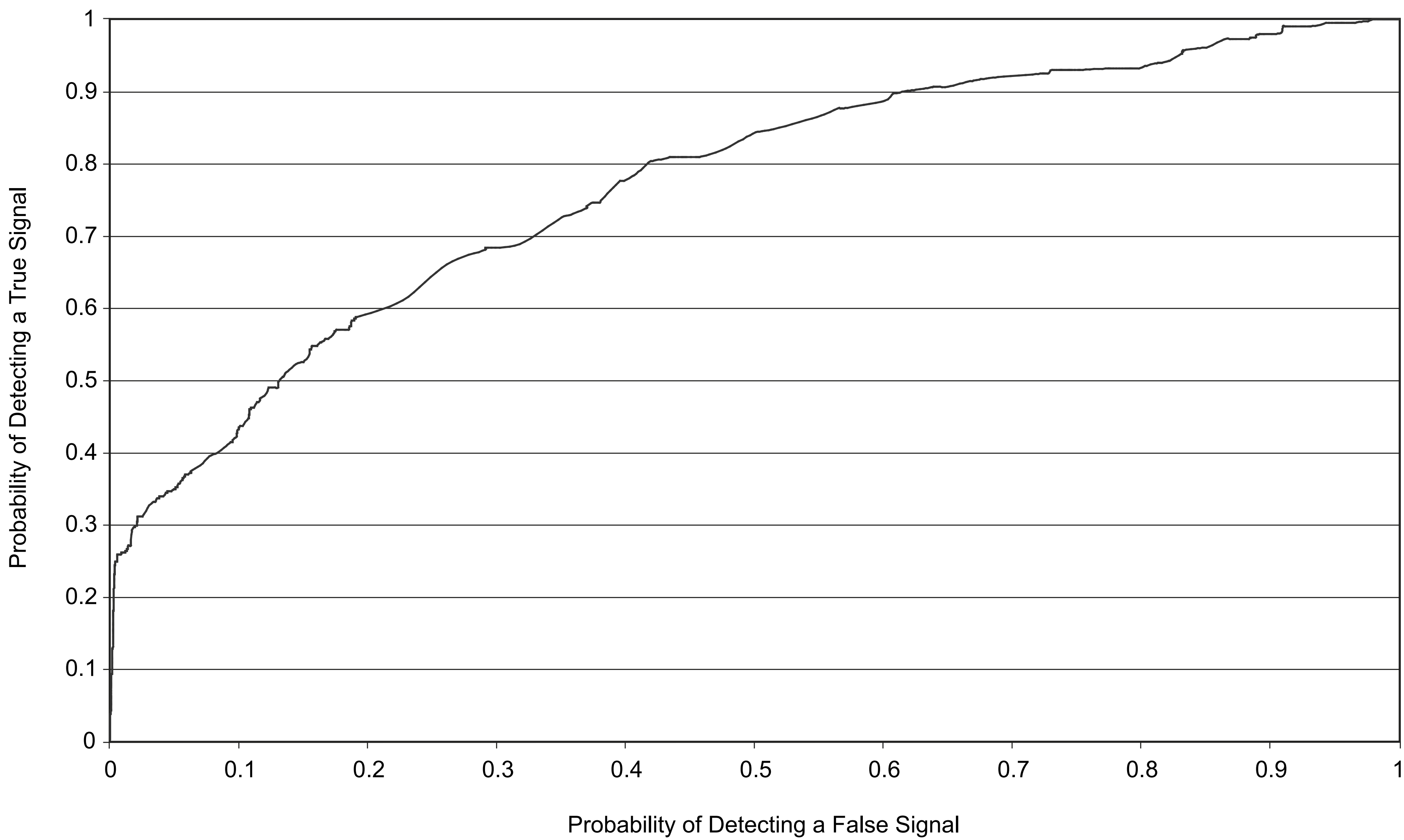
### *Assessment of goodness of fit (Phase II)*

A key component of the data modeling process is to provide an assessment of how well the model fits the data. The methods include the Hosmer and Lemeshow goodness-of-fit test and the calculation of the area under the Receiver Operator Characteristic (ROC) curve. An ROC curve plots the probability of detecting true signal (sensitivity) versus the probability of detecting a false signal (1—specificity) over a range of cutpoints (Figure 17).

The assessment of goodness of fit indicated adequate overall model fit and adequate discrimination. The Hosmer and Lemeshow goodness-of-fit test indicated that the model adequately fit the data used ($\chi(8) = 4.25$, $p = 0.80$). The second evaluation, calculating the area under the ROC curve, also suggested acceptable discrimination between the crashes and near-crashes and baseline epochs.

In plotting an ROC curve, the predicted outcome is determined by comparing the predicted probability for an observation to a predetermined value or cutpoint; that is, if the predicted probability exceeds the cutpoint, the observation is classified as an event, and if the predicted probability is less than the cutpoint, the outcome is classified as a non-event. A common cutpoint value is 0.5.

**Figure 17.** **The Receiver Operating Characteristic Curve demonstrating that the Regression Model obtains acceptable discrimination between crashes and near-crashes and baseline epochs.**



The area under the ROC curve, which ranges from 0 to 1, indicates the model's ability to distinguish between observations that demonstrate the event of interest and those that do not. To assist in interpreting Figure 17, a model with near-perfect discrimination would have a 0.9 probability of detecting a true signal at a 0.05 probability of detecting a false signal. Hosmer and Lemeshow (2000) state that an area of between 0.7 and 0.8 under the ROC curve indicates acceptable discrimination. The final main effects model obtained an area of 0.753 under the ROC curve. Thus, the model appears to be able to discriminate and adequately fit the data.

### *Odds ratios*

The ratio of odds is a commonly employed measure of association between the presence of cases (crash and near-crash events) and the controls (baseline driving epochs). Odds ratios are used to approximate relative risk in case-control designs. This is necessary due to the separate sampling employed for the events and baselines and is valid for evaluations of rare events (Greenberg, Daniels, Flanders, Eley, and Boring 2001).

This analysis assesses which behaviors are associated with increased risk. Odds ratios not statistically different from 1.0 reveal no evidence that engaging in the specific behavior in question is associated with increased risk of involvement in a crash or near-crash, relative to the same risk when not engaging in that behavior. An odds ratio that is statistically greater than 1.0 indicates the particular behavior is associated with increased risk of being involved in a crash or near-crash while engaging in the behavior in question, relative to the same risk when not engaging in that behavior. Similarly, an odds ratio statistically less than 1.0 indicates the particular behavior is associated with decreased risk of being involved in a crash or near-crash while engaging the behavior in question, relative to the same risk when not engaging in that behavior.

### *Logistic regression-based odds ratio calculations*

The odds ratios and corresponding 95% confidence intervals are presented in Table 14. Ratios significantly different from 1.0 are shown in bold typeface.

Of primary interest is that speeding inappropriately, driving while drowsy, driving aggressively, and looking away from the forward roadway for greater than 2 s, were all associated with increased risk of being involved in a crash or near-crash, and thus are deemed potentially risky behaviors. Driving in close proximity to other vehicles, which occurred frequently for both crashes and near-crashes as well as during baseline epochs, was associated with an odds ratio significantly lower than 1.0, suggesting that it may be associated with a reduction in the risk of being involved in a crash or near-crash. This apparently counterintuitive finding is discussed further in the Summary of Phase II Results at the end of this section.

**Table 14. Odds ratios and 95% confidence intervals for all independent variables included in the main effects model.**

| Risky Driving State or Risky Driving Behavior | 95% Lower Confidence Interval | Odds Ratio | 95% Upper Confidence Interval |
|---|---|---|---|
| **Inappropriate Passing** | **36.2** | **72.7** | **146.0** |
| **Inappropriate Avoidance Maneuver** | **10.0** | **31.7** | **100.8** |
| **Drowsiness** | **2.0** | **2.9** | **4.3** |
| **Inappropriate Speed** | **1.7** | **2.9** | **4.8** |
| **Aggressive Driving/Intimidation/ Purposeful Violation of Traffic Laws** | **1.3** | **2.1** | **3.4** |
| **Total Time EOR > 2 s** | **1.4** | **1.9** | **2.5** |
| Age | 0.98 | 0.99 | 1.0 |
| Safety Belt Usage | 0.5 | 0.8 | 1.0 |
| **Close Proximity to Other Vehicle** | **0.3** | **0.4** | **0.6** |

**"Bolded"** odds ratios were significant at $p < 0.05$.
**These odds ratios are based upon 376 crashes and near-crashes and 4,033 baseline epochs.**

Note that the odds ratios for Inappropriate Avoidance maneuver and Improper Passing were 32 and 73, respectively. These may be confounded by the operational definition of a crash or near-crash in which the driver was inappropriately avoiding an object or passing another vehicle to attempt to avoid a collision. Also note the wide confidence intervals surrounding these extremely high odds ratio point estimates. This suggests the point estimates are not stable and further indicates that these data are confounded.

The odds ratio associated with safety belt use was not significantly different from 1.0; thus, the current study provides no evidence that safety belt use or non-use affects the risk of being involved in a crash or near-crash. This result should not be interpreted as implying that safety belt use does not affect safety. Extensive safety literature corroborates that drivers are at considerably less risk of sustaining injuries during a crash when wearing their safety belts. Rather, this result suggests that the mere act of wearing one's safety belt does not directly affect whether a driver becomes involved in a crash or near-crash.

Age was analyzed as a continuous variable for 1-year increments. The odds ratio for Age was not significantly lower than 1.0. Again, note that all primary drivers in the study sample were between 18 and 68 years of age. Most transportation research suggests that the most dramatic age differences occur for drivers younger than 18 and older than 70 years of age. This may explain why no affect for age was shown in this analysis.

The odds ratios presented in Table 14 represent the odds that the Driver State or Driving Behavior in question was observed during a crash or near-crash, relative to the odds that the state or behavior was observed during an epoch. These odds ratios are adjusted to estimate the impact on the odds of observing an event while holding constant, and controlling for the effects of all other states and behaviors included in the model except the one in question. Crude (unadjusted) odds ratios for these Driver Behaviors and Driving States can be computed directly from the data presented in Tables 11 and 12, by computing the odds of observing each state or behavior during a crash or near-crash, and dividing by the odds of observing the same state or behavior during a baseline epoch.

For example: using data from Table 12, reproduced in Table 15, the odds of a driver exhibiting drowsiness, in the case of a crash or near-crash ("event"), are given by:

$$\textbf{Odds(drowsiness | event)} = \frac{\textbf{events involving drowsiness}}{\textbf{events not involving drowsiness}} = \frac{\textbf{47}}{\textbf{398 – 47}} = \textbf{.1339}$$

The odds of a driver being drowsy in the case of a baseline epoch ("epoch") is calculated similarly, as:

$$\textbf{Odds(drowsiness | epoch)} = \frac{\textbf{epochs involving drowsiness}}{\textbf{epochs not involving drowsiness}} = \frac{\textbf{174}}{\textbf{4,136 – 174}} = \textbf{.0439}$$

The crude odds ratio of observing drowsiness in a crash or near-crash, relative to observing drowsiness in an epoch, is given by the ratio of the above odds:

$$\textbf{OR} = \frac{\textbf{Odds(drowsiness | event)}}{\textbf{Odds(drowsiness | epoch)}} = \frac{\textbf{.1339}}{\textbf{.0439}} = \textbf{3.05}$$

Comparisons between the crude odds ratios associated with the driver states and driving behaviors included in the regression model, and the model-based adjusted odds ratios, are presented in Table 15.

**Table 15. Comparison of adjusted odds ratios from logistic regression model and crude odds ratios.**

| Driver State or Driving Behavior | Crashes and Near-Crashes (Total N=376) | | Epochs (Total N=4,033) | | Crude Odds Ratio | Adjusted Odds Ratio |
|---|---|---|---|---|---|---|
| | N | Odds | N | Odds | | |
| Inappropriate Passing | 21 | 0.0592 | 4 | 0.0010 | 59.20 | 72.70 |
| Inappropriate Avoidance Maneuver | 60 | 0.1899 | 4 | 0.0010 | 189.90 | 31.70 |
| Drowsiness | 47 | 0.1429 | 174 | 0.0451 | 3.17 | 2.90 |
| Inappropriate Speed | 33 | 0.0962 | 107 | 0.0273 | 3.52 | 2.90 |
| Aggressive Driving/ Intimidation/Purposeful Violation of Traffic Laws | 66 | 0.2129 | 120 | 0.0307 | 6.93 | 2.10 |
| Total Time EOR > 2 s | 92 | 0.3239 | 569 | 0.1643 | 1.97 | 1.90 |
| Safety Belt Usage | 58 | 0.1824 | 493 | 0.1393 | 1.31 | 0.80 |
| Close Proximity to Other Vehicle | 46 | 0.1394 | 806 | 0.2498 | 0.56 | 0.40 |

As Table 15 shows, the model-based adjusted odds ratios generally agreed with the crude odds ratios computed directly. The two ratios disagreed more substantially for Inappropriate Passing and Inappropriate Avoidance Maneuver, both of which were deemed unstable, for Safety Belt Use, which was not statistically significant in the regression model, and for Aggressive Driving. The crude odds ratio and the adjusted odds ratios agreed very well in Drowsiness, Inappropriate Speed, Total Time EOR ≥2 s, and Close Proximity to Other Vehicle.

### *High-risk vs. low-risk drivers*

An exploratory analysis was conducted to determine whether a difference exists in the frequency of engaging in potentially risky driving behaviors between drivers with a high rate of crashes and near-crashes and those who did not experience any crashes or near-crashes. For the purpose of the analysis, the top and bottom octiles (i.e., 12.5%) of drivers in the 100-Car Study were selected, using 25% of the data.

These drivers were selected based on their rate of events (crashes, near-crashes, and incidents) per 10,000 mi. The Low Risk group was comprised of 3 females and 10 males (Mean Age = 39.6, Range = 24 to 57) and an event rate of 2.06/10,000 mi (Range 0 to 6.6). The High Risk group was comprised of 7 females and 6 males (Mean Age = 26.2, Range = 19 to 43) and an event rate of 219.5/10,000 mi (Range 135.7 to 447). Table 16 displays the frequency of each driver state and driving behavior for the High- and Low-Risk groups during the baseline epochs.

**Table 16.** **Frequency and percentage of baseline epochs for the High- and Low-Risk groups in each Driver State or Driving Behavior category.**

| Driver State/ Behavior Category | Specific Driver State/ Behavior | Low-Risk Group | High-Risk Group |
|---|---|---|---|
| Impairment | Drowsiness | 6 (2.8% of low risk) | 56 (6.1% of high risk) |
| | No impairment | 209 (97.2% of low risk) | 856 (93.9% of high risk) |
| Driving Behavior | Inappropriate avoidance maneuver | 0 (0% of low risk) | 2 (.2% of high risk) |
| | Close proximity | 42 (19.5% of low risk) | 166 (18.2% of high risk) |
| | Improper passing | 0 (0% of low risk) | 5 (.5% of high risk) |
| | Inappropriate speed | 5 (2.3% of low risk) | 28 (3.1% of high risk) |
| | Traffic sign/signal violation | 2 (.9% of low risk) | 14 (1.5% of high risk) |
| | No driving behavior | 166 (77.2% of low risk) | 697 (76.4% of high risk) |
| Safety Belt | None used/unknown | 21 (9.8% of low risk) | 156 (17.1 of high risk) |
| | Lap/shoulder belt, lap only | 194 (90.2% of low risk) | 756 (82.9% of high risk) |
| Willful Behavior | Aggressive driving/ intimidation | 4 (1.9% of low risk) | 33 (3.6% of high risk) |
| | No willful behavior | 211 (98.1% of low risk) | 879 (96.4% of high risk) |
| Total Time EOR | Total time EOR > 2 s | 25 (11.6% of low risk) | 124 (13.6% of high risk) |
| | Total time EOR ≤ 2 s | 190 (88.4% of low risk) | 788 (86.4% of high risk) |

Chi-Square tests were performed on each of the significant risk categories in Table 16 except Age (which was excluded from the analysis). Since more than 20% of the cells in the Driving Behavior risk category had expected counts of < 5, a Fisher's Exact test was performed. The Chi-Square tests for Drowsiness ($X^2_{(2)} = 3.8$, $p < 0.05$) and Safety Belt Use ($X^2_{(1)} = 7.1$, $p < 0.05$) found a significant difference between the High- and Low-Risk groups. These results suggest that high-risk drivers drive without a safety belt more frequently and also drive drowsy more frequently than the low-risk drivers, as operationally defined by this analysis.

The Chi-Square tests indicated no significant difference between the High and Low Risk groups for the Driving Behavior risk category. Similarly, the Chi-Square for the Willful Behavior ($X^2_{(1)} = 1.67$, $p > 0.05$) and EOR ($X^2_{(1)} = 0.625$, $p > 0.05$) risk categories did not find a significant difference between the High- and Low-Risk groups.

Finally, note the rate of involvement in crashes, near-crashes, and incidents of the drivers defined as High Risk exceeded that of those defined as Low Risk by a factor of more than 100.

## Summary of Phase II Results

The logistic regression analysis performed using a main effects model demonstrates that nearly all of the driving states and behaviors (all except Safety Belt Use) significantly contribute to the regression model. Four driving states and behaviors had odds ratios significantly greater than 1.0, suggesting those behaviors are associated with increased risk of being involved in a crash or near-crash. Those behaviors were:

- Inappropriate speed
- Driver drowsiness
- Total time EOR > 2 s
- Aggressive driving/willful behavior

After adjusting for other potentially risky behaviors and driver states included in the regression model, driving at inappropriate speed was found to be associated with roughly triple the odds of involvement in a crash or near-crash, relative to driving at appropriate speed (OR = 2.9, 95% CI = 1.7 – 4.8).

With regard to drowsiness, the odds of a crash or near-crash were nearly tripled when drivers were drowsy, than when not drowsy (OR = 2.9, 95% CI = 2.0 – 4.3). This is not all that surprising since drowsiness makes drivers less attentive, slows their reactions, and impairs their judgment (Lyznicki et al. 1998; Leger 1995). Driving while drowsy has been estimated to contribute to 76,000 to 100,000 crashes each year in the United States, resulting in 1,500 fatalities and thousands of injuries (Knipling and Wang 1995; Wang et al. 1996).

Looking away from the forward roadway for greater than 2 s was associated with nearly a doubling of the odds of being involved in a crash or near-crash, as compared to periods when the driver's eyes were not diverted from the forward roadway for as long as 2 s (OR = 1.9, 95% CI = 1.4 – 2.5). A growing body of evidence suggests that tasks requiring longer and more frequent glances are detrimental to safe driving (Klauer, Dingus, Neale, Sudweeks, and Ramsey 2006). Inattention has been cited in 39% of rear-end crashes and 33% of lane-change crashes in the 1997-2000 Crashworthiness Data System (Campbell, Smith, and Najm 2003). Nevertheless, inattention to the forward roadway (especially for total glance time ≥ 2 s) is very dangerous.

Lastly, drivers were more likely to be involved in a crash or near-crash when exhibiting aggressive driving behavior than when not driving aggressively (OR = 2.1, 95% CI = 1.3 – 3.4). This is not all that surprising because aggressive driving is composed of a constellation of potentially risky driving behaviors occurring together (driving at excessive speeds, weaving through traffic, and running stop lights and signs, among others). Public uneasiness over driver aggression has risen over the past several years, as it has become an increasingly familiar danger on roadways (e.g., James and Nahl 2000). Incidents of aggressive driving have risen 51% since 1990 (Vest, Cohen, and Tharp, 1997). Aggressive driving often results in negative outcomes, such as property damage, injury, and death (e.g., Mizell 1997).

Drivers in close proximity to another vehicle, while cutting in too closely, for example: or following another vehicle too closely, were less likely to be involved in a crash or near-crash, than drivers maintaining a headway of 2 s or greater. This, however, should not be interpreted to mean that tailgating is a safe driving behavior. Rather, this is most likely an artifact of the heavy traffic conditions that are common in and around the Washington, DC area, combined with the fact that forward TTC was a trigger for crash and near-crash events.

When a driver is in heavy or "stop-and-go" traffic, the environmental conditions may, in fact, dictate that the driver pay closer attention to the leading traffic. In other words, in very dense urban traffic conditions, drivers may be more attentive and exhibit faster reaction times than they would in less dense traffic. Thus, driving with relatively short headways may be associated with decreased crash risk only under certain conditions (e.g., dense traffic) because of confounding associated with different levels of driver alertness under different traffic conditions.

Similarly, the sub-population of drivers in the 100-Car Study who accounted for most occurrences of following too closely may have been more skillful or more alert than other drivers in the study, and that the finding reported here may be confounded by individual differences in driving skill or performance. As noted earlier, analyses were conducted on all crashes, near-crashes, and epochs in aggregate, because crashes and even near-crashes are too rare to model statistically at the individual driver level while maintaining adequate statistical power, even with the great quantity of data available in the 100-Car database. The findings reported here may have also been confounded by other factors, such as road type, time of day, or weather conditions. Controlling for such factors was beyond the scope of this study, but could, and perhaps should, be attempted in a future study.

Age did not demonstrate an effect, which is most likely due to the fact that the primary drivers in the 100-Car Study did not include those age groups with the most dramatic risks, e.g., novice teenage drivers and elderly drivers. Future analyses should be conducted on driving populations that include these age groups.

The odds ratio of safety belt use was not significantly different from 1.0, thus providing no evidence to support that wearing a safety belt is associated with involvement in crashes or near-crashes. The mere act of wearing a safety belt was included in the analysis to assess whether this behavior correlated with other behaviors. Safety belt use among the drivers in the 100-Car Study was comparable to national averages, as the June 2004 *National Occupant Protection Use Survey* (NOPUS) indicated that 80% of front-seat passengers use safety belts (Glassbrenner 2004).

This research did not directly support the contention by Ludwig and Geller (1997) that various risky driving behaviors are inter-related. Although a tremendous quantity of data was collected in the 100-Car Study, crashes, and even near-crashes, proved to be too rare to allow for the stable modeling of interactions between specific behaviors in crashes and near-crashes. Nonetheless, the data were used to assess which of these behaviors actually increase crash risk by conducting a simultaneous analysis of the risk of various driving behaviors.

While the 100-Car database could provide precise odds ratios for involvement in crashes and near-crashes for nearly all of the driving behaviors and driver states, some issues emerged when calculating odds ratios for inappropriate avoidance maneuvers and improper passing. These odds ratios were both very high and rather unstable; however, the manner in which crashes and near-crashes were identified confounds these results. The avoidance or passing maneuver was typically part of the crash and near-crash event itself; in other words, in most crashes and all near-crashes an avoidance maneuver takes place. This indicates that an extreme avoidance maneuver is not likely to exist outside of a near-crash or crash event, thereby making the odds ratio very high.

These data are more detailed than the crash database statistics because they compare the driver behaviors occurring just prior to crashes and near-crashes, to behaviors during normal baseline driving conditions. While crash databases provide information regarding the contributing factors involved in crashes, they cannot be used to describe the relative crash risk associated with various behaviors. Crash database statistics, for example: indicate speeding is a contributing factor in 30% of all fatal crashes (NHTSA 2005c); however, at any given time, 30% of drivers may be exceeding the posted speed limits. Thus, we would expect 30% of fatal car crashes to involve speeding as a contributing factor given the base rate of speeding under normal driving conditions. Without baseline data, the risk of being involved in a crash while speeding, relative to the risk of crashing when not speeding, cannot be determined. Adding baseline data overcomes this deficiency and allows inferences to be made about how frequently particular driving behaviors occur in certain events compared to normal or baseline driving conditions. Applying this analytical method demonstrates the power of naturalistic driving data and its importance in relating driving behavior to involvement in crashes and near-crashes.

Nonetheless, the Phase II analyses did support prior epidemiological studies (Hendricks, Fell, and Freedman 1999; Treat et al. 1979) and crash database statistics (NHTSA 2005a) indicating that various driving behaviors are related to crashes and near-crashes. The Phase II analyses found that drivers in the 100-Car Study were more likely to be involved in a crash or near-crash when speeding, drowsy, driving aggressively, or looking away from the forward roadway for 2 s or longer.

The hypothesis that risky drivers engage in various risky driving patterns during both events and non-events, while safe drivers infrequently engage in potentially risky driving behaviors, was partially supported. While no significant differences existed between the High- and Low-Risk groups for the Driving Behavior, Willful Behavior, and Total Time EOR risk categories, significant differences existed for Drowsiness and Safety Belt risk categories. High-risk drivers were more likely than low-risk drivers to drive while drowsy or without using safety belts. These results could be applied to traffic schools and driver education programs because fatigue management training and safety belt use should be important aspects of driver training. Finally, this analysis showed the high-risk drivers in the 100-Car Study were involved in crashes, near-crashes, and incidents at more than 100 times the per-mile rate of the low-risk drivers; a remarkable finding in and of itself.

# GENERAL CONCLUSIONS

The present report assessed the effect of specific driving behaviors on the risk of being involved a crash or near-crash. Additionally, differences in engaging in potentially risky behaviors between high- and low-risk drivers (based on the frequency of events per mile) were also assessed.

Applying these analytical methods demonstrates the power of naturalistic driving data and its importance in relating driving behavior to crash and near-crash involvement. While some may argue that the crashes and near-crashes reported in this study are less severe than crashes in crash databases, an important benefit to naturalistic driving data collection is collecting non-police-reported crashes, as these are not accessible for analyses in any other type of database. While many would argue that we already knew many of these behaviors were dangerous; the actual degree of heightened risk of crash or near-crash involvement has never before been assessed. The detailed recording of driving behavior that occurs seconds prior to crashes and near-crashes yields new insights. The most important findings of this study are briefly discussed here.

- Four behaviors have odds ratios that show an increased risk of being involved in a crash or near-crash and should, therefore, be deemed risky. These behaviors are:
  - Inappropriate speed
  - Driver drowsiness
  - Total time EOR > 2 s
  - Aggressive driving/willful behavior

- Older drivers were found to have a lower risk of being involved in crashes and near-crashes than younger drivers. While increasing age was shown to have a protective effect, this should be interpreted with some caution, since the population of drivers in the 100-Car Study did not include very young and very old drivers. If newly licensed drivers, aged 16 and 17, and drivers older than 65 were included in the analysis, crash statistics would suggest that a somewhat different relationship might emerge (NHTSA 2005a).

- The hypothesis that drivers with higher rates of involvement in crashes and near-crashes engage in various potentially risky driving patterns, while drivers with low rates of involvement infrequently engage in these behaviors, was partially supported. High-risk drivers were more likely than low-risk drivers to drive while drowsy or without their safety belts.

These findings resulted from significant effort in hardware and software development and installation, data collection, reduction, and analyses. While these types of analyses using naturalistic driving databases are incredibly useful, they are also unique due to the incredible effort required to collect these types of data. There were many challenges and obstacles to overcome in designing the instrumentation, installing the instrumentation, and maintaining this equipment for 1 year for 100 vehicles. The large amount of data collected also was reduced into more manageable databases by a team of trained data reductionists working for over a 12-month period. These analyses, while in manageable databases, were not trivial.

Naturalistic driving studies may be both logistically and financially demanding, but are not as resource intensive as high-fidelity, motion platform simulators. Technological advancements have made this type of large-scale data collection not only possible, but economically feasible as well. Large-scale naturalistic driving studies are able to assess driving behavior in new ways that are not possible with any other type of research method.

## Future Research Directions and Limitations

Data used in the present study were gathered in only one metropolitan area of the country; therefore, the odds ratios are more readily generalizable to other metropolitan areas and less so to the United States at large. Future research efforts should be conducted in different types of areas to get a more complete view of driving behaviors across different driving environments.

In addition, the population of drivers studied here was, by design, biased toward younger drivers (40% of the drivers were under age 28). This produced a sample with a higher percentage of younger drivers than is present in the general population. While caveats are in place to account for these discrepancies (frequency per vehicle miles traveled), future research should be conducted using more representative driver samples, including the very young and the very old, which more closely resemble the driving population at-large.

Also, even though 12 to 13 months of continuous data were collected from 109 drivers, there was still not enough data to perform all the analyses attempted in this study. The issue is not that enough data were collected (note that 7 terabytes of data were collected). The issue stems from the modeling of rare events. Crashes and near-crashes are relatively rare events, and when attempting to model combinations of behaviors that occurred for these rare events, the data did not support stable estimations of such rare combinations. The attempt was made to more broadly define behaviors in fewer categories. While this increased statistical power, it may have reduced the meaning of these associations. These issues further indicate the need of a larger-scale, nationwide naturalistic driving data collection effort to fully understand the impact of driving behavior on crash risk.

Specific driver distractions and general inattention were aggregated in this study according to Total Time EOR greater vs. less than 2 s. Klauer, Dingus, Neale, Sudweeks, and Ramsey (2006) found that secondary tasks with a total glance time > 2 s significantly increase the risk of being involved in a crash or near-crash. Klauer, Dingus, Neale, Sudweeks, and Ramsey (2006) also investigated secondary tasks in terms of the number of glances or button presses required to complete the task. These analyses suggest the tasks requiring more eye glances or button presses were all associated with increased risk. While investigating individual distraction types would have been valuable, only eye-glance duration was used as a measure of distraction for this report, because it greatly simplified the modeling procedure without removing driver distraction from the analysis.

The identification of potentially risky driving behaviors using continuous video were subjective judgments and sometimes difficult to ascertain. While the inter- and intra-rater reliability scores suggested high reliability between the data reductionists, these scores were obtained toward the end of the data reduction task (last 3 months). Future research should attempt to obtain inter- and intra-rater reliability scores earlier in the data reduction process to ensure a high quality of data reduction throughout the process.

Video data reduction also impeded the identification of some risky driving behaviors, as some were not observable, such as daydreaming, or difficult to assess without more environmental context, such as speeding without knowing the posted speed limit of the section of roadway. Future research could greatly enhance current results in this area. New technologies, such as portable eye trackers and driver monitoring devices, are currently being developed to assist drivers. A method to better assess the impacts of some of these behaviors would provide valuable information for transportation safety professionals and designers alike.

This study may provide conservative estimates of relative risks because the vehicles were sampled based upon how often those vehicles were involved in crashes, near-crashes, and incidents. Because the drivers of those particular vehicles may have been more likely to engage in particular behaviors, this may have increased the frequency of risky behaviors present in the baseline sample. This would cause the odds ratio estimates to be somewhat lower than if a different sampling method had been used. Other sampling methods could have better matched baseline epochs to crashes and near-crashes; however, this was beyond the scope of the current effort. Such a study could provide further insight into the impact of specific driving behaviors and driver states on individual drivers, and better control for the specific conditions and circumstances under which crashes and near-crashes occur.

It should also be noted that the analyses conducted in this study used the crash/near-crash as the unit of analysis and not the driver. This may also have slightly altered the results of this analysis; however, it is unknown if using the driver as the unit of analysis would alter the results. Future analyses may be conducted using the driver as the unit of analysis; however, current methods for conducting this type of analysis with this type of data are relatively experimental and very complex.

More research is needed to further understand interactions among driving behaviors. Rather than assessing unitary behaviors, a future research effort should assess which combinations of driving behaviors increase crash risk. Of course, as stated previously, this may require an even larger database.

## Application of Results

Driving faster than surrounding traffic, driving while drowsy, looking away from the forward roadway longer than 2 s, and driving aggressively are directly linked to driving performance degradation, as has been shown in previous research and in being involved in crashes and near-crashes. Previous research has shown (Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. 2006) near-crashes to be kinematically similar (i.e., involve similar levels of braking and swerving) to crashes. The primary difference between crashes and near-crashes is a successful evasive maneuver. While crashes lead to property damage, injury, and possibly death, near-crashes have similar properties. Including both near-crash and crash events in calculating relative risk produces a more accurate estimate that can help direct future research.

Given these risky behaviors, these results can be used to educate the public on the dangers of looking away from the forward roadway, driving while drowsy, driving faster than surrounding traffic, and aggressive driving. The results also have implications for collision avoidance warning systems. A system, for example: that can determine whether the driver's eyes are closed or away from the forward roadway could potentially have greater efficiency and accuracy. In general, this research highlights those driving behaviors that produce the greatest driving risk, which, if avoided, could greatly reduce near-crash and crash events.

# REFERENCES

Allison, P. 2004. Convergence problems in logistic regression. In *Numerical Issues in Statistical Computing For the Social Scientist* by Micah Altman, Jeff Gill, Michael P. McDondald, eds. (pp. 238-252) New Jersey: John Wiley & Sons.

Blincoe, L., A. Seay, E. Zaloshnja, T. Miller, E. Romano, S. Luchter, and R. Spicer. 2002. *The economic impact of motor vehicle crashes,* 2000. DOT HS 809 446. Washington, DC: National Highway Traffic Safety Administration.

Campbell, B. N., J. D. Smith, and W. G. Najm. 2003. *Examination of crash contributing factors using national crash databases.* DOT HS 809-664. Washington, DC: National Highway Traffic Safety Administration.

Carr, E. G. 1988. Functional equivalence as a mechanism of response generalization. In R. H. Horner, G. Dunlap, and R. L. Koegel, eds. *Generalization and maintenance.* (pp. 221-241). Baltimore: Paul H. Brooks.

Dingus, T. A., V. L. Neale, S. A. Garness, R. J. Hanowski, A. S. Keisler, S. E. Lee, M. A. Perez, G. S. Robinson, S. M. Belz, J. G. Casali, E. F. Pace-Schott, R. A. Stickgold, and J. A. Hobson. 2002. *Impact of sleeper berth usage on driver fatigue: Final project report.* DTFH61-96-00068. Washington, DC: U.S. Department of Transportation, Federal Motor Carrier Safety Administration.

Dingus, T. A. 2003. Human factors applications in surface transportation. *Frontiers of Engineering,* 8:39-42.

Dingus, T. A., S. G. Klauer, V. L. Neal, A. Petersen, S. E. Lee, J. Sudweeks, M. A. Perez, J. Hankey, D. Ramsey, S. Gupta, C. Bucher, Z. R. Doerzaph, J. Jermeland, and R. R. Knipling. 2006. *The 100-car naturalistic driving study, Phase II—Results of the 100-car field experiment.* (Contract No. DTNH22-00-C-07007). Washington, DC: National Highway Traffic Safety Administration.

Elvik, R., P. Christensen, and A. Amundsen. 2004. *Speed and road accidents.* TOI report 740/2004. Oslo, Sweden: The Institute of Transport Economics.

Evans, L.. 1991. *Traffic safety and the driver.* New York: Van Nostrand Rienhold.

Geller, E. S. 2001. *The psychology of safety handbook.* Boca Raton, FL: CRC Press.

Glassbrenner, D. 2004. *Safety belt use in 2004–Overall results.* DOT HS 809 783. Washington, DC: National Highway Traffic Safety Administration.

Greenberg, R. S., S. R. Daniels, W. D. Flanders, J. W. Eley, and J. R. Boring. 2001. *Medical epidemiology,* 3rd ed., New York: McGraw-Hill.

Hanowski, R. J., W. W. Wierwille, S. A. Garness, and T. A. Dingus. 2000. *Impact of local/short haul operations on driver fatigue, final report.* DOT-MC-00-203. Washington, DC: U.S. Department of Transportation, Federal Motor Carriers Safety Administration.

Hendricks, D. L., J. C. Fell, and M. Freedman. 1999. *The relative frequency of unsafe driving acts in serious traffic crashes.* DTNH22-94-C-05020. Washington, DC: National Highway Traffic Safety Administration.

Hosmer, D. W. and S. Lemeshow. 2000. *Applied logistic regression,* 2nd ed., New York: John Wiley and Sons, Inc.

James, L., and D. Nahl. 2000. *Road rage and aggressive driving: Steering clear of highway warfare.* Amherst, NY: Prometheus Books.

Klauer, S. G., T. A. Dingus, V. L. Neale, J. D. Sudweeks, and D. J. Ramsey. 2006. *The impact of driver inattention on near crash/crash risk: An analysis using the 100 Car Naturalistic Driving Study Data* (Contract No. DTNH22-00-C-07007, Task order 23). Washington, DC: National Highway Traffic Safety Administration.

Knipling, R. R., and J. S. Wang. 1995. Revised estimates of the US drowsy driver crash problem size based on general estimates system case reviews. *Proceedings of the 39th Annual Association for the Advancement of Automotive Medicine,* Chicago, IL, 451–466.

Leger, D. 1995. The cost of sleepiness: a response to comments. *Sleep* 18:281–284.

Ludwig, T. D., and E. S. Geller. 1991. Improving the driving practices of pizza deliverers; Response generalization and moderating effects of driving history. *Journal of Applied Behavior Analysis,* 24 (1):31-44.

Ludwig, T. D., and E. S. Geller. 1997. Assigned versus participatory goal setting and response generalization: Managing injury control among professional pizza deliverers. *Journal of Applied Psychology,* 82 (2):253-261.

Ludwig, T. D., and E. S. Geller. 1999. Behavior change among agents of a community safety program: Pizza deliverers advocate safety belt use. *Journal of Organizational Behavior Management,* 19 (2):3-24.

Ludwig, T. D., and E. S. Geller. 2000. Intervening to improve the safety of delivery drivers: A systematic behavioral approach. Monograph. *Journal of Organizational Behavior Management,* 19:1-124.

Ludwig, T. D. 2001. On the necessity of structure in an arbitrary world: Using concurrent schedules of reinforcement to describe response generalization. *Journal of Organizational Behavior Management,* 21 (4):13-38.

Lyznicki, J. M., T. C. Doege, R. M. Davis, and W. A. Williams. 1998. Sleepiness, driving, and motor vehicle crashes. *Journal of the American Medical Association,* 279:1908–1913.

Mizell, L. 1997. Aggressive driving. In, *Aggressive Driving: Three Studies.* Washington, DC: AAA Foundation for Traffic Safety.

National Center for Health Statistics. 2004. *Fast Stats A to Z: Accidents/Unintentional Injuries.* http://www.cdc.gov/nchs/fastats/acc-inj.htm.

National Highway Traffic Safety Administration. 2005a. *Traffic Safety Facts 2003.* DOT HS 809 775. Washington, DC: National Highway Traffic Safety Administration.

National Highway Traffic Safety Administration. 2005b. *Traffic Safety Facts 2004: Occupant protection.* DOT HS 809 909. Washington, DC: National Highway Traffic Safety Administration.

National Highway Traffic Safety Administration. 2005c. *Traffic Safety Facts 2004: Speeding.* DOT HS 809 915. Washington, DC: National Highway Traffic Safety Administration.

National Safety Council. 1995. *Accident facts.* Chicago: National Safety Council.

Patterson, T. L., W. J. Frith, L. J. Povey, and M. D. Keall. 2002. The effect of increasing rural interstate speed limits in the United States. *Traffic Injury Prevention,* 3 (4):316-320.

Pedhazur, E. J., and L. P. Schmelkin. 1991. *Measurement, design, and analysis: An integrated approach.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Recarte, M. A., and L. M. Nunes. 2003. Mental workload while driving: Effects on visual search, discrimination, and decision making. *Journal of Experimental Psychology: Applied,* 9 (2):119-137.

Recarte, M. A., and L. M. Nunes. 2000. Effects of verbal and spatial-imagery tasks on eye fixations while driving. *Journal of Experimental Psychology: Applied,* 6 (1):31-43.

Roads and Traffic Authority, NSW. 2005. Speeding research crash risk. http://www.rta.nsw.gov.au/roadsafety/speedandspeedcameras/speedingresearch.html.

Russo, D. C., M. F. Cataldo, and P. J. Cushing. 1981. Compliance training and behavioral covariation in the treatment of multiple behavior problems. *Journal of Applied Behavior Analysis,* 14:209-222.

Stokes, T. F., and D. M. Baer. 1977. An implicit technology of generalization. *Journal of Applied Behavior Analysis,* 10:349-367.

Streff, F. M., M. J. Kalsher, and E. S. Geller. 1993. Developing efficient workplace safety programs: Observations of response covariation. *Journal of Organizational Behavior Management,* 13 (2):3-15.

Stutts, J., J. Feaganes, E. Rodgman, C. Hamlett, T. Meadows, D. Reinfurt, K. Gish, M. Mercadante, and L. Staplin. 2003. *Distractions in everyday driving.* Washington, DC: AAA Foundation for Traffic Safety.

Stutts, J. C., D. W. Reinfurt, and E. A. Rodgman. 2001. The role of driver distraction in crashes: An analysis of the 1995-1999 Crashworthiness Data System data. In the *45th Annual Proceedings of the Association for the Advancement for Automotive Medicine,* 287-301.

Treat, J. R., N. S. Tumbas, S. T. McDonald, D. Shinar, R. D. Hume, R. E. Mayer, R. L. Stansifer, and N. J. Catellan. 1979. *Tri-level study of the causes of traffic accidents: Final report,* vol.1: *Causal factor tabulations and assessments.* DOT HS-805 085. Indiana University: Institute for Research in Public Safety.

Uebersax, J. S. 1987. Diversity of decision-making models and the measurement of interrater agreement. *Psychological Bulletin,* 101:140-146.

Waller, J. A. 1987. Injury: Conceptual shifts and prevention implications. *Annual Review of Public Health,* 8:21-49.

Wang, J. S., R. R. Knipling, and M. J. Goodman. 1996. The role of driver inattention in crashes: New statistics from the 1995 Crashworthiness Data System. In the *40th Annual Proceedings of the Association for the Advancement of Automotive Medicine,* 377-392.

Wasielewski, P. 1984. Speed as a measure of driver risk: Observed speeds versus driver and vehicle characteristics. *Accident Analysis and Prevention,* 16 (2):89-103.

Wierwille, W. W., and L. A. Ellsworth. 1994. Evaluation of driver drowsiness by trained raters. *Accident Analysis and Prevention,* 26 (4):571-578.

# APPENDIX A: OPERATIONAL DEFINITIONS OF SPECIFIC/ GENERAL DRIVING BEHAVIORS

## AVOIDING OBJECT

**Avoiding animal**—Inappropriate maneuver made to avoid hitting an animal. Example: braking or swerving into oncoming traffic.

**Avoiding pedestrian**—Inappropriate maneuver made to avoid pedestrian, Example: braking or swerving into oncoming traffic.

**Avoiding other vehicle**—Inappropriate maneuver made to avoid hitting another vehicle. Example: braking or swerving into traffic or onto a sidewalk where pedestrians are present.

## APPARENT UNFAMILIARITY

**Apparent general inexperience driving**—Driver's behaviors demonstrate general inexperience driving. Examples include, hyper-focused driving, overly cautious maneuvers, etc.

**Apparent unfamiliarity with roadway**—Driver's behavior is consistent with being lost in a particular location. Examples: performing repeated U-turns, reading maps/papers, etc.

**Apparent unfamiliarity with vehicle**—Driver's behavior demonstrates lack of knowledge of vehicle controls. Examples: turning on wipers instead of turn signal, etc.

**DRIVER IMPAIRMENT**—The driver's behavior, judgment, or driving ability is altered or hindered. Includes drowsiness, anger, use of drugs or alcohol, illness, lack of or incorrect use of medication, or disability. See Dingus, Klauer, Neale, Petersen, Lee, Sudweeks et al. (2006) for a complete description.

**Anger**—Any behaviors observed that are highly associated with anger such as facial expressions, vocalizations, or gesturing.

**Drug or alcohol use or suspected use**—Recorded if drug/alcohol use was observed or was suspected based upon time of day, lack of vehicular control, and facial expressions.

**Drowsiness**—Those driving behaviors that include eyelid closures, minimal body/eye movement, repeated yawning, and/or other behaviors based upon those defined by Wierwille & Ellsworth (1994).

**Illness**—Any driver behavior observed exhibiting behaviors indicating that the driver was not feeling well, e.g., blowing nose, profuse coughing, etc.

## FAILURE TO SIGNAL

**Failure to signal with other violations or unsafe actions**—Examples, failing to signal during a lane change that was illegally executed in the middle of an intersection.

**Failure to signal, without other violations or unsafe actions**—Examples, changing lanes without signaling or turning without signaling.

## IMPROPER BACKING

**Improper backing, did not see**—Subject driver did not check mirrors or area behind vehicle when backing.

**Improper backing, other**—Example: backing into traffic.

## IMPROPER BRAKING

**Sudden or improper braking on roadway**—The subject brakes suddenly, or in an improper manner that could put the subject or other vehicles at risk (late braking, hard braking).

**Sudden or improper stopping on roadway**—The subject stops suddenly, or in an improper manner that could put the subject or other vehicles at risk (hard or late braking when coming to a stop, or stopping on roadway putting self and others at risk).

## IMPROPER PARKING

**Improper start from a parked position**—Subject driver did not check mirrors or windows while exiting the parking spot.

**Parking in improper or dangerous location**—Parking in an undesignated area put self and others at risk. Example: parking on shoulder of interstate.

## IMPROPER PASSING

**Illegal passing**—Example: crossing double solid yellow line or passing on the shoulder.

**Passing on the right**—The subject driver intentionally moves to the right lane to pass a vehicle.

**Other improper or unsafe passing**—Example: passing on a two-lane road with limited sight distance or with other vehicle present.

## IMPROPER TURN

**Making turn from wrong lane**—Example: subject driver turns across lanes or turns from a non-turning lane.

**Improper turn, cut corner on left turn**—Example: the subject driver makes a left turn and cuts into the adjacent lane to the left or into oncoming traffic.

**Improper turn, wide right turn**—Example: subject driver makes a right turn wide and cuts into left lane or into the oncoming traffic lane.

**Other improper turning**—Example: turning from a non-turn lane.

## INAPPROPRIATE SPEED

**Exceeds speed limit**—Speed limit is estimated by video analysts based upon locality and speed of surrounding traffic; the driver must exceed this speed limit by 10 mph or more.

**Exceeds safe speed but not speed limit**—Driver exceeds safe speed for current driving conditions (weather, traffic situation) that call for slower speeds.

**Speeding or other unsafe actions in work zone**—Speeding or any other action in a work zone that could put the driver or others at risk.

**Driving slowly below speed limit**—Speed limit is estimated by video analysts based upon locality and speed of surrounding traffic; the driver is traveling 10 mph below the estimated speed limit.

**Driving slowly in relation to other traffic but not below speed limit**—Example: the driver is on the interstate driving the speed limit and being passed by most traffic.

## PROXIMITY

**Cutting in too closely in front of other vehicle**—Subject driver changes lanes or turns into the lane too close in front of other vehicle.

**Cutting in too closely behind other vehicle**—Subject driver changes lanes or turns into the lane too close behind other vehicle.

**Following too closely**—This was determined by video analysts, using speed, distance from the radar, and dash marks in the road. If the estimated distance was consistently less than 2 s from the lead vehicle, following too closely was marked.

**TOTAL TIME EYES OFF FORWARD ROADWAY**—Operationally defined as the sum total of all eye glances away from the forward roadway. This could potentially be one glance or multiple glances away from the forward roadway within a given time period.

## TRAFFIC CONTROL DEVICE VIOLATION

**Disregarded officer or watchman**—Subject driver was unaware of watchman or was too late to react.

**Signal violation, apparently did not see signal**—Subject driver was unaware of signal or was too late to react.

**Signal violation, intentionally ran a red light**—Subject driver ran a red light and was purposeful (e.g., Driver purposefully accelerated through intersection).

**Signal violation, tried to beat signal change**—Subject ran a red light trying to pass through the intersection while the light was yellow.

**Stop-sign violation, apparently did not see stop sign**—Subject driver was unaware of stop sign or was too late to react.

**Stop-sign violation, intentionally ran stop sign at speed**—Subject purposefully ran the stop sign without decelerating below a speed of 15 mph.

**Stop-sign violation, "rolling stop"**—the subject slowed to a speed less than 15 mph for the stop sign but did not come to a complete stop.

**Other sign violation, apparently did not see sign**—Example: did not see yield sign.

**Other sign violation, intentional disregard**—Purposefully disregard sign.

**Other sign violation**—Any other sign violation not accounted for by the other sign violation categories.

**Non-signed crossing violation**—Example: driveway entering road.

**Right-of-way error, decision failure**—Subject misjudged the situation. Example: subject turns into traffic and misjudges the gap.

**Right-of-way error, recognition failure**—Subject inadvertently did not recognize the right of way.

**Right-of-way error, unknown cause**—Subject did not recognize who had right of way, caused by an unknown factor.

## VISUAL

**Did not see other vehicle during lane change or merge**—The subject driver did not see other vehicle while changing lanes or merging. This does not have to be a complete lane change. The subject could start to change lanes, then noticed a vehicle in the other lane, and jerked back.

**Driving in other vehicle's blind zone**—The subject driver is continuously driving in another driver's blind zone.

**WILLFUL BEHAVIOR**—Driver behavior that is intentional including the following:

**Aggressive driving, specific, menacing actions**—Intentional, aggressive actions directed toward another vehicle or pedestrian.

**Aggressive driving, other**—This includes reckless driving without menacing actions. Examples; excessive speed, weaving in and out of traffic, tailgating, etc.

**Failed to signal or improper signal**—Subject driver did not use turn signal in accordance with traffic laws (changing lanes or turning with no signal; or signaling late, after lane change, or after turn has already begun).