

Analysis of Naturalistic Driving Study Data: Safer Glances, Driver Inattention, and Crash Risk

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The Second
S T R A T E G I C H I G H W A Y R E S E A R C H P R O G R A M

 **SHRP 2 REPORT S2-S08A-RW-1**

Analysis of Naturalistic Driving Study Data: Safer Glances, Driver Inattention, and Crash Risk

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The Second Strategic Highway Research Program

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The research reported on herein was performed by SAFER Vehicle and Traffic Safety Centre at Chalmers, Gothenburg, Sweden. SAFER is a joint research center of excellence in vehicle and traffic safety composed of 25 partners from the Swedish automotive industry, academia, and other organizations (www.chalmers.se/safer). SAFER's host and legal entity is Chalmers University of Technology. Principal investigator Trent Victor is an adjunct professor at Chalmers and worked on the project as borrowed personnel to Chalmers, but his main employer is Volvo Cars. The other authors of this report are co-principal investigator Marco Dozza, Jonas Bärgrman, and Christian-Nils Boda of Chalmers University of Technology (as a SAFER partner); Johan Engström and Gustav Markkula of Volvo Group Trucks Technology (as a SAFER partner); John D. Lee of the University of Wisconsin–Madison (as a consultant to SAFER); and Carol Flannagan of University of Michigan Transportation Research Institute (as a consultant to SAFER). The authors acknowledge the contributions to this research from Ines Heinig, Vera Lisovskaja, Olle Nerman, Holger Rootzén, Dmitrii Zholud, Helena Gellerman, Leyla Vujić, Martin Rensfeldt, Stefan Venbrant, Akhil Krishnan, Bharat Mohan Redrouthu, and Daniel Nilsson of Chalmers; Mikael Ljung-Aust of Volvo Cars; Erwin Boer; and Christer Ahlström and Omar Bagdadi of VTI.

FOREWORD

James Hedlund, *SHRP 2 Special Consultant, Safety Coordination*

The SHRP 2 Naturalistic Driving Study (NDS) was the largest and most comprehensive study of its kind ever undertaken. Its central goal was to produce unparalleled data from which to study the role of driver performance and behavior in traffic safety and how driver behavior affects the risk of crashes. Such research involves understanding how a driver interacts with and adapts to the vehicle, the traffic environment, roadway characteristics, traffic control devices, and other environmental features. After-the-fact crash investigations can only provide this information indirectly. The NDS data recorded how drivers really drove and what they were doing just before they crashed or almost crashed.

The Roadway Information Database (RID), created in parallel with the NDS, contains detailed roadway data collected on more than 12,500 centerline miles of highways in and around the six study sites, about 200,000 highway miles of data from the highway inventories of the six study states, and additional data on crash histories, traffic and weather conditions, work zones, and ongoing safety campaigns in the study sites.

The NDS and RID data can be linked to associate driving behavior with the roadway environment. The data will be used for years to come for developing and evaluating safety countermeasures designed to prevent or reduce the severity of traffic crashes and injuries.

The NDS collected data from more than 3,000 male and female volunteer passenger-vehicle drivers, aged 16 to 98, during a 3-year period. Most drivers participated from 1 to 2 years. It was conducted at one site in each of six states: Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington. Data collected included vehicle speed, acceleration, and braking; vehicle controls, when available; lane position; forward radar; and video views forward, to the rear, and on the driver's face and hands. The NDS data file contains about 50 million vehicle miles, 5 million trips, more than 3,900 vehicle years, and more than 1 million hours of video—a total of about 2 petabytes of data.

Four contracts were awarded in 2012 under SHRP 2 Safety Project S08, Analysis of the SHRP 2 Naturalistic Driving Study Data, to study specific research questions using the early NDS and RID data. An open competition solicited proposals to address topics of the contractor's own choosing that would have direct safety applications and that would

- Lead to real-world applications and safety benefits (theoretical knowledge without potential applications was not a priority);
- Be broadly applicable to a substantial number of drivers, roadways, or vehicles in the United States; and
- Demonstrate the use of the unique NDS data (i.e., similar results could not be obtained from existing nonnaturalistic data sets).

In addition to these goals, SHRP 2 expected the projects to serve as both pilot testers and advisers. As they conducted these first substantial NDS and RID analyses, these studies' experienced researchers would discover valuable insights on a host of both pitfalls and opportunities that others should know about when they use the data.

The four projects began in February 2012 and were conducted in two phases. In Phase 1, which concluded in December 2012, contractors obtained an initial set of data, tested and refined their research plans, and developed detailed plans for their full analyses. Three projects successfully completed this proof of concept and were selected for Phase 2. These three projects obtained and analyzed a much richer, though still preliminary, data set and reported their results in July 2014. This report, *Analysis of Naturalistic Driving Study Data: Safer Glances, Driver Inattention, and Crash Risk*, documents one of the three projects.

These projects were conducted while the NDS and RID data files were being built. This circumstance imposed constraints that substantially affected the researchers' work. The constraints included the following:

- *Sample size.* In summer 2013, when the projects requested full data sets, the NDS data file was only 20% to 30% complete. As a result, each project could only obtain a fraction of the trips of interest now available in the full NDS data.
- *RID not complete and not linked to the NDS.* Projects based on roads of specific types or locations could not identify these roads from the RID but instead had to use Google Earth or a similar database to identify them. They then obtained trips of interest by using searches through the NDS that were less efficient than will be possible when the NDS and RID are linked.
- *Data processing.* Some data, such as radar, had not been processed from their raw state to a form where they were fully ready for analysis.
- *Data quality.* NDS data are field data, and field data are inherently somewhat messy. At the time these projects obtained their data, some data had not been quality controlled, and some characteristics of the data were not yet well understood.
- *Tools for data users.* Not all crashes and near crashes had been identified, and a separate small data set containing only crashes, near crashes, and baseline exposure segments had not been built. In addition, a small trip summary file containing key features of each trip had not been built. Users can conduct initial analyses on many subjects quickly and easily using a trip summary file.
- *Other demands on data file managers.* The first priority for the NDS manager, Virginia Tech Transportation Institute (VTTI), and the RID manager, Iowa State University's Center for Transportation Research and Education (CTRE), was to complete data processing and quality control. Field data were being ingested continually. Data delivery for users was sometimes delayed because of these demands on their resources.

These issues are being resolved in 2014. The NDS and RID data are complete and are being linked. Data processing and quality control are being completed. Crash and near-crash files and trip summary files are being built.

If this project and the other two were to begin in 2015, each would have more data and would obtain the data far more easily and quickly. Readers should keep these constraints in mind as they read this report. Despite working under these constraints, the three NDS projects have produced valuable new insights into important traffic safety issues that will help reduce traffic crashes and injuries.

For an overview of the study, see the following article: K. L. Campbell, The SHRP 2 Naturalistic Driving Study: Addressing Driver Performance and Behavior in Traffic Safety, *TR News*, No. 282, September–October 2012, pp. 30–35. Additional details may be found at the study's InSight website: <https://insight.shrp2nds.us/>.

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Executive Summary

Background

Communication technology pervades our daily living and is increasingly integrated into the car, where it has the potential to distract drivers. Consequently, there is a critical need to better understand distraction and the limits of attention while driving. Distracted driving, which has long been a contributor to motor vehicle crashes, is flourishing in the fertile environment of communication, information, and entertainment technology that is transforming the car. The term *distraction* refers to both instances when drivers take their eyes off the road—visual distraction—and instances when drivers take their mind off the road—cognitive distraction. According to the United States–European Union (EU) Driver Distraction and Human Machine Interaction (HMI) Working Group, *driver inattention* is defined as a mismatch between the current attention allocation (distribution) and that demanded by activities critical for safe driving, whereas *driver distraction* is defined as diversion of attention away from *activities critical for safe driving* to one or more activities that are not critical for safe driving (Engström, Monk et al. 2013). In the current context, the activity critical for safe driving is attention to and control of headway to the lead vehicle.

The specific mechanisms and indicators of the risk of inattention are unfortunately not definitively quantified. Initial analyses of the Virginia Tech Transportation Institute’s 100-car naturalistic driving study focused on general relationships, such as the proportion of crashes involving inattention as a contributing factor (Dingus et al. 2006), or the relative and population-attributable risk associated with different inattention-related activities (Klauer et al. 2006). Subsequent analyses have examined the influences of various characteristics, such as total eyes-off-roadway time (glance history), single glance duration, and glance location. Previous work has also focused on calculating the risk associated with (human-identified) classifications of distracting tasks, such as talking, dialing, eating, and texting (e.g., Fitch et al. 2013; Klauer et al. 2006, 2010, 2014; Olson et al. 2009). Although this task risk approach has merit, especially for policy decisions and education on what tasks should or shouldn’t be done while driving, it does not explain *why* the tasks are dangerous—nor does it provide the inattention performance risk information needed for many countermeasures. It is important to be able to determine whether the particular *way* a driver is doing a task (e.g., radio tuning) is dangerous, rather than simply detecting what task is being done. The radio can be tuned in a safe or unsafe way, and the inattention performance quantification approach presented here focuses on being able to measure this and, in various ways, provide countermeasures based on this.

Compared with data from driving simulator and field experiments, naturalistic driving data are valuable because they are able to quantify real crash risk (e.g., NHTSA 2013). But naturalistic driving data, until now with the SHRP 2 data set, have had a limited number of crashes. Risk has generally been calculated for safety-critical events, which group crashes, near crashes, and

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incidents together. Detailed driving behavior data recorded in the seconds leading up to crashes and near crashes cannot be obtained from test tracks, simulators, or observational data (e.g., crash databases).

The SHRP 2 Naturalistic Driving Study can provide the data that are needed to provide inattention performance measures associated with precrash situations. The data are essential to improve the understanding of driver inattention, for guidelines to reduce distraction from electronics devices, for countermeasures that detect and act to reduce distraction while driving, and for regulation and education.

Research Questions

The current research aims to determine the relationship between driver inattention and crash risk in Lead-vehicle precrash scenarios (corresponding to rear-end crashes). It aims to develop *inattention-risk relationships*, describing how an increase in inattention performance variables combines with context in Lead-vehicle precrash scenarios to increase risk. The inattention-risk relationships are intended to show which glance behaviors are safer than others and pinpoint the most dangerous glances away from the road. A *glance* is the time from the moment the eyes move toward an area of interest (such as the radio, rearview mirror, or forward path) to the moment they move away from it. The results aim to (1) support distraction policy, regulation, and guidelines; (2) improve intelligent vehicle safety systems; and (3) teach safe glance behaviors.

The main research question is this: *What is the relationship between driver inattention and crash risk in Lead-Vehicle Precrash Scenarios?* Rear-end crashes corresponding to Lead-Vehicle Precrash Scenarios are as follows (Najm and Smith 2007):

- Scenario 22: Following vehicle (SHRP 2 driver) making a maneuver and approaching lead vehicle.
- Scenario 23: Following vehicle approaching an accelerating lead vehicle.
- Scenario 24: Following vehicle approaching lead vehicle moving at lower constant speed.
- Scenario 25: Following vehicle approaching decelerating lead vehicle.
- Scenario 26: Following vehicle approaching a stopped lead vehicle.

These Lead-Vehicle Precrash Scenarios constitute about 29%, or 1.7 million, of the crashes that occurred in the United States in 2004 (Najm and Smith 2007).

The specific research questions needed to answer the main question are these:

- What are the most dangerous glances away from the road, and what are safer glances?
- Can risk from distracting activities (secondary tasks) be explained by glance behavior?
- How does the timing of lead-vehicle closing kinematics in relation to off-road glances influence crash risk?
- What crash severity scale is best suited for analysis of risk?
- How can we change glance behavior to be safer, and how do the results of this research translate into countermeasures?

Data Formation and Methods

The SHRP 2 Naturalistic Driving Study (NDS) is the largest and most comprehensive ever undertaken—and the largest coordinated safety program ever undertaken in the United States. The study collected data from 3,147 volunteer drivers of all age and gender groups, during a 3-year data collection period (most drivers participated for 1 to 2 years), amounting to about 49.7 million vehicle miles, 5 million trip files, 3,958 data years, more than 1 million hours of video, and 2 petabytes of data. Data were collected across six sites in Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington. An onboard data acquisition system (DAS) was

designed, manufactured, and installed in each volunteer's own vehicle. Data were recorded continuously while the participant's vehicle was operating and sampled at the original resolution of the sensors. Recorded data included vehicle speed, acceleration, and braking; all vehicle controls; lane position; forward radar; and video views forward, to the rear, and on the driver's face and hands.

According to Najm and Smith (2007), five Lead-vehicle precrash scenarios were targeted because they were (a) highly ranked in crash frequency, functional years lost, and economic cost; (b) proven to be of particular relevance for inattention; and (c) suitable for planned analyses. These Lead-Vehicle Precrash Scenarios correspond approximately to rear-end crashes in National Automotive Sampling System (NASS) crash databases.

The final data set that was used for analyses contained 46 rear-end crash events, 211 near-crash events, 257 matched baseline events, and 260 random baseline events. Because this project was one of the first to have access to the SHRP 2 data set in fall 2013 and spring 2014, while data collection was ongoing, the final data set was not yet ready. All crashes and near crashes that were available at the time of data extraction were used. It was estimated that about 20% to 30% of the expected final data set was fully surveyed through kinematic triggers but that the full data set was "surveyed" by automatic notification processes (such as onboard Automatic Crash Notification algorithms, incident button presses, and site reports).

One random baseline (RBL) per crash or near-crash event was extracted completely at random from all trips in the available data and across all drivers and locations. The random baselines are used as controls in a case-control approach.

One matched baseline (MBL) per crash or near-crash event was selected to match each crash or near-crash event. The matched baselines are used as controls in a case-crossover approach. Analysis using the matching baseline was expected to be more robust to possible confounding contextual factors such as traffic density, weather, and road type. The matching criteria (e.g., driver, trip, no standstill, traffic flow, intersections, speed, weather, day/night) were intended to control for contextual factors that could influence glance behavior and thus create controls that provide a more similar context for comparison between baseline (control) events and crash or near-crash events than the random baselines.

Event data, time-series data, and video were delivered for each event. Event data variables describe each event as a whole (in a single value such as precrash scenario type or driver age). Time-series data describe the event over time at a sampling frequency that is specific to each variable. The primary common time period for analyses was 12 seconds before the crash point (in crash events), 12 seconds before minimum time to collision (in near-crash events), and 12 seconds before a reference point in the matched and random baselines.

As a complement to the variables defined in the SHRP 2 data dictionaries, a number of other variables were defined. A method was developed to derive kinematic and optical variables related to the lead vehicle (LV) by manually annotating lead-vehicle width in forward video. From this, many lead-vehicle-related variables were derived, such as optically defined range and range rate variables. Manual video annotation of eyeglance location variables and a number of other variables were also coded from video. The main glance variable, Eyes off Path, was defined as glances away from the vehicle's path, the direction of the vehicle's travel; a number of glance metrics were derived from this variable. Many other variables were defined and used in the detailed analyses of driver behavior (such as reaction points or start of evasive maneuvers), vehicle kinematics (such as time to collision), and driving context (such as brake light onsets).

Several methods were used estimate the risk of having a critical event (crash, near crash, or both, depending on the analysis) as a function of various predictors. The primary method used to estimate risk was odds ratios, as calculated by conditional logistic regression: the higher the odds ratio, the higher the likelihood of being involved in a crash or near crash. The purpose of logistic regression is to develop models of crash or near-crash risk as a function of various predictors associated with driver behavior and environment.

Key Results

Risk from Distracting Activities (Secondary Tasks)

The analysis started by replicating previous findings. The analysis shows generally similar results that are consistent with previous findings regarding distracting activities and glance metrics. In general, distracting activities occurred frequently—much more frequently in crashes, near crashes, and baselines than impairments such as drowsiness. In line with previous naturalistic driving studies (e.g., Fitch et al. 2013; Klauer et al. 2006, 2010, 2014; Olson et al. 2009), visually demanding tasks were associated with the highest risk. When considering crash and near-crash situations combined (CNC), the results showed that the aggregate category of Portable Electronics Visual-Manual [odds ratio (OR) 2.7, confidence interval (CI) 1.4–5.2] and, in particular, one individual activity in that category, Texting (OR 5.6, CI 2.2–14.5), had the highest odds ratios, suggesting a substantial risk.

Talking/Listening on Cell Phone (Figure ES.1) was found to decrease crash/near-crash risk significantly compared with not engaging in a phone conversation (OR 0.1, CI 0.01–0.7), representing an estimated 10-fold reduction in risk compared with the baseline (OR 10 if the sign of the coefficient is reversed). There were no crashes when drivers were Talking/Listening on Cell Phone.

Odds ratios for more than 50 distracting activities were examined. However, many of the activities did not occur frequently enough to achieve statistical significance. Distracting activities do not occur as frequently as glances and thus need larger sample sizes. Other individual categories, such as Locating/Reaching/Answering a Cell Phone or Adjusting/Monitoring the Radio, or other aggregate categories, such as Original Equipment or Vehicle External Distraction, were not significantly risky.

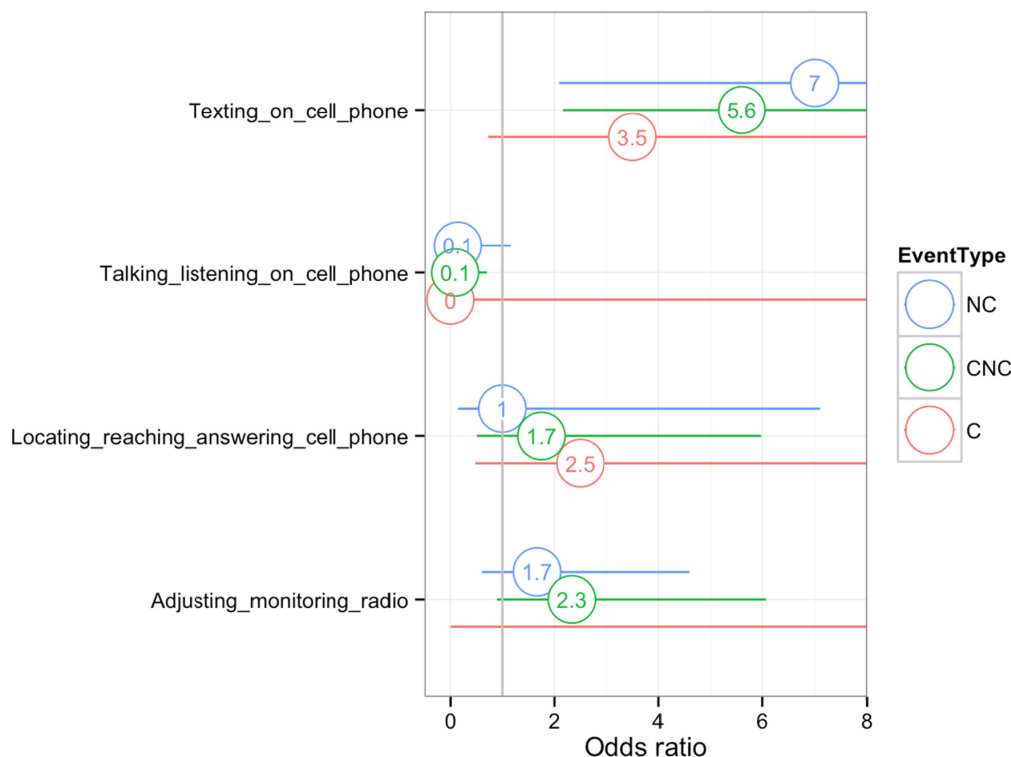


Figure ES.1. Odds ratios (numbers inside circles) and confidence intervals (horizontal lines) for specific distracting activities in crashes (C), near crashes (NC), and crashes and near crashes combined (CNC). An odds ratio is significant only when the confidence interval is fully above or below 1 (does not cross the vertical line at 1).

Figure ES.1 shows the ORs associated with specific distracting activities. The precise OR is shown in the center of each dot, and the lines surrounding the dots indicate the 95th percentile confidence interval. Odds ratios are significant only when the confidence interval does not cross the vertical line at 1. Figure ES.1 indicates that texting is significantly risky for crashes and near crashes combined and for near crashes alone. The figure also indicates that Talking/Listening on a Cell Phone shows a significantly reduced risk for crashes and near crashes combined.

Glance Location and Eyes-off-Path Timelines Before Crash or Minimum Time to Collision

Figure ES.2 indicates that the glance locations in the crash events are predominantly toward the cell phone and interior objects, followed by left and right windows/mirrors. Noticeably, there is a reduction in forward path location viewing until about 1.5 seconds before the crash. The eyes return quickly to the forward path location after the 1.5-second mark.

Figure ES.3 provides a concise summary, showing only the percentage of Eyes off Path for crashes, near crashes, matched baselines, and random baselines. Figure ES.3 plots Eyes off Path over the 12-second period preceding the crash point in crash events, the minimum time to collision (TTC) in near-crash events, and the reference points for the baselines. It seems that there is generally more Eyes off Path in crashes than in other events and that Eyes off Path is increasingly off the road until 1.5 seconds before the crash. In near crashes, a similar but less pronounced effect is shown.

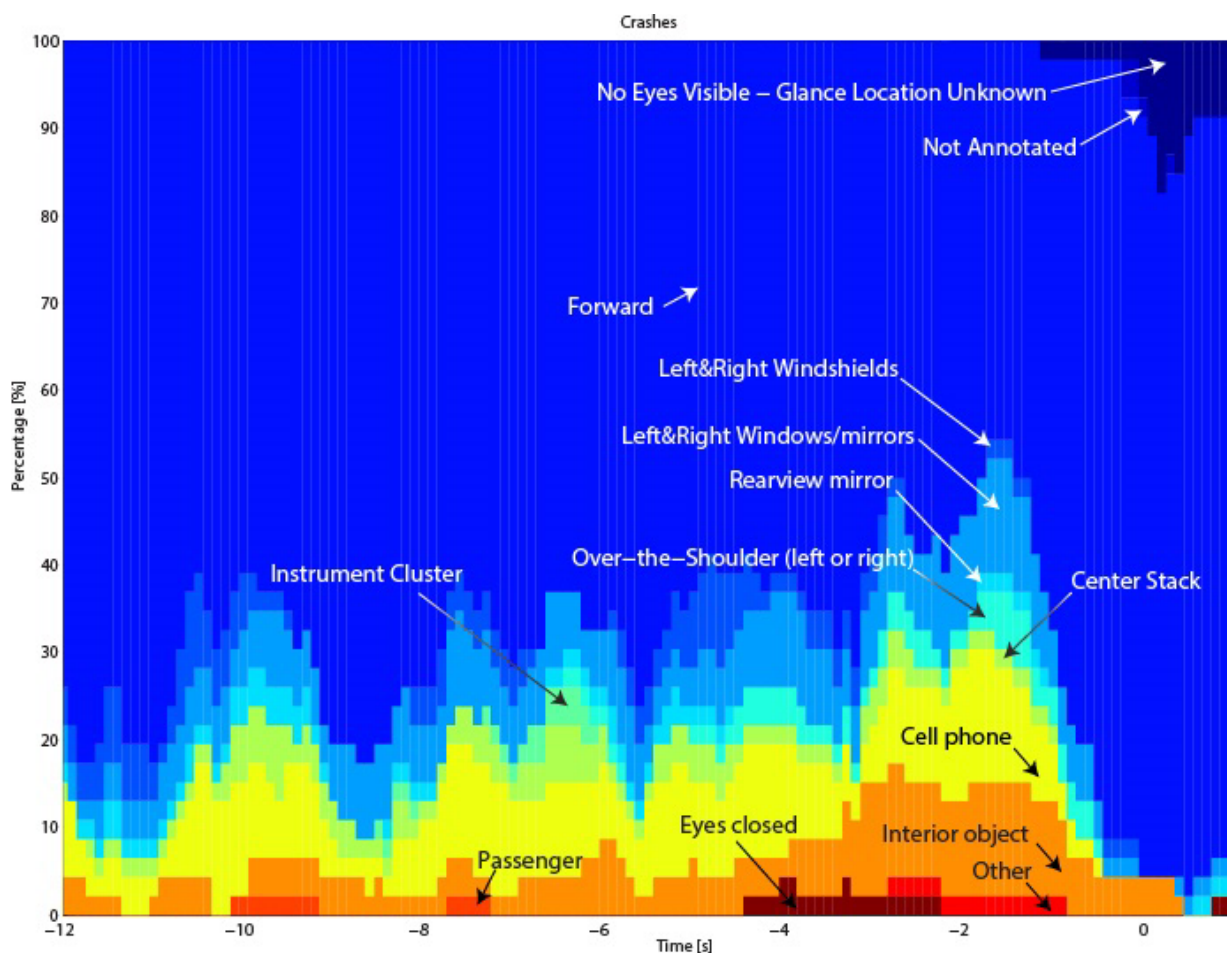


Figure ES.2. Glance locations over time in crash events for the 12 seconds before and 1 second after the crash point (at 0 seconds).

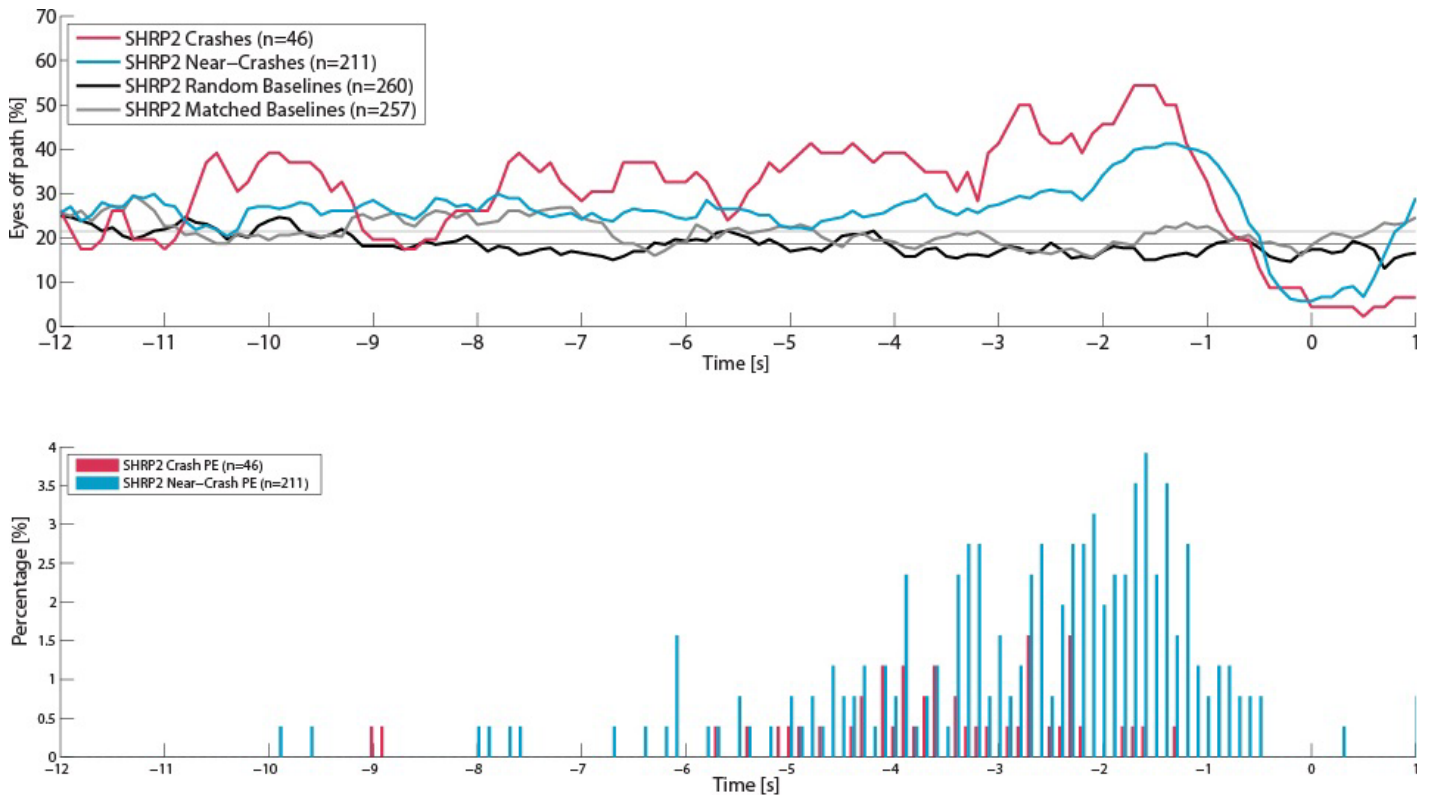


Figure ES.3. Percentage of Eyes off Path (for each event type at each time point) in relation to minimum TTC or crash point (zero point), and a histogram of the time of the precipitating events associated with each crash and near crash. Precipitating events correspond to the lead-vehicle brake light onsets.

Most Sensitive Glance Risk Metrics

To determine whether risk from distracting activities (secondary tasks) can be explained by glance behavior, it was necessary to first find the most predictive glance metrics. We found that many Eyes-off-Path glance behavior metrics were powerful drivers of risk, much more so than the type of distracting activity (secondary task). The finding that glance behavior has a key contributing role in crashes and near crashes is in line with existing research (e.g., Klauer et al. 2006, 2010, 2014). However, our analyses of single glance metrics quantified this risk more strongly. In general, the greatest risk estimates were shown when crashes were analyzed separately from near crashes.

Although very strong Eyes-off-Path–risk relationships were shown in separate glance metrics, the relationship between glance behavior and risk cannot be reduced to a single metric, as there is no separate metric that fully accounts for risk on its own. The relationship is analogous to accounting for discomfort associated with heat. Temperature is a good metric that accounts for much of the variance, but including humidity would result in better predictions, as would including wind speed. Each glance metric helps inform the risk estimates.

The most sensitive glance metric model was a linear combination of three-glance metrics because it was most predictive of crashes and near crashes. The first glance metric, Off3to1, denotes the proportion of time the eyes were off path from 3 seconds until 1 second before the crash or minimum time to collision. The second glance metric is the mean duration of off-path glances, mean.off. The third metric, mean uncertainty, is the mean value of a composite measure based on the Senders et al. (1967) uncertainty model of the driving situation. Of the three metrics, the Off3to1 metric is the strongest individual risk-predicting metric.

Clearly, factors other than Eyes off Path contribute to rear-end crashes. For example, factors such as age (younger and older) and visibility problems (visual obstructions or rain) were significantly different in crashes compared with near crashes.

Timing of Eyes off Path Relative to Situation Kinematics and Visual Cues

In Figure ES.4, it can be observed that the crashes, near crashes, and matched baselines are relatively well separated in this state space (i.e., Glance Length and the rate of change of inverse Time to Collision). In particular, the majority of the crashes—and a subset of the near crashes—are organized along a line with a negative slope.

This analysis revealed a distinct mechanism for many of the crashes. In line with Tijerina et al. (2004), we found that drivers in most cases did not start to look away when lead vehicle was closing. Rather, drivers who crashed typically looked away just before the lead vehicle started closing and did not look back until collision was unavoidable. The criticality when looking back, and hence the crash risk, is largely determined by an interaction between last glance duration and the rate at which the situation changed during the glance (operationalized here in terms of inverse TTC change rate). The event outcome is also determined by the vehicle's braking capacity and the driver's time to react.

Thus, the key mechanism behind these types of rear-end crashes (grouped as Category 1, Inopportune glance, in Figure ES.4) can be understood as a “perfect mismatch” between last glance duration and situation change rate (in line with the general mismatch conceptualization of inattention suggested in Engström, Monk et al. 2013). The crashes grouped under a different category (Category 2, Looking away in an already critical situation) followed a similar pattern, but here the driver looked away when the vehicles were already closing, often because of visibility problems that presumably impaired looming detection.

The probability of such a mismatch depends on the joint probability distributions of glance durations and situation kinematics. Since long glances are very rare and short glances are very common, many crashes occur due to the combination of a relatively short glance and a high

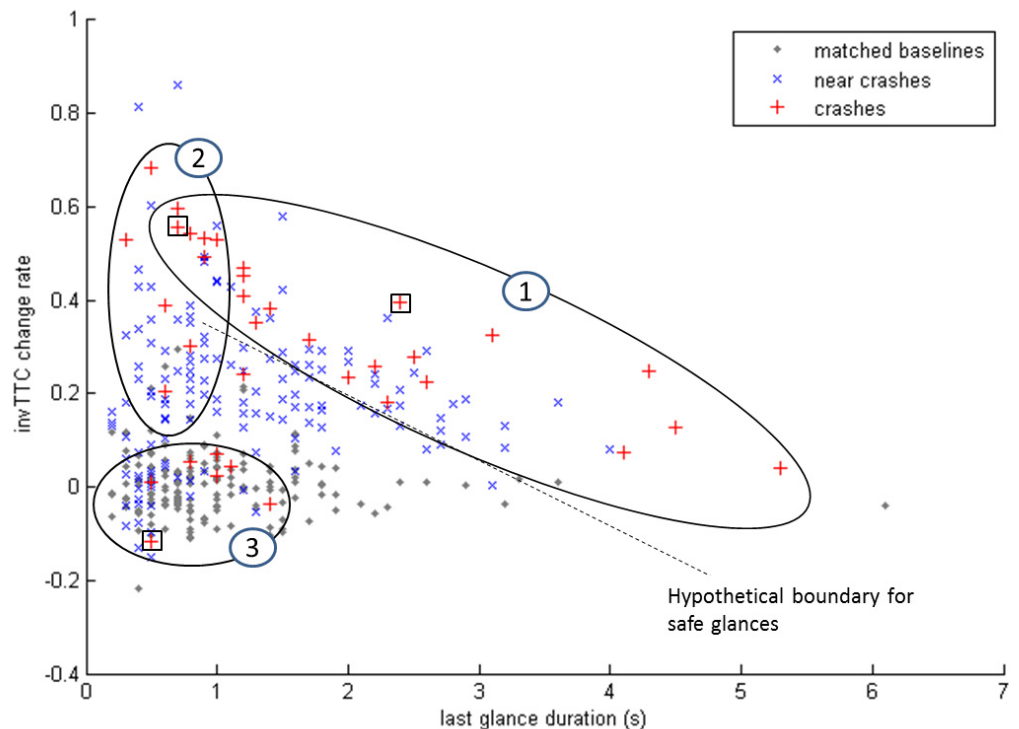


Figure ES.4. Last glance duration versus inverse TTC change rate (the change rate of lead-vehicle looming). Ovals mark the three main categories of crashes identified through video inspection. Cases marked by squares are included as examples in text. The dashed line represents a hypothetical boundary for safe glances.

change rate. Thus, an important finding of the present analysis is that glances that lead to crashes may not necessarily have to be long. In fact, the majority of the crashes in the present sample were associated with glances shorter than 2 seconds.

A prototypical case for the general mechanism in Category 1 can be seen in Figure ES.5. Here, the driver does not expect the lead vehicle to brake and thus looks away from the road while the situation is not yet critical (when inverse TTC is close to zero). During the glance away, the lead vehicle initiates braking. The level of criticality the driver faces when looking back depends on the interaction between the duration of the glance and the rate at which the situation develops, yielding the linear organization with a negative slope in Figure ES.4.

Category 2 cases (Figure ES.4) represent situations in which the driver looks away at a point when the situation is already critical (i.e., the vehicles are already closing and the inverse TTC has already risen significantly above zero). This typically involves a very brief glance (around 0.5 second) before the gaze is presumably redirected to the road by the strong looming cues.

In Category 3 cases (Figure ES.4), the driver looks away and back again before the situation turns critical, leading to a small change rate during the last glance and varying glance durations. Here the off-path glance most likely did not interfere with the reaction to the event (although it may possibly have affected the detection of available predictive cues). Thus, these events can be regarded as functionally similar to crashes in which the driver did not look away at all within 8 seconds. Category 3 events typically involve a strong violation of expectation [e.g., the lead vehicle stops late at yellow light or a traffic queue builds in front of the principal other vehicle (POV) in an unexpected location].

Analyses of driver reactions in the crashes and near crashes showed that driver reactions were not notably affected by the lead-vehicle brake lights but were instead strongly coupled to situation kinematics. Brake light onsets occurring while the driver looked forward were generally ignored and do not seem to have influenced the willingness of the driver to take the eyes off the road. Instead, the data indicate that drivers did not seem to react below an inverse TTC threshold of 0.2 and had progressively faster reactions for larger looming values above this 0.2 threshold. This behavior was successfully predicted by an accumulator model of reaction timing. Another key finding was that reactions in eyes-off-threat situations were generally faster for near crashes compared with crashes.

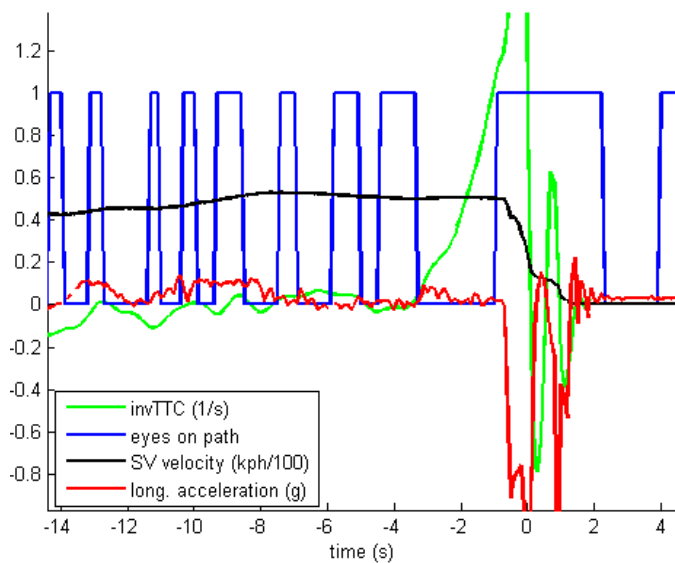


Figure ES.5. Example of Category 1 crash (event ID 19147492). Y-axis units in legend.

Discussion and Conclusions

What are the most dangerous glances away from the road, and what are safer glances? The team's initial answer to this question was that the most dangerous and safest glances are quantified by a three-metric glance model. The model combines a metric of inopportune glance, mean glance duration, and a composite measure estimating the driver's uncertainty of the driving situation.

Can risk from distracting activities (secondary tasks) be explained by glance behavior? The three-metric glance model and many of the individual glance behavior metrics were substantially more predictive than the models based on distracting activities. Portable Electronics Visual-Manual interactions were explained by the proportion of Eyes off Path in the 2 seconds overlapping the precipitating event, but Texting and Talking/Listening on Cell Phone were not. However, the three-metric model could not be compared with the distracting activities because the distracting activities were only coded in the 5 seconds preceding the precipitating event until 1 second after. This comparison with the three-metric model should be made in future research.

How does the timing of lead-vehicle closing kinematics in relation to off-road glances influence crash risk? A key finding in this report was a distinct mechanism for many of the crashes. The mismatch depends on the joint probability distributions of glance durations and situation kinematics. Thus, an important finding of the present analysis is that glances that lead to crashes may not necessarily have to be long.

This key finding motivates reconsideration of the first question: What are the most dangerous glances away from the road, and what are safer glances? One way to think about which glances are safer than others is in terms of the boundary drawn in Figure ES.4. Under normal conditions (e.g., a dry road surface, normal braking capacity, normal visibility conditions), glances can be regarded as safe as long as they appear under this line, which is determined by the interaction of glance duration and kinematics change rate. Thus, the answer to the first part of the question can be reformulated like this: Dangerous glances are those during which the driver gets exposed to the risk of a rapidly changing situation. This answer is naturally partly related to the glance duration: the longer the glance, the greater the probability that the kinematics will develop in such a way that the perfect mismatch occurs. However, the second part of the equation is the natural variability in vehicle-following situation kinematics. Drivers are normally successful in controlling this variability by means of anticipation. However, as shown in the present analysis, the safety margins adopted by drivers when looking away are often insufficient to protect them from rapid changes in situation kinematics. For a given glance duration, a certain minimum change rate is needed to produce a crash. Conversely, for a given change rate, the glance has to be sufficiently long for a crash to happen. A reformulated answer to the second part of Question 1 is thus as follows: *An off-road glance is only perfectly safe when the safety margins adopted are sufficient to protect the driver if the situation changes rapidly during the glance.*

Further, driver reactions were found to be strongly coupled to situation kinematics and not notably affected by lead-vehicle brake lights. Driver reactions do not occur below a 0.2 inverse TTC threshold (i.e., while there is no perceived looming), and driver reactions are progressively faster with larger inverse TTC values (a looming lead vehicle) once the eyes return to the road. Many researchers have assumed a constant, situation-independent distribution of driver reaction times to the situation itself (Sugimoto and Sauer 2005; Kusano and Gabler 2012). The present results indicate that such an assumption is inadequate.

What crash severity scale is best suited for analysis of risk? Our analyses resulted in the formulation and proposal of two potential severity scales: Model-estimated Injury Risk (MIR) index and Model-estimated Crash Risk (MCR) index. These scales are created using mathematical simulations and applying a model of driver glance behavior to kinematics based on actual crashes and near crashes; they represent what may have happened had the event played out according to a specific driver model. The two scales (MIR and MCR) provide continuous values and can be calculated for actual crash and near-crash events. However, further work is necessary to validate these scales. It should be noted that the severity scales are simulated. Actual severity scales—Delta Velocity (DeltaV) for

crashes and minimum time to collision (minTTC) for near crashes—are still the most relevant metrics when analyzing actual severity (what actually happened in the event). The main drawback with the actual severity scales is that they cannot be used to compare both crashes and near crashes. This property—the ability to compare potential severity across crashes and near crashes—is enabled by the proposed MIR and MCR scales. It is important to note that these scales are also enabled by naturalistic data. Without the detailed time-series data leading up to crashes and near crashes, it would not be possible to compute the MIR and MCR scales.

The answer to the main research question—*What is the relationship between driver inattention and crash risk in Lead-Vehicle Precrash Scenarios?*—can be found in the general pattern of our results. In line with previous naturalistic driving studies, the results show that some activity types significantly increase risk (such as Texting and the aggregate category of Portable Electronics Visual-Manual). However, for Talking/Listening on Cell Phone, a strong significant decrease in risk was found. Notably, there were no crashes while talking/listening on the phone. Three types of glance metrics showed the largest odds ratios: (1) the proportion of time the eyes were off path between 3 seconds and 1 second before the crash or minimum time to collision, (2) mean duration of off-path glances, and (3) the mean value of a composite measure estimating the driver's uncertainty of the driving situation. However, it was when these three-glance metrics were combined in a model that they were most predictive of crashes and near crashes.

Analyses of the timing of off-path glances with lead-vehicle closing kinematics and visual cues revealed a distinct mechanism behind most of the crashes that can be understood in terms of a “perfect mismatch” between last glance duration and the change rate of the lead vehicle closing. Crashes occur with short glances and high closure rates, just as crashes occur with long glances with slow closure rates. These mismatches can be understood in terms of a joint probability distribution for glance durations and closure rates in which the most likely combinations will show up in a crash sample like the present one. Since long glances are rare, many crashes occur due to the combination of a relatively short glance and a high change rate. Another group of crashes followed a similar pattern in which the driver looked away when the vehicles were already closing, often due to visibility problems that presumably impaired looming detection. This pattern of results, or mechanism, was further confirmed in what-if simulation and modeling of reaction time.

The main pattern is that lead-vehicle crashes can be understood as the mismatch between glance duration and the lead-vehicle closure rate. Timing matters greatly, and taken together, the analyses strongly reflect this mechanism.

How can we change glance behavior to be safer, and how do the results of this research translate into countermeasures? The findings from this project have clear implications for countermeasures, as summarized below.

Regarding human-machine interaction design, distraction guidelines, and other regulatory agency countermeasures, the results emphasize the need to tackle the distraction problem as a joint probability problem. Risk can most effectively be reduced by removing the timing mismatch of eyes off road and lead-vehicle closure rates (inverse TTC change rate). A reduction of both sides of the equation—reducing eyes-off-road occurrence and reducing closure rates—is recommended. The results point to the importance of designing interfaces that minimize the need for visual interaction, particularly in portable electronic devices. They also indicate that eliminating long glances (e.g., glances above a limit of 2 seconds) will not eliminate the distraction problem, because inopportune glances of normal short duration with the wrong timing relative to high lead-vehicle closure rates often produce rear-end crashes. Further, the results support the potential for nonvisual interfaces because Talking/Listening on a Cell Phone significantly reduced risk. In other words, reduction of off-road glances alone will not solve the problem; a reduction of lead-vehicle closure rates is needed.

The results provide strong support for vehicle design and driving support countermeasures, in particular active safety systems such as autonomous emergency braking (AEB) systems, forward collision warning (FCW), and autonomous cruise control (ACC). Active safety systems provide

the safety margins needed to protect the driver if the situation changes rapidly during an off-path glance by creating more time headway, issuing warnings to alert the driver to rapid closure rates, and actively braking.

For education and behavioral change, it is recommended that the public be made aware of the inopportune glance mismatch mechanism, that the importance of adopting safe headways be emphasized (particularly for ages 16–17 and 76+), and that usage-based insurance be encouraged (e.g., rewarding longer time headways).

Regarding road and infrastructure design, emphasis should be placed on creating smooth flowing traffic, reducing the occurrence of sudden, unexpected kinematic changes. Further, improving road surfaces to decrease stopping distances and developing self-explaining roads to reduce unexpected situations are also needed.

CHAPTER 1

Background

To illustrate the central topic of the present research, consider the following examples. A driver is following a lead vehicle at a constant headway with the intention of merging into a lane on the freeway. While she glances over her shoulder for an appropriate gap to merge into, the lead vehicle suddenly brakes. When she looks back at the lead vehicle, it is too late to brake in time and a rear-end crash occurs. Alternatively, a driver could be reading a text message on his cell phone when the lead vehicle suddenly brakes in stop-and-go traffic. In each scenario, the driver is looking away from the forward view. The first example is perhaps more interesting because it illustrates that the driving task itself, not only secondary tasks, can cause inattention. Although the argument could be made that a good driver is always aware that an emergency situation could occur at any time, it is very difficult, if not impossible, to remain vigilant and keep attention on all relevant sources of information while driving. In particular, the simultaneous occurrence of an unexpected event with eyes-diverted has been hypothesized to play a key role in the causation of crashes and near crashes and has been a central motivating factor to pursue the present research.

Communication technology pervades our daily living and is increasingly integrated into the car, where it has the potential to distract drivers. Consequently, there is a critical need to better understand distraction and the limits of attention while driving. Distracted driving, which has long been a contributor to motor vehicle crashes, is flourishing in the fertile environment of communication, information, and entertainment technology that is transforming the car. Distraction includes instances when drivers take their eyes off the road—visual distraction—and instances when drivers take their mind off the road—cognitive distraction. According to the US-EU Driver Distraction and HMI Working Group, *driver inattention* is defined as a mismatch between the current attention allocation (distribution) and that demanded by activities critical for safe driving, whereas *driver distraction* is defined as diversion of attention away from activities critical

for safe driving to one or more activities that are not critical for safe driving (Engström, Monk et al. 2013). Driver inattention is thus conceived of in terms of mismatches between the current allocation of attention and that demanded by activities critical for safe driving. In the current context the activity critical for safe driving is attention to and control of headway to the lead vehicle.

One of the greatest traffic safety challenges of our time is to eliminate or moderate crashes that are caused by driver inattention. Driver inattention is a long-standing major factor related to morbidity and mortality in motor vehicle crashes (Evans 2004). It is also a renewed problem associated with modern technology-based distractions such as the cell phone (NHTSA 2010a). In 2009 distraction was involved in crashes, causing 5,474 deaths and leading to 448,000 traffic injuries across the United States (NHTSA 2010b). *Inattention to forward roadway*—because of secondary tasks engagement, driving-related inattention to the forward roadway, nonspecific eyeglances, and fatigue—was identified as the primary contributing factor in 78% of all crashes, 93% of rear-end crashes, and 65% of near crashes in the National Highway Traffic Safety Administration (NHTSA) 100-car study (Dingus et al. 2006). The first three categories involve looking away from the forward roadway, and the last category involves loss of forward roadway vision from eyelid closure.

Two main developments have combined in the past few years to create an escalation in priority of the driver distraction and inattention issue: (1) research has been showing a much clearer association between driver inattention and crash risk, and (2) there is a growing concern over the compatibility with driving of the ever-increasing functionality available through electronic devices (such as smartphones and intelligent vehicle systems). The safety problem at issue in both these developments centers on problems related to driver inattention. Driver inattention is very high on the political and scientific agenda, and the industry is moving fast to respond both to enable the use of electronic functionality in a safe

manner and to reduce driver inattention through safety systems that are capable of monitoring it.

The specific mechanisms and indicators of the risk of inattention are unfortunately not definitively quantified. Initial analyses of the 100-car study focused on general relationships, such as the proportion of crashes involving inattention as a contributing factor (Dingus et al. 2006), or the relative and population-attributable risk associated with different inattention-related activities (Klauer et al. 2006). Subsequent analyses have examined the influences of various characteristics, such as total eyes-off-road time (glance history), single glance duration, and glance location. Previous work has also focused on calculating the risk associated with (human-identified) classifications of distracting tasks, such as talking, dialing, eating, and texting (e.g., Fitch et al. 2013; Klauer et al. 2006, 2010, 2014; Olson et al. 2009). Although this task risk approach has merit, especially for policy decisions and education on what tasks should or shouldn't be done while driving, it does not explain *why* the tasks are dangerous—nor does it provide the inattention performance risk information needed for many countermeasures. It is more important to be able to determine whether the particular *way* a driver is doing a task (e.g., radio tuning) is dangerous, rather than simply detecting what task is being done. The radio can be tuned in a safe or unsafe way; the inattention performance quantification approach presented here focuses on being able to measure this and, in various ways, provide countermeasures based on this.

Klauer et al. (2006) and Olson et al. (2009) show that critical events are associated with high eyes-off-road times during the 6-second period preceding an event onset. In a reanalysis of the 100-car data, Klauer et al. (2010) showed that total Time Eyes off the forward Roadway (total TEOR) within a time period is associated with increased crash/near-crash risk. The shortest significant amounts were 20% (3 seconds) total TEOR for a 15-second task duration, or 30% (2 seconds) total TEOR for a 6-second task duration. These studies indicate that accumulated eyes-off-road time (glance history) is associated with higher crash probability, but they did not actually test independently the effect of single glance duration or assess how single glance duration combines with glance history to influence crash risk. Previous naturalistic data analyses have generally not looked at the timing aspect of eyes off road—how the temporal location of off-road glances within the time window relates to crash risk.

Using the 100-car data, Liang et al. (2012) compared 24 different ways to combine various glance characteristics, such as single glance duration, glance history, and glance location. They found that single off-road glance duration was the best crash predictor. Glance history (such as Total Glance Time) and glance location did not improve risk estimation above single glance duration but they were still predictive of crash/near-crash risk. Further analyses of the 100-car data have

revealed that risk is pinpointed to the timing of off-road glances in relation to external events. Risk is primarily associated with an inopportune single glance duration (Victor and Dozza 2011; Victor et al., forthcoming). The most sensitive measures for risk were those that quantified an overlap of the off-road glance with the precipitating event—a change in the state of environment or action that began the sequence leading to the crash or near crash (e.g., a lead vehicle that begins braking). The longer the driver looks away from the road at the time of the precipitating event, the greater the risk of a crash or near crash. However, these analyses did not look at what happened closer to the crash or near crash; rather, they looked only at the time of the precipitating event, which was at the start of the sequence leading to the crash or near crash and could be many seconds before the crash. More work is needed with the larger SHRP 2 data set to examine the relative contributions of different glance characteristics in relation to context, and specifically to examine the detailed mechanisms in the period of time between the precipitating event and the crash or near crash.

In comparison with driving simulator and field experiments, naturalistic driving data are valuable because they are able to quantify real crash risk (e.g., NHTSA 2013). Until now, with the SHRP 2 data set, naturalistic driving data—have included a limited number of crashes. Risk has generally been calculated for safety-critical events, which groups together crashes, near crashes, and incidents. Detailed driving behavior data recorded in the seconds leading up to crashes and near crashes cannot be obtained from test tracks, simulators, or observational data (e.g., crash databases).

The SHRP 2 Naturalistic Driving Study can provide the data that are needed for inattention performance measures associated with precrash situations. The data are essential to improve the understanding of driver inattention, for guidelines to reduce distraction from electronics devices, for countermeasures that detect and act to reduce distraction while driving, and for regulation and education.

1.1 Summary of Project Aims

This S08A research targets two of the highest prioritized global research questions identified for SHRP 2 in the S02 Phase 1 report (Boyle et al. 2010):

- How do dynamic driver characteristics (e.g., inattention, fatigue, workload), as observed through driver performance measures, influence crash likelihood? (SHRP 2–GRQ1)
- How does driver distraction influence crash likelihood? (SHRP 2–GRQ3)

This effort focuses primarily on “driver characteristics, behavior, and performance”—one of the four priority areas

set out by SHRP 2 (Boyle et al. 2010). However, this research is also relevant for the “intersection crashes or other infrastructure-related crashes” priority area because Lead-Vehicle Precrash Scenarios are overrepresented in intersection crashes.

The current research aims to determine the relationship between driver inattention and crash risk in Lead-Vehicle Precrash Scenarios. Inattention is conceptualized as a mismatch between attention and situation, in line with the recent U.S.-EU taxonomy of inattention (Engström, Monk et al. 2013). The research aims to develop inattention-risk relationships describing how an increase in inattention performance variables combines with context in Lead-Vehicle Precrash Scenarios to increase risk. The inattention-risk relationships are intended to show which glance behaviors are safer than others and pinpoint the most dangerous glances away from the road. The results aim to (1) support distraction policy, regulations, and guidelines; (2) improve intelligent vehicle safety systems; and (3) teach safe glance behaviors.

Three key developments were proposed as a basis for this effort: (1) the development of observable performance-based quantifications of inattention; (2) the development of measures relating inattention to event context characteristics, such as stimulus onset; and (3) the development of a validated, continuous event severity measure combining a measure of safety margin and a measure of injury risk.

The main research question is this: *What is the relationship between driver inattention and crash risk in Lead-Vehicle Precrash Scenarios?*

The specific research questions needed to answer this question are the following:

- Can risk from distracting activities (secondary tasks) be explained by glance behavior?
- What are the most dangerous glances away from the road, and what are safer glances?
- How does the timing of lead-vehicle closing kinematics in relation to off-road glances influence crash risk?
- What crash severity scale is best suited for analysis of risk?
- How can we change glance behavior to be safer, and how do the results of this research translate into countermeasures?

This report is structured to focus on these research questions in progression. Each step in the progression of analysis is intended to add more detailed knowledge, going from simpler analyses to more precise analyses. The analysis starts with an examination of crashes, near crashes, and baselines in descriptive (contextual) data. Next, an analysis of the risk from distracting activities (secondary tasks) is implemented. Thereafter, a replication and extension of previous research examines risk from eyes off forward path in the period of time at the precipitating event. Next, risk is examined from eyes off forward path in the period of time

leading up to the crash point (in crash events) or the minimum time to collision (in near-crash events). Then, the timing of Eyes off Path in relation to situation kinematics and visual cues is examined. In the final analyses, actual and potential severity is examined. Lastly, we discuss lessons learned, provide recommendations for how the results of this research can be translated into countermeasures, and identify further research needs.

1.2 SHRP 2 Naturalistic Driving Study Background

The second Strategic Highway Research Program (SHRP 2) conducted the largest and most comprehensive naturalistic driving study (NDS) ever undertaken. The study collected data from over 3,000 male and female volunteer passenger-vehicle drivers, ages 16–98, during a 3-year period, with most drivers participating for 1 to 2 years. The study was conducted at a site in each of six states: Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington. Data collected included vehicle speed, acceleration, and braking; vehicle controls when available; lane position; forward radar; and video views forward, to the rear, and on the driver’s face and hands. The NDS data file contains about 50 million vehicle miles, 5 million trips, more than 3,900 vehicle-years, and more than 1 million hours of video, for a total of about 2 petabytes of data.

In parallel, the Roadway Information Database (RID) contains detailed roadway data collected on more than 12,500 centerline miles of highways in and around the study sites; about 200,000 highway miles of data from the highway inventories of the six study states; and additional data on crash histories, traffic and weather conditions, work zones, and ongoing safety campaigns in the study sites. The NDS and RID data can be linked to associate driving behavior with the roadway environment.

Campbell (2012) provides an excellent overview of the study. Additional details may be found at the study’s InSight website (<https://insight.SHRP2nds.us/>).

The study’s central goal is to produce unparalleled data from which to study the role of driver performance and behavior in traffic safety and how driver behavior affects the risk of crashes. This involves understanding how the driver interacts with and adapts to the vehicle, the traffic environment, roadway characteristics, traffic control devices, and other environmental features. After-the-fact crash investigations can do this only indirectly. The NDS data record how drivers really drive and what they are doing just before they crash or almost crash. The NDS and RID data will be used for years to come to develop and evaluate safety countermeasures designed to prevent or reduce the severity of traffic crashes and injuries.

First SHRP 2 NDS Analysis Projects

Four contracts were awarded in 2012 under SHRP 2 Project S08, Analysis of the SHRP 2 Naturalistic Driving Study Data, to study specific research questions using the early SHRP 2 NDS and RID data. An open competition solicited proposals to address topics of the contractor's own choosing that would have direct safety applications. The request for proposals required proposals that would

- Lead to real-world applications and safety benefits (theoretical knowledge without potential applications was not a priority);
- Be broadly applicable to a substantial number of drivers, roadways, and/or vehicles in the United States; and
- Demonstrate the use of the unique NDS data—similar results could not be obtained from existing nonnaturalistic data sets.

In addition to these goals, SHRP 2 expected the project teams to serve as both pilot testers and advisers. As they conducted these first substantial NDS and RID analyses, these studies' experienced researchers would discover valuable insights on a host of both pitfalls and opportunities that others should know about when they use the data.

The four projects began in February 2012 and were conducted in two phases. In Phase 1, which concluded in December 2012, the contractors each obtained an initial set of data, tested and refined their research plan, and developed a detailed plan for their full analyses. Three projects—of which this study, *Analysis of Naturalistic Driving Study Data: Safer Glances, Driver Inattention, and Crash Risk*, is one—successfully completed this proof-of-concept phase and were selected for the full Phase 2. The three projects obtained and analyzed a much richer though still preliminary data set and reported their results in July 2014.

Constraints of the First SHRP 2 NDS Studies

These initial projects were conducted while the NDS and RID data files were being built. This imposed constraints that affected the work substantially. The constraints included the following:

- **Sample size:** In summer 2013, when the projects requested their full data sets, the NDS data file was only 20% to 30%

complete. As a result, each project could obtain only a fraction of the trips of interest, which are now available in the full NDS data.

- **RID not complete and not linked to the NDS:** Projects based on roads of specific types or locations could not identify those roads from the RID but instead had to use Google Earth or some similar database to identify them. They then obtained trips of interest using less efficient searches through the NDS than will be possible when the NDS and RID are linked.
- **Data processing:** Some data, such as radar, had not been processed from their raw state to a form in which they were fully ready for analysis.
- **Data quality:** NDS data are field data, and field data are inherently somewhat messy. At the time these projects obtained their data, some data had not been quality controlled and some characteristics of the data were not yet well understood.
- **Tools for data users:** Not all crashes and near crashes had been identified, and a separate small data set containing only crashes, near crashes, and baseline exposure segments had not been built. Also, a small trip summary file containing key features of each trip had not been built. Users can conduct initial analyses on many subjects quickly and easily using the trip summary file.
- **Other demands on data file managers:** The first priority for the NDS manager, Virginia Tech Transportation Institute (VTTI), and the RID manager, Center for Transportation Research and Education (CTRE), was to complete data processing and quality control. Field data were being ingested continually. Data delivery for users sometimes was delayed due to these demands on their resources.

These issues are being resolved in 2014. The NDS and RID data are complete and are being linked. Data processing and quality control are being completed. Crash and near-crash files and trip summary files are being built. If the initial three projects were to begin in 2015, each would have more data and would obtain the data far more easily and quickly. Readers should keep these constraints in mind as they read this report. Despite working under these constraints, this project and the other two NDS projects have produced valuable new insights on important traffic safety issues that will help reduce traffic crashes and injuries.

CHAPTER 2

Data Set Formation and General Methodology

2.1 SHRP 2 Naturalistic Driving Study Data

An onboard data acquisition system (DAS) was designed, manufactured, and installed in each volunteer's own vehicle. Data were recorded continuously while the participant's vehicle was operating and sampled at the original resolution of the sensors. Recorded data included vehicle speed, acceleration, and braking; all vehicle controls; lane position; forward radar; and video views forward, to the rear, and on the driver's face and hands (see Figure 2.1). Additional details may be found at the study websites www.SHRP2nds.us/ and <http://forums.SHRP2nds.us/>.

2.2 Formal Data Access Procedures

Institutional Review Board (IRB) approval was received through the Swedish IRB 00005875 Regional Ethical Review Board. The Federal Wide Assurance on file with the Department of Health and Human Services is FWA00016822, Chalmers University of Technology. The IRB review for Phases 1 and 2 was done by IRB 00005875; the continuing review was taken care of by IRB 00001183. A data requirements specification was formulated in cooperation with the data supplier, VTTI. After the data requirements specification was finalized, a data sharing agreement was executed and the data were received.

2.3 Targeted General Crash Population

Five Lead-Vehicle Precrash Scenarios were selected according to the 37 precrash scenario typology for crash-avoidance research (Najm and Smith 2007). Najm and Smith established a common typology that is useful for both crash and near-crash scenarios. These scenarios were targeted (each crash or near-crash was classified into one of these scenarios) because they

were (a) highly ranked in crash frequency, functional years lost, and economic cost, (b) proven to be of particular relevance for inattention, and (c) suitable for planned analyses:

- Scenario 22: Following vehicle making a maneuver (following vehicle making a maneuver and approaching lead vehicle).
- Scenario 23: Lead vehicle accelerating (following vehicle approaching an accelerating lead vehicle).
- Scenario 24: Lead vehicle moving at lower constant speed (following vehicle approaching lead vehicle moving at lower constant speed).
- Scenario 25: Lead vehicle decelerating (following vehicle approaching decelerating lead vehicle).
- Scenario 26: Lead vehicle stopped (following vehicle approaching a stopped lead vehicle).

These five Lead-Vehicle Precrash Scenarios are approximately mapped to the rear-end crash type used in National Automotive Sampling System (NASS) crash databases, including the General Estimates System (GES) and the Crashworthiness Data System (CDS) (Najm et al. 2003). Together, these five precrash scenarios constitute about 29%, or 1.7 million, of the crashes that occurred in the United States in 2004 (see Table 2.1).

2.4 Event Sample-Size Request

Four types of events were requested for analyses: crash events (C), near-crash events (NCs), matched baseline events (MBLs), and random baseline events (RBLs). The Phase 2 data request was for a minimum of 220 event clusters. An event cluster is composed of three events: (1) one crash or near-crash event, plus (2) one random baseline event, and (3) one matched baseline event. That is, each crash or near-crash event was accompanied by two baseline events that make up an analysis "cluster." Thus, the request was for a minimum of 220 crash



Figure 2.1. The four video views of the car's interior.

Table 2.1. Characteristics of Targeted Crash Population, by Precrash Scenario Type

	22. Following Vehicle Making a Maneuver	23. Lead Vehicle Accelerating	24. Lead Vehicle Moving at Lower Constant Speed	25. Lead Vehicle Decelerating	26. Lead Vehicle Stopped	Total
Crashes	85,000 (1.44%)	19,000 (0.32%)	210,000 (3.53%)	428,000 (7.2%)	975,000 (16.41%)	1,717,000 (28.9%)
Vehicles involved	180,000 (1.69%)	40,000 (0.38%)	445,000 (4.16%)	936,000 (5.33%)	2,162,000 (20.21%)	3,763,000 (31.77%)
People involved	249,000 (1.66%)	54,000 (0.36%)	612,000 (4.07%)	1,283,000 (8.54%)	3,032,000 (20.18%)	5,230,000 (34.81%)
Economic cost (U.S. dollars)	1,212,000 (1.01%)	243,000 (0.23%)	3,910,000 (3.26%)	6,390,000 (5.33%)	15,388,000 (12.84%)	27,143,000 (22.67%)
Functional years lost	18,000 (0.67%)	4,000 (0.15%)	78,000 (2.81%)	100,000 (3.62%)	240,000 (8.69%)	440,000 (15.94%)

Source: 2004 GES Statistics.

or near-crash events, a minimum of 220 MBLs, and a minimum of 220 RBLs, for a total minimum of 660 events.

The exact proportion of crash versus near-crash events in the minimum 220 was difficult to predetermine as it was not known how many crashes would be available. The SHRP 2 database was not finalized at the time of extraction. However, a minimum of 100 crash events was requested. This 100-crash minimum was based on an estimation of how many lead-vehicle crashes (precrash Scenarios 22–26) should be available in the final SHRP 2 data set and on the expectation that in-vehicle Automatic Crash Notification algorithms would immediately identify most crashes for immediate processing, even if the database was not fully uploaded. This estimate was calculated in the following manner. Because the five targeted precrash scenarios make up about 29% of the total number of crashes in the general population, and 29% of the 700 projected SHRP 2 crashes equals 203 Lead-Vehicle Precrash Scenario-type crashes, and as half of these should be crashes in which the subject vehicle strikes a lead vehicle (as opposed to the following vehicle hitting the subject vehicle), it could be expected that there should be about 100 crashes in the SHRP 2 database that are eligible for our analysis. Further, for near crashes, it should be relatively easy to find a minimum of 100 near crashes, as the projected total number of near crashes was 7,000, or about 1,000 eligible Lead-Vehicle Precrash Scenario near crashes.

The sample-size request was driven by an analysis of effect-size requirements for computation of odds ratios (ORs) and by budget considerations. An odds ratio is computed as a ratio of the odds in a safety-critical event (crash or near crash) and a comparison event (baseline event):

$$OR = \frac{\text{Odds (Safety - Critical Event)}}{\text{Odds (Comparison Event)}} \quad (2.1)$$

Previous analyses of glance variables in the 100-car data showed that odds for comparison events are relatively independent from the glance variables, and significant ORs were as low as 1.3 (Victor and Dozza 2011; Liang et al. 2012). Further, OR significance depends on its confidence interval (CI), which can be calculated by computing the standard error (SE) and applying Equation 2.2.

$$CI = \exp^{\log(OR) \pm 1.96 * SE} \quad (2.2)$$

In general, the lower the OR and the odds, the more samples are needed to show statistical significance. Increasing the number of baselines helps achieve statistical significance; however, the beneficial effect of adding more baselines dissipates when the number of baselines is approximately four times as large as the number of safety-critical events. Figure 2.2 illustrates these features and trends by examining four different scenarios with different OR and odds values

inspired by previous analyses of the 100-car data set (Victor and Dozza 2011; Liang et al. 2012). The high scenario corresponds to reaching a significant OR equal to 1.5, with odds for comparison events equal to 0.2. In this high scenario, it is possible to compute ORs in separate analyses of 200 crashes and 300 near crashes. In the medium scenario, OR = 1.7 and odds = 0.2. In the low scenario, OR = 2 and odds = 0.2. In the minimum scenario, OR = 2 and odds = 0.6. In the medium and low scenarios, crashes and near crashes are grouped together for the OR calculation.

Figure 2.2 can be used, for instance, to appreciate that if 300 safety-critical events are available (vertical dashed line), then at least 300 baselines are necessary to show significance for OR as low as 1.5. Figure 2.2 also shows that if safety-critical events are less than 200, then achieving significance for OR equal to 1.5 may be hard even if a larger number of baselines is available.

Figure 2.2 was generated using real data (up to 828 safety-critical events and 5,000 baselines) from the 100-car study (available at <http://forums.vtti.vt.edu/index.php?/files/category/3-100-car-data/>). However, in this context, it should be considered a qualitative indication primarily because of differences in scenarios used. The safety-critical events expected from SHRP 2 for this project's analyses are restricted to a specific set of precrash scenarios (lead-vehicle). As a consequence, both the odds and the OR may be different than in the 100-car study, in which many different scenarios were considered together. For reference, the significant OR levels found by Klauer et al. (2006, 2010) and Liang et al. (2012) were all above 2.02 for the Total Glance Time variable.

2.5 Event Sampling

A desired sampling procedure was formulated and requested. However, this procedure encountered many practical constraints, and the actual sampling procedure used all crashes and near crashes that were available at the time of data extraction.

A description of the amount of available, searchable data in the database when data were extracted was requested as multiple data deliveries took place throughout fall 2013 and spring 2014. It proved difficult to determine the amount of data that was searched because data were in various stages of processing and there were many technical difficulties. The data provider, VTTI, estimated that about 20% to 30% of the expected final data set was fully surveyed through kinematic triggers but that the full data set was “surveyed” by automatic notification processes (such as onboard Automatic Crash Notification algorithms, incident button presses, and site reports). That is, many crashes and some near crashes were found through automatic notification processes while the study was being run and were therefore prioritized for data processing above other incoming data. Thus, it is currently difficult to know how many of the final set of lead-vehicle crashes are included in the current data set.

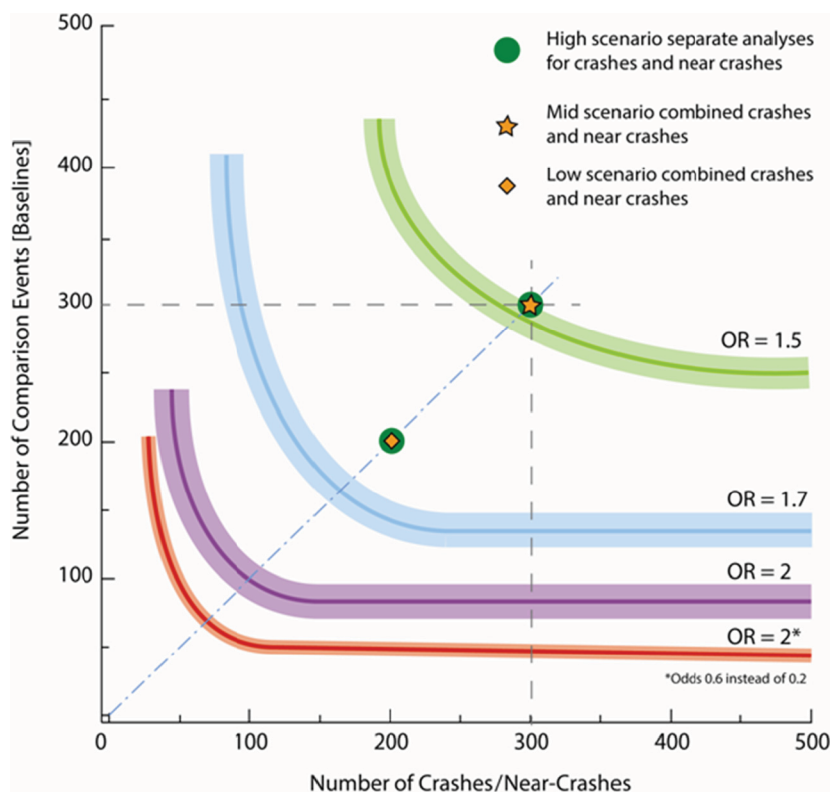


Figure 2.2. Estimation of sample size for crashes/near crashes (safety-critical events) and comparison events (baselines) in different scenarios corresponding to different levels of significant ORs (at odds 0.2, except for the bottom line at odds 0.6). In general, higher scenarios correspond to lower OR significance and lower odds (Equation 4.1). Dark lines are the trends; the bands around the lines cover all possible combinations of events and baselines. This variation is due to the nature of odds ratios.

Crash and Near-Crash Selection

The formation of a *candidate event pool* for crashes and near crashes was suggested; a subset of crashes and near crashes would be sampled from that pool. The idea was that crashes should be found by whatever manner possible (e.g., site reports or with kinematic triggers) and compiled into a list of candidate crash and near-crash events: the candidate event pool. From this candidate event pool, a subset of crashes and near crashes would be selected. However, for the final data set, a sampling approach was not possible. Instead, all available crashes and near crashes were selected.

Random Baseline Event Selection

One random baseline (RBL) per crash or near-crash event was extracted completely at random from all trips in the available data and across all drivers and locations. The random baselines are used as controls in a case-control approach. Analysis

using the random baseline was expected not to be biased by the trips in which a safety-critical event took place.

Matched Baseline Event Selection

One matched baseline (MBL) per crash or near-crash event was selected to match each crash or near-crash event. The matched baselines are used as controls in a case-crossover approach. Analysis using the matching baseline was expected to be more robust to possible confounding contextual factors such as traffic density, weather, and road type. The matching criteria were intended to control for contextual factors that could influence glance behavior and thus create controls that provide a more similar context for comparison between baseline (control) events and crash or near-crash events than the random baselines.

The following matching criteria were formulated. For each crash or near crash, the matching baseline must have the same driver, must not overlap in time with the crash or near-crash

event, and must have a maximum amount of 1.5 seconds of standstill (<0.1 km/h). In addition to these three absolute criteria, the following optional matching criteria were defined (ordered from most important to least important): a lead vehicle should be present during the entire event (but the lead vehicle could change), a lead vehicle should not change, traffic flow should be matched to divided or undivided, the relation to intersection should be matched (not including interchange), the event should be taken from the same trip, speed should not vary more than ± 15 km/h in comparison with the crash or near-crash event, the event should be matched according to adverse weather (if present in crash or near crash), locality should be matched to limited access or not, traffic density should be within one category, and daylight should be matched to day or night. If a matched baseline could not be found to meet all criteria, then the order of importance was used to assist with prioritization in finding matches.

2.6 Final Sample Size

The present analysis uses data extracted from the SHRP 2 Naturalistic Driving Study database up until the last data delivery was received April 7, 2014—before all SHRP 2 data were available to be searched.

The final data set that was used for analyses comprises 46 crash events, 211 near-crash events, 257 matched baseline events, and 260 random baseline events. VTTI provided 47 crash events, 213 near-crash events, 260 matched baseline events, and 260 random baseline events in accordance with our data request. However, three events (one crash and two near crashes) were excluded because more than 30% of the glance data was missing in the 12 seconds preceding the crash point (in the crash events) or minimum time to collision (in the near-crash events). As a consequence, the corresponding matched baselines for these three events were also excluded.

2.7 Export Format

Data were provided from VTTI to SAFER in this format:

- A CSV file with all the time-series standard data from the data acquisition system along with a column for eyeglance location and one for lead-vehicle brake light activation, provided at a 10-Hz rate;
- A CSV file with all the time-series standard data from the data acquisition system along with a column for eyeglance location and one for lead-vehicle brake light activation, provided in a rectangular asynchronous format (i.e., each data value is accompanied by its exact timestamp instead of being linked to the closest 10-Hz time bin);
- A MATLAB workspace with data structures containing the information exported into the CSV files;

- A clip of the forward video corresponding to the time-series data segment;
- A clip of the rear video corresponding to the time-series data segment;
- A data dictionary spreadsheet;
- A baseline reduction spreadsheet; and
- An event reduction spreadsheet, containing the full contents of the SHRP 2 crash event video reduction and additional reduction specified by SAFER.

2.8 Event Data

Event data were delivered for each event as a set of variables that describes each event as a whole (in a single value such as precrash scenario type or driver age).

For all events (C, NC, RBL, MBL), SHRP 2–defined event data variables were delivered by the data provider. All event data variables were delivered, as defined in the SHRP 2 event data dictionary (SHRP 2 NDS Event Definitions and Variables v 2_1.pdf, available at <https://insight.SHRP2nds.us/>). In addition, demographic questionnaire data and driving history questionnaire data were delivered, as defined in SHRP 2 NDS Driver Assessment and Data Dictionary v1_1.xls (available at <https://insight.SHRP2nds.us/>). In addition to the SHRP 2 event data variables, SAFER defined and asked the data provider for additional event data variables. Additional event data variables were calculated after the data were delivered.

Key Event Data Variables

Only the key event data variables are defined here (for other variables, see the SHRP 2 data dictionaries).

Event Severity. This is a general term referring to all valid triggered occurrences of an incident, near crash, or crash that begin at the precipitating event and end when the evasive maneuver has been completed. There were two categories. (1) A *crash* involves any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated (examples and hints: includes other vehicles, roadside barriers, objects on or off of the roadway, pedestrians, cyclists, or animals). (2) A *near crash* involves any circumstance that requires a rapid, evasive maneuver by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal to avoid a crash. A rapid, evasive maneuver is defined as a steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle capabilities. As a general guideline, subject-vehicle braking greater than 0.5 g or steering input that results in a lateral acceleration greater than 0.4 g to avoid a crash constitutes a rapid maneuver.

Precipitating Event. This is the state of environment or action that began the sequence under analysis. Put another

way, what state or action by this vehicle, another vehicle, person, animal, or nonfixed object was critical to this vehicle becoming involved in the crash or near crash? This is a vehicle kinematic measure (based on what the vehicle does—an action, not a driver behavior). It occurs outside the vehicle and does not include factors such as driver distraction, fatigue, or interaction with a child. This is the critical event that made the crash or near crash possible. Use the “but for” test: but for this event, would the crash or near crash have occurred? This is independent of who caused the conflict (fault). For example, Vehicle A is speeding and then Vehicle B crosses Vehicle A’s path; the precipitating event is Vehicle B crossing Vehicle A’s path. If two events occur simultaneously, choose the event that imparted the greatest effect on the crash or near crash. If more than one sequential event contributed to the crash or near crash, determination of which is the precipitating event depends on whether the driver had enough time or vehicular control to avoid the latter event. If the driver avoids one event and immediately encounters another potentially harmful event (with no time or ability to avoid the latter), then the precipitating event is the first obstacle or event that was successfully avoided (this is where the critical envelope begins and is the reference point for the other variables). If the driver has ample time or vehicular control to avoid the latter event, then that latter event is coded as the precipitating event (the critical envelope begins here, and all other variables are coded on the basis of this event). Note that for cases in which the origin of the precipitating event is not visible (e.g., Other vehicle ahead, stopped on roadway more than 2 seconds; or Pedestrian in roadway), the start point for the precipitating event is when the event is first visible in the forward view of the subject vehicle. Note also that a parking lot is considered a roadway; thus, for instance, a barrier or light pole in the parking lot is considered an object in the roadway.

Distraction 1, 2, 3. Distractions involve observable driver engagement in any of the listed secondary tasks, beginning at any point during the 5–6 seconds before the onset of the precipitating event. Note that there is no lower limit for distraction duration. If there are more than three distractions present, select the most critical or those that most directly affect the event (defined by event outcome or closest in time to the event occurrence). Populate this variable in numerical order (if there is only one distraction, name it Distraction 1; if there are two, name them Distractions 1 and 2). This variable was modified and renamed Secondary Task 1, 2, 3 in a later update to the SHRP 2 dictionary.

Lead-Vehicle Precrash Scenario Type. This system of classifying the crashes is based on the precrash scenarios from Najm and Smith (2007) corresponding to rear-end crashes. The categories are Scenario 22, following vehicle making a maneuver; Scenario 23, lead vehicle accelerating; Scenario 24, lead vehicle moving at lower constant speed; Scenario 25, lead vehicle decelerating; and Scenario 26, lead vehicle stopped.

2.9 Time-Series and Video Data

Time-series data describe the event over time at a sampling frequency that is specific to each variable. The time-series data used in this project are complex; the aim of this section is to provide only the essential details that are needed to understand the analyses, not a complete documentation as that would be too lengthy.

For all events (C, NC, RBL, MBL), SHRP 2–defined time-series data variables were delivered by the data provider. All event data variables were delivered, as defined in the SHRP 2 data dictionary (SHRP 2 Researcher Dictionary for Time-Series Data, Version December 2, 2010). In addition to the SHRP 2 time-series variables, SAFER defined and requested that the data provider deliver additional time-series variables. Additional time-series variables were calculated after the data were delivered. This section describes the key processing issues and derivation of new variables that were done in addition to those provided in the SHRP 2 time-series data set.

Data Preprocessing

Once the data were downloaded from the VTTI Scholar website, they were (1) processed to check quality and add new measures, (2) restructured to be compatible with the NatWare tools (Dozza 2010), and (3) complemented with information from the data dictionaries, demography, and vehicle type (to make them self-descriptive).

Data processing. Data processing consisted of running a script to read all events from VTTI, checking the consistency of the data, and deriving new measures (e.g., Eyes off Path). This step highlighted which data were available for each of the events and pointed out possible incongruences. For example, speed from GPS and the network must be highly correlated, and some values of acceleration are definitely impossible.

Data restructuring. Data restructuring is not essential but is of great help to simplify further analyses. In that respect it is a time investment at the beginning of the analyses. Besides making the data more user friendly and self-explanatory, data restructuring improves computation speed and makes it harder for the analyst to make mistakes (e.g., data are not referred to by arbitrary indexes but by labels). Also, by restructuring the data according to the NatWare 2.0 format, which is an evolution of the format used to analyze the 100-car public data (Dozza 2010), it was possible to reuse NatWare’s existing scripts and graphical user interfaces (GUIs) to speed up the analysis and pay off the time investment (Dozza 2013).

Data completion. Data completion, similar to data restructuring, is not essential but highly desirable because it makes analysis easier and faster. The data dictionary, demographics, protocol, and vehicle information were linked through identifiers to the data in the database.

Data quality analysis. The initial data processing (above) checked the data consistency and pointed to some quality issues. Further analyses identified other quality issues. The following key issues were identified and dealt with:

- *Transition time coding procedure.* The current International Organization for Standardization (ISO) standard specifies that glance time consists of transition time toward a target plus the subsequent dwell time on that target (ISO 15007). In Phase 1, we determined that the initial coding procedure added transition time to the preceding target's dwell time (e.g., as in Klauer et al. 2006). The transition classification procedure was modified for the final data set so that transitions were coded independently, thus enabling the researcher to add the transition time to the subsequent target's dwell time (as in the ISO standard) or to the preceding target's dwell time (as in Klauer et al. 2006). The present data set uses glance coding according to the ISO standard method with the transition time added to the subsequent target's dwell time.
- *Mask Head Tracker signal quality.* In Phase 1, an evaluation of the feasibility of using the Mask Head Tracker for automatic glance classification was performed by comparing it to manual video annotation. This evaluation indicated that it is not advisable to use head tracking data for Phase 2. Manual video annotation of eye glances was chosen for Phase 2.
- *Lead-Vehicle Precrash Scenario-type classification.* This classification included difficulties in classification. The Najm and Smith (2007) descriptions were not as easily interpreted as we had hoped, and there seems to be a lot of room for interpretation. For example, we were uncertain how to deal with lane-change conflicts, conflicts occurring during turns at intersections, and in particular, conflicts when the lead vehicle was stopped. Najm and Smith (2007) state in the description of Scenario 26 (lead vehicle stopped), "In about 50% of the lead vehicle-stopped crashes, the lead vehicle first decelerates to a stop and is struck afterwards by a following vehicle. This typically happens in the presence of a traffic control device or [when] the lead vehicle is slowing down to make a turn. Thus, this particular scenario overlaps with the lead vehicle-decelerating scenario." As it is not stated how long the stop lasted, we decided to use the reaction-time point as the deciding time (if vehicle was stopped when the driver started to react, then Scenario 26; if decelerating but not yet stopped or never stops, then Scenario 25). Development of standardized definitions is recommended.
- *Data synchronization.* Data synchronization quality issues were encountered and dealt with in various ways.
- *Inconsistencies in format.* Data formats were not uniform; for example, event data categories sometimes had additional spaces or commas or different spellings.
- *Spatial offsets between sensors.* When performing post-processing of radar with complementary data from manual annotation of the lead-vehicle width from video, the distance between the radar and the front facing camera for each unique car model is desired but not available. Radar-camera distance is used to get more accurate width estimates of the vehicle ahead and more seamless merging of the radar and lead-vehicle-width video annotation data sets. Additionally, to achieve optical parameters as the driver sees them; it would have been preferable to also know the forward-looking camera position in relation to the head of the driver in different seating positions. As this is not available in the SHRP 2 data set, generic estimates were made. Also, the distance between the radar and the front bumper may play a (small) role in calibration.
- *Subject-vehicle speed quality.* The CAN speed precision, synchronization, and general quality vary greatly between the different events. The CAN speed quality can thus be different from one event to another. Several quality issues were identified, like gaps in the data (missing data) or low resolution (large "steps"). Furthermore, the sampling rate of the CAN speed varies from 1 Hz to 10 Hz. Reasonability checks of the data were performed throughout the project, one example being speed comparison between CAN speed data and video, and comparison between by GPS speed and CAN speed. The CAN data were processed to get the subject-vehicle speed (SVspeed). Because of issues with synchronization and SVspeed resolution, attempts were made to combine GPS speed data, CAN speed data, and accelerometer data, but in the end only a simple linear interpolation of CAN speed was used. The interpolation was verified using integrated longitudinal acceleration. Analysis requiring SVspeed excluded certain events for which CAN speed was missing (due to nonexisting CAN on older model cars), and this is noted where needed in the analyses.
- *Radar data quality.* The radar quality was problematic, and the radar signals were generally not used in the final analyses. Instead, forward video manual annotation of vehicle width was used (see the time-series variable definitions below). Estimated range and range rate were derived from video-based width estimation.
 - VTTI is in the midst of conducting a project addressing radar quality (the VTTI RADAR data project). The objective of this project is to postprocess the data streams into measures characterizing driver behavior and forward conditions through automated means, extracting the following items from the radar:
 - Filter, interpolate, extrapolate;
 - Reorganize data to support analysis and research;
 - Select closest target in path of participant vehicle;
 - Eliminate ghost targets;

- Allow trip summary data to be calculated, including number of targets tracked, time headway, and time to collision;
- Path prediction in the context of determining lead vehicles;
- Parse targets into lanes; and
- Develop and refine the necessary data to be applied to the crash and near-crash algorithms that use radar variables.

At this point there is insufficient information on the outcome of the VTTI RADAR data project to comment on how the identified quality issues will be addressed in the future. We believe that the video-based techniques described in this report will help improve radar data quality. These techniques can be used to fill in missing data, smooth data, and verify potentially inaccurate data. We recommend that researchers who are using radar data use forward video to provide verification and context to the radar data.

- *Optical distortion in the forward video.* When working with image processing or manual annotation of distances in an image, distortion of the image needs to be taken into account by rectification. Oak Ridge National Laboratory provided a set of calibration (checker board) videos and a first set of calibration parameters. However, after evaluation of this first parameter set, it was determined that the edges and corners of the images were not rectified enough for use in this project. Recalibration was made, but this produced results similar to the Oak Ridge parameter set's. Yet another recalibration was performed, more focused on edge rectification using the Camera Calibration Toolbox for MATLAB (Bouguet 2010). The new calibration parameters provided a significantly better rectification at the edges and corners of the image than the original data set and avoided much under- and overestimation of lead-vehicle widths when manually annotating video.

Duration of Events

For each event, 60 seconds of data from the data acquisition system were delivered if data were available in the trip for that period. For the crash events, the 60 seconds included 40 seconds before and 20 seconds after the crash point. For the near-crash events, the 60 seconds included 40 seconds before and 20 seconds after the minimum distance to lead vehicle. For the random baseline events, 60 seconds of data were selected at random from the available data. For the matched baseline events, 60 seconds of data were selected according to the matching criteria below if that much data were available in that particular trip.

A prerequisite for many analyses was the manual video annotation of crash, near-crash, and baseline events. This manual video annotation produced, for example, glance behavior, event data, and data regarding lead-vehicle width (as

specified below). Video annotation was performed by VTTI for all annotated variables except the lead-vehicle width, which was annotated by SAFER. For each event, VTTI manually annotated 20 seconds of data by viewing video and associated data (such as speed) for each frame of video. For the crash events, these 20 seconds included 15 seconds before and 5 seconds after the crash point, with the additional requirement that the data should include at least 5 seconds before the precipitating event. For the near-crash events, the 20 seconds included 15 seconds before and 5 seconds after the minimum distance to lead vehicle, with the additional requirement that the data should include at least 5 seconds before the precipitating event. The minimum distance was used because it was easily determined by video annotators. For the matched baseline and random baseline events, the 20 seconds of data for manual video annotation were annotated in the middle of the corresponding 60-second data from the data acquisition system (i.e., 20–40 seconds into the 60 seconds).

Reference points. For time-series analyses, a reference point needs to be specified for each event type.

- *Matched and random baseline reference points:* For random baselines and matched baselines, the reference point was always set to 0 seconds at 15 seconds into the annotated 20-second data set that was received from VTTI, and that can be seen as a random point.
- *Crash event reference points:* For most analyses here (Chapters 6–8), crash events are aligned to the crash point (as determined from video annotation by VTTI) as the reference point and set to 0 seconds. In analyses concerned with the precipitating event (Chapter 5), each crash event is realigned, or shifted, to match up in time to the precipitating event, which is the reference point.
- *Near-crash reference points:* For most analyses here, near-crash events are aligned to the optically defined minimum time to collision (minTTC) as the reference point and set to 0 seconds. In analyses concerned with the precipitating event (Chapter 5), each near-crash event is realigned, or shifted, to match up in time to the precipitating event as the reference point. Note that the data were originally delivered from VTTI to SAFER with minimum distance as the reference point set to 0 seconds because that was easiest to determine from video before minTTC was known. After SAFER manually video annotated the lead-vehicle width for each near-crash, the near-crash events were realigned to minTTC as the reference point set to 0 seconds, instead of the minimum distance point. MinTTC was chosen as the point within the near-crash event that was most safety critical.

The consequence of this change of the near-crash reference point meant that a 12-second window was the maximum length that was used that included all events before the crash

point or minTTC. This was because the minimum distance point for some near crashes was up to 3 seconds later than the minTTC. Therefore, the 12 seconds before the crash point (in crash events), 12 seconds before minTTC (in near-crash events), and 12 seconds before the reference point in the matched and random baselines was chosen as the primary common time period for analyses.

In analyses using data from manually coded lead-vehicle width (Chapters 7 and 8), a shorter time window is used because of limitations related to the size of the lead vehicle at far distance, as described there.

Manual annotation of vehicle width in forward video. Given that the radar data were difficult to work with, a method was developed to derive kinematic and optical variables related to the lead vehicle (LV) by manually annotating lead-vehicle width in forward video. After an image rectification, the lead-vehicle-width annotation was performed for all crash, near-crash, and matched baseline events by viewing forward video and clicking on the outer edges of the left and right brake lights in every other video frame in a purpose-built tool. Random baselines were not annotated as they did not contain much lead-vehicle presence. The main steps of annotation are chronologically listed below.

The real lead-vehicle width was set by identifying the car model or by selecting a standard width. After applying the distortion rectification on the frames, the LV width was annotated. The annotation process was done on every other frame; therefore the annotation had a frequency of 7.5 Hz. To transform this annotation into the range between the SV and the LV, the following steps were undertaken: (1) apply a square-kernel smoothing filter on the annotated signal (see definition of filtered lead-vehicle pixel width), (2) up-sample the signal to 15 Hz, (3) transform the annotated pixel width into the range between the LV and the SV. The spatial offset between the camera and the front bumper was set to 2.128 meters (see definition of *range*).

For analyses using lead-vehicle-width-derived data (Chapters 7 and 8), we used a window of annotated lead-vehicle data (in crash events) from –10 seconds preceding the crash point (0 seconds) until 2 seconds after, (in near-crash events) from –10 seconds preceding the minTTC (0 seconds) until 2 seconds after, and (in matched baselines) from –10 seconds preceding the baseline reference point (0 seconds) until 2 seconds after.

Inter-rater reliability testing was performed as part of the process to ensure quality of the lead-vehicle-width coding. This method was developed and described by Bärghman et al. (2013) using Video Even Recorders. According to Bärghman et al., the method accurately predicts ranges less than 10 meters. For ranges between 10 meters and 40 meters (car following), the error is less than 5% if the lead-vehicle-width estimation is accurate. The method should be used with care for ranges

over 40 meters. To ensure high quality (low variance between annotators) of data used for analysis, a training process was used. Two events were annotated by five human reductionists (annotators) and analyzed for variability in coding. The results confirmed the conclusions from Bärghman et al. (2013) that annotator comparability is high for ranges up to 40 meters. The closer the lead vehicle, the more comparable (smaller coding variation, measured by smaller standard deviation) different annotations are.

Eyeglance Time-Series Variables

Glance Location. Eyeglance locations were manually annotated by VTTI by viewing the driver face video for every video frame (15 Hz). Technically, these glance locations are actually dwell times, as the transitions are coded separately (see ISO 15007). The following categories and locations were used.

- –4. *No Video.* Unable to complete glance analysis because the face video view is temporarily unavailable. Note that this sometimes occurs for one to two syncs at a time, and a “video not available” message may appear. If the glance location is the same before and after this occurs and the period is only one to two syncs long, then code through this period as the glance location present before and after. If the video-not-available period is longer than two syncs or it occurs during a transition, use the “No Video” option.
- –3. *Transition.* Any frame that is between fixations as the eyes move from one fixation to the next. Note that the eyes often fixate while the head is still moving. This category is based on the eye’s fixation rather than the head’s movement, unless sunglasses preclude the eyes from being seen.
- –2. *No Eyes Visible.* Glance location unknown: Unable to complete glance analysis due to an inability to see the driver’s eyes/face. Video data are present, but the driver’s eyes and face are not visible due to an obstruction (e.g., visor, hand) or glare. Use this category when there is no way to tell whether the participant’s eyes are on or off the road. This is the default and most often used “unknown” option, but there may be times when the “off road” option listed below may be appropriate.
- –1. *Not annotated.* Time-series data for which glance annotation was not performed.
- *Forward (Center).* Any glance out the forward windshield directed toward the direction of the vehicle’s travel. Note that when the vehicle is turning, these glances may not be directly forward but toward the vehicle’s heading. Count these as forward glances. Note also that when the vehicle is driving in reverse, forward will be out the back window.
- *Left Windshield.* Any glance out the forward windshield when the driver appears to be looking specifically out the left margin of the windshield (e.g., as if scanning for traffic before turning or glancing at oncoming traffic). This glance

- location includes anytime the driver is looking out the windshield but clearly not in the direction of travel (e.g., at road signs or buildings).
- *Right Windshield*. Any glance out the forward windshield when the driver appears to be looking specifically out the right side of the windshield (e.g., as if scanning for traffic before turning, at a vehicle ahead in an adjacent lane, or reading a road sign). This glance location includes anytime the driver is looking out the windshield but clearly not in the direction of travel (e.g., at road signs or buildings).
 - *Left Window/Mirror*. Any glance to the left-side mirror or window.
 - *Right Window/Mirror*. Any glance to the right-side mirror or window.
 - *Rearview Mirror*. Any glance to the rearview mirror or equipment located around it. This glance generally involves movement of the eyes to the right and up to the mirror. This includes glances that may be made to the rearview mirror to look at or interact with back seat passengers.
 - *Over-the-Shoulder (left or right)*. Any glance over either of the participant's shoulders. In general, this will require the eyes to pass the B-pillar. If over the left shoulder, the eyes may not be visible, but this glance location can be inferred from context. Note that if it is clear from context that an over-the-shoulder glance is being made not to check a blind spot but instead to interact with a rear seat passenger (e.g., food/toy is being handed back), then code the glance as Passenger. If context cannot be known with a high level of certainty, then code as Over-the-Shoulder.
 - *Instrument Cluster*. Any glance to the instrument cluster underneath the dashboard. This includes glances to the speedometer, control stalks, and steering wheel.
 - *Center Stack*. Any glance to the vehicle's center stack (vertical). Not to be confused with center console (cup holder area between driver and passenger), which is discussed under Interior Object.
 - *Cell Phone (electronic communications device)*. Any glance at a cell phone or other electronic communications device (e.g., Blackberry), no matter where it is located. This includes glances to cell phone–related equipment (e.g., battery chargers).
 - *Portable Music Player (iPod or similar MP3 device)*. Any glance at an iPod or other personal digital music device, no matter where it is located.
 - *Interior Object*. Any glance to an identifiable object in the vehicle other than a cell phone. These objects include personal items brought in by the participant (e.g., purse, food, papers), any part of the participant's body that he or she may look at (e.g., hand, ends of hair), electronic devices other than cell phones (e.g., laptop, PDA), and also original equipment manufacturer (OEM)–installed devices that don't fall into other categories (e.g., door lock, window and seat controls). Glances to the center console (cupholder area between passenger seat and driver seat) are also included in this category. The object does not need to be in the camera view for a specific frame to be coded with this category. If it is clear from surrounding video that the participant is looking at the object, this category may be used. This category can be used regardless of whether the participant's hands are/are not visible. Note that if the driver is looking at something that the passenger is handing over, code the eyeglance as Passenger until the object is fully in the driver's hand, then code it as Interior Object (unless it is a cell phone, in which case code it as Cell Phone). Also, if the driver is looking at something that the passenger is holding (but never hands to the driver), code it as Passenger Glance (not Interior Object). Individual studies may ask reductionists to identify objects in logs or drop down menus, or may categorize specific objects as Systems of Interest.
 - *Passenger*. Any glance to a passenger, whether in front seat or rear seat of vehicle. Context will be needed (e.g., they're talking or handing something) to determine this in some situations. Note that this does *not* include glances made to rear seat passengers via the rearview mirror. Such glances should be coded as Rearview Mirror. Note that if the driver is looking at something that the passenger is handing over, code the eyeglance as Passenger until the object is fully in the driver's hand, then code it as Interior Object (unless it is a cell phone, in which case code it as Cell Phone). Also, if the driver is looking at something that the passenger is holding (but never hands to the driver), code it as Passenger Glance (not Interior Object).
 - *Other*. Any glance that cannot be categorized using the above codes. The lab manager should be informed of anything that could fall under this category, for appropriate follow-up. Some preapproved uses of the Other option are the following: when the driver is looking forward and then looks straight up at the sky as if watching a plane fly by; and when the driver is tilting his or her head back to drink and the eyes leave the forward glance but do not really focus on anything at all.
 - *No Eyes Visible. Eyes Are off Road*. Unable to enter specific glance location due to an inability to see the driver's eyes/face. However, it is clear that the participant is not looking at the roadway. Video is present, but the driver's eyes and face are not visible due to an obstruction (e.g., visor, hand), head position, or glare. Use this category when the eyes are not visible, and it is not clear what the participant is looking at, but the eyes are obviously not on the roadway.
 - *Eyes Closed*. Any time that both the participant's eyes are closed outside of normal blinking (e.g., the subject is falling asleep or rubbing eyes). As a rule of thumb, if the eyes are closed for five or more timestamps ($\frac{1}{3}$ second) during a slow blink, code it as Eyes Closed. Otherwise, code it as the Glance

Location present before the eyes closed. If one eye remains open, code the location according to the open eye. If only one eye is visible, code according to the visible eye.

Eyes on Path. Eyes on Path represents a reduction of the Glance Location variable that is converted into Eyes-on-Path and Eyes-off-Path glances. It has three values: Eyes on Path, Eyes off Path, and Not a Number (NaN). First, glances are created by adding transition time toward a target to the subsequent dwell time on that target (ISO 15007 definition). Note that the Glance Location variable has transitions separately coded. Thus, *Eyes on Path* corresponds to the Forward (Center) Glance Location with transitions added. *Eyes off Path* corresponds to Glance Location Categories 1–15 with transitions added. NaN corresponds to cases in which glance location was unknown (Glance Location Categories –2 and –1). There were no instances of No Video (Category –4). Eye closures were examined to decide how to handle them in relation to the Eyes-off-Path glance time-series variable. An eye closure was coded if the eyes were closed for five or more timestamps ($\frac{1}{3}$ second). In total, there were only eight eye closures in the entire data set. The duration of these ranged from $\frac{1}{3}$ second to 3 seconds. In random baselines, there were two eye closures between $\frac{1}{3}$ and 1 second long. In near crashes, there were two eye closures lasting between $\frac{1}{3}$ and 1 second and one eye closure, between 2 and 3 seconds. In crashes, there were two eye closures between $\frac{1}{3}$ and 1 second duration and one between 1 and 2 second duration. Based on these results, eye closures were coded as Eyes off Path. The following variables were derived using the Eyes off Path time-series variable above:

- *Proportion of Eyes off Path.* Proportion (a proportion from 0 to 1) of time the eyes were off path during a given period of time. These include Off5to1afterPE, Off5to3PE, Off3to1PE, Off1to1afterPE, Off11to9, Off9to7, Off7to5, Off5to3, Off3to1, and Off1to1after. For example, Off5to1-afterPE denotes the proportion of time the eyes were off path in the 5 seconds before until 1 second after the precipitating event, Off1to1afterPE is from 1 second before until 1 second after the precipitating event, and so on. Similarly, Off3to1 denotes the proportion of time the eyes were off path from 3 seconds before until 1 second before the crash point (in crash events) or minimum time to collision (in near-crash events). Likewise, Off11to9 is from 11 seconds before until 9 seconds before the crash or minTTC point. These variables are directly comparable to the Total Eyes off Roadway Time (TEORT) variable used previously by, for example, Klauer et al. (2006) and to the Percent Road Center variable used by Victor et al. (2009) and evaluated in the multidistraction detection algorithm in NHTSA (2013).
- *Eyes off Path.* The amount of time (in seconds) the eyes were off path longer than a certain amount within a given period

of time. These include Off0, Off0.1-0.5, Off0.5-1.0, Off1.0-1.5, Off1.5-2.0, and Off2.0-6.0. For example, Off0.1-0.5 denotes the number of observations with Eyes off Path between 0.1 and 0.5 second in the 5 seconds before and 1 second after the precipitating event. Similarly, Off2.0-6.0 is the number of observations with Eyes off Path between 2 and 6 seconds in the 5 seconds before and 1 second after the precipitating event, and so on. This variable was defined as a categorical variable so that each window of 6 seconds could be classified as belonging to one mutually exclusive category or another.

- *tg.off.* Total glance time off path, the amount of time (in seconds) the eyes were off path in the 12 seconds before and 1 second after the crash or minTTC.
- *Overlap.* The duration of a glance that overlaps (intersects) with the 2-second point before the crash or minTTC. This can be either on the path (overlap.on) or off the path (overlap.off).
- *pre.overlap.* The duration of a single glance immediately preceding the off-path glance that overlaps with the 2-second point before the crash or minTTC. This can be either on the path (pre.overlap.on) or off the path (pre.overlap.off).
- *max.off.* The maximum off-path glance duration in the 12 seconds before the crash or minTTC.
- *min.on.* The minimum on-path glance duration in the 12 seconds before the crash or minTTC.
- *Glances.* The number of glances in the 12 seconds before the crash or minTTC.
- *Complexity.* A composite measure of off-path glance sequence complexity, according to Gabadinho et al. (2011). The index uses the number of transitions in the sequence as a measure of the complexity induced by the state ordering and the longitudinal entropy as a measure of the complexity induced by the state distribution in the sequence.
- *Uncertainty.* A composite measure based on the “uncertainty model” of the driving situation (Senders et al. 1967). These include uncertainty.3to1, min.uncertainty, m.uncertainty, and max.uncertainty. The model is based on the assumption that during off-path glances, uncertainty cumulatively increases about the road and the possible presence of other vehicles or obstacles, and that certainty cumulatively increases during on-path glances. Uncertainty.3to1 is the value in the 3 seconds to 1 second before the crash or minTTC point. Min.uncertainty is the minimum value in the 12 seconds before the crash or minTTC, m.uncertainty is the mean value in the 12 seconds before the crash or minTTC, and max.uncertainty is the maximum value in the 12 seconds before the crash or minTTC.

Other Time-Series Variables

Event Time. The time domain within each event plays out with negative values before 0 seconds—which is defined as

the crash point in crash events and the minimum time to collision in near-crash events, and is set at 15 seconds into the video annotated data in the random and matched baseline events.

Driver Reaction Point. The onset of the first visible reaction of the subject-vehicle (SV) driver to the principal other vehicle, that is, the time at which the driver is first seen to recognize and begin responding to the event. This can involve any physiological reaction including body movement, posture, a change in facial expression, a movement of the leg toward the brake—whichever came first. Note that this is a time-series variable and different from the Driver Reaction event data variable, which is a specification of *how* the driver reacted (e.g., braking or steering) rather than a specific timestamp (when) as is defined here.

Start of Evasive Maneuver. Ideally the point when the driver is initiating a brake or steering response, but here defined as the first time after the driver reaction point (time) when the SV speed has a negative derivative (i.e., deceleration). If the derivative is negative already at the Driver Reaction Point, the Driver Reaction Point is used as the Start of Evasive Maneuver.

Lead-Vehicle Pixel Width. The manually annotated (video-reduced) width of the lead vehicle in pixels, as seen from the forward video. This is used for all optical parameter and range/range rate–based variables. The annotations are made on rectified (undistorted) images.

Filtered Lead-Vehicle Pixel Width. Limited resolution, noise, and compression artifacts combined with the human factor (reductionist precision in “clicking” at the edges of the lead vehicle) lowers the ability to consistently and accurately detect lead-vehicle pixel width over subsequent frames (for more detail, see Bärghman et al. 2013). In addition, the tool used for lead-vehicle-width annotation has a limited subpixel resolution. The noise propagates to the calculation of optical variable (Theta, ThetaDot, Tau, invTau, etc.) and range-based variables (range and range rate). This noise is especially problematic for quantities involving a time derivative (e.g., ThetaDot and invTau) and especially at low pixel widths, for which the estimation uncertainty is large compared with the pixel width being estimated. Therefore, a square-kernel smoothing filter (convolution-like) with amplitude-adapted width is applied to the raw manually reduced pixel width time-series data. The basic idea behind the filter is as follows: Assuming there is a certain pixel width, W_0 , for which only one observation is enough to satisfactorily determine the pixel width, combined with the assumption of Gaussian noise with constant variance regardless of the pixel width being measured, a constant *relative* uncertainty can be obtained by averaging $N = (W_0/W)^2$ observations. This expression can be obtained by noting that if the measured pixel width W is normally distributed around the true value W^* , with variance σ^2 , the average

of N measurements is also normally distributed around W^* , but with variance $s_N^2 = \sigma^2/N$. Thus, to obtain a certain relative error $C = s_N/W^*$, we need $N = \sigma^2/C^2W^{*2}$ measurements, and we can set C by choosing a $W^* = W_0$ for which we believe that $N = 1$ yields an acceptable relative error. As only one observation is available at each frame, the observed pixel widths from N consecutive frames are averaged. Rapid changes in the distance to the lead vehicle may result in rapid changes in the observed pixel width, which violates the assumption that N consecutive frames could be averaged. Therefore, the maximum kernel size is limited, and the filter is applied multiple times instead.

On the one hand, as the filter size is adaptive, an observation at time t_i with a filter width of N_i is influenced by a higher-amplitude observation at t_{i+k} if $k \leq N_i/2$. On the other hand, the observation at time t_{i+k} is not influenced by the observation at time t_i if $k > N_{i+k}/2$. Thus, the filter does not conserve the energy of the signal, but given other sources of error for this application, the effect should be negligible.

Practically, this filter runs a square-kernel across the raw lead-vehicle pixel width time series, averaging across a dynamic number of width measurements (frames). The number of measurements used (kernel width) was determined by $N = (W_0/W)^2$, where we used $W_0 = 170$ pixels, where W is the measured pixel width at each point in time. The implementation we used ran the filter three consecutive times and we allowed the N (kernel width) to be a maximum of only 5 pixels to minimize peak attenuation and phase shift. An example application can be seen in Figure 2.3.

Range. The time-series range from the following vehicle to the lead vehicle, in meters. Calculated via manual annotation of lead-vehicle width in pixels, calculated as $\text{Range} = W_{\text{real}}/W_{\text{pixels}} * f - R_{\text{offset}}$, where W_{real} is the estimated real width of the lead vehicle, W_{pixels} is the filtered annotated width of the lead vehicle in pixels, f is the focal length of the camera in pixels, and R_{offset} is the mean offset between the camera and the front bumper estimated from crashes. The real width of the lead vehicle was estimated by either identifying vehicle make and model from the image or, when that was not possible, using standard category widths per vehicle type (Table 2.2). The mean R_{offset} between the camera and the front bumper was estimated by getting the mean of the range at the time of crash (i.e., only crashes), $M = 2.13$ m, $SD = 0.25$ m.

Range Rate. The time-series range rate between the subject vehicle and the lead vehicle—that is, the derivative of the range between the two vehicles, effectively the relative speed, in meters per second. The derivative of the range was made with a three-point floating window linear regression.

Subject-Vehicle Speed (SVspeed). The time-series speed of the following (instrumented) vehicle throughout the event; interpolated CAN speed.

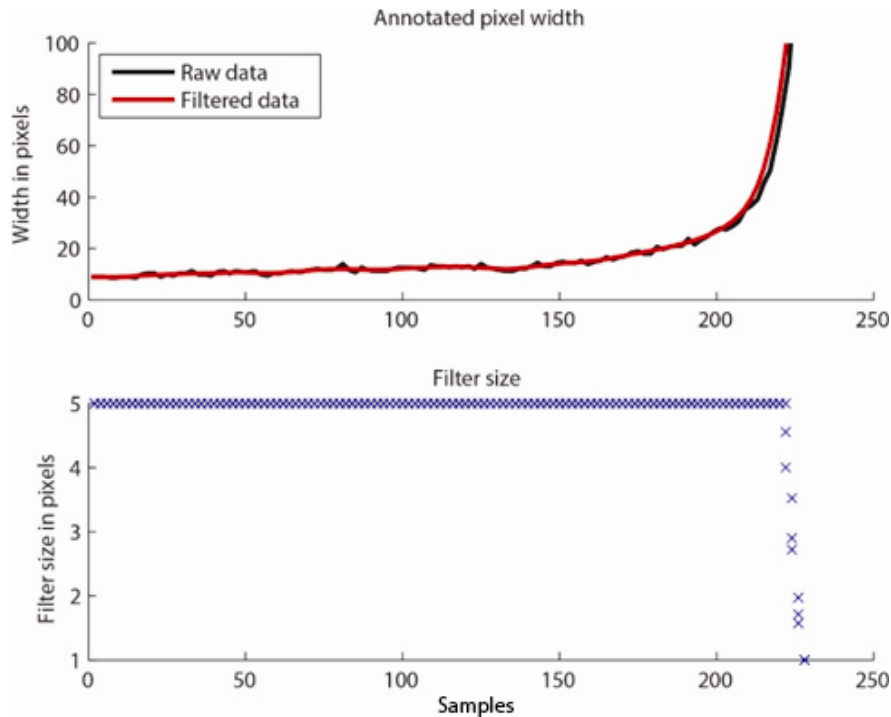


Figure 2.3. Annotated (raw) and filtered lead-vehicle pixel width in relation to filter size.

Lead-Vehicle Speed (LVspeed). The time-series speed of the lead vehicle throughout the event, calculated by adding SVspeed and range rate.

Theta (θ). The angle of the rear end of the lead vehicle, as seen from the camera. The lead-vehicle pixel width is manually annotated on a rectified image. Calculated by $\theta = 2 * \arctan(W_{\text{pixels}} / (2 * f))$, where W_{pixels} is the filtered manually

annotated lead-vehicle width, and f is the camera focal length in pixels.

ThetaDot ($\theta\text{-dot}$). The optical expansion of the rear of the lead vehicle. $\text{ThetaDot} = d(\text{Theta})/dt$. The derivative is practically calculated through a three-point floating window linear regression.

Tau (τ). Calculated by $\text{Tau} = \text{Theta}/\text{ThetaDot}$.

invTau (τ^{-1}). Calculated by $\text{invTau} = 1/\text{Tau}$.

Time to Collision (TTC). The time left until crash, given no actions by either the lead or the following (subject) driver. Two different uses/definitions. See Inverse Time to Collision.

Minimum Time to Collision (minTTC). The smallest TTC in the event. Set to zero at the crash point for crashes. See also Inverse Time to Collision.

Inverse Time to Collision (invTTC). In this analysis, invTau has two different definitions. First, it is the simple range rate divided by range (as defined previously). This version of invTTC (and TTC alike) is used in only a few sections in the report. In those cases, it is explicitly stated that invTTC is the range rate over range implementation. Second, in most parts of the report, invTTC is calculated through optically defined TTC, estimated directly from the optical angle in terms of Tau (τ)—that is, Theta (θ) divided by its time derivative ThetaDot ($\theta\text{-dot}$) (Lee 1976). This assumes small angles. Optically, θ and $\theta\text{-dot}$ characterize the looming (optical expansion) of the lead vehicle. An advantage of using the optically (rather than the physically) specified TTC is that

Table 2.2. Standard Lead-Vehicle Widths

Vehicle Type	Standard Width (m)
Coupe	1.7
Sedan	1.75
Wagon	1.76
SUV	1.8
Pickup truck	~1.9
Semitrailer truck	2.5
Van	2.5
Car trailer	~1.9
Large car trailer	2.1
Customized sports car	1.82

Note: The “standard” lead-vehicle widths were used when make and model could not be extracted from images. For use in transformation from pixel width to range.

this is the type of information that humans presumably use to perceive and control the situation kinematics in driving and other forms of locomotion (although it is debated exactly what optical information is used for different types of tasks). Another benefit of using optically defined TTC is that no estimate of the real lead-vehicle width is needed, minimizing sources of error. Since TTC goes to infinity at zero relative velocity (e.g., at constant distance in normal following situations), its inverse $1/\text{TTC}$ —referred to as invTTC —is used in most analyses. Note that a main difference between the range rate/range implementation and the optical implementation is that the former is the estimated invTTC at the vehicle bumper, while the latter is the invTTC at the camera (by the rearview mirror).

Time Headway (Headway). The headway and closing distances were calculated on the basis of optical variables manually annotated from the forward video, as further described above. The headway between the subject vehicle and lead vehicle was calculated on the basis of the manually annotated optical angle θ subtended by the POV at the camera and assumptions on vehicle width (see Range), as well as the SVspeed.

Model-Estimated Injury Risk (MIR) index. An index related to the risk of an injury of a specific level (MAIS3+) for an event, given a hypothetical driver behavior (glance off-path behavior) and simulated following-vehicle kinematics, calculated through mathematical simulations.

Model-Estimated Crash Risk (MCR) index. An index related to the probability of an event becoming a crash, given a hypothetical driver behavior (glance off-path behavior) and simulated following-vehicle kinematics, calculated through mathematical simulations.

Delta Velocity (DeltaV). Change in velocity of the involved vehicles because of the crash. This variable takes into account masses, and in our implementation assumes a fully plastic impact. It is based on range rate at impact and only available for crashes. For details, see Appendix A.

Maximum Severity Delta Velocity (MSDeltaV). The relative velocity at impact if the subject vehicle continues with the same speed as just before the start of evasive maneuver (that is, not performing any evasive maneuver), multiplied with the mass ratio $m_2/(m_1 + m_2)$, where m_1 and m_2 are masses of the two involved vehicles, where m_2 is the heavier of the two. For details, see Appendix A.

CHAPTER 3

Differences Between Event Types in Descriptive Variables

This analysis primarily focuses on providing the context for which subsequent analyses can be interpreted. It provides an orientation regarding the context, conditions, and driver demographics from which the data were collected. It also aims to confirm the matching criteria for the matched baselines.

For each descriptive variable, differences were inspected among the four event types: random baseline, matched baseline, near crash, and crash. In some cases, such as demographic variables (e.g., age), it was not appropriate to include a matched baseline because the variable is guaranteed to match the combined crash/near-crash population. However, random baseline, near-crash, and crash events can vary on demographics. Event-type constraints are indicated in each section.

Logistic regression using either a binomial (for comparing two event types) or multinomial (for comparing more than two event types) distribution function was used to test whether descriptors differ among event types. *Event type* was treated as the dependent measure, and each descriptor was tested individually.

3.1 Overview of Differences

Crashes differed significantly from near crashes in the following ways. There were more younger drivers and more older drivers in crashes than near crashes, and the crash-involved drivers had driven less mileage in the previous year. There were more “lead vehicle stopped” (precrash Scenario 26) in crashes and more “lead vehicle decelerating” (precrash Scenario 25) in near crashes. Similarly, regarding the precipitating event types, there were more “vehicle slowed and stopped for less than 2 seconds” in crashes and more “vehicle decelerating” in near crashes. Crashes involved a greater proportion of “no driver reaction” (17%) and “braking with lockup” (15%); near crashes involved more “braking without lockup” and more “braking and steering.” Crashes were also more likely to include a visual obstruction than near crashes, and

more likely to occur in rainy or clear weather than near crashes, which were more likely to occur in cloudy conditions. Crashes and near crashes were found with different triggers.

Crashes and near crashes did not significantly differ with regard to preincident maneuver, relation to junction, traffic flow, locality, traffic density, number of travel lanes, or mean speed.

When comparing all four event types, we found significant differences in relation to junction, traffic flow, locality, traffic density, and travel lanes, with a marginally significant difference for weather. Among demographic variables, gender and driving experience did not differ by event type.

With regard to the 11 matching criteria for matched baselines and their corresponding CNC events, the degree of matching was high:

1. Same driver—required and met.
2. Must not overlap in time with the crash or near-crash event—required and met.
3. Must have a maximum amount of 1.5 seconds of standstill (<0.1 km/h)—required and met.
4. Traffic flow should be matched to divided or undivided—met.
5. The relation to intersection should be matched (not including interchange)—met for crashes; near crashes were more likely to be at intersections or intersection-related than their matched baselines, which were more likely to not be at a junction.
6. The event should be taken from the same trip—78% of the crash–matched baselines and 79% of the near-crash–matched baselines were taken from the same trips.
7. Speed should not vary more than ± 15 km/h in comparison with the crash or near-crash event—met.
8. The event should be matched according to adverse weather (if present in crash or near crash)—met.
9. Locality should be matched to limited access or not—met.

- 10. Traffic density should be within one category—met.
- 11. Daylight should be matched to day or night—met.

3.2 Differences in Descriptive Variables

Age

The distribution of age groups is shown in Figure 3.1. The figure indicates that both older and younger drivers are more represented in crashes than in other event types. Logistic regression using age groups as indicated in the figure showed a significant effect of age [Wald $X^2(14) = 29.9, p = 0.0079$]. The model indicates that, as shown in the figure, older and younger drivers are significantly overrepresented in crashes, relative to random baseline and near crashes. Random baseline events also include more older drivers than near crashes do.

Gender

Driver gender did not significantly differ between event types. The male (M)/female (F) distribution was as follows: random baselines (53% M, 47% F), matched baselines (52% M, 47% F), near crashes (52% M, 47% F), and crashes (52% M, 48% F).

Mileage

In the driving history questionnaire, drivers responded to the question “Approximately how many miles did you drive last year?” Mileage was treated as a continuous variable in the logistic regression, and it was marginally significantly associated with event type [Wald $X^2(2) = 5.72, p = 0.0570$]. Mileage for crashes ($\bar{x} = 9,000$) was lower than for near crashes ($\bar{x} = 12,840$) and random baselines ($\bar{x} = 12,082$).

Precrash Scenario Types

The precrash scenario types, as defined by Najm and Smith (2007), are shown for crashes and near crashes in Figure 3.2. All but one crash and six near crashes fell into the two categories of Lead Vehicle Decelerating and Lead Vehicle Stopped. *Lead Vehicle Stopped* is a common source of confusion, as it is often interpreted as the subject vehicle approaching a lead vehicle that was stopped from the beginning. Recall that the team decided to use the reaction-time point as the deciding time (if stopped when the driver started to react, then Scenario 26; if decelerating but not yet stopped or never stops, then Scenario 25). Logistic regression indicates that crashes are significantly more likely to fall into the Lead-Vehicle-Stopped Scenario, while near crashes are more likely to fall into

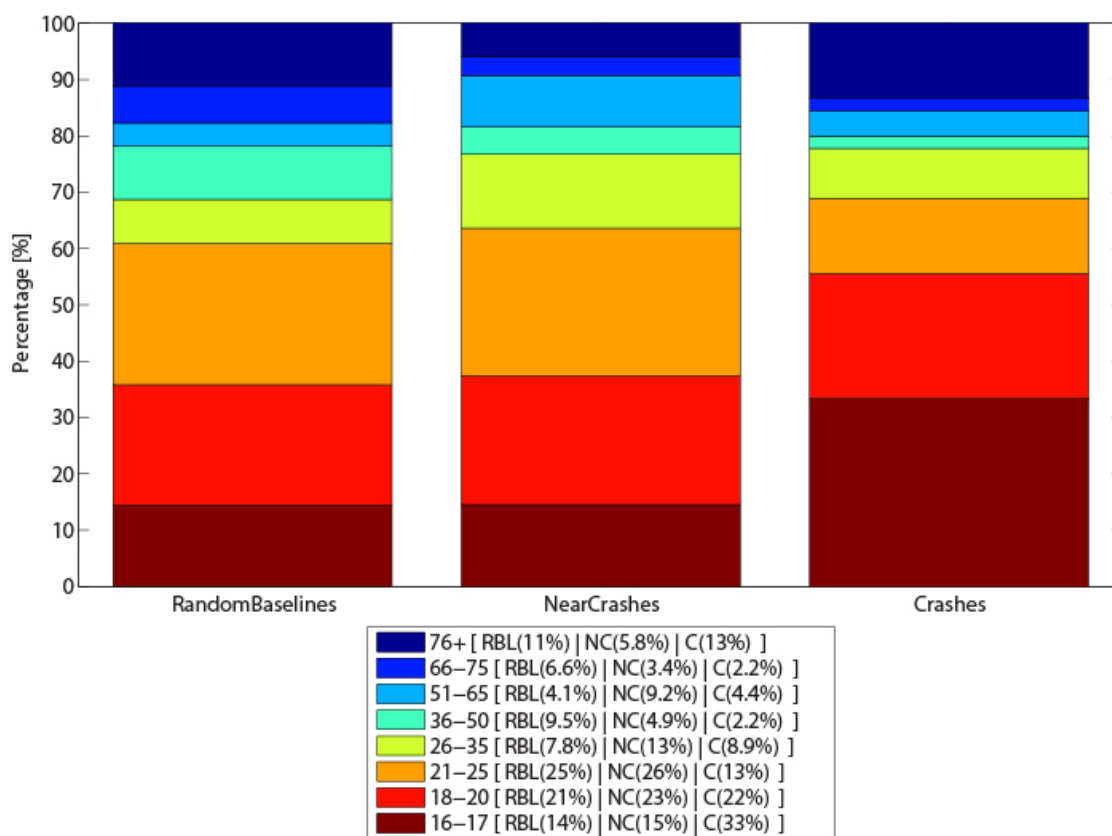


Figure 3.1. Percentage of random baselines, near crashes, and crashes by driver age.

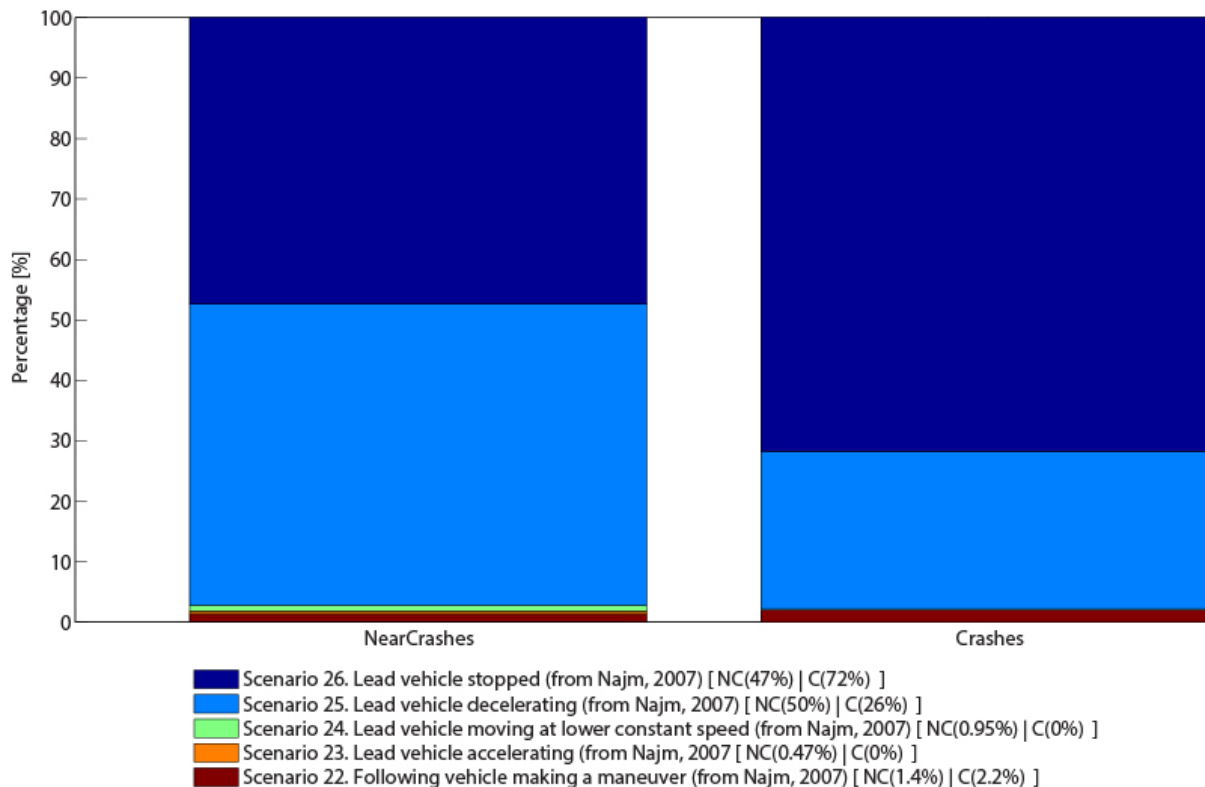


Figure 3.2. Percentage of precrash scenarios in near-crash and crash events, according to precrash Scenarios 22–26 from Najm and Smith (2007).

The Lead-Vehicle-Decelerating Scenario [Wald $X^2(1) = 8.44$, $p = 0.0037$].

Precipitating Events

The distribution of precipitating events for crashes and near crashes is shown in Figure 3.3. Many categories were represented by only one or two events, so for analysis purposes, these were recoded into three categories: (1) Other or subject vehicle decelerating, (2) Other or subject vehicle slowed and stopped for less than 2 seconds, and (3) Other or subject vehicle stopped in roadway for more than 2 seconds. Other categories in Figure 3.3 had too few observations to include in analysis, so they were dropped. The distribution of these categories differed significantly for crashes and near crashes [Wald $X^2(2) = 8.67$, $p = 0.0131$] such that crashes were more likely to involve a vehicle slowed and stopped for less than 2 seconds, while near crashes were more likely to involve a vehicle decelerating.

Trigger Type

Trigger type for finding crashes and near crashes was not analyzed statistically but is presented here in Figure 3.4. The

trigger represents the filter component by which a given event was included in the set of cases to be evaluated further through video review. These triggers can introduce certain qualities in the events that are likely to drive the overall differences between crashes and near crashes. The near crashes were almost entirely found using a high deceleration threshold. Crashes were found primarily through site reports and Automatic Crash Notification (ACN). ACN is a VTTI-proprietary real-time crash detection algorithm with unknown trigger values. Given the differences in how crashes and near crashes were found, it is unlikely that the events are homogeneous in origin. Wu and Jovanis (2012) discuss the implications of using dissimilar filters when crash and near-crash events are analyzed jointly.

Driver Reaction

Driver reaction was significantly different for crashes and near crashes [Wald $X^2(7) = 25.29$, $p = 0.0007$]. The pattern of reaction is shown in Figure 3.5. Crashes involve a greater proportion of no reaction (17%) and braking with lockup (15%) than near crashes. In near crashes, braking without lockup made up 75% of cases, and braking and steering made up another 18% of near crashes.

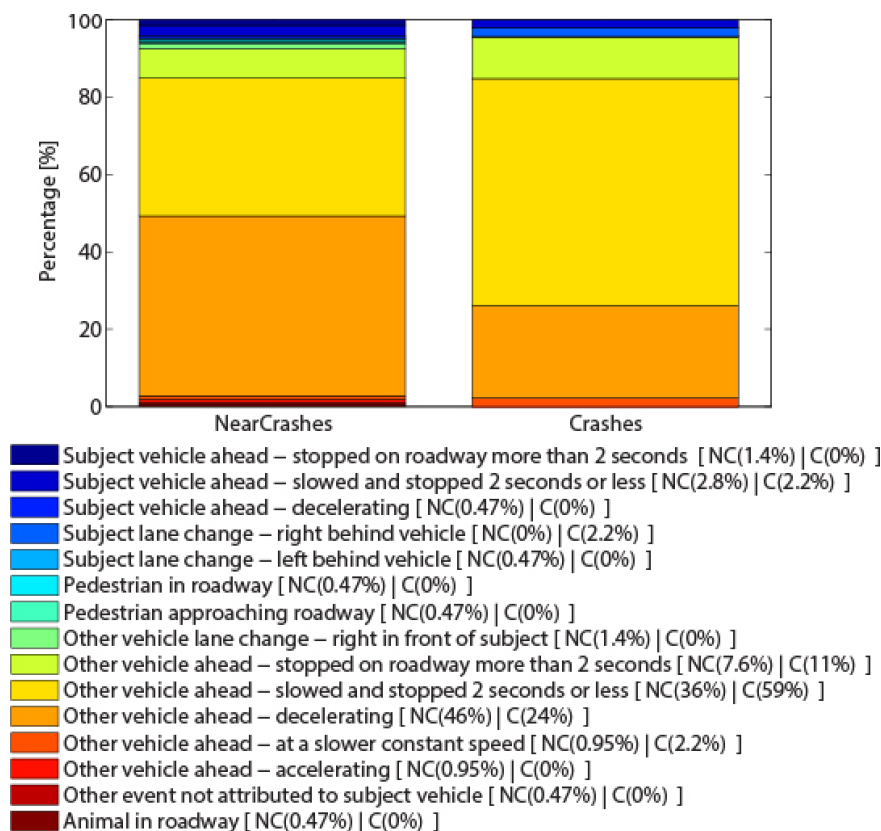


Figure 3.3. Percentage of precipitating events in near-crash and crash events.

Visual Obstructions

Visual obstructions were originally categorized into a variety of elements as shown in Figure 3.6. However, since there were few observations in each unique category, we recategorized the data into “Obstruction Present” and “No Obstruction.” Based on this simple categorization, crashes were significantly more likely to include an obstruction compared with near crashes [Wald $X^2(1) = 4.54, p = 0.0331$]. Nonetheless, 70% of crashes and 83% of near crashes involved no visual obstruction.

Speed

Mean speed did not differ for crashes and near crashes, but it did differ between crash/near-crash events and random baseline events [Wald $X^2(3) = 28.61, p < 0.0001$]. Mean speed was 57.1 km/h during random baselines, 52.2 km/h during matched baselines, 46.6 km/h during near crashes, and 39.8 km/h during crashes. The lower speeds during crash and near-crash events may be due to slowing in response to the precipitating event.

Maximum speed also varied as a function of event type across the four events [Wald $X^2(3) = 17.32, p = 0.0006$], but the difference between near crashes and crashes was only

marginally significant [Wald $X^2(1) = 3.18, p = 0.0746$]. Maximum speed was highest in random baselines (62.2 km/h on average), followed by matched baselines (59.0 km/h), near crashes (55.7 km/h), and crashes (48.1 km/h). See Figure 3.7.

Speed Similarity Between Matched Baselines and Crashes/Near Crashes

A matching criterion was requested such that the matched baseline events should be within ± 15 km/h of their corresponding crash or near-crash event. Mean speed was significantly lower for near crashes compared with their matched baselines [Wald $X^2(1) = 6.98, p = 0.0082$] but within the ± 15 km/h criteria. Crashes were not different from their matched baselines. Similarly, maximum speed was marginally lower for near crashes compared with their matched baselines [Wald $X^2(1) = 3.33, p = 0.0679$] but not different for crashes. Means across events are shown in Table 3.1.

Traffic Flow

Traffic flow is defined as “roadway design (including the presence or lack of a median) at the start of the precipitating

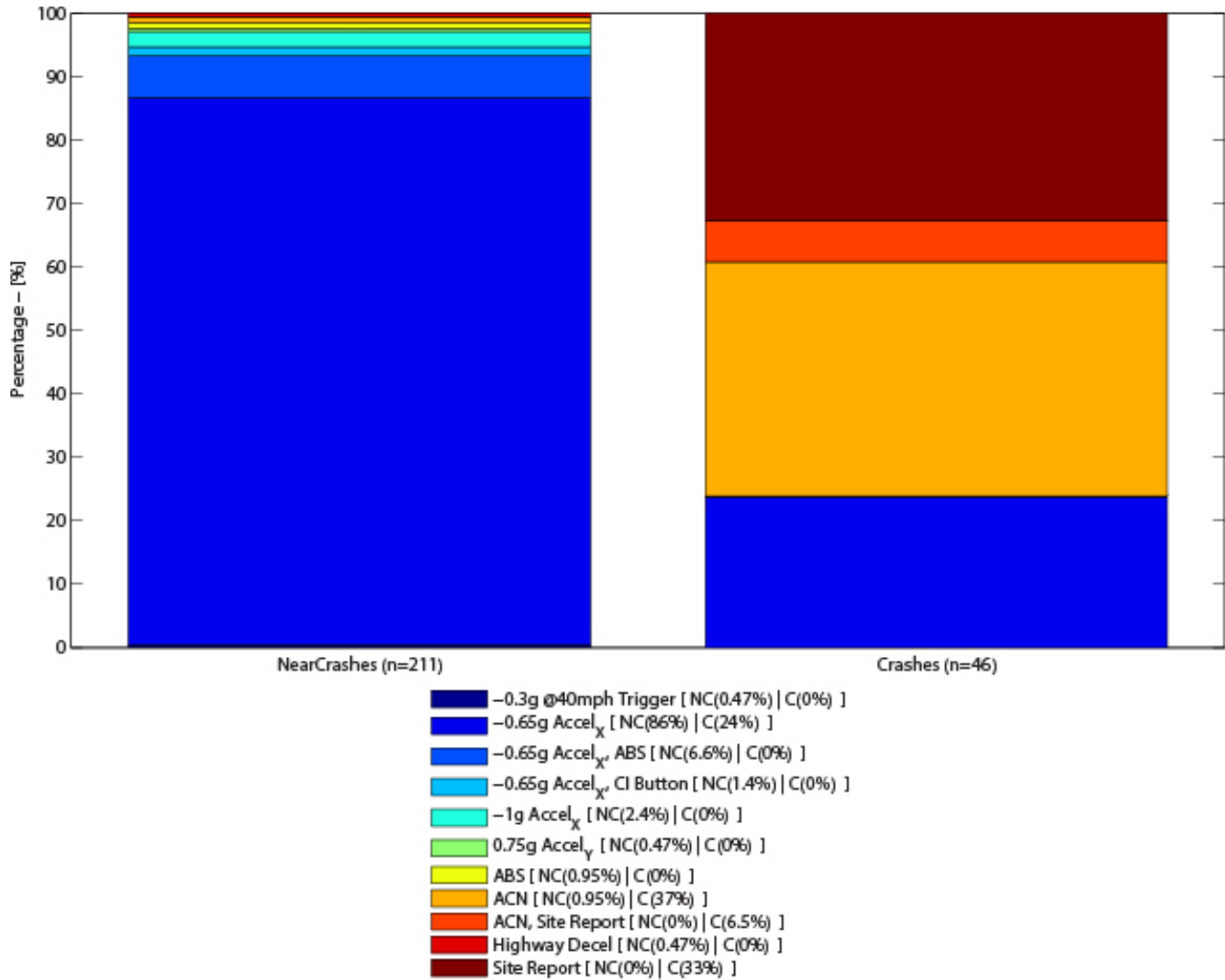


Figure 3.4. Percentage of trigger types that found near-crash and crash events.

event. If the event occurs at an intersection, the traffic flow conditions just before the intersection should be recorded.”

Crashes and near crashes were not different from their matched baseline cases or from each other on traffic flow. However, crashes, near crashes, and all matched baselines were different from random baselines on this variable [Wald $X^2(12) = 36.50, p = 0.0003$]. See Figure 3.8. In particular, random baseline events were more likely than the other three event types to occur on undivided roads.

Relation to Junction

Relation to junction is defined as “the relation of the involved driver or drivers to a junction (point where two roads meet) at the time of the start of the precipitating event. If the incident occurs off of the roadway, the relation to junction is determined by the point of departure. Note that this is different than GES in that this database records relation to junction

at the beginning of the precipitating event, while the GES manual codes this variable at the beginning of the first harmful event.”

Crashes did not differ from their matched baselines on relation to junction, but near crashes did [Wald $X^2(7) = 33.60, p < 0.0001$]. Near crashes are more likely to be at intersections or to be intersection-related, while their matched baselines are more likely not to be at a junction. Across all event types, this pattern was significant, with crashes and near crashes more likely to be at or related to an intersection and both baseline types not at a junction [Wald $X^2(24) = 85.41, p < 0.0001$]. This pattern is shown in Figure 3.9.

Locality

Locality is defined as “the best description of the surroundings at the time of the start of the precipitating event. If there are *any* commercial buildings, indicate as business/industrial

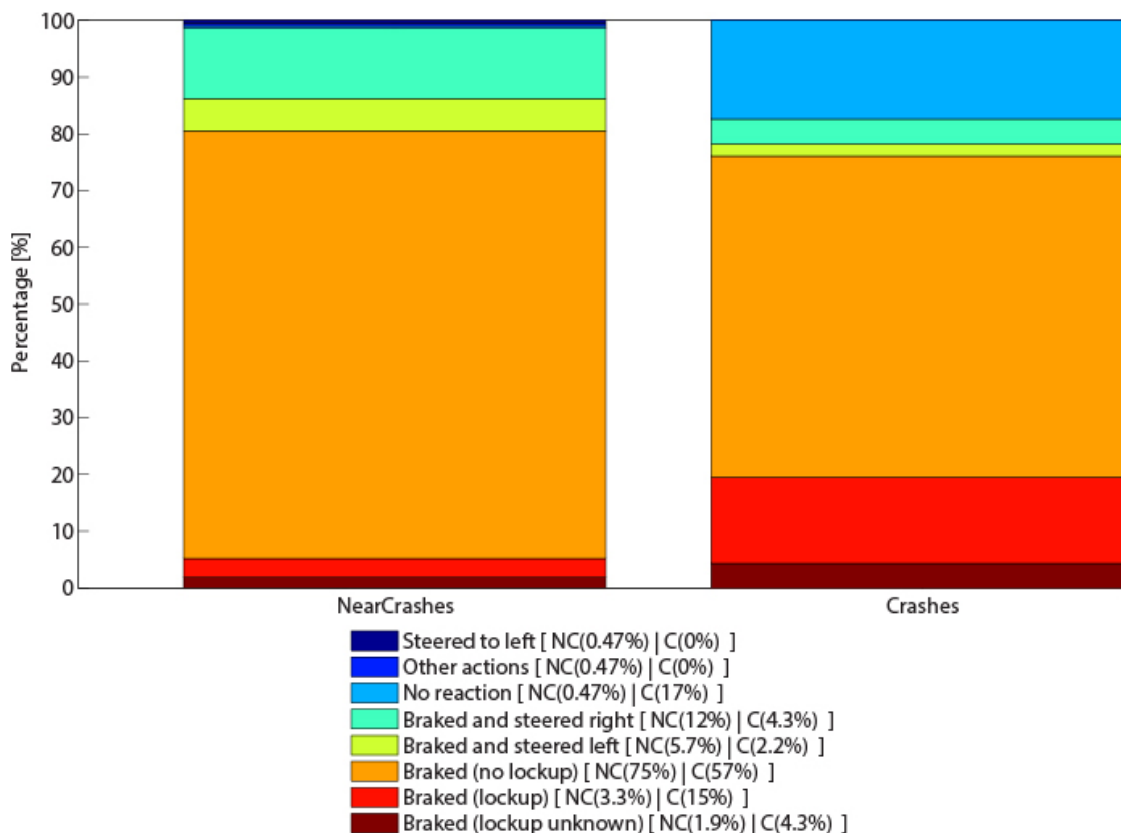


Figure 3.5. Percentage of driver reactions for near-crash and crash events.

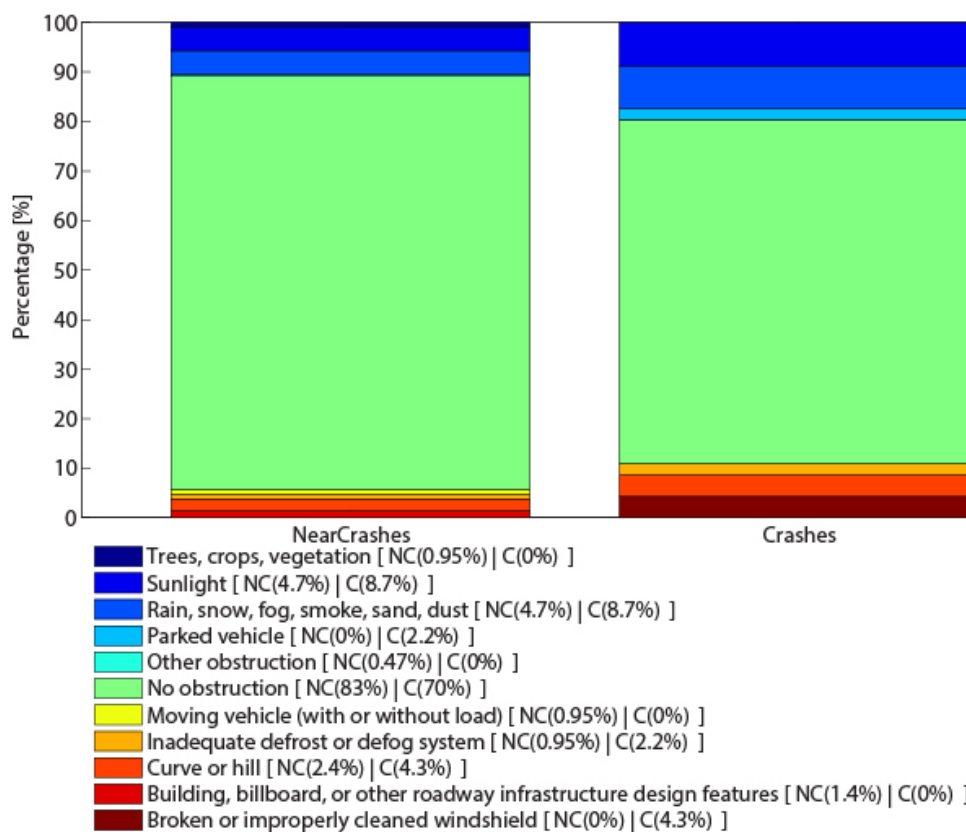


Figure 3.6. Percentage of visual obstructions in near-crash and crash events.

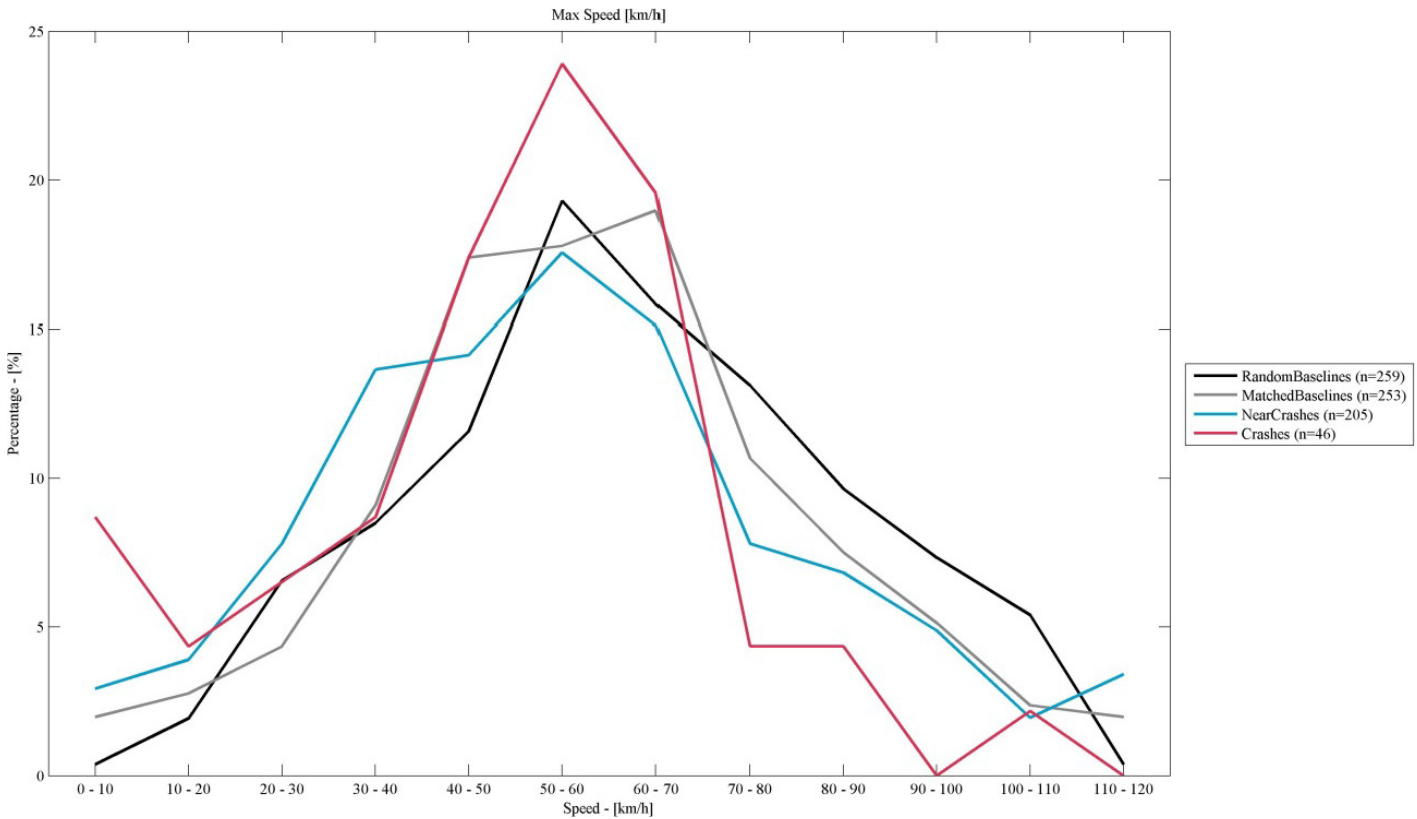


Figure 3.7. Percentage of maximum speed by event type.

area (this category takes precedence over others). Indicate school, church, or playground if the driver passes one of these areas at the same time as the beginning of the event (these categories take precedence over any other categories except business/industrial).”

Locality did not differ between crashes and their matched baselines or between near crashes and their matched baselines. However, random baseline events were significantly more likely to occur in residential areas and less likely to occur on interstate highways than the other three event types [Wald $X^2(30) = 57.47, p = 0.0018$]. See Figure 3.10.

Table 3.1. Comparison of Speed Similarity Between Matched Baselines and Crashes/Near Crashes

Event Type	Mean Speed (km/h)	Maximum Speed (km/h)
Crash	39.8	48.1
Matched baseline for crash	46.2	53.3
Near crash	46.6	55.7
Matched baseline for near crash	53.5	60.1

Traffic Density

Traffic density is defined as “the level of traffic density at the time of the start of the precipitating event, based entirely on number of vehicles and the ability of the driver to select the driving speed.” The results for traffic density mirror those of locality. Crashes and near crashes were not different from each other or their matched baselines. However, the random baseline was significantly more likely to occur in free-flowing traffic than any of the other event types [Wald $X^2(18) = 165.98, p < 0.0001$]. The pattern is shown in Figure 3.11.

Weather

Weather is defined as “the weather condition at the time of the start of the precipitating event.” Relative to their matched baselines, crashes were not different with respect to weather. Crashes are more likely than near crashes to occur in rainy or clear weather [Wald $X^2(1) = 10.32, p = 0.0354$]. See Figure 3.12. Near crashes were significantly more likely to occur in cloudy conditions and less likely to occur in clear conditions than their matched baselines [Wald $X^2(4) = 10.87, p = 0.0281$].

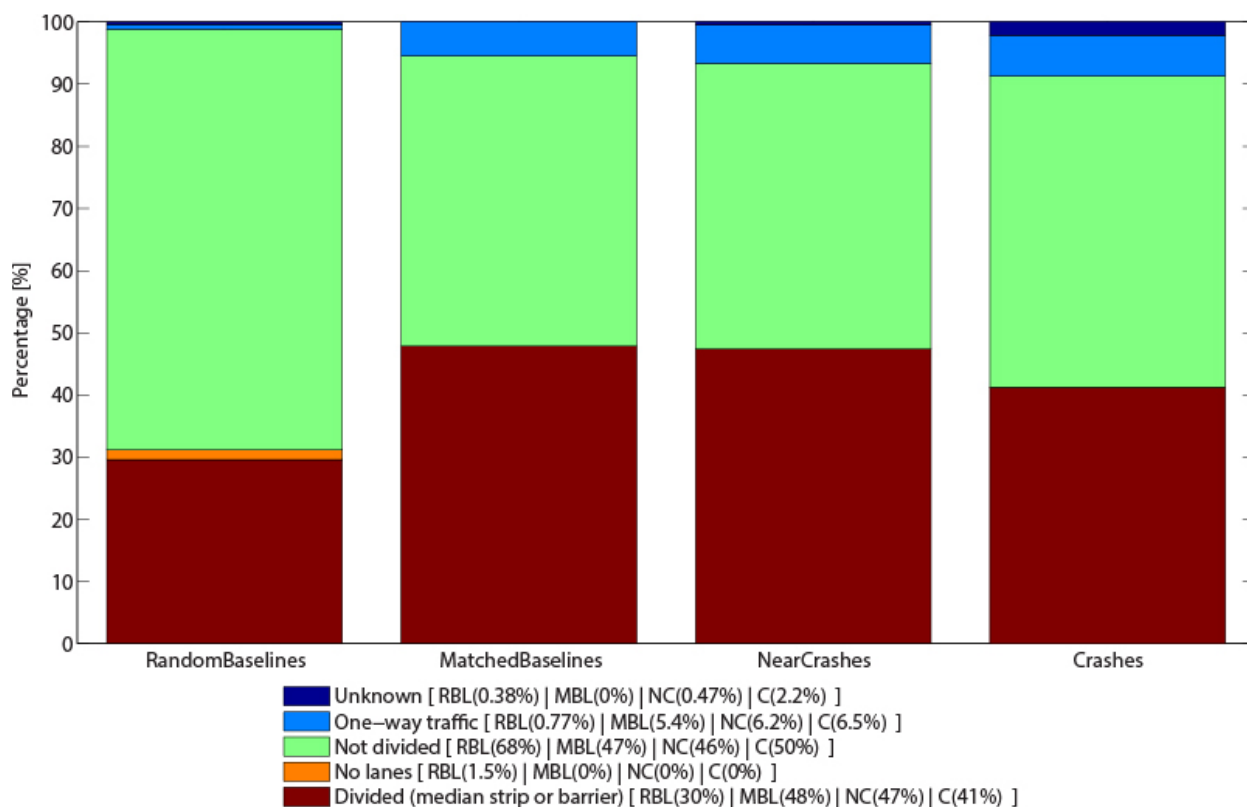


Figure 3.8. Percentage of types of traffic flow by event type.

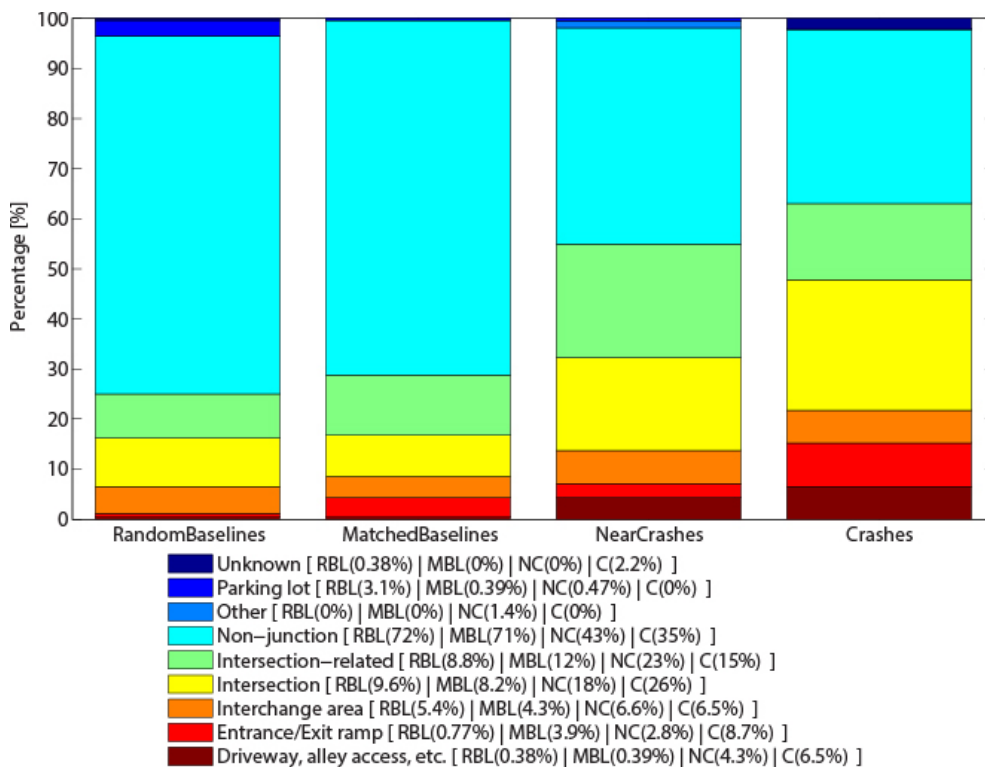


Figure 3.9. Percentage of relation to junction by event type.

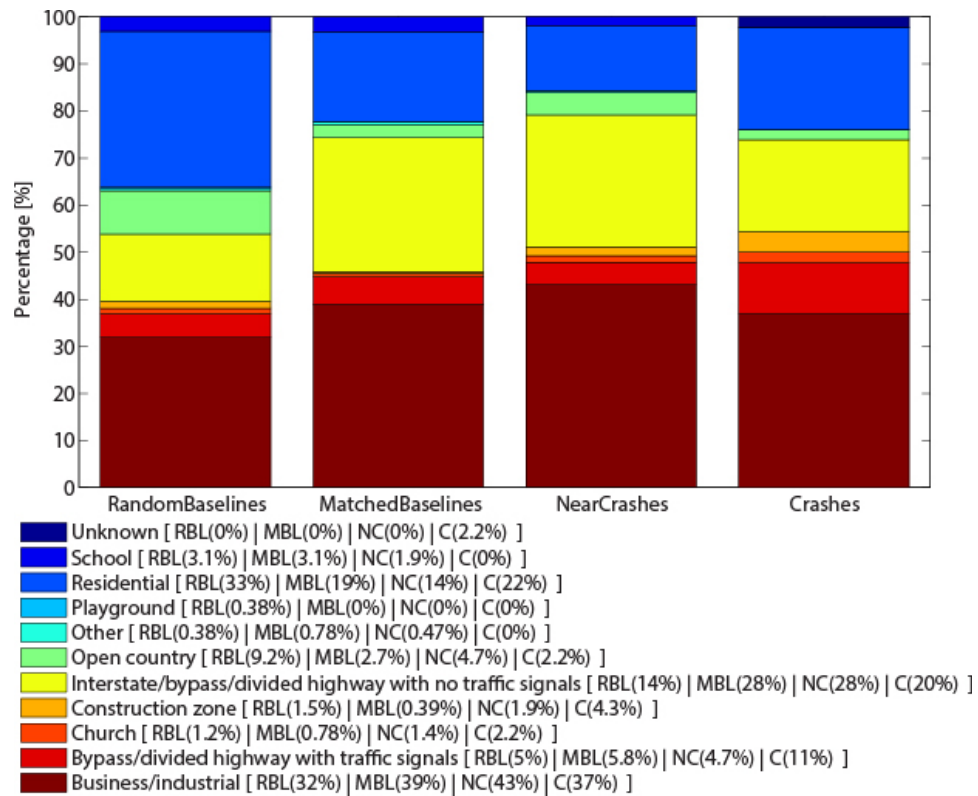


Figure 3.10. Percentage of locality type by event type.

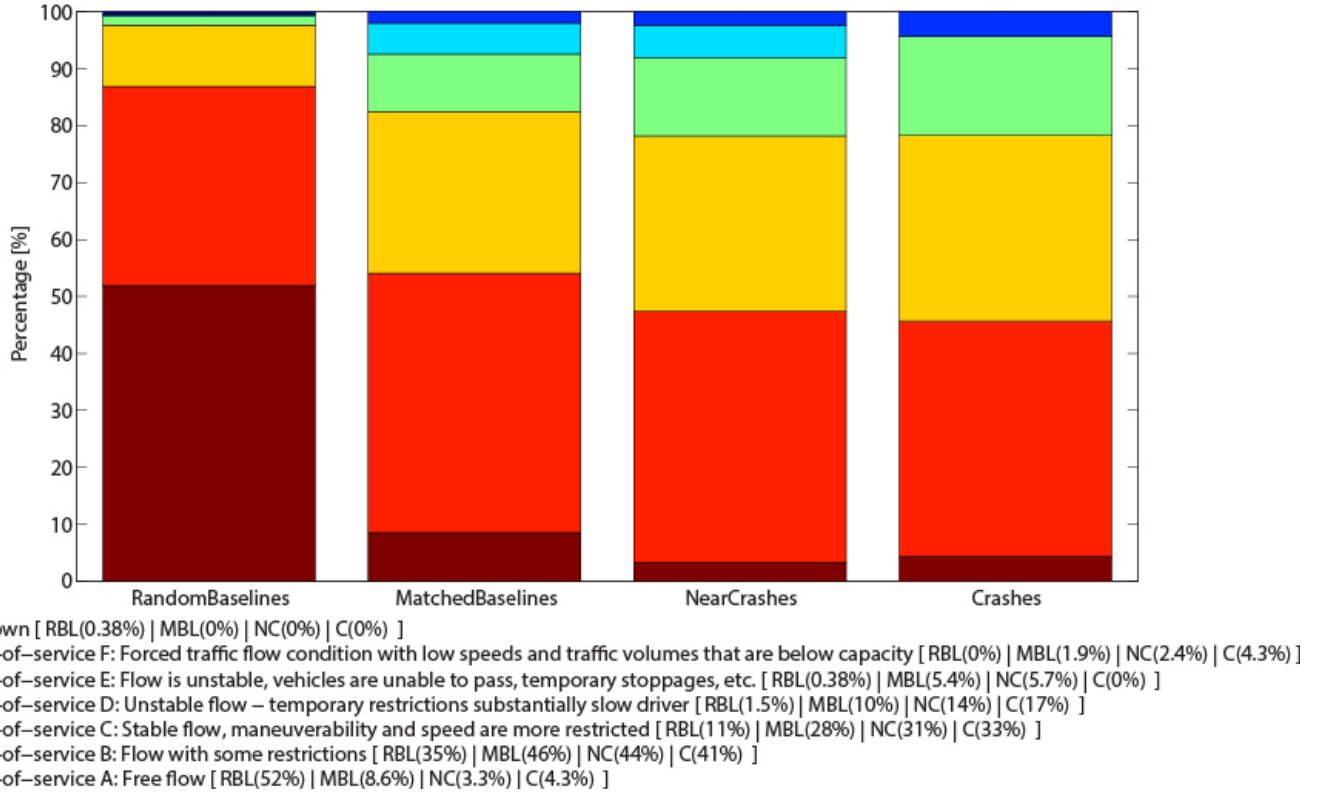


Figure 3.11. Percentage of traffic density by event type.

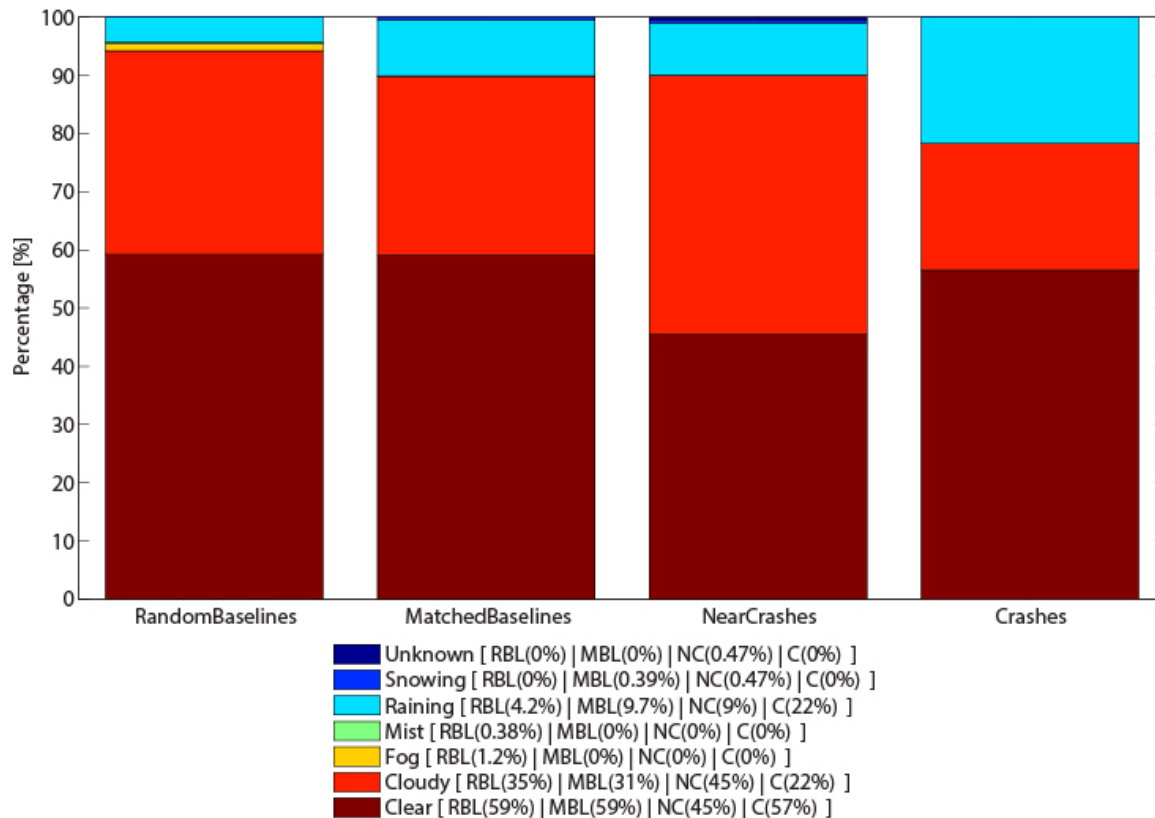


Figure 3.12. Percentage of weather type by event type.

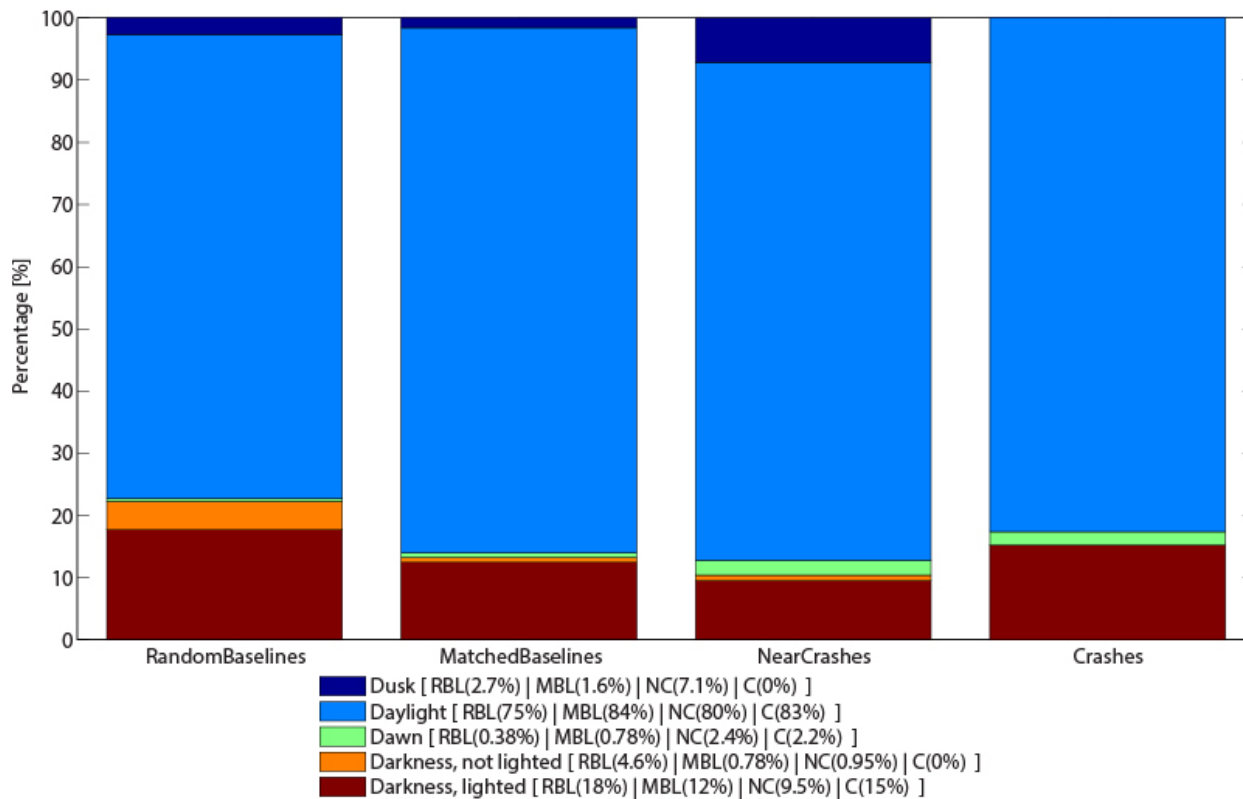


Figure 3.13. Percentage of lighting type by event type.

Surface Condition

Surface condition is defined as “the type of roadway surface condition that would affect the vehicle’s coefficient of friction at the start of the precipitating event.” Surface condition did not differ among any of the event types, including comparisons between crashes, near crashes, and their respective matched baselines.

Lighting

Lighting is defined as “the lighting condition at the time of the start of the precipitating event.” Lighting did not vary between

near crashes and crashes, or between each of these and their matched baselines. However, random baselines were significantly more likely to occur in dark-but-lighted conditions than the other groups [Wald $X^2(12) = 29.41, p = 0.0034$]. See Figure 3.13.

Same Trip

Of the 46 crashes, 36 (78%) matched baselines came from the same trip (preceding the crash). This was also true for 167 (79%) of the 211 near crashes. The remaining matched baselines were selected from a different trip by the same driver.

CHAPTER 4

Risk from Distracting Activity Types

One central topic in naturalistic driving study research has been the calculation of risk associated with (human-identified) classifications of distracting activity types (also called secondary tasks), such as talking, dialing, eating, and texting (Fitch et al. 2013; Klauer et al. 2006, 2010, 2014; Olson et al. 2009). This task risk approach has had particular influence on policy and rulemaking decisions regarding tasks that should or should not be done while driving. Thus, it is of particular relevance for the present research to be able to relate the team's inattention performance approach (quantifying Eyes off Path and lead-vehicle closing in later chapters of this report) to the task risk approach. We began by examining task risk in distracting activities.

4.1 Methods

For Chapters 4–6, we estimated the odds ratio of having a critical event (crash, near crash, or both, depending on the analysis) as a function of various predictors. Chapter 4 covers activity types as predictors, Chapter 5 focuses on the precipitating event and behavior surrounding it, and Chapter 6 focuses on glance behavior preceding minimum time to collision.

The primary method used to estimate odds ratios in this study is conditional logistic regression. However, it is useful to understand unconditional logistic regression first and then contrast the conditional approach. The purpose of logistic regression is to develop models of crash or near-crash risk as a function of various predictors associated with driver behavior and environment. Logistic regression is used in a wide variety of applications when the response variable has a small number of possible outcomes. The binary outcome case is most common and is described here.

Suppose the response variable, y , for a driving event is assigned a value of 1 if it resulted in a crash (or near crash) and is assigned the value of 0 if it did not result in a crash. The data set also has a set of r predictors, x_1, x_2, \dots, x_r , each of which describes a characteristic of the situation, driver, or behavior (e.g., glance pattern, distracting activity) in each case.

The logistic regression model uses these data to predict the *risk* of crashing, given the predictors, according to the formula given in Equation 4.1.

$$\hat{p} = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^r \beta_i x_i)}} \quad (4.1)$$

where \hat{p} is the predicted probability of crashing, β_0 is the intercept, the β_i are coefficients of the predictors, and the x_i are the predictor values. The model-fitting process results in estimates of the β s and an additional error component that measures model uncertainty using any lack of fit of the model to the data.

Logistic regression is a type of general linear model in that a simple transformation of the predicted outcome is related to a linear function of predictors (though individual predictors can also be transformed). Here, the *odds* of crashing are defined as $p/(1-p)$. Logistic regression models the natural logarithm (\ln) odds of crashing on the left side of the model equation as a linear function of predictor variables on the right side of the model equation. For N events, the model equation is shown in Equation 4.2.

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{i1} + \dots + \beta_r x_{ir} \quad i = 1, \dots, N \quad (4.2)$$

where β_0 is the intercept parameter, $\beta_j, j = 1, \dots, r$ are regression coefficients or slope parameters, and x_{ij} are known predictor variables such as distracting activity. Note that this formulation is equivalent to Equation 4.1 but focuses on the linear portion of the equation. Like many models, logistic regression models are fit using the method of maximum likelihood.

Since the left side of the model equation represents the \ln odds of a crash, the slope parameters have interpretations as \ln odds ratios. For a continuous predictor x such as inverse Tau, the slope parameter attached to it represents the \ln odds of a crash for a unit increase in inverse Tau at fixed values of

all other predictors. For a binary predictor such as cell phone use that is coded 0 if the occupant did not use a cell phone and 1 if the occupant did use a cell phone, the slope parameter represents the ln odds of a crash for occupants who used a cell phone, compared with those who did not. Because multiple predictors are included in the model, an odds ratio for a variable is interpreted under the assumption that it has been adjusted for the other predictors included in the model.

One challenge with logistic regression is interpreting odds ratios. Most readers find risk ratios to be more intuitive, and there is a tendency to want to interpret odds ratios as risk ratios. However, risk has a significant analytical disadvantage in that it is bounded between 0 and 1. If the risk of an event is, say, 50% under Condition A, then the risk ratio cannot be more than 2 for Condition B compared with Condition A. However, odds can range from zero to infinity, and their ratio is not constrained by the size of the denominator. However, in circumstances when the outcome of interest is rare (<5% probability), an odds ratio can be interpreted as relative risk. In that case the odds ratio approximates a relative risk, and it is appropriate use logistic regression as an exposure-based risk model (Greenland and Thomas 1982).

In this study, we used an adaptation of logistic regression that is often used in epidemiology to increase efficiency of sampling (Rothman 2012). Instead of selecting a large number of events and identifying crashes among them, we selected crashes and near crashes and then found one matching event in the baseline for each crash or near crash. This is called a matched case–control study, and in this case, because matched events are from the same driver, it falls into the class of studies known as case-crossover.

Because this method controls the percentage of analyzed cases that are crashes (50%), the intercept in logistic regression is meaningless. Instead, conditional logistic regression estimates the probability that each specific event is the event in its group that resulted in a crash. Matching characteristics cannot be used as predictors because they do not distinguish between crashes and baseline within each group. However, other characteristics (e.g., gaze patterns or distractions) as well as interactions between matching variables and other characteristics can be used.

Although the intercept, or β_0 , is not estimated with conditional logistic regression, the remaining coefficients are still interpretable in the same way as for logistic regression. Indeed, if there were only one group, conditional and unconditional logistic regression would produce the same estimates (other than the intercept). In addition, with unconditional logistic regression, coefficients of predictors are unbiased, even when the underlying sample is biased, as it is here (Breslow 1996).

Although both forms of logistic regression produce comparable coefficients, unconditional logistic regression is not appropriate for matched data sets. The matching itself is a

feature of the sampling, not the underlying process, and therefore must be taken into account using conditional logistic regression.

Although we control the base risk by using a 1–1 match, the odds ratios for predictors can be interpreted in this context as risk ratios. Because the odds ratios are unbiased, they are expected to be the same, even if sampled differently. In driving, crashes and even near crashes are extremely rare events that would fall under the “rare disease assumption” level. The next sections present odds ratios for crashes, near crashes, or both as a function of a variety of predictors.

4.2 Distracting Activities

Distracting activities were manually coded by reviewing video by VTTI according to the SHRP 2 data dictionary (Variables Distraction 1, Distraction 2, and Distraction 3 in the SHRP 2 NDS Event Definitions and Variables v 2_1 from December 2010). In accordance with the SHRP 2 data dictionary, distracting activities were coded if present within the 6-second time window including 5 seconds before and 1 second after the precipitating event (or a random point for the baselines). There are more than 50 categories of distracting activities in the data dictionary and many subtle nuances in classification of the various categories. Therefore, caution should be taken when interpreting categories, and the data dictionary should be used as support for interpretation. For example, the Talking/Listening on Cell Phone category excludes locating, reaching for, and answering a cell phone but actually does include hanging up (this is discussed in greater detail in Section 6.1). The rationale within the data dictionary is unclear for including an explicitly visual-manual interaction (hanging up) in an activity that seems to be clearly designated as nonvisual (talking/listening). This seems problematic as it creates a category that is not easily mapped onto clearly defined dimensions of distraction and makes it more difficult to draw conclusions regarding nonvisual/nonmanual interaction.

Classes of distracting activities (Distraction 1, 2, 3 event variables) present in the 5 seconds before the precipitating event and 1 second after were developed, because relatively few observations were present in the individual categories (see below). Note that the individual categories Lost in Thought (three cases), Looked but Did Not See (three cases), and Cognitive, Other (zero cases) were not included in the classes as they were believed to be questionable categories and difficult to group together with other nonvisual activities.

Classes of distracting activities are as follows:

1. *Portable Electronics Talking/Listening*: Talking/Listening on Cell Phone.
2. *Portable Electronics Visual-Manual*: Dialing Hands-Free Cell Phone Using Voice-Activated Software; Texting on

Cell Phone; Dialing Handheld Cell Phone; Dialing Handheld Cell Phone Using Quick Keys; Locating/Reaching/Answering Cell Phone; Cell Phone, Other; Locating/Reaching PDA; Operating PDA; Viewing PDA; PDA, Other.

3. *Original Equipment*: Reaching for object that is a manufacturer-installed device; Adjusting/Monitoring Climate Control; Adjusting/Monitoring Radio; Inserting/Retrieving Cassette; Inserting/Retrieving CD; Adjusting/Monitoring Other Devices Integral to Vehicle.
4. *Nonelectronics, Nonvisual*: Talking/Singing ~~Lost in thought~~; ~~Looked but did not see~~; Cognitive, other (deleted, as described above).
5. *Nonelectronics Other*: Dancing; Reading; Writing; Moving Object in Vehicle; Insect in Vehicle; Pet in Vehicle; Object Dropped by Driver; Reaching for Object, Other; Object in Vehicle, Other; Reaching for Food-Related or Drink-Related Item; Eating with Utensils; Eating without Utensils; Drinking with Lid and Straw; Drinking with Lid, No Straw; Drinking with Straw, No Lid; Drinking from Open Container; Reaching for Cigar/Cigarette; Lighting Cigar/Cigarette; Smoking Cigar/Cigarette; Extinguishing Cigar/Cigarette; Reaching for Personal Body-Related Item; Combing/Brushing/Fixing Hair; Applying Makeup; Shaving; Brushing/Flossing Teeth; Biting Nails/Cuticles; Removing/Adjusting Jewelry; Removing/Inserting/Adjusting Contact Lenses or Glasses; Other Personal Hygiene.
6. *Nonelectronics, Passenger-Related*: Passenger in Adjacent Seat—Interaction; Passenger in Adjacent Seat—No Interaction or Cannot Tell; Passenger in Rear Seat—Interaction; Passenger in Rear Seat—No Interaction or Cannot Tell; Child in Adjacent Seat—Interaction; Child in Adjacent Seat—No Interaction or Cannot Tell; Child in Rear Seat—Interaction; Child in Rear Seat—No Interaction or Cannot Tell.
7. *Vehicle-External Distraction*: Looking at Previous Crash or Incident; Looking at Pedestrian; Looking at Animal; Looking at an Object External to the Vehicle; Distracted by Construction; Other External Distraction.
8. *Inattention to the Forward Roadway*: Inattention to the Forward Roadway—Left Window; Inattention to the Forward Roadway—Left Mirror; Inattention to the Forward Roadway—Center Mirror; Inattention to the Forward Roadway—Right Mirror; Inattention to the Forward Roadway—Right Window; Inattention to the Forward Roadway—Back Window.
9. *Other*: Other nonspecific Eyeglance; Inattention, Other; Unknown Type (Distraction Present); Unknown.
10. *Not Distracted*: Not Distracted.

Figure 4.1 shows the odds ratio for several variables. The precise OR is shown in the center of each dot, and the lines

surrounding the dots indicate the 95th percentile confidence interval. Odds ratios are significant when the confidence interval does not cross 1 on the x -axis. For each activity three ORs are shown: the near-crash (NC) situations, the crash and near-crash (CNC) situations combined, and the crash (C) situations. In some cases, there are insufficient data to calculate precise confidence intervals, such as the OR of crashes associated with phone conversations. There were no crashes when drivers were engaged in Portable Electronics Talking/Listening and so the OR and its confidence interval (CI) are undefined, represented by the CI that extends across the full width of the graph. Note that Portable_electronics_talking_listening in Figure 4.1 corresponds to the Talking_listening_on_cell_phone category in Figure 4.2.

Talking_listening_on_cell_phone in Figure 4.2 is part of the Portable_electronics_talking_listening aggregate category in Figure 4.1. Not surprisingly, Texting has a high OR of 5.6 (CI 2.2–14.5) for crash and near-crash situations, but Talking_listening_on_cell_phone has an OR of only 0.1—representing a large reduction in risk. The magnitude of the risk reduction (a protective effect) can be directly compared with the magnitude of the risk by reversing the sign of the coefficient before converting it to an odds ratio. In this case, the odds ratio would be approximately 10—greater than the risk of texting.

Odds ratios for more than 50 distracting activities were examined. However, many of the activities did not occur frequently enough to achieve statistical significance. Distracting activities do not occur as frequently as glances and thus need larger sample sizes. Individual categories, such as Locating/Reaching for/Answering a Cell Phone or Adjusting/Monitoring the Radio, or other aggregate categories, such as Original Equipment or Vehicle External Distraction, were not significantly risky.

4.3 Driver Impairments

The Driver Impairments event data variable was examined (see Figure 4.3). Distraction occurred frequently in the events collected for this study, and the odds ratios associated with these distractions suggest they contribute to crashes. There is an association of distraction and crashes [OR = 3.0, CI (1.1, 8.3)], near crashes [OR = 1.6, CI (1.0, 2.4)], and crashes and near crashes together [OR = 1.8, CI (1.2, 2.6)]. Impairments associated with drowsiness, drugs, and alcohol were much less frequent. Figure 4.3 shows the distribution of these impairments relative to distraction. Of these impairments, only drowsiness occurred frequently enough to merit investigation. A conditional logistic regression model found an odds ratio of 2.7, but the relatively few cases leads to large confidence intervals and a failure to achieve statistical significance [Wald $X^2(1) = 2.1$, $p = 0.147$]. Distraction is dominant, and the other behaviors or impairments are rare in this sample of driving.

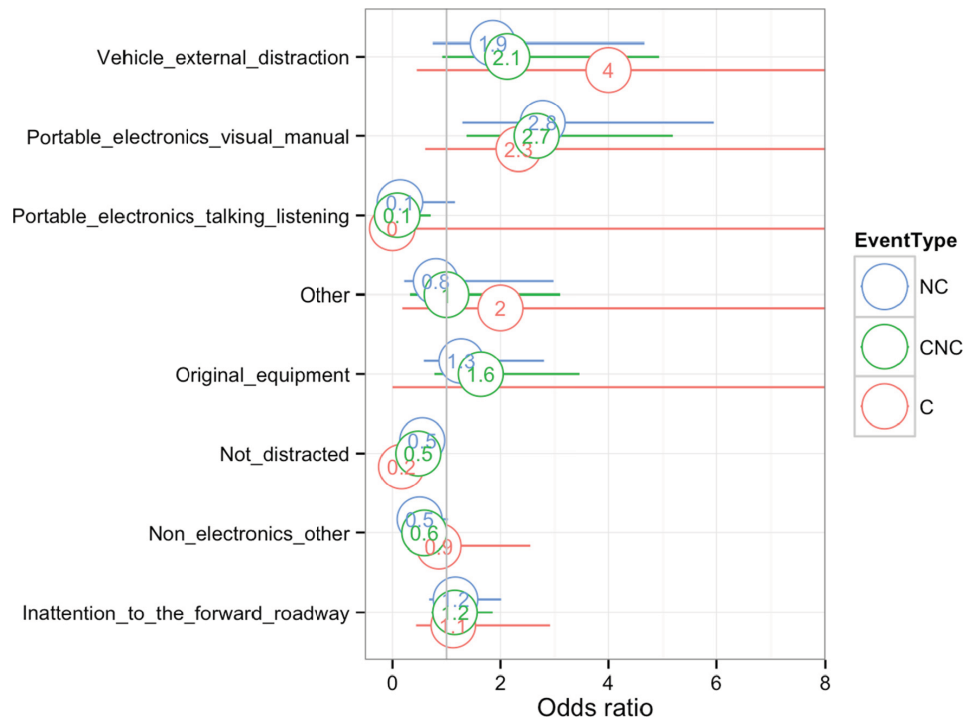


Figure 4.1. Odds ratios (numbers inside circles) and confidence intervals (horizontal lines) for classes of distracting activities in crashes, near crashes, and crashes and near crashes combined. Odds ratios are significant only when confidence intervals are fully above or below 1 (do not cross vertical line at 1). Presence of a distracting activity was coded between 5 seconds before and 1 second after the precipitating event.

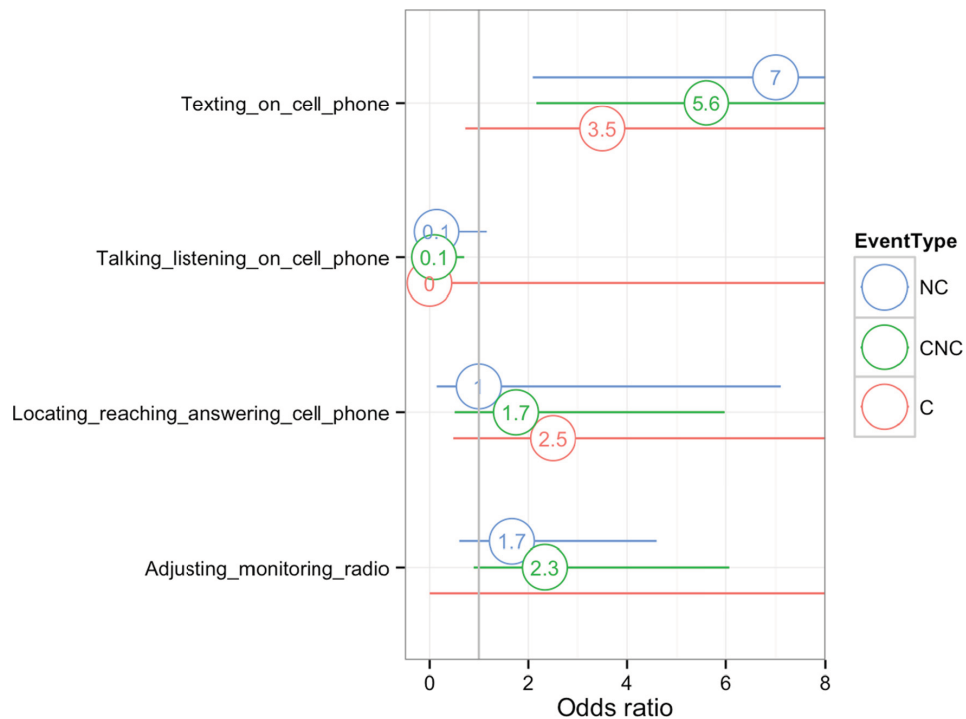


Figure 4.2. Odds ratios (numbers inside circles) and confidence intervals (horizontal lines) for specific distracting activities. Odds ratios are significant only when confidence intervals are fully above or below 1 (do not cross vertical line at 1). Presence of distracting activity was coded between 5 seconds before and 1 second after the precipitating event.

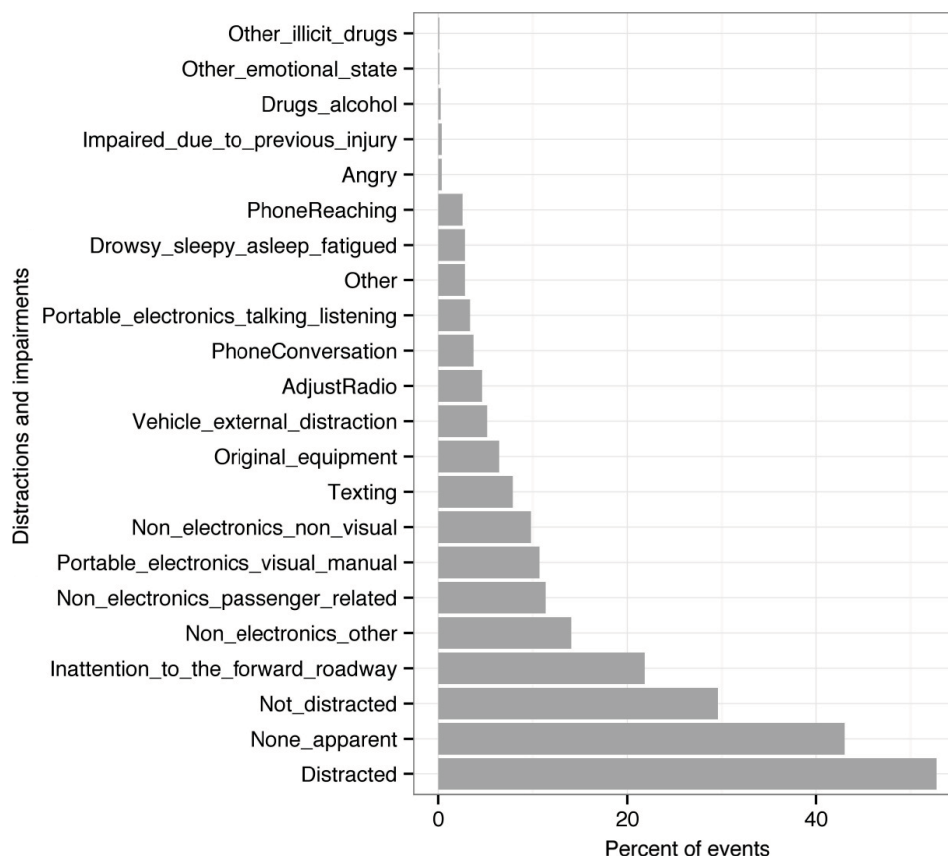


Figure 4.3. Distribution of driver impairments relative to distracting activities across all event types together (crashes, near crashes, matched baselines, and random baselines).

4.4 Conclusions

The effect of these distracting activities on the likelihood of crashes and near crashes varies tremendously. Some activities, such as Talking/Listening on Cell Phone, have an odds ratio substantially less than one, suggesting a protective effect; others, such as Texting, have an odds ratio much greater than one, suggesting a substantial risk. Texting (OR 5.6, CI 2.2–14.5) and the aggregate category of Portable Electronics Visual-Manual (OR 2.7, 1.4–5.2) had the highest odds ratios, suggesting a substantial risk. Talking/Listening on Cell Phone was found to decrease risk significantly compared with not engaging in a phone conversation (OR 0.1, CI 0.01–0.7), representing an estimated 10-fold reduction in risk compared with baseline (OR 10 if the sign of the coefficient is reversed). In line with predictions regarding sample-size limitations, significant differences for distracting activities were not found for crash events alone as there were too few observations in this category. However, notably, there were no crashes when

drivers were engaged in Talking/Listening on a Cell Phone. The limitation in sample size also influenced the ability to detect significant odds ratios in other distracting activities (such as dialing a cell phone or adjusting the radio). Note that the limitation in sample size affects the odds ratio analysis of distracting activities because distracting activities are not found in all events. The odds ratio analysis of glance data is not affected in the same manner because off-path glances occur in almost all events, providing more data to work with.

Other behaviors and impairments (drowsiness, drugs, and alcohol) are rare. Of these, only drowsiness occurred frequently enough to merit investigation and showed an odds ratio of 2.7, but was not statistically significant.

In sum, distracting activities occur frequently, much more frequently than impairments such as drowsiness. Some activities, such as phone conversations, have an odds ratio substantially less than one, suggesting a protective effect, and others, such as texting, have an odds ratio much greater than one, suggesting a substantial risk.

CHAPTER 5

Risk at the Precipitating Event

Chapters 5 and 6 focus on the research question, What are the most dangerous glances away from the road, and what are safer glances? To begin the analysis of which glance characteristics are associated with the most risk, the logical place to start is to use the SHRP 2 NDS data to perform a replication of or comparison with the 100-car analyses (Klauer et al. 2006, 2010; Liang et al. 2012; Victor and Dozza 2011). The 100-car glance analyses focused on comparing the relative influence of various glance characteristics on risk (expressed as ORs). Conducting a replication analysis makes it possible to set the SHRP 2 OR results into context with previous research.

Previous 100-car reanalysis research analyzed 6 seconds of data aligned to the precipitating event; this is the reason for the setup of alignment and the 6-second window in this chapter. The analyzed events here comprise a 6-second interval, 5 seconds before the precipitating event (PE) and 1 second after, for each crash, near-crash, and baseline event.

5.1 Risk from Total Eyes off Path Time at the Precipitating Event

Previous analyses have focused on analyzing crash/near-crash risk from Total Eyes off Roadway Time (TEORT) at the precipitating event (Klauer et al. 2006, 2010, 2014; Fitch et al. 2013; Olson et al. 2009). The present analysis replicates these earlier analyses so that we can directly compare OR estimates between the present SHRP 2 data and previous data. The TEOR variable is directly comparable to this project's variable, Total Eyes off Path Time (TEOPT). The only difference is that we believe it is more correct to refer to the variable as *Eyes off Path* than *Eyes off Road*, even though it is coded in the same manner.

The odds ratios were calculated in two ways. First, the crude odds ratios were calculated to allow direct comparisons with similarly calculated odds ratios in previous studies (e.g., Klauer et al. 2006). Crude odds ratios are based directly on the ratios of event occurrence (e.g., crashes) and nonoccurrence

(e.g., random baseline) for situations that contain the potential risk factor (e.g., cell phone conversation) and those that do not. Random baselines have no matching variables and so are analyzed using standard logistic regression, which produces odds ratios that are exactly equivalent to crude odds ratios when no other variables are present.

Second, conditional logistic regression was used for comparison with previous case-crossover analyses (e.g., Klauer et al. 2010). Here the team used matched baselines instead of random baselines and estimated ORs for the same set of predictors.

Using conditional logistic regression is critical with data that include matched baselines because the crude odds ratios provide biased estimates of the true odds ratios for this data type—typically underestimating the odds ratios. Crude odds ratios also neglect the dependence between events and the baselines and so can underestimate the confidence interval surrounding the estimates. Crude odds ratios are provided here to facilitate comparison with previous analyses and are shown as small solid dots in the figures.

TEOPT Risk in 5 Seconds Before and 1 Second After the Precipitating Event

Eyes off Path time was calculated for a window of 5 seconds before and 1 second after the precipitating event. Here, Eyes off Path time is the amount of time (in seconds) the eyes were off path longer than a certain amount within this 6-second period. Bins of 0.1–0.5 second, 0.5–1.0 second, 1.0–1.5 seconds, 1.5–2.0 seconds, and 2.0–2.6 seconds were used. Note that each bin is compared with the case in which the driver's eyes were on the path for the entire 6 seconds (Off0).

Figure 5.1 shows the odds ratios and 95th percentile confidence intervals calculated with matched baselines using conditional logistic regression (OR), with matched baselines as controls. The figure also shows the odds ratios for the crude odds ratios as small dots.

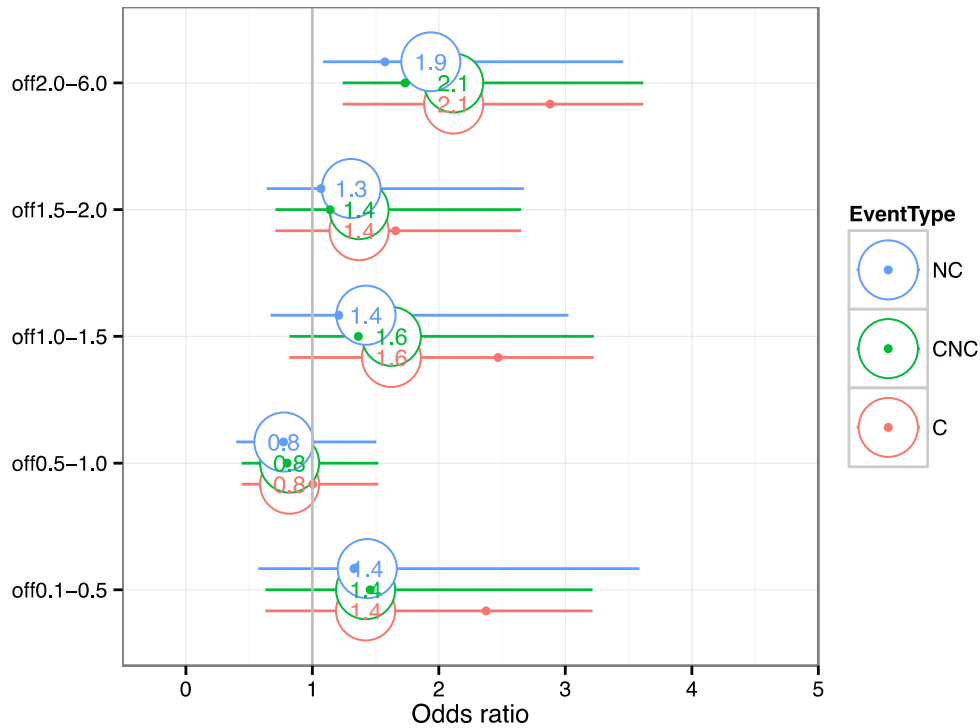


Figure 5.1. Odds ratios and confidence intervals for total off-path glance durations in the 5 seconds before and 1 second after the precipitating event.

Only the TEOPTs greater than 2 seconds (Off2.0-6.0) produce an odds ratio with a confidence interval that does not include 1.0. The small filled dots show the crude odds ratios; for the near crashes (NC) and the combination of crashes and near crashes (CNC), the crude odds ratios are lower than the odds ratios from the conditional logistic regression, indicated by the large open circles and the numeral at the center of those circles.

In analyses of risk in the 6 seconds around the time of the precipitating event (5 seconds leading up to the precipitating event and 1 second after), TEOPTs above 2 seconds were shown to be significantly risky for crashes (OR 2.1), near crashes (OR 1.9), and crashes and near crashes combined (OR 2.1). Lower TEOPTs were not significantly risky. This result is directly comparable to the very similar 100-car study findings (Klauer et al. 2010) concerning Total Eyes off Roadway Times (TEORTs). Klauer et al. showed an odds ratio of 1.6 (CI 1.3, 2.0) compared with this project's odds ratio of 2.1 (CI 1.2, 3.6) for the case-crossover (matched baselines) comparison. In the case-control (random baselines) comparison, Klauer et al. showed an odds ratio of 2.1 (CI 1.7, 2.8), while this project found an odds ratio of 2.0 (CI 1.2, 3.2).

Eyes-off-Path Timeline

Figure 5.2 shows a potential explanation for the OR results: the percentage of glances directed off the road increases in the 5 seconds before the event onset and 1 second after for crashes

and near crashes. Each point in the graph represents the average proportion of time eyes are off road at every tenth of a second. For reference, the SHRP 2 data are plotted with the 100-car data (Victor and Dozza 2011).

A key observation in Figure 5.2 is that the Eyes-off-Path patterns for crashes and near crashes are markedly different. For near crashes, the peak is lower. For crashes, there is actually a dip just before the PE, and the highest peak is about a second after. The SHRP 2 data in Figure 5.2 show an increase in eyes off the forward path as the precipitating event approaches in time, similar to that found in the 100-car data. However, in the SHRP 2 data, the increase continues after the PE for the crashes.

Figure 5.2 also seems to indicate that there is generally more Eyes off Path time in crashes and near crashes, that there is generally more Eyes off Path time in matched baselines than random baselines, and that these baselines are comparable to the 100-car baselines. Figure 5.2 also shows variation in when the crash point (in crashes) and minimum TTC (in near crashes) occurs relative to the precipitating event.

Another general observation that should be noted is that proportions of crashes to near crashes matter in the combined crash/near-crash values. When combining crashes with near crashes, the fact that there are many more near crashes influences the combined crash/near-crash values toward near crashes, a simple weighting effect. Thus, we need to be mindful of this weighting effect in which proportions of event types change the data in a combined data set. This is particularly

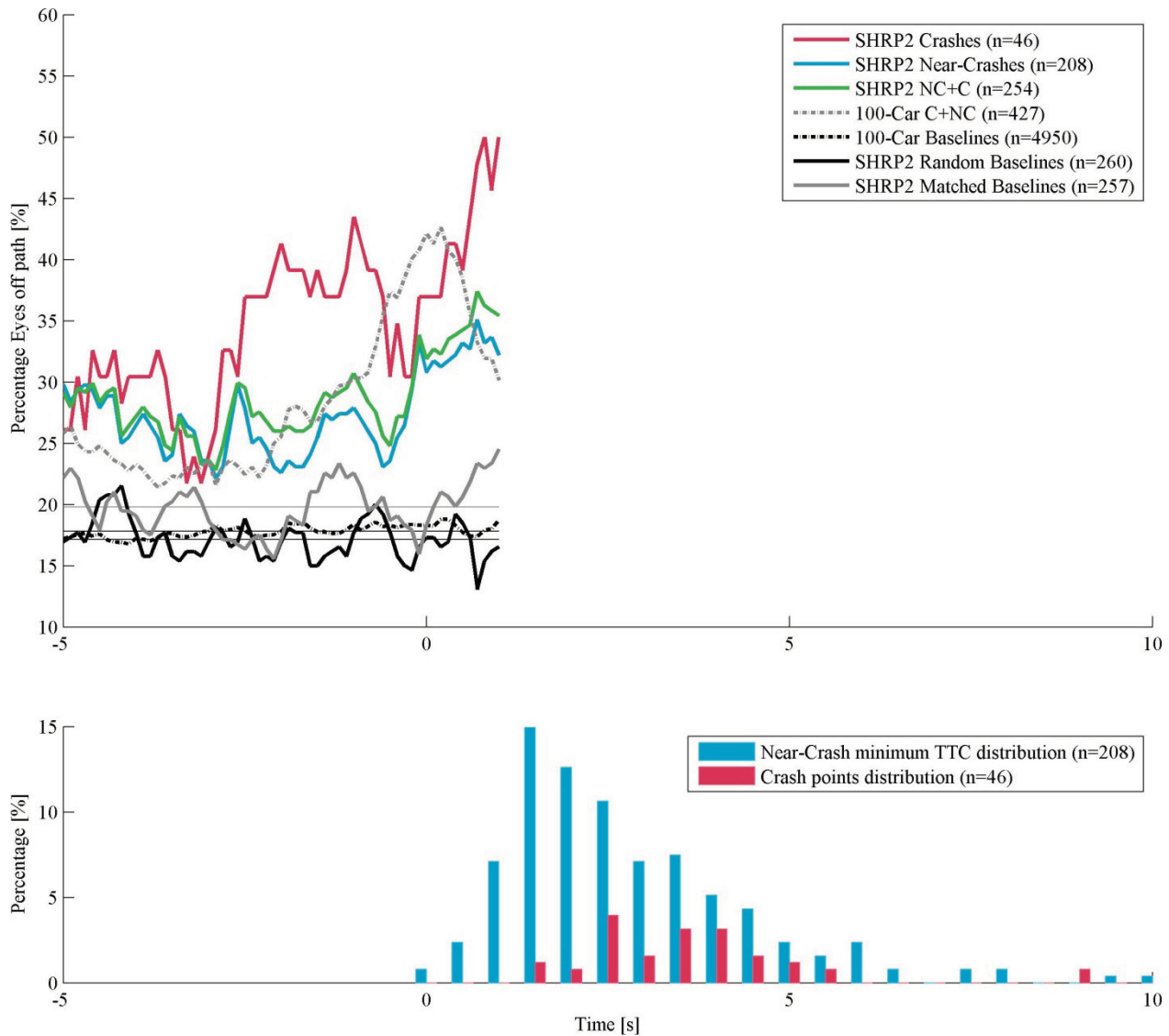


Figure 5.2. Percentage of glances off path in relation to the precipitating event, crash points, and minimum time to collision (TTC) (for near crashes). The zero point on the x-axis indicates the onset of the precipitating event.

important because incidents and near crashes are often much more numerous than crashes. Reconsidering the 100-car Eyes-off-Path data and other naturalistic driving study data with this in mind may prove important, as the patterns that emerge from crashes may be very different from near crashes and incidents, if separated.

Timing Difference Between Precipitating Event and Brake Light Onset

To understand in more detail what the precipitating event was, a comparison of whether the precipitating event represented the brake light onset was calculated. Figure 5.3 clearly shows that the precipitating events coincided with a brake

light onset. Thus, in our data set, the precipitating event (PE) can be largely seen as brake light (BL) onset. That is, it was largely the brake light onset that was annotated as “the state of environment or action that began the sequence under analysis.”

5.2 Eyes-off-Path Risk in Time Segments at the Precipitating Event

An important feature of Figure 5.2 is that the proportion of Eyes off Path is not uniform—there is a pronounced increase around the precipitating event. Consequently, analysis of windows of time preceding the precipitating event might

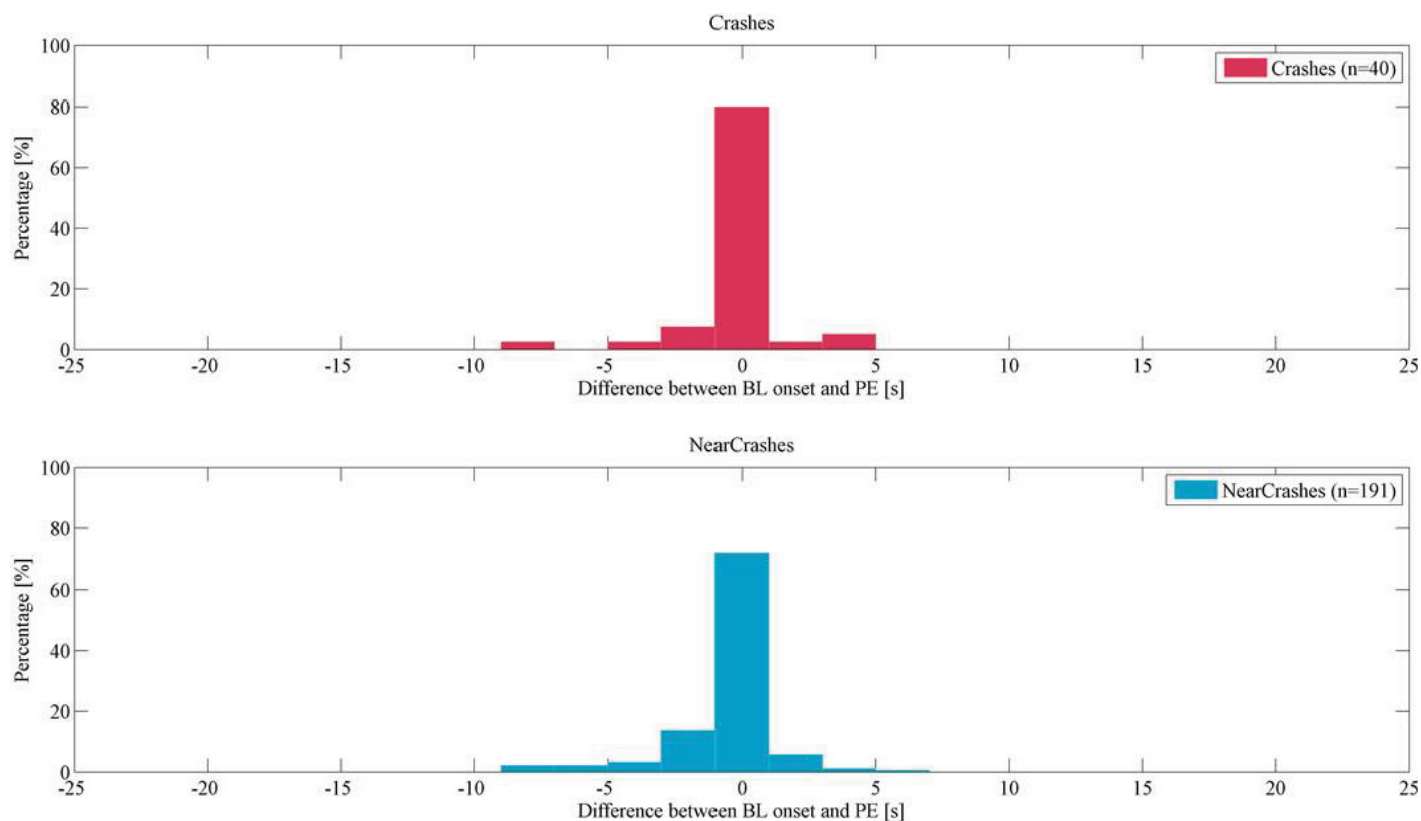


Figure 5.3. Comparison between when the precipitating event (PE) occurred (at 0 seconds) and the brake light (BL) onset that was closest in time for crashes and near crashes.

reveal how the timing of glances away from the road influence crash and near-crash risk.

Odds ratios were calculated for four windows of time before the precipitating event. One window encompasses the 1 second preceding and the 1 second following the precipitating event (Off1to1afterPE). Two other windows capture the influence of glances that occur earlier. Off3to1PE is a window from 3 seconds to 1 second before the precipitating event, and Off5to3PE is a window from 5 seconds to 3 seconds before the precipitating event. The final period, Off5to1afterPE, calculates the overall proportion the eyes were off the forward path during the entire 6-second period. These variables are coded as proportion of Eyes off Path for the stated window and so have a maximum value of 1.0. The odds ratio is relative to zero for each variable. See Figure 5.4.

Figure 5.4 has several notable features. First, the odds ratios shown in this figure are notably greater than those in Figure 5.1. The scale in Figure 5.1 ranges from 0 to 5, and the scale in this figure extends from 0 to 15. The proportion of eyes off the road over various windows can be a very sensitive measure of distraction-related risk. Second, the highest odds ratios occur with the time window that overlaps the precipitating event, as shown by the points at the bottom of the figure. The proportion of time the eyes are off the forward path during

the time of the precipitating event is a particularly good predictor of crash and near-crash involvement. Third, the crude odds ratios are systematically lower than those estimated through conditional logistic regression. Most interesting, the odds ratios associated with crashes are substantially greater than those associated with near crashes; however, the relatively few crashes lead to large confidence intervals and preclude any definitive interpretation of these results.

5.3 Conclusions

In contrast to the analysis (in Figure 5.1) that calculated Eyes off Path time as the amount of time (in seconds) the eyes were off path between 2 and 6 seconds within the 6-second period (i.e., the Off2.0-6.0 variable), the Off5to1afterPE variable calculated the *proportion* of time the eyes were off path in the 5 seconds before until 1 second after the precipitating event. The key difference between these calculations is that in Off5to1afterPE, all Eyes off Path data are included, whereas the Off2.0-6.0 only counts instances with values above 2 seconds. This is an important difference because the Off5to1afterPE variable showed significantly elevated odds ratios for crashes (OR 13.2), near crashes (OR 2.8), and crashes and near crashes combined (OR 3.6).

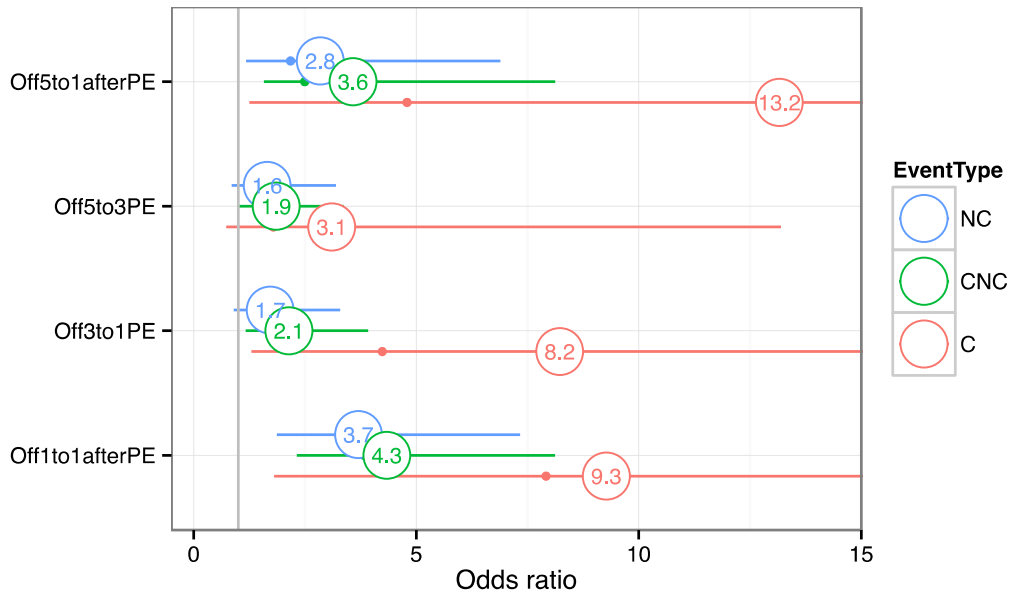


Figure 5.4. Odds ratios and confidence intervals for various windows in the 5 seconds before and 1 second after the precipitating event.

The analysis that divided the 6-second window at the precipitating event into three 2-second segments revealed significantly high odds ratios. The 2-second segment surrounding the precipitating event (Off1to1afterPE) was riskiest, showing significantly high odds ratios for crashes (OR 9.3), near crashes (OR 3.7), and crashes and near crashes combined (OR 4.3). Similarly, for the 2-second segment 3 seconds to 1 second before the precipitating event, significance was shown for crashes (OR 8.2) and for crashes and near crashes combined (OR 2.1). The only other significant effect using the 2-second segments was found for 5 seconds to 3 seconds before the precipitating event in near crashes (OR 1.9). This analysis indicates that the risk is highest closer in time to the precipitating event. The results show that higher risk for larger proportions of Eyes off Path closer to the precipitating event is strongest in crash events. This effect is clearly visible in Figure 5.2, which shows how the percentage of Eyes off Path is greatest in crashes and greatest around the precipitating event for both crashes

and near crashes in the SHRP 2 data and in the 100-car data. Figure 5.2 also seems to indicate that there is generally more Eyes off Path time in crashes than near crashes, that there is generally more Eyes off Path time in matched baselines than random baselines, and that these baselines are comparable to the 100-car baselines.

In sum, one objective of the analysis presented in this chapter was to replicate previous findings. The analysis shows generally similar results that are consistent with previous findings and are within the margin of error of the studies. Interestingly, these consistent findings were achieved with far fewer baselines as a comparison [e.g., Klauer et al. (2006) used five baselines per crash or near crash, while this analysis used only one]. Analysis of eyes off the road in the time windows preceding and overlapping the critical event shows that the timing of glances matters—glances away from the road during the precipitating event are particularly strongly associated with crashes and near crashes.

CHAPTER 6

Risk from Eyes off Path Before Crash or Minimum Time to Collision

This chapter conducts a series of analyses targeting the research question, What are the most dangerous glances away from the road, and what are safer glances? It also examines the research question, Can risk from distracting activities (secondary tasks) be explained by glance behavior?

6.1 Distribution of Glances Over Time

The plot of Eyes off Path over time surrounding the precipitating event (Figure 5.2) clearly coincided with the odds ratios in Chapter 5 and may be a useful tool to understand more precisely which mechanisms are behind the risk from Eyes off Path. To examine further the more specific relationships of Eyes-off-Path glance behavior in the next sections, it is useful to examine the distribution of glances and the distribution of glance locations over time.

Glance Location Timelines

Figures 6.1 through 6.4 show timelines that indicate the proportion of various glances in the 12 seconds preceding the crash, the 12 seconds preceding the minimum time to collision for the near crashes, and a random point for the baselines. These figures show glance locations over time for the crash, near-crash, matched baseline, and random baseline events. The glance locations include the transition time toward the locations according to ISO 15007. The crash data are aligned with the crash point at zero seconds, and the near-crash data are aligned with the minimum time to collision at zero seconds. Matched and random baselines are aligned to a randomly chosen reference point at zero seconds. It should be noted that the values for each glance location, at each point in time, are mean values for the all observations. For example, Figure 6.1 *cannot* be interpreted to mean 30% of the drivers looked at the forward path the full time. In fact, for the crashes, only four drivers (9%) looked at the forward path for the full

12 seconds preceding the crash or minTTC, and for the matched baselines, only 32 (12%) did.

Figure 6.1 indicates that the glance locations in the crash events are predominantly toward the cell phone and interior objects, followed by left and right windows and mirrors. Noticeably, there is a reduction of forward path location viewing up until about 1.5 seconds before the crash. The eyes return quickly to the forward path location after the 1.5-second mark. Figure 6.2 shows a similar, but less pronounced pattern for near crashes.

These patterns contrast sharply with those for the matched and random baseline events, shown in Figures 6.3 and 6.4; a much larger proportion of eyes is directed to the forward path—dark blue dominates Figures 6.3 and 6.4 in a way that it does not in Figures 6.1 and 6.2. In the matched baseline events (Figure 6.3), there is proportionally more forward path viewing; glances to the cell phone and interior objects are also predominant, but to a lesser degree. In the random baselines (Figure 6.4), glance locations are comparable to the matched baselines (Figure 6.3); however, there seems to be proportionally more forward path viewing, and this seems to be because there is less cell phone viewing. These differences have important implications for generalizing the odds ratios calculated from the matched baselines to more general driving situations. It may be more due to the fact that there are differences in driver’s willingness to engage in secondary tasks than differences in the traffic situation. The drivers included in the matched baselines were those who eventually crashed or nearly crashed. These drivers thus seemed to have a higher prevalence of phone interaction than those in the random baselines.

To shed further light on potential mechanisms behind the protective effect of Talking/Listening on a Cell Phone (OR 0.1; see Figure 4.2), we compared the glance locations for matched baseline and near-crash events in which at least one of Distraction 1, 2, or 3 was coded as Talking/Listening on Cell Phone with glance locations for all remaining matched baselines.

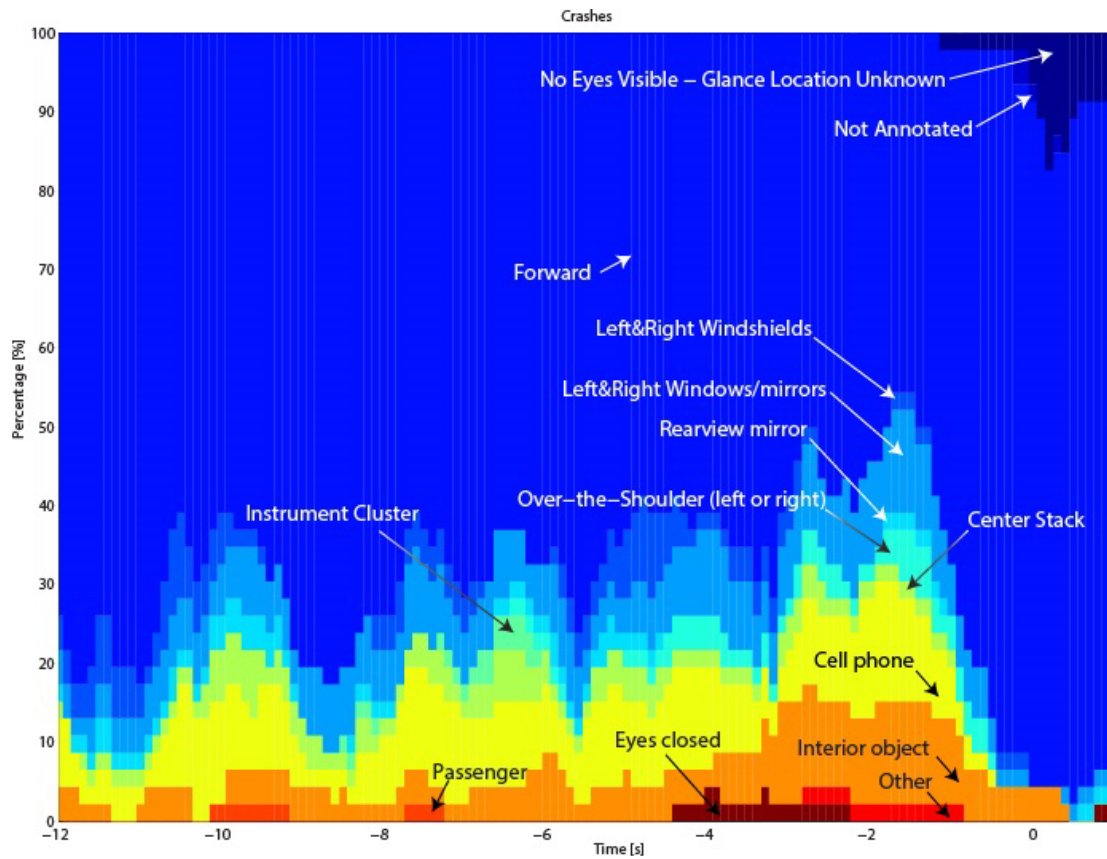


Figure 6.1. Percentage of glance locations over time in crash events for the 12 seconds before and 1 second after the crash point (at 0 seconds).

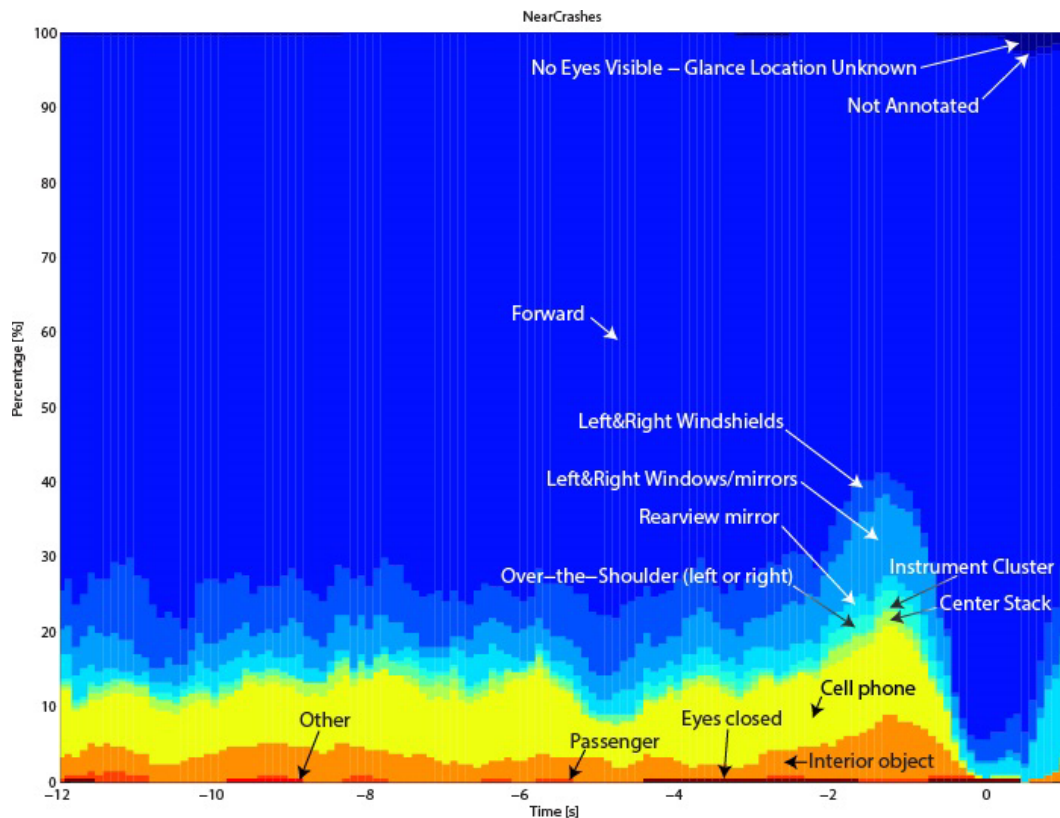


Figure 6.2. Percentage of glance locations over time in near-crash events for the 12 seconds before and 1 second after the minimum time to collision (at 0 seconds).

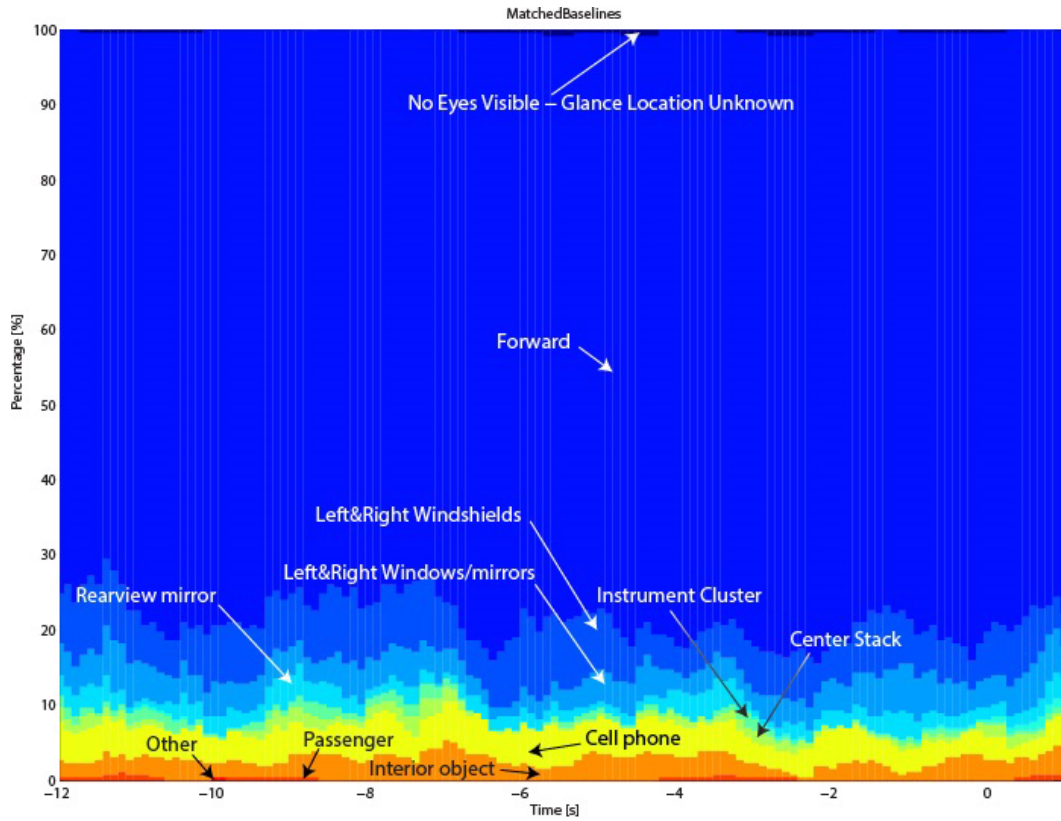


Figure 6.3. Percentage of glance locations over time in matched baseline events for the 12 seconds before and 1 second after a randomly chosen reference point (at 0 seconds).

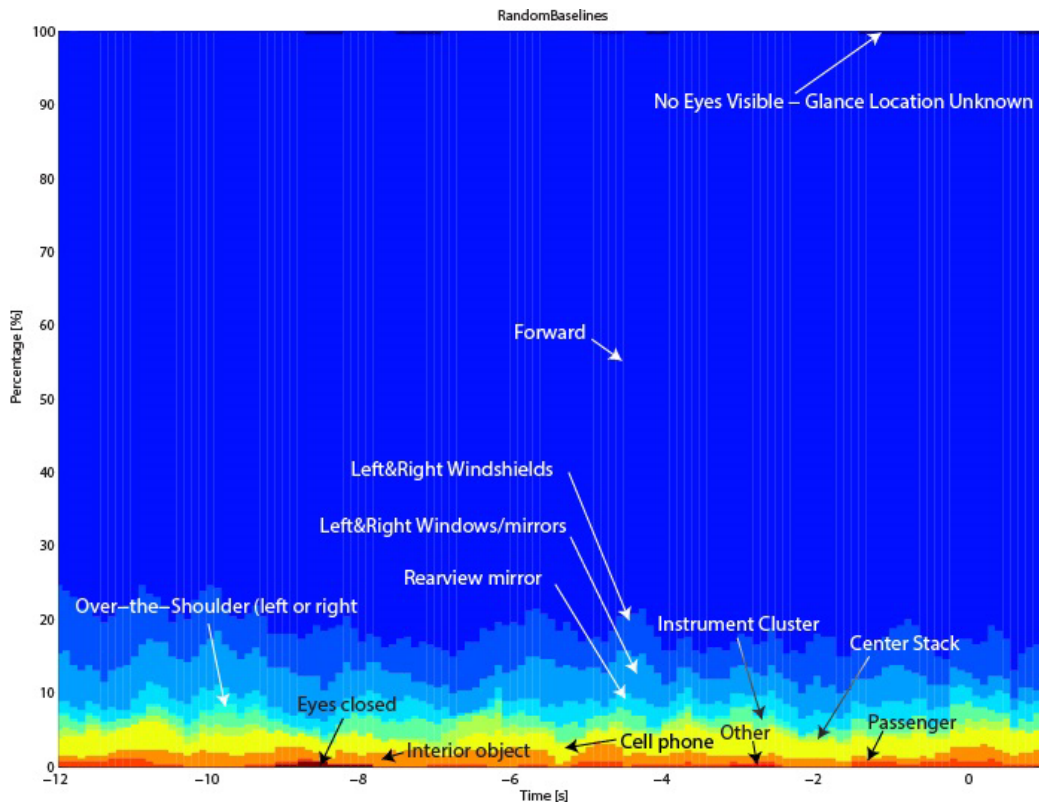


Figure 6.4. Percentage of glance locations over time in random baseline events for the 12 seconds before and 1 second after a randomly chosen reference point (at 0 seconds).

(Recall from Chapter 4 that Talking/Listening on Cell Phone was not present in any crash.) In this calculation, the mean values rather than time series were used.

The results are shown in Figure 6.5. The comparison of main interest is between matched baselines with and without phone conversation. The proportion of off-path glances (i.e., not on forward path) is very similar between talking/listening events and the remaining events, with values just above 20% proportion Eyes off Path. However, the *distribution* of the various glance locations seems to differ. In particular, the proportion of windshield and mirror glances is substantially higher for talking/listening cases while glances related to other secondary tasks than the phone substantially fell, especially glances to interior objects.

Somewhat surprisingly, the matched baseline events with Talking/Listening on Cell Phone still contain some glances to toward the phone. To understand this result, it is important to understand exactly how the beginning and end of the Talking/Listening on Cell Phone distraction type was annotated. Recall from Section 4.2 that Distractions 1, 2, and 3 were always coded during the 6-second time window including 5 seconds before and 1 second after the precipitating event (or a random point for the baselines). In many cases, the talking/listening

was already ongoing at the beginning of the time window and continued after the end of the time window. However, in some events, the talking/listening began or ended during the time window. In such cases, the start and end points of the talking/listening were defined as follows (SHRP 2 dictionary v2.1):

- *Event start point.* “Phone is at the driver’s ear. If using an earpiece, it begins when the driver has pushed the last button on his or her phone.”
- *Event end point.* “Phone is away from the ear and the driver has let go of the phone, OR (if driver does not release phone) the phone is no longer moving (i.e., driver puts the phone down in their lap but doesn’t let go of the phone). Once they put the phone in their lap and it is still (even if still holding it), this should be recorded as ‘Cell phone, other.’ If they are using an earpiece, it is when they push a button on their phone to end the call.”

From this definition, it is clear that talking/listening may also involve glances related to the visual-manual interaction required for hanging up, which is the reason some glances toward the phone are coded as belonging to the talking/listening time segment. If the end point of talking/listening had been defined so

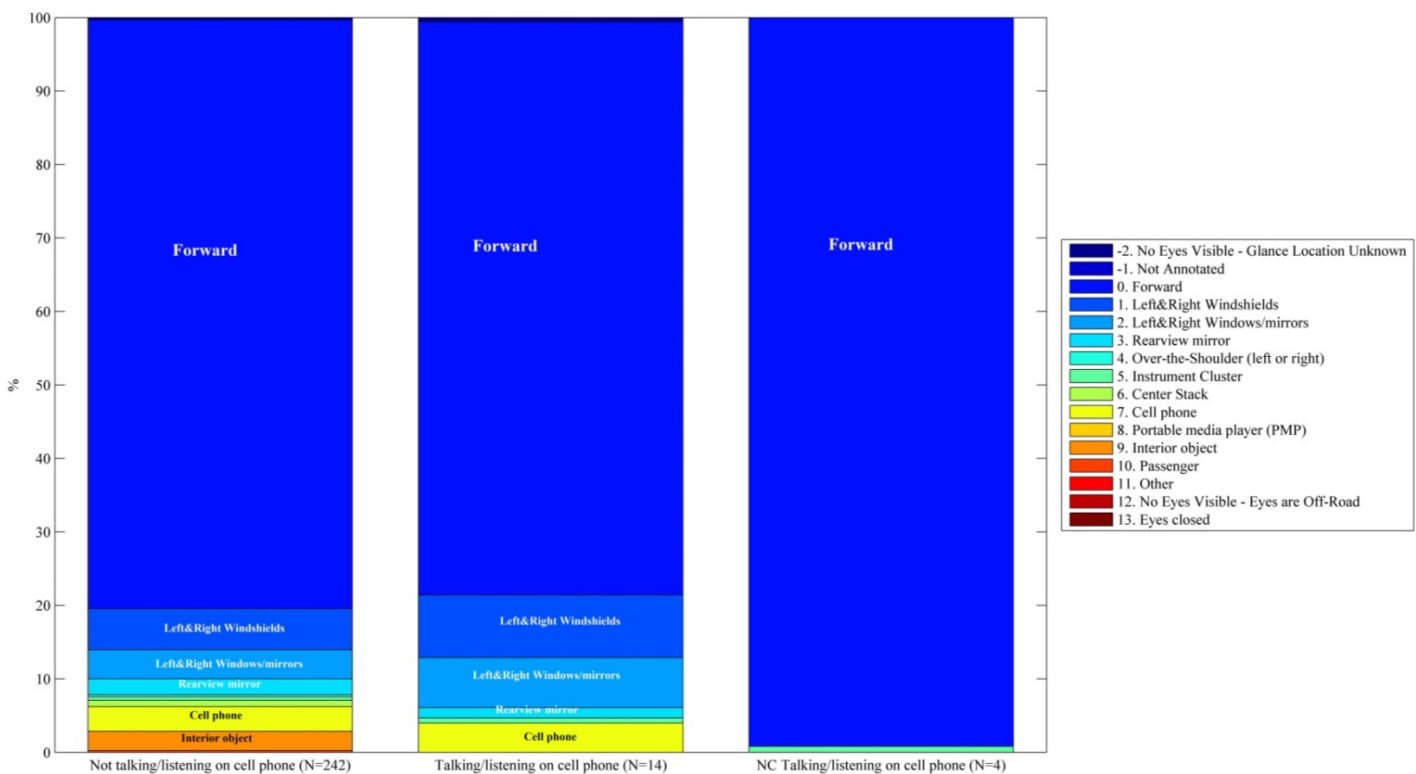


Figure 6.5. Percentage of glance locations for matched baselines in which talking/listening was coded as distraction compared with remaining matched baselines, and glance locations for the four near crashes that occurred while Talking/Listening on Cell Phone. Glance locations only represent the time periods when the talking/listening distracting activity was coded (i.e., for 5 seconds before and 1 second after the reference point in the baselines and for 5 seconds before and 1 second after the precipitating event in near crashes).

that glances associated with the hanging up activity were excluded, the total proportion of off-path glances would have been somewhat lower for the talking/listening cases and thus indicative of a general gaze-concentration effect. Moreover, almost 100% of the glances in the talking/listening events would have been driving-related (left or right windshield and mirrors).

In the four near-crash events involving Talking/Listening on Cell Phone, glances away from the road hardly occurred at all. However, due to the limited number of events it is difficult to draw any firm conclusions based on this result.

Eyes-off-Path Timelines

Figure 6.6 provides a concise summary of the preceding figures, showing only the percentage of Eyes off Path for crashes, near crashes, matched baselines, and random baselines. Figure 6.6 plots Eyes off Path over the 12-second period preceding the crash point (in crash events), the minimum time to collision (in near-crash events), and the reference points for the baselines. Similar to Figures 6.1–6.4, there seem to be generally more Eyes off Path in crashes than in the other events, and Eyes off Path are increasingly off road up until 1.5 seconds before the crash. In near crashes a similar, but less

pronounced, effect is shown. The Figure 6.6 also shows the location of the precipitating events relative to the crash point, with most precipitating events occurring between 1 second and 5 seconds before the crash point.

Glance Histograms for Eyes on Path and Eyes off Path

Figure 6.7 shows the frequency distribution and the cumulative distribution of Eyes off Path. A Kolmogorov-Smirnov test for the equality of the Eyes-off-Path distributions shows that all event-type distributions are significantly different from each other (at the $p < 0.05$ level), except the crash and near-crash glance distributions, which are not significantly different from each other ($p = 0.115$).

These results generally confirm the impression conveyed by Figures 6.1 through 6.4. Drivers in the matching baselines drivers look away from road more than those in the random baselines. The difference between the random and matched baselines might be due to the same drivers doing more secondary tasks or it might reflect the other matching variables, such as road type or being part of the same trip. Figure 6.7 suggests a difference between crashes and near crashes, with crashes having more long glances, but the KS

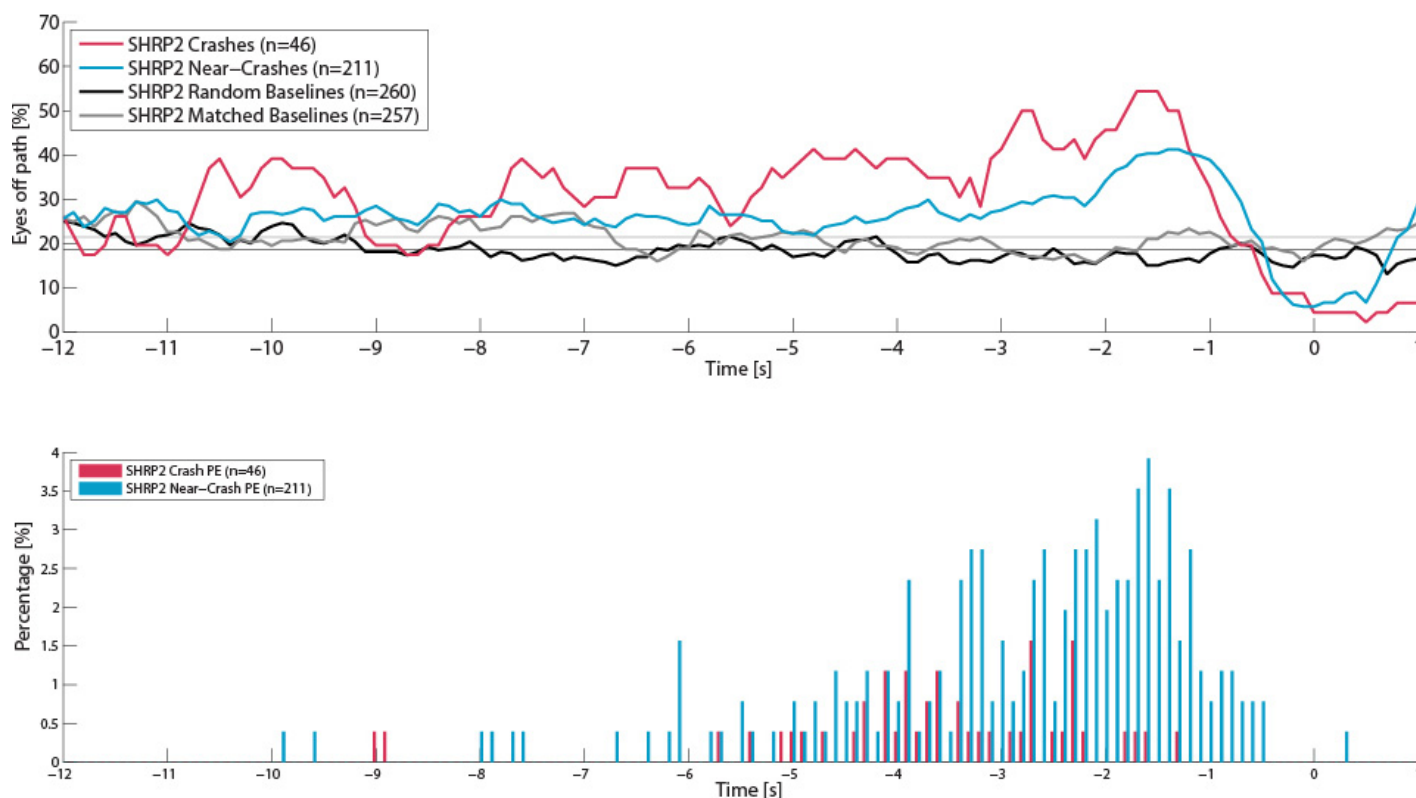


Figure 6.6. Percentage of glances off path (for each event type at each time point) in relation to minimum time to collision or crash point (at 0 seconds), and a histogram of the time of the precipitating events associated with each crash and near crash. The precipitating events correspond to the lead-vehicle brake light onsets.

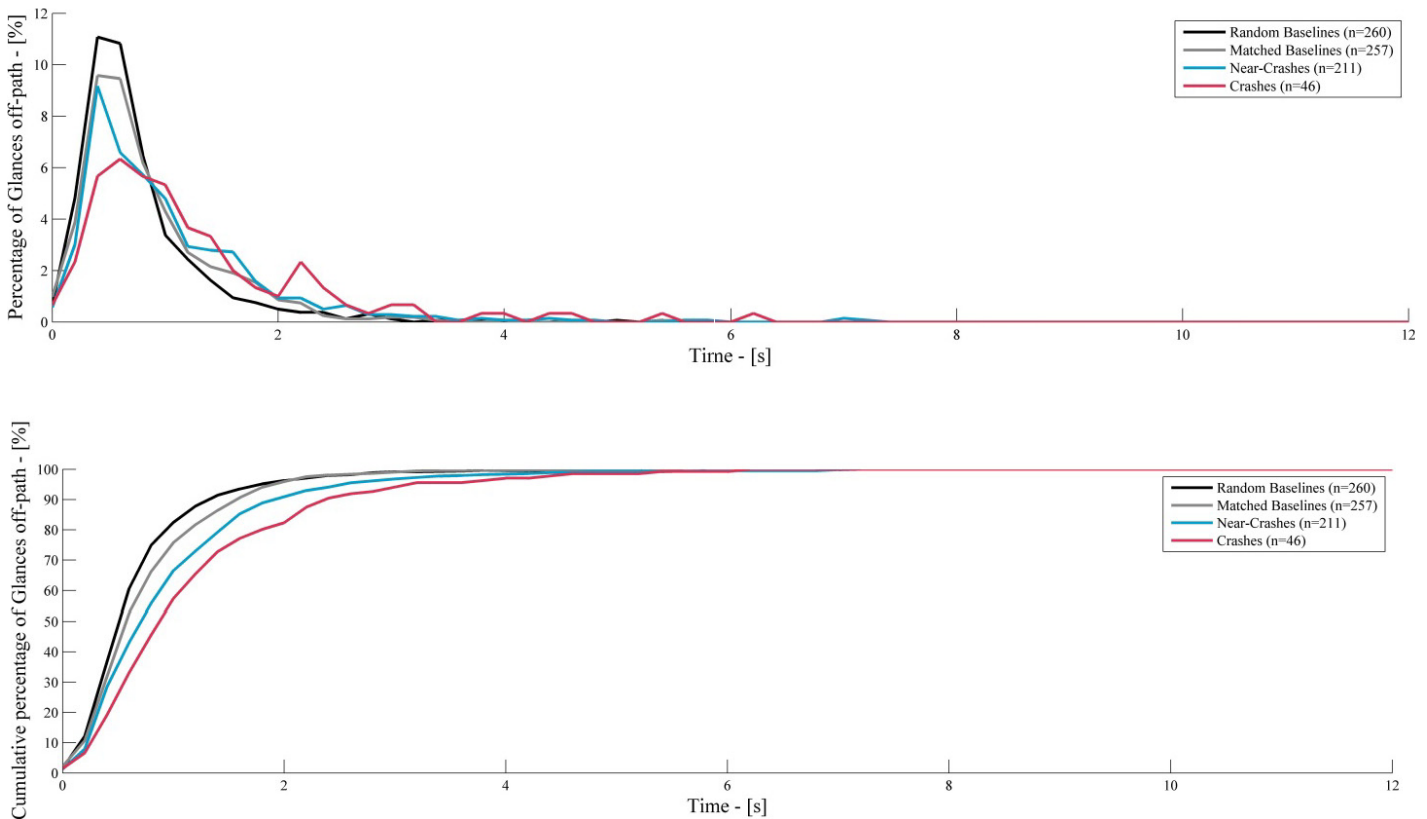


Figure 6.7. Distributions of Eyes-off-Path Glance Lengths (percentage and cumulative percentage) for the 12-second period before the crash points (crash events) and minimum time to collision (near-crash events), and a random point for random and matched baselines.

test shows no significant difference. This likely reflects a lack of statistical power associated with the small sample of crashes.

6.2 Eyes-off-Path Risk in Time Segments Preceding Crash or Minimum Time to Collision

Similar to the analysis of the proportion off-path glances associated with time windows preceding the precipitating event, an analysis was conducted for time windows preceding the crash point or minimum time-to-collision point. Odds ratios were calculated for six windows at six points relative to the crash point. One window encompasses the 1 second preceding and 1 second following the reference point (Off1to1after). Five other windows capture the influence of glances that occur earlier. Off3to1 is a window of from 3 seconds to 1 second before the reference point (crash or minTTC), and Off5to3 is from 5 seconds to 3 seconds before. The other windows step sample the timeline even earlier, with the last one considering the proportion of eyes off the forward path from 11 seconds to 9 seconds before the crash point. For example, within the

time from 3 seconds to 1 second preceding the reference point, we have calculated the proportion of time eyes are off the road out of these 2 seconds. As with the analysis of the 2-second windows over the 6 seconds surrounding the precipitating event (in Figure 5.4), these variables are coded as the proportion of Eyes off Path for the stated window and so have a maximum value of 1.0. The odds ratio is relative to zero for each variable.

Total Eyes-off-Path Risk Preceding Crash or Minimum Time to Collision

Figure 6.8 shows that the proportion of glances off path in the window immediately preceding the crash point or minTTC is most strongly associated with crashes and near crashes, but the proportion of glances off path that overlap the crash point is not. The odds ratio for the window that overlaps the crash point is small, which corresponds to the tendency of drivers to return their eyes to the road just before or just after a crash, associated with the time window immediately preceding the crash point. The odds ratio declines as the window used to summarize the off-path glances moves further from the crash point.

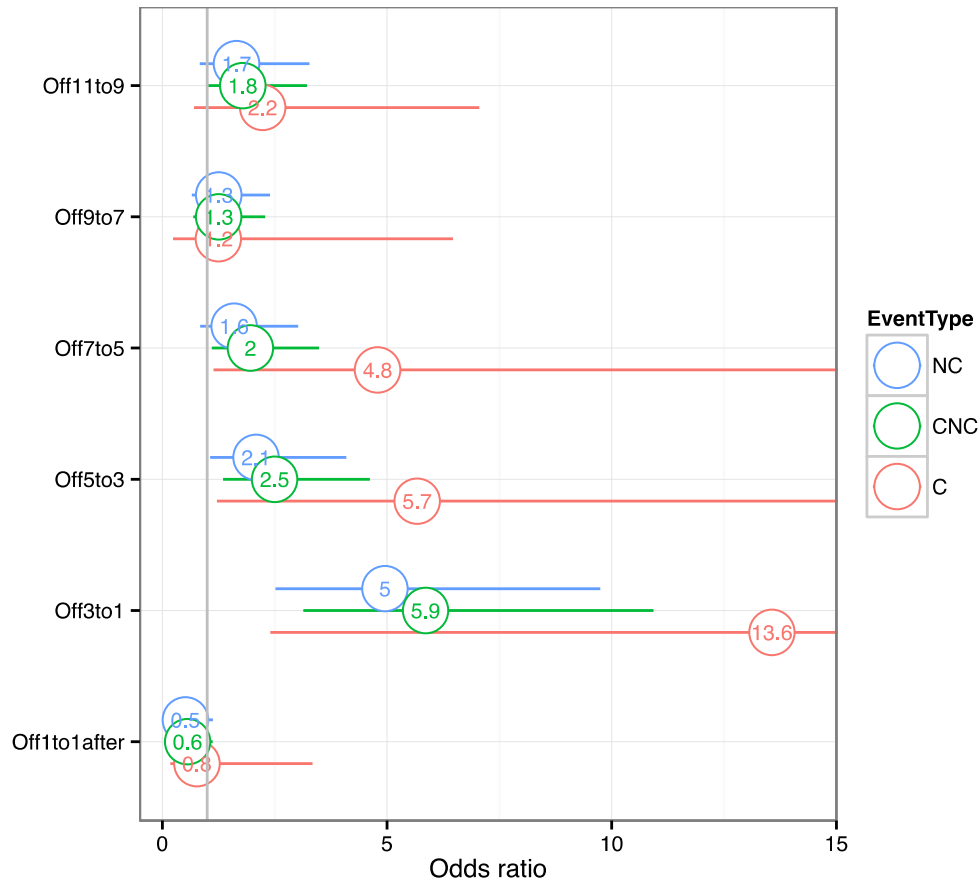


Figure 6.8. Odds ratios and confidence intervals for various windows in the 12 seconds before and 1 second after the crash point.

Cumulative Risk for Time Segments Preceding Crash or Minimum Time to Collision

The preceding analysis of the proportion of time eyes were off the forward path shows that eyes off the forward path during windows of time near the precipitating event or the minimum time to collision are particularly risky but that earlier windows may also be influential. That is, the odds ratios are highest for the window from 3 seconds to 1 second before the crash point, but the odds ratios in the two preceding windows also achieve statistical significance. Extended periods of eyes off the road might be expected to add to the risk associated with the eyes being off the road in the period immediately preceding the crash.

This analysis considers the degree to which the proportion of Eyes off Path in the earlier windows contributes to risk after the most risky periods are considered. This is done by fitting a series of models starting with the most risky window—the window at 3 seconds to 1 second preceding the crash or minTTC. The models were assessed using the Akaike information criterion (AIC); lower values of AIC indicate better

models, and differences of less than 2 suggest the models do not differ substantially (Burnham et al. 2010).

The models for each time window were created so that the estimated odds ratios of crashes and near crashes are the same as those in Figure 6.8. The best of these models, Off3to1, was extended by adding the other time windows. That is, the other time windows were added as predictors in addition to Off3to1. Of these models, the one including only Off3to1 emerged as most likely; the other most likely model included both the time window 2 seconds before the minimum time to collision and the time window 10 seconds before the minimum time to collision. Interestingly, none of these models had a lower AIC value than the model that used only the 2-second time window from 3 seconds to 1 second preceding the crash or minimum time to collision (Off3to1). This Off3to1 model has an odds ratio of 5.9 (see Figure 6.8) for cases in which the driver looks away from the forward path compared with a driver who looks to the forward path.

Table 6.1 summarizes these models, with the first column indicating the predictors used in the model. The model description indicates the linear combination used in the logistic regression, which is based on the proportion of time

Table 6.1. Contribution of Cumulative Effect of Proportion of Eyes off Path

Model	AICc	Delta_AICc	Model Likelihood
Off3to1	320.39	0.00	1.00
Off3to1+Off11to9	320.66	0.28	0.87
Off3to1+Off9to7	321.47	1.09	0.58
Off3to1+Off7to5	322.40	2.01	0.37
Off3to1+Off5to3	322.40	2.02	0.37
Off3to1+ Off11to9+ Off3to1X Off11to9	322.66	2.27	0.32
Off5to3	349.30	28.92	0.00
Off7to5	352.89	32.51	0.00
Off11to9	353.03	32.65	0.00
Off9to7	357.74	37.35	0.00

Note: The models are assessed using Akaike information criterion (AIC). Lower values of AIC indicate better models, and differences of AIC less than 2 suggest the models do not differ substantially (Burnham et al. 2010).

the eyes are off the forward path during a 2-second window. All these are additive, except for the case in which the interaction was tested (i.e., Off3to1+ Off11to9+ Off3to1X Off11to9). The second column shows the AIC, the third shows the difference from the model with the lowest AIC, and the final shows the model likelihood. A lower AIC indicates the model fits the data better, but a difference of less than 2 is typically required to justify including another variable based on statistical significance. Based on the AIC criterion, the Off3to1 model is best, and adding the proportion of time off road in the time from 11 to 9 seconds before the crash does not lower the AIC enough to justify including this variable. The model likelihood, indicated in the last column, shows the simplest model is substantially more likely than the others. This analysis shows there is no substantial cumulative effect from the proportion of Eyes off Path in the windows preceding the Off3to1 variable.

Further examination of the cumulative effect of proportion of Eyes off Path can be made by comparing these results (Table 6.1) with the glances leading to and overlapping the precipitating event. Table 6.2 indicates the combined influence of Eyes-off-Path metrics during windows leading to and overlapping the precipitating event. Similar to the odds ratios in Figure 5.4, the AIC values show that the best model is one that includes the window overlapping the precipitating event and the window that includes the entire 6-second period. The AIC of other models that include the overlapping window differ by less than 2, suggesting that they also fit the data well and that the period overlapping the precipitating event is an important determinant of risk. Models with only the earlier time windows of 5 to 3 seconds before and 3 to 1 second before the precipitating event perform relatively poorly.

However, the Delta AIC between the best glance model in Table 6.2 (pe.Off1to1after_pe.Off5to1after, AIC 337.86) and

Table 6.2. Contribution of the Cumulative Effect of the Proportion of Eyes off Path in the 5 Seconds Before and 1 Second After the Precipitating Event

Model	AICc	Delta_AICc	Model Likelihood
pe.Off1to1after_pe.Off5to1after	337.86	0	1
pe.Off1to1after_pe.Off5to3	338.88	1.02	0.6
pe.Off1to1after_pe.Off3to1	339.16	1.3	0.52
pe.Off5to1after	339.3	1.44	0.49
pe.Off1to1after	339.43	1.57	0.46
pe.Off3to1	347.54	9.68	0.01
pe.Off5to3	351.96	14.1	0

the best model in Table 6.1 (Off3to1, AIC 320.39) is 17.47. Delta AICs from the best models indicate how much inferior they are. A Delta AIC difference of 2 is significant; a difference of 10 or more means there is little support for the competing model ($p < 0.00001$). Thus, the risk estimation from the period overlapping the precipitating event is substantially poorer than the risk estimation 3 to 1 second before the crash (Table 6.1); this further confirms the observation that there is no substantial cumulative effect from the proportion of Eyes off Path in the windows preceding the Off3to1 variable.

6.3 Risk from Glance Sequences Preceding Crash or Minimum Time to Collision

The preceding analysis focused on the proportion of time the driver's eyes were off the forward path, without consideration of individual glance characteristics. The next step is to assess

the risk contributions of different glance characteristics, where glances are considered the unit of analysis rather than proportion of eyes off the forward path during a window of time. In the following analysis of glance characteristics, the cumulative effect of multiple glances is considered using an estimate of the hypothetical uncertainty that builds when the eyes are off the forward path and then diminishes when the eyes return to the forward path (Senders et al. 1967; Zwahlen et al. 1988).

Figure 6.9 summarizes the association between the glance parameters and crashes and near crashes. Some of these parameters are closely related to the window-based measures of proportion of Eyes off Path. For example, overlap.off is the duration of the glance that overlaps the point 2 seconds before the crash point, and pre.overlap.on is the duration of the glance preceding the overlapping glance that is directed to the forward path. Not surprisingly, a glance that overlaps this point is associated with an increase in crashes and near crashes. Importantly, the units of these metrics is seconds rather than proportion, so the odds ratios

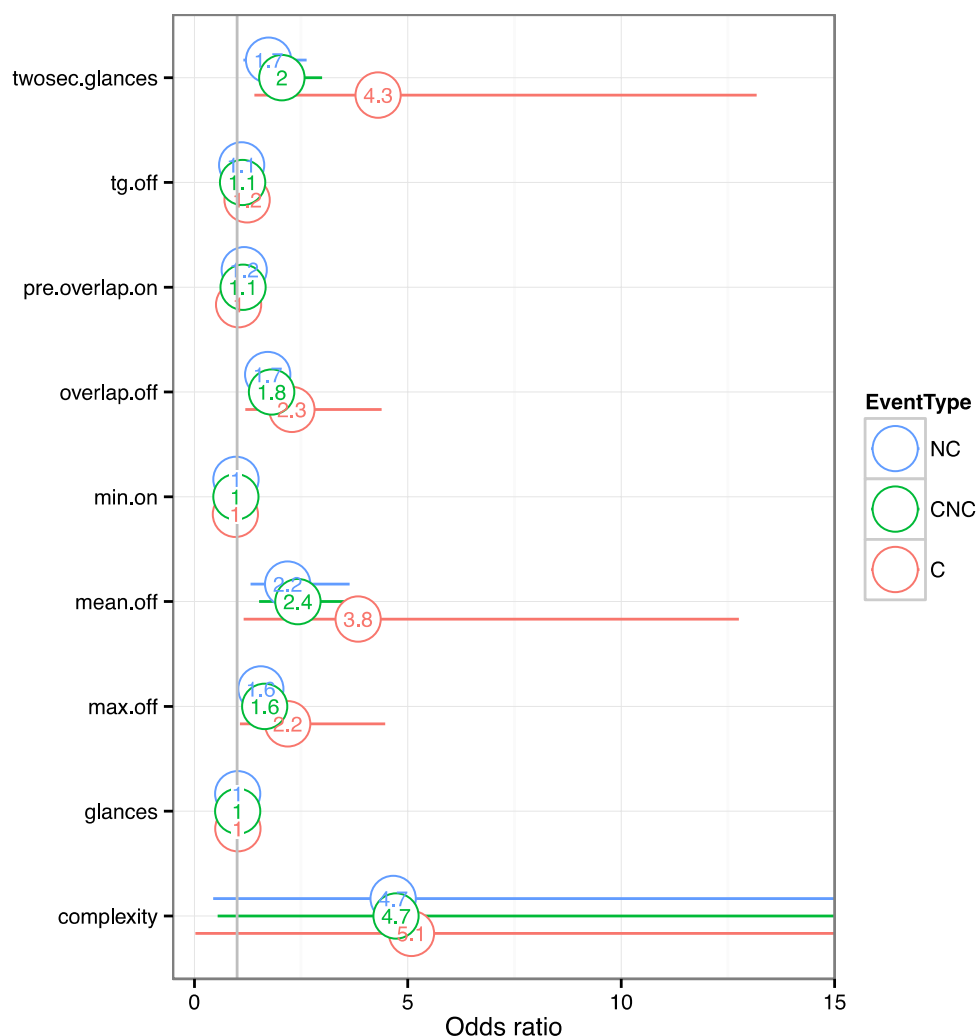


Figure 6.9. Odds ratios and confidence intervals for glance characteristics.

shown in Figure 6.9 represent the incremental increase in odds associated with one unit of change in the glance metric. Glances can last 13 seconds, whereas time proportion of the time windows in the previous section ranged between zero and 1. Although the duration of off-path overlapping glances has a strong association with crashes, the risk contribution of the on-path glance that precedes this overlapping glance is small.

Three related glance parameters had a strong influence on crashes and near crashes: the number of off-path glances longer than 2 seconds (*twosec.glances*), the maximum duration of off-path glances (*max.off*), and the mean duration of off-path glances (*mean.off*). In contrast, the number of glances (*glances*) and the minimum duration of on-path glances had little effect (*min.on*). The complexity of the glance pattern (*complexity*), shown at the bottom of the figure, shows an odds ratio larger than any other metric, but the confidence intervals are also very wide. Further investigation of this parameter seems warranted because it might provide a holistic assessment of how the combination of glances over the 12 seconds preceding a crash might contribute to risk. One such holistic glance metric is *uncertainty*, which is examined in the next section. The remaining glance characteristics in the figure are Total Glance Time off path (*tg.off*), duration of a single glance on path immediately preceding the off-path glance that overlaps with the 2-second point before the crash or *minTTC* (*pre.overlap.on*), and duration of off-path glance that overlaps (intersects) with the 2-second point before the crash or *minTTC* (*overlap.off*).

Figure 6.10 shows the level of uncertainty as defined by an exponential accumulation and dissipation model, in which uncertainty increases when the driver's eyes are off path and

decreases when they are on path (Senders et al. 1967). The timelines in Figure 6.10 are for a selection of five crash events; they show that with extended off-path glances, uncertainty can increase to 1, and with extended on-path glances, uncertainty can decline to zero. Uncertainty arises from long glances away from the road, as well as from short glances to the road. It can also accumulate over time if drivers fail to look toward the road long enough to recover from previous off-path glances. The parameters for the uncertainty model were not fit to the data but were fixed to a level that produces reasonable behavior, such as no uncertainty with a glance to the forward path of several seconds. Optimizing these parameters to maximize the odds ratio associated with differences in uncertainty is likely to produce a substantially better account of the risk associated with a sequence of off-path glances.

Figure 6.11 shows several summary metrics of uncertainty and their corresponding odds ratios. “*Uncertainty.3to1*” is the mean uncertainty over the window from 3 seconds to 1 second before the crash or point of minimum time to collision. Minimum uncertainty and maximum uncertainty over the 12 seconds are labeled “*min.uncertainty*” and “*max.uncertainty*,” respectively. Finally, mean uncertainty in the 12 seconds is labeled “*m.uncertainty*.” All the uncertainty metrics have both high odds ratios and large confidence intervals for crashes, with reductions in both for near crashes. Minimum uncertainty and maximum uncertainty do not reach significance as predictors. However, both mean uncertainty metrics (either 3 seconds to 1 second or over the 12 seconds) have odds ratios significantly higher than 1. Near-crash and CNC odds ratios for both are similar, but crash odds ratios are quite high for both (OR 11.5

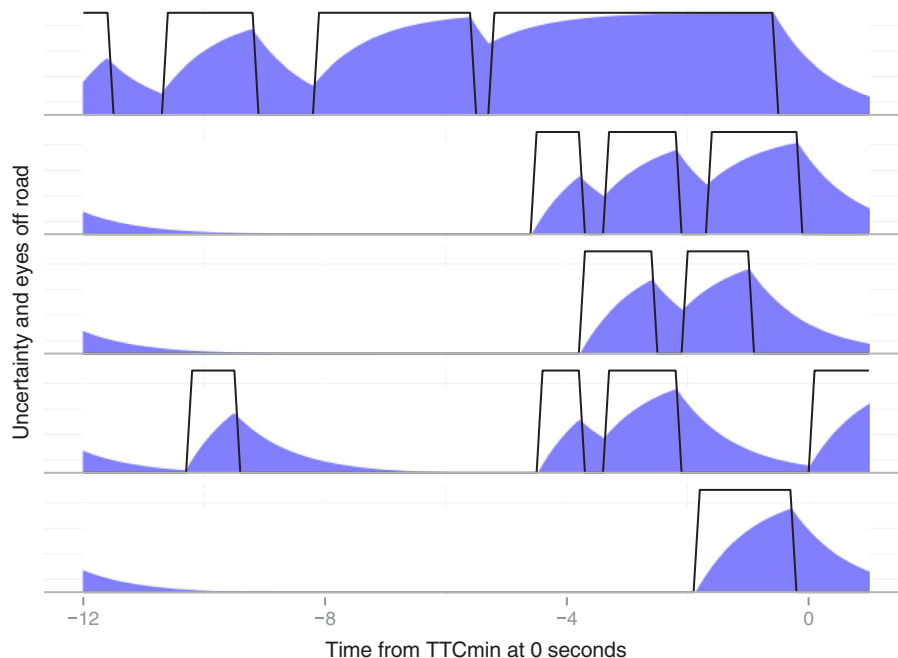


Figure 6.10. Timelines of glances and corresponding uncertainty for five crashes.

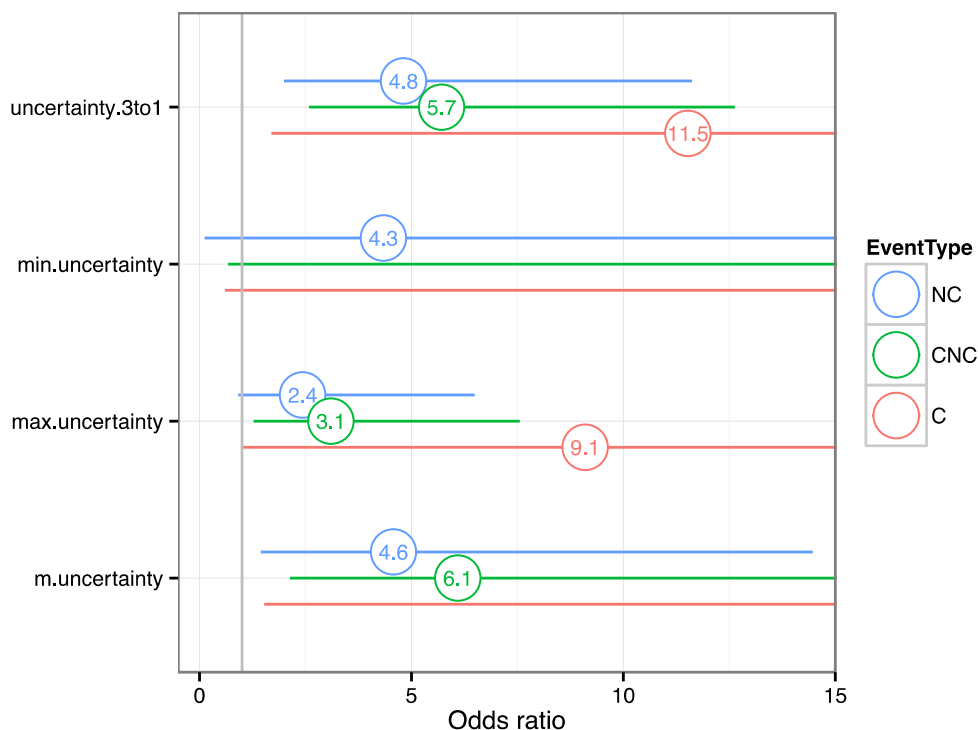


Figure 6.11. Odds ratios and confidence intervals for various uncertainty characteristics.

for the 3-seconds-to-1-second window and OR 22.2. for the full window). These confidence intervals overlap each other.

Combinations of Glance Metrics Within the 12 Seconds Before Crash or minTTC

Three classes of glance metrics were considered for combination in a model: metrics based on the proportion of glances off-path during various time windows, metrics based on individual glances, and metrics based on uncertainty associated with off-path glances. An important application of these metrics is to assess the incremental risk associated with distracting activities (secondary tasks) beyond what can be expected from the glance distribution (see Section 6.4). For this, we need to identify the

most sensitive glance metric combinations. The most promising metric from each class was selected: Off3to1 from the window-based approach (Off3to1), mean off-path glance duration (mean.off), and mean uncertainty from the uncertainty function (m.uncertainty). Models were fit with each of these metrics and their interactions. The models were assessed using Akaike information criterion (AIC); lower values of AIC indicate better models, and differences of AIC less than 2 suggest the models do not differ substantially (Burnham et al. 2010).

As shown in Table 6.3, a model based on a linear combination of all three metrics (Off3to1_mean.off_m.uncertainty) emerged as most predictive of crashes and near crashes as it had the lowest AIC value (AIC 317.07). This three-metric model was substantially better than the second most predictive

Table 6.3. Glance Metric Combinations Most Closely Associated With Crashes and Near Crashes in the 12 Seconds Before the Crash or minTTC

Model	AICc	Delta_AICc	Model Likelihood
Off3to1_max.off_m.uncertainty	317.07	0.00	1.00
Off3to1	320.39	3.31	0.19
Off3to1Xmax.off	321.44	4.37	0.11
Off3to1Xmax.offXm.uncertainty	321.59	4.51	0.10
Off3to1Xm.uncertainty	322.01	4.94	0.08
max.off	337.58	20.50	0.00
m.uncertainty	345.86	28.79	0.00

model based only on the proportion of glances off-path (AIC 320.39), at a Delta AIC difference of 3.31. As an individual metric, the Off3to1 metric was a very good model in comparison with max.off and m.uncertainty.

6.4 Risk Contributions from Distracting Activities Over and Above What Can Be Explained by Glance Behavior

Recall the research question, Can risk from distracting activities (secondary tasks) be explained by glance behavior? The risk of distracting activities (secondary tasks) might be explained largely by the off-path glances they induce; alternatively, the risk associated with secondary tasks might be associated with other properties of the distracting activities. Risk from additional properties such as manual distraction or cognitive distraction may add to the risk explained by Eyes off Path.

To assess the incremental risk (of crash and near-crash events) associated with distracting activities beyond that expected from the Eyes off Path, we had originally intended to compare the glance behavior within the *full* 12-second period leading up to the crash/minTTC and the full periods within baselines, with the presence of distracting activities within those periods of time. Unfortunately, due to a misunderstanding in interpretation of the data requirements document, the distracting activities were not coded for the full periods. Distracting activities were only coded for the 5 seconds preceding and 1 second after the precipitating event in crashes and near crashes or the reference point in baselines (as discussed in Chapters 4 and 5). Thus, to assess the potential additive risk associated with distracting activities over and above the Eyes-off-Path glance

metrics, we need to use the most predictive glance model for the 6 seconds surrounding the precipitating event (the 5 seconds preceding and 1 second after the precipitating event).

The combined effects of glance metrics for the timeline anchored by the precipitating event showed a different pattern of glance metrics (Table 6.4) than in Table 6.3. The best indicator included the proportion of eyes off the road in the 2 seconds overlapping the precipitating event (pe.Off1to1after, AIC 339.43). For the relatively short timeline of 5 seconds preceding and 1 second after the precipitating event, the other glance metrics failed to improve the prediction substantially. Note that the three-metric glance model of the longer glance history preceding the crash/minTTC (Off3to1_max.off_m.uncertainty, AIC 317.07, in Table 6.3) was a far better predictor of risk of a crash or near crash than the 2 seconds overlapping the precipitating event (pe.Off1to1after, AIC 339.43), with a Delta AIC of 22.36 between these two models.

As already discussed, the distracting activities were only coded for the 5 seconds preceding and 1 second after the precipitating event. For this reason, the proportion of eyes off path in the 2 seconds overlapping the precipitating event (pe.Off1to1after) was used to assess the contribution of distracting activities because the comparison has to use the glance behavior from the same period of time.

Table 6.5 shows that the proportion of Eyes off Path in the 2 seconds overlapping the precipitating event (pe.Off1to1after, AIC 339.43) is substantially more predictive than the models based on distracting activities alone (e.g., Texting), as the difference compared with the pe.Off1to1after model is greater than 2—a significant difference.

Because the model based on the proportion of eyes off path in the 2 seconds overlapping the precipitating event is so superior to the models based on distracting activities, it might be expected to fully account for the effect of distracting

Table 6.4. Glance Metric Combinations Most Closely Associated With Crashes and Near Crashes in the 5 Seconds Before and 1 Second After the Precipitating Event

Model	AICc	Delta_AICc	Model Likelihood
pe.Off1to1after	339.43	0	1
pe.Off1to1afterXm.uncertainty	339.86	0.43	0.81
pe.Off1to1after_max.off_m.uncertainty	340.21	0.77	0.68
pe.Off1to1afterXmax.off	340.67	1.23	0.54
pe.Off1to1afterXmax.offXm.uncertainty	342.36	2.93	0.23
pe.max.off	343.81	4.38	0.11
pe.m.uncertainty	345.69	6.26	0.04
pe.complexity	351.37	11.94	0

Table 6.5. Risk Predicted by the Proportion of Eyes off Path in the 2 Seconds Overlapping the Precipitating Event and Distracting Activities in the 5 Seconds Before and 1 Second After the Precipitating Event

Model	AICc	Delta_AICc	Model Likelihood
pe.Off1to1after	339.43	0	1
Texting	341.66	2.23	0.33
TalkingListening	348.53	9.1	0.01
VisualManual	349.59	10.16	0.01

activities (secondary tasks). To test this assertion, a series of models was created in which the effect of each class of distracting activities was added to the effect of the glances metrics. If the proportion of Eyes-off-Path metric fully accounts for distraction risk, then adding the distracting activities to the model will result in no reduction in the AIC value of 339.43 for the pe.Off1to1after model.

Table 6.6 explicitly shows the contribution of the distracting activity to that of the proportion of Eyes-off-Path metric (pe.Off1to1after). When Talking/Listening on Cell Phone is combined with the proportion of Eyes-off-Path metric (pe.Off1to1after.TalkingListening, AIC 333.03), the model is substantially better than the pe.Off1to1after metric alone (a Delta AIC reduction of 6.41). Similarly, when Texting is combined with the proportion of Eyes-off-Path metric (pe.Off1to1after.Texting, AIC 334.23), the model is substantially better than the pe.Off1to1after metric alone (a Delta AIC reduction of 5.2). In both cases the activity does contribute to improving the risk estimation over and above the Eyes-off-Path metric, but the activity has more affect for talking than for texting. In both cases, not considering

glances provides a very poor indicator of risk (as the individual AICs for Texting and Talking/Listening are substantially lower than pe.Off1to1after). Thus, in the case of Talking/Listening on Cell Phone, the combined model provides a better estimation of the risk reduction, and in the case of Texting, the combined model provides a better estimation of the risk increase.

When the Portable Electronics Visual-Manual activity is combined with the proportion of Eyes-off-Path metric (pe.Off1to1after.VisualManual, AIC 347.92), the model is substantially poorer than the pe.Off1to1after metric alone (a Delta AIC increase of 8.49 between these two models). Thus, for more general visual-manual interactions, the risk estimation is not improved by adding the distracting activity. Rather, the risk increase is better explained by the proportion of Eyes off Path.

The interpretation of this pattern is that the effect of Texting and Talking/Listening on Cell Phone is not fully accounted for by the particular Eyes-off-Path model, but the effect of the general category of Portable Electronics Visual-Manual is fully accounted for. The risk-increasing (Texting) and risk-decreasing (Talking/Listening on Cell Phone) influences may go beyond glance patterns. This hypothesis should be explored in future work, but it is intriguing to consider the possibility that task demands (e.g., cognitive distraction) or other characteristics (e.g., drivers may keep longer headways when talking on the phone) for these tasks may provide additional disbenefit or benefit in terms of risk in rear-end striking crashes, beyond their influence on glances.

Note that this analysis of the risk contributions from distracting activities over and above what can be explained by glance behavior was limited by the fact that the distracting activities were not coded for the period of time up until the crash or near-crash minTTC. Future work should compare the much more powerful model based on a linear combination of all three metrics (Off3to1_mean.off_m.uncertainty, AIC 317.07) with distracting activities occurring in a

Table 6.6. Contribution to Risk Estimation from Distracting Activities in the 5 Seconds Before and 1 Second After the Precipitating Event and Proportion of Eyes off Path in the 2 Seconds Overlapping the Precipitating Event

Model	AICc	Delta_AICc	Model Likelihood
pe.Off1to1after.TalkingListening	333.03	0	1
pe.Off1to1after.Texting	334.23	1.21	0.55
pe.Off1to1after	339.43	6.41	0.04
Texting	341.66	8.63	0
pe.Off1to1after.VisualManual	347.92	14.90	0
Talking	348.53	15.51	0

comparable window of time closer to the crash or near-crash minTTC. It is possible that the influences of distracting activities can be explained by this more powerful three-metric glance model.

6.5 Conclusions

This chapter considered the contribution to risk of three classes of glance metrics: proportion of eyes off the forward path during the time window preceding crashes and near-crash minTTC, summary of metrics of glance sequences, and uncertainty that reflects the sequence of glances. Individually, each class of metric indicated risk more strongly and precisely than the classes of distracting activities. The risk indicated by each class of glance metric is not redundant with the others because a model that includes the interactions

between metrics provides the most precise indicator of crashes and near crashes.

Interestingly, the protective effect of cell phone conversation (Talking/Listening on Cell Phone) is not fully accounted for by this combination of glance metrics and neither is the risk associated with activities such as texting, but the risk associated with the more general class of Visual-Manual Distractions associated with visual-manual interactions is accounted for by glance metrics.

An important limit of the glances model, including the three-glance metrics, is that it assumes risk is purely a function of the driver's attention to the road (Eyes-off-Path metrics). However, risk likely stems from both drivers' attention to the road and the demands of the road. The following chapter considers how the changes in the lead-vehicle kinematics affect the risk of a crash or near crash.

CHAPTER 7

Timing of Eyes off Path Relative to Situation Kinematics and Visual Cues

This chapter examines the research question, How does the timing of lead-vehicle closing kinematics in relation to off-road glances influence crash risk? The previous chapters have demonstrated, in line with existing results (e.g., Klauer et al. 2006, 2010), that the performance of activities requiring eyes off the forward path is associated with significantly increased risk for crashes and near crashes. Moreover, it was shown that the *timing* of off-path glances within the time window preceding the crash strongly determines the risk level. In particular, for a time window aligned to the precipitating event (PE), off-path glances around the PE appear to be the most risky. For a time window aligned to the crash point or minimum time to collision, the risk was highest for glances occurring within 3 seconds to 1 second before the crash/minTTC. To better understand why the timing of glances matters for crash risk, a more detailed analysis of the timing relations between, on the one hand, the driver’s visual behavior and reactions and, on the other, visual cues and situation kinematics was conducted. This analysis also aimed to determine to what extent these timing relations distinguish crashes from near crashes.

This addresses the general hypothesis that the simultaneous occurrence of Eyes off Path and an unexpected event plays a key role in the causation of rear-end crashes, which—as mentioned in Chapter 1, Background—was a key motivation for the present research. In line with this hypothesis, Tijerina et al. (2004), in a study on eyegance behavior during car following, found that drivers in normal following situations generally did not take their eyes off the road unless the range rate was near zero (i.e., the distance between the vehicles is not closing). They also found that distance or time headway was generally not taken into account when deciding on an off-road glance. Thus, drivers’ decisions on whether to take the eyes off the road seem to be largely based on expectations of whether or not the lead vehicle will brake in the next few seconds. However, driver expectations are sometimes violated. If the lead vehicle brakes during the off-path glance and the driver has not adopted a sufficient headway, the situation

may end up in a crash. Tijerina et al. suggested that this may be the key mechanism explaining why inattention is the leading factor contributing to rear-end crashes.

One objective of the present analysis was to investigate to what extent this “inopportune glance due to expectation violation” mechanism applied to the rear-end crashes in the present data set. A further key issue concerns what factors made the critical difference in situations when the driver successfully escaped collision (i.e., near crashes).

One important aspect concerns the timing of glances in relation to brake lights. Experimental studies have found that brake light onsets reliably trigger reactions in vehicle-following situations (e.g., Lieberman et al. 2007). If these results generalize to real-world driving, it would be expected that missed brake light onsets are associated with crashes and near crashes. More specifically, brake light onsets occurring during off-road glances should be more prevalent for crashes and near crashes compared with baselines. Thus, one objective of the present analysis was to investigate whether this hypothesis was supported by the present data. Furthermore, if brake light onsets are used by drivers to predict that the lead vehicle will soon brake, drivers should generally be reluctant to take their eyes off the road if the brake light onset occurs at a moment when they have their eyes on the road (assuming the brake lights are salient enough to be detected). Thus, brake light onsets were also analyzed in relation to subsequent off-path glances.

Another key objective of the present analysis was to analyze the kinematic situation (e.g., speed, headway, and time to collision) at the start and end of the last glance before the crash/near crash. According to the inopportune glance mechanism hypothesized above, the kinematics for crashes and near crashes should be similar to normal driving (i.e., the matched baselines) at the beginning of the last glance but more critical when looking back. A further question of interest is whether the drivers who crashed adopted a smaller initial headway than those who successfully escaped or if the key difference between crashes and near crashes relates more to how the

criticality of the situation developed while looking away. Furthermore, to what extent did the duration of the last glance influence the event outcome? Did the situation develop into a crash rather than a near crash mainly because the driver was looking away for a long time period, or was it rather the rate at which the situation changed during the glance away that produced the crash? This latter question is of fundamental importance for answering the key question addressed by the present project: What characterizes safe glances?

A final objective was to analyze driver reactions after looking back the last time before the crash or near crash. Are such reactions triggered mainly by brake lights or by the perceived kinematics of the driving situation (i.e., the optical expansion, looming, of the lead vehicle)? Can differences in driver reactions further explain why an event develops into a crash rather than a near crash? It was also investigated how last-second driver reactions in critical rear-end situations could be modeled to enable computer simulation of these phenomena. A specific analysis was also carried out on drivers' reactions when they were talking/listening on a cell phone. As reported in Chapter 4, this activity was associated with a reduced risk of a crash/near crash, that is, a protective effect. Similar results have been found in previous studies (Olson et al. 2009; Hickman et al. 2010), but the basic mechanism behind this effect is still not well understood. This analysis specifically aimed to investigate whether the protective effect of talking/listening on a cell phone could be explained in terms of differences in driver reactions relative to situation kinematics.

7.1 Method

Glance annotation. This analysis used the same Eyes-on-Path signal as the previous analyses, further described in Section 2.9.

Kinematics. Due to the limited quality of the radar data, the headway and closing distances were calculated on the basis of optical variables manually annotated from the forward video, as further described in Section 2.9. It should be noted that the time to collision (TTC) was estimated directly from the optical angle θ subtended by the lead vehicle at the camera in terms of τ , that is, θ divided by its time derivative $\dot{\theta}$ (Lee 1976). Optically, θ and $\dot{\theta}$ characterize the looming (optical expansion) of the lead vehicle. An advantage of using the optically (rather than the physically) specified TTC is that this is the type of information that humans presumably use to perceive and control the situation kinematics in driving and other forms of locomotion, although it is debated exactly what optical information is used for different types of tasks (e.g., Flach et al. 2004). One consequence is that TTC here refers to the TTC for the camera rather than the subject vehicle's front bumper. Since TTC goes to infinity at zero relative velocity (e.g., at constant distance in normal following

situations), its inverse $1/\text{TTC}$ (referred to as invTTC) was used in the analysis.

Event Selection

This analysis included crashes, near crashes, and matched baselines. Since the analysis focused specifically on glance timing, events that did not include an off-path glance were excluded. As described in Section 2.9 for the matched baselines, the optical angle (θ) was only annotated for approximately 10 seconds before the reference point (i.e., the point corresponding to the crash point and minTTC for crashes and near crashes, respectively) and 5 seconds after. Since the exact duration of the precrash annotations varied somewhat, a time window of 8 seconds before the reference point was used in the present analysis. Only events in which the lead vehicle was continuously present within a time window of 8 seconds to 1 second before the crash/ minTTC were included in the analysis. Thus, the analysis focused on "pure" vehicle-following or approach situations, excluding cut-in and lane-change scenarios in which the lead vehicle appeared or changed in the last second, leading to a discontinuous optical angle signal. The main reason for excluding these events was that they represented very different kinematic situations which would have made the analysis substantially more complicated. However, it is important to keep this in mind when interpreting the results. In addition, the optical angle annotation was sometimes missing because of other reasons, such as reduced visibility (e.g., heavy rain, fog, or darkness) or limited video quality.

As described in Section 2.6, the total data set used in this project consisted of 46 crashes, 211 near crashes, and 257 matched baselines. In total, 5 crashes, 34 near crashes, and 25 matched baselines were excluded because of missing or insufficient annotation of optical angle according to the criteria above. This led to a basic data set of 41 crashes, 177 near crashes, and 232 matched baselines used as the starting point for all analysis in this chapter. In addition, some further cases were excluded due to constraints in the specific analyses, as further described below.

7.2 Results

Timing of Glances Relative to Brake Lights

First, the analysis considers the timing of brake light onsets in relation to off-road glances. In this analysis, only those events that contained at least one brake light onset were included. This led to a data set containing 35 crashes, 156 near crashes, and 75 matched baselines. The results are shown in Table 7.1.

First, the prevalence of co-occurrences of brake light onsets and Eyes off Path were compared between crashes, near crashes, and matched baselines. Brake light onsets co-occurred with an

Table 7.1. Analysis of the Timing of Off-Path Glances Relative to Brake Light Onsets (BLOs)

Event Type	Total Number of Valid Events	Number of Events With Brake Light Onset (N BLO)	Number of Events With BLO When Any BLO Occurred During Eyes off Path (EOP) (% of N BLO)	Number of Events With BLO When the Last BLO Occurred During EOP (% of N BLO)	Number of Events With BLO When Driver Looked Away After Seeing Last BLO (% of N BLO)
Crashes	41	35 (85%)	8 (23%)	8 (23%)	17 (49%)
Near crashes	177	156 (88%)	53 (34%)	48 (31%)	43 (28%)
Matched baseline	232	75 (32%)	23 (31%)	21 (28%)	23 (31%)

off-path glance in 23% of the crashes, 34% of near crashes, and 31% of matched baselines. This comparison thus includes co-occurrence of Eyes off Path with *any* brake light onset in the 8-second time window. Table 7.1 also gives the numbers and percentages of co-occurrences of eyes off path and the *last* brake light onset in the time window, which are generally similar to those obtained for co-occurrence with any brake light onset. These results indicate that co-occurrences of eyes off path and brake light onsets were about as prevalent for the matched baselines as for the near crashes and slightly less prevalent for crashes. Thus, drivers who crashed or nearly crashed were not more likely to have looked away at the last brake light onset than baseline drivers. This indicates that whether drivers missed brake light onsets by looking away did not play any significant role in the development of the crashes and near crashes in the present sample.

Given that the majority of drivers had their eyes on the road when the brake light illuminated, to what extent did drivers then look away from the forward path? If drivers reliably

interpret brake light onset as a sign of a potential threat, then one would expect to see very few cases where the driver looked away after having seen a brake light onset, particularly in the baselines. Similarly, drivers generally do not look away when they see the lead vehicle closing (Tijerina et al. 2004). However, the results show (Table 7.1) that situations in which the driver looked away after a last brake light onset when the eyes were on the forward path are indeed common and occur in almost half of the crashes, and in about 30% of near crashes and matched baselines. Figure 7.1 shows two examples of time-series plots for crashes in which the driver looked toward the forward path at the last brake light onset and but then looked away.

Taken together, these results suggest that brake lights have a negligible effect on driver behavior in real-world driving situations. In the majority of crashes, near crashes, and matched baselines, the driver looked forward at the moment when the lead vehicle's brake lights illuminated for the last time. However, this did not prevent the crashes and near crashes,

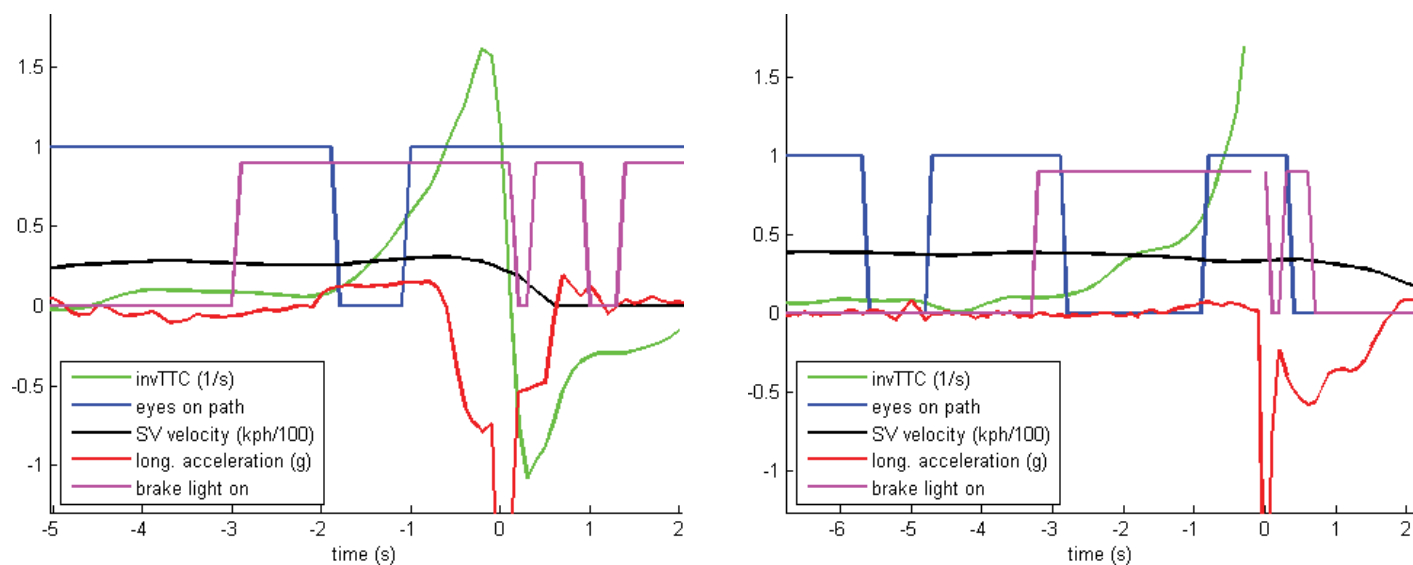


Figure 7.1. Examples of time-series plots for two crash events (event IDs 10631463 and 10631469 for left and right plots, respectively) in which the drivers eventually looked away despite having the eyes on the road at the last brake light onset.

indicating that the drivers generally ignored this predictive information. Moreover, a significant proportion of these drivers even looked away from the road just after having seen the brake lights illuminate. This tendency to look away after presumably having seen a brake light onset was stronger for crashes than for near crashes and matched baselines.

This last finding, that drivers who crashed more often looked forward at the last brake light onset, and also often looked away after having seen the brake lights illuminate, is somewhat difficult to interpret. One possibility is that this is a side effect of the kinematic conditions that typically lead to rear-end crashes. Chapter 9, Conclusions and Recommendations, returns to this issue, but first, the following section considers the timing of glances in relation to situation kinematics.

7.3 Timing of the Last Glance Relative to Situation Kinematics

This section reports on the analysis of situation kinematics relative to the last glance. The last glance was defined as the last glance away from the forward path initiated before the reference point (the crash point for crashes, the minimum TTC for near crashes, and a random point for the matched baselines). Thus, the end of the last glance could sometimes occur after the reference point, that is, outside the -8 -to- 0 -seconds time window.

In this analysis, some events were excluded over and above those excluded due to missing optical angle information (described above)—for several possible reasons. The main reason for exclusion was that no off-path glances occurred within the 8-second time window. In total, there were 6 such crashes, 34 near crashes, and 51 matched baselines. Since some of these cases were already excluded due to missing optical angle, this led to the exclusion of an additional 4 crashes, 29 near crashes, and 46 matched baselines.

Another reason for excluding events was that the last glance began before the start of the 8-second time window, which only affected measures related to the glance onset. The end of the last glance was searched for outside the time window and thus, last glance end data were only missing if the glance did

not end within an additional 5 seconds after the 8-second time window (this happened in only a single case, a near crash). The number of excluded events due to missing optical angle and missing/incomplete glances is summarized in Table 7.2.

Data could also be missing in other signals, which affected the total number of data points used in each of the specific analyses below. The total number of valid events used in the analyses is indicated in each subplot.

For the different kinematic variables investigated, t -tests were used to test for statistically significant differences at last glance (LG) start and LG end as well as between the event types. The planned comparisons of main interest were as follows:

- Crashes versus near crashes at LG start (two-sample t -test);
- Crashes and near crashes versus matched baselines at LG start (paired sample t -test);
- LG start versus LG end for crashes (paired sample t -test);
- LG start versus LG end for near crashes (paired sample t -test); and
- Crashes versus near crashes at LG end (two-sample t -test).

A significance level of $\alpha = 0.05$ was used in all tests.

Relative Velocity

Figure 7.2 plots the relative velocity (range rate) between the subject vehicle and the lead vehicle at the start and end of the last glance way from the forward path. At LG start, the mean values for crashes and near crashes were not significantly different. However, the relative velocity was significantly higher (more negative) for crashes and near crashes compared with the matched baselines [$t(133) = -4.99$, $p < 0.001$]. In the majority of cases for all event types, the relative velocity at the start of the last glance is close to zero (thus indicating a normal following situation in which the subject vehicle and lead vehicle are traveling with roughly equal velocities). However, the negative tails indicate the presence of cases in which the subject vehicle was already closing in on the lead vehicle at LG start. This seems to be more common for crashes and near crashes but also occurs in the matched baselines. Video inspection revealed that these matched baseline cases typically involve

Table 7.2. Summary of Exclusion of Events for Analysis of Last Glance Timing

Event Type	Original Number of Events	Cases Excluded Due to Missing Optical Angle	Additional Cases Excluded Due to Lack of Off-Path Glances	Additional Cases Missing LG Starts	Additional Cases Missing LG Ends	Remaining Number of LG Starts	Remaining Number of LG Ends
Crashes	46	5	4	1	0	36	37
Near crashes	211	34	29	5	1	143	147
Matched baselines	257	25	46	8	0	178	186

Note: LG = last glance.

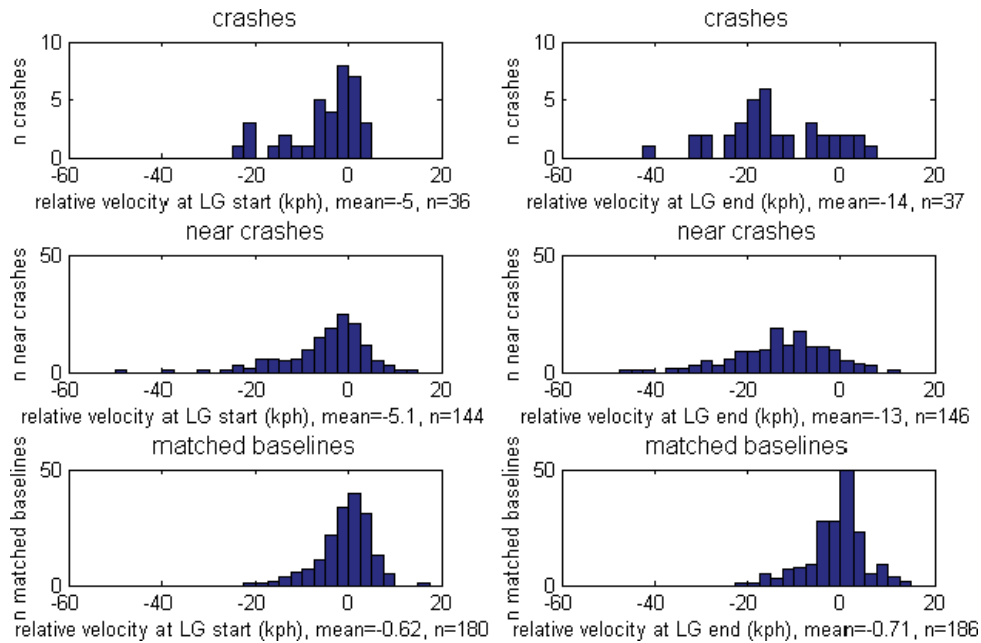


Figure 7.2. Relative velocity at the beginning and end of the last glance by event type.

situations in which the subject vehicle closes in rapidly on the lead vehicle, but at a larger distance than in crash and near-crash situations.

The distributions of relative velocity at LG end indicate a strong average change in relative speed during the last glance away, both for crashes [$t(35) = 8.54, p << 0.001$] and near crashes [$t(141) = 10.77, p << 0.001$]. While the change was slightly larger for crashes, the difference from the near crashes

was minor and not statistically significant. Thus, the shift in relative velocity during the LG does not seem to influence whether the event develops into a crash or near crash.

Time Headway

Figure 7.3 plots the initial time headway (THW) at the beginning and end of the last glance. The distributions of time

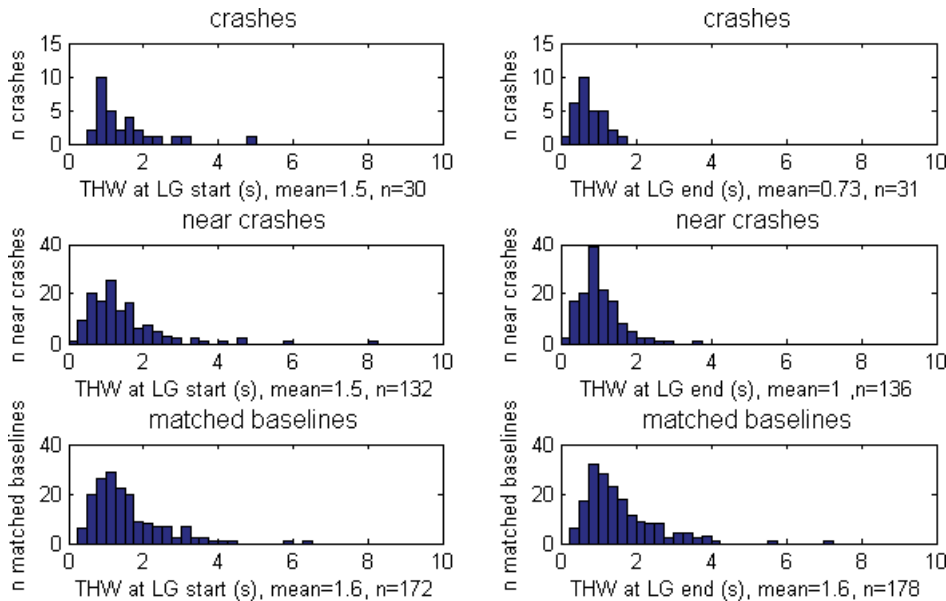


Figure 7.3. Time headway at beginning and end of the last glance by event type.

headway when the drivers looked away are very similar for all three event types (with no statistically significant differences between the means). This again indicates, in line with Tijerina et al. (2004), that the situation at the beginning of the last glance generally represented a normal following situation, in which the driver judged it safe to take his or her eyes off the road. It can be noted that drivers generally adopted relatively small headways when looking away, and this did not differ between the event types. It can also be noted that crashes with initial headways above 2 seconds were very rare.

For both crashes and near crashes, the time headway was significantly reduced when looking back [$t(28) = 4.04, p < 0.001$ and $t(129) = 6.41, p < 0.001$]. In contrast with the results for relative velocity, the time headway when looking back was significantly smaller for crashes than for near crashes [$t(165) = -2.87, p = 0.005$]. This indicates that for the majority of the crashes and near crashes, a large portion of the initial safety margin was consumed during the last glance, where the reduction was significantly larger for crashes than for near crashes.

Figure 7.4 plots the THW at LG start against the duration of the last glance. Although there is some indication of longer adopted time headways for the extreme glance durations (>2 seconds), the minimum tolerance margin adopted by the driver is still often very small. Thus, again in line with Tijerina et al. (2004), drivers apparently do not generally take time headway into account when deciding on how long to look away from the road. It can also be noted that the few crashes for headways larger than 2 seconds only occurred for the extreme glances longer than 4 seconds. Thus, most events occurred at short headways with relatively short glances.

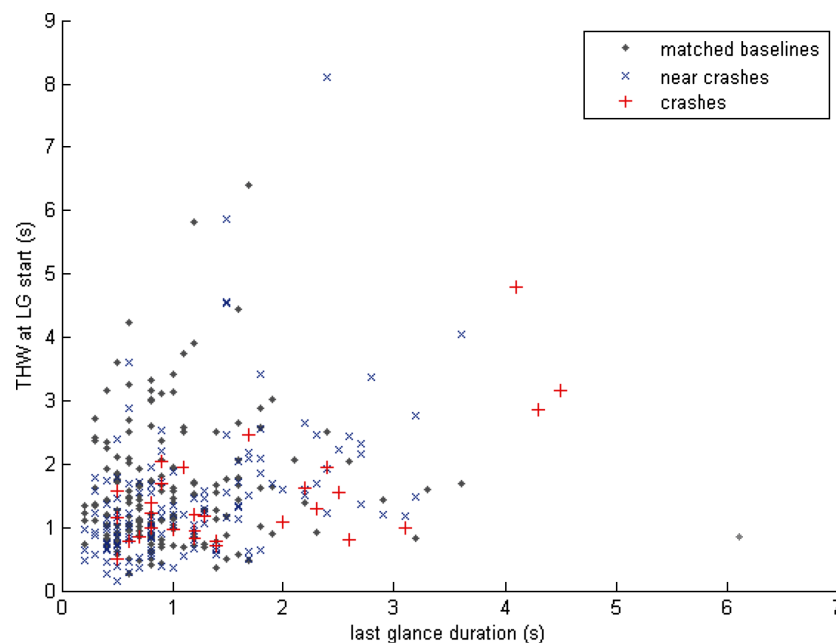


Figure 7.4. Time headway at the start of the last glance versus the last glance duration.

Inverse Time to Collision

The inverse time to collision (invTTC) at the beginning and end of the last glance is plotted in Figure 7.5. At the LG start, it can be observed that, for the majority of all drivers, the last glance begins when invTTC is near zero (i.e., the situation is still not critical, at least kinematically). The invTTC distribution for the matched baselines at both LG start and LG end is relatively narrow and symmetrical around zero. For crashes and near crashes, the distributions at LG start shift slightly toward the positive side, where the means for both crashes and near crashes are close to $\text{invTTC} = 0.1$. There was no significant difference between the crashes and near crashes for invTTC at LG start. However, the difference between matched baselines and crashes and near crashes combined was statistically significant [$t(141) = 3.91, p < 0.001$]. In line with the results on relative velocity above, this indicates that at least some crash/near crash-involved drivers looked away at a moment when the gap between the vehicles was already closing.

At the LG end, invTTC had generally changed significantly, both for crashes and near crashes [$t(35) = 5.97, p < 0.001$ and $t(140) = 14.1, p < 0.001$, respectively]. Furthermore, the invTTC at LG end was significantly larger for crashes than for near crashes [$t(180) = 3.47, p < 0.001$]. This indicates that the situation when looking back was on average more critical for the crashes than the near crashes.

Summary

Taken together, the results reported in this section support the initial general hypothesis that many rear-end crashes occur because of an unexpected closing of the lead vehicle

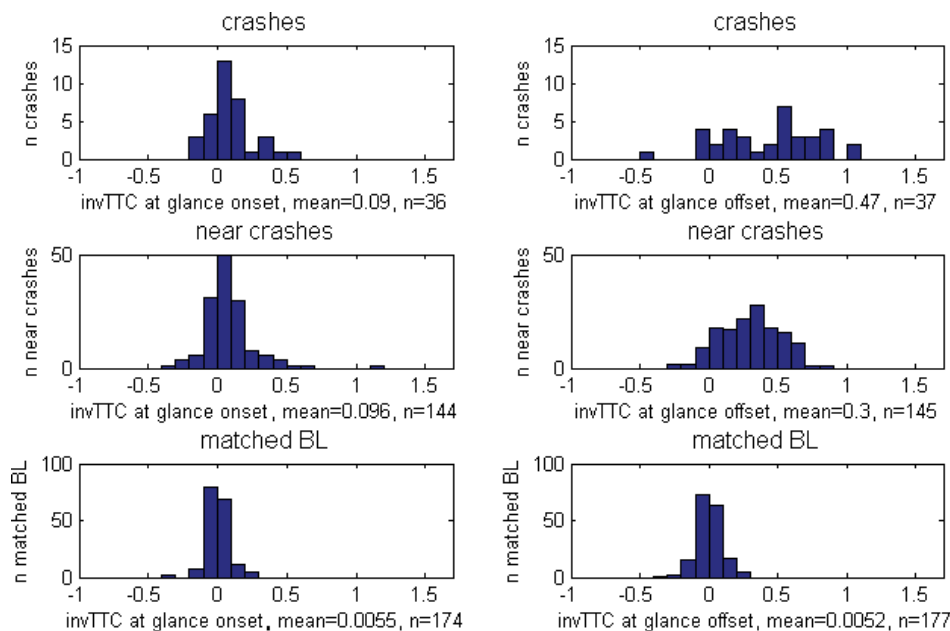


Figure 7.5. Inverse time to collision (invTTC) at the onset and offset of the last glance by event type.

while the driver is looking away from the forward path. When the last glance is initiated, the situation is generally still kinematically similar to a normal following situation and the driver considers it safe to look away. However, in a few cases, the driver looked away when the lead vehicle was already closing. In general, drivers do not seem to adapt their headway based on the expected duration of the glance to be initiated. The time headway when looking away is on average relatively short and does not differ between crashes, near crashes, and baselines. When the driver looks back, the situation has generally turned critical for crashes and near crashes. Crashes are clearly distinguished from near crashes by a higher criticality at LG end, as reflected by significantly shorter time headways and larger invTTC.

However, this analysis does not tell to what extent this higher criticality when looking back is due to the duration of the last glance and to what extent it relates to the rate at which the kinematics changed during the glance. This question is addressed next.

7.4 Mismatch Mechanisms: Last Glance Duration Versus invTTC Change Rate

For two kinematically identical rear-end scenarios, the LG duration could make the difference between a crash and a near crash; the longer the glance, the more time the criticality (e.g., invTTC) of the situation has to develop. Conversely, for two off-path glances of the same duration, the rate at which the criticality changes during the glances determines the criticality when looking back at the road.

To analyze the relative contribution of these two factors to crash and near-crash risk, a multivariate logistic regression analysis was carried out for last glance (LG) duration and invTTC change rate. The invTTC change rate was computed as the slope of a linear function fitted to the invTTC data during the last glance (by means of the MATLAB robustfit function), as illustrated in Figure 7.6.

Figure 7.7 plots the distribution of LG duration and invTTC change rate for the three event types. It can be observed that

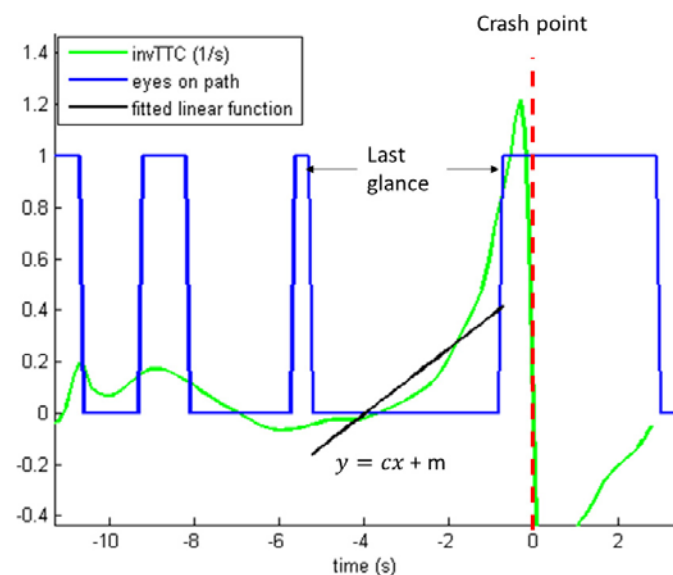


Figure 7.6. Illustration of the calculation of invTTC change rate (c) as the slope of a linear function fitted to the invTTC data during the last glance off the forward path (event ID 10631432).

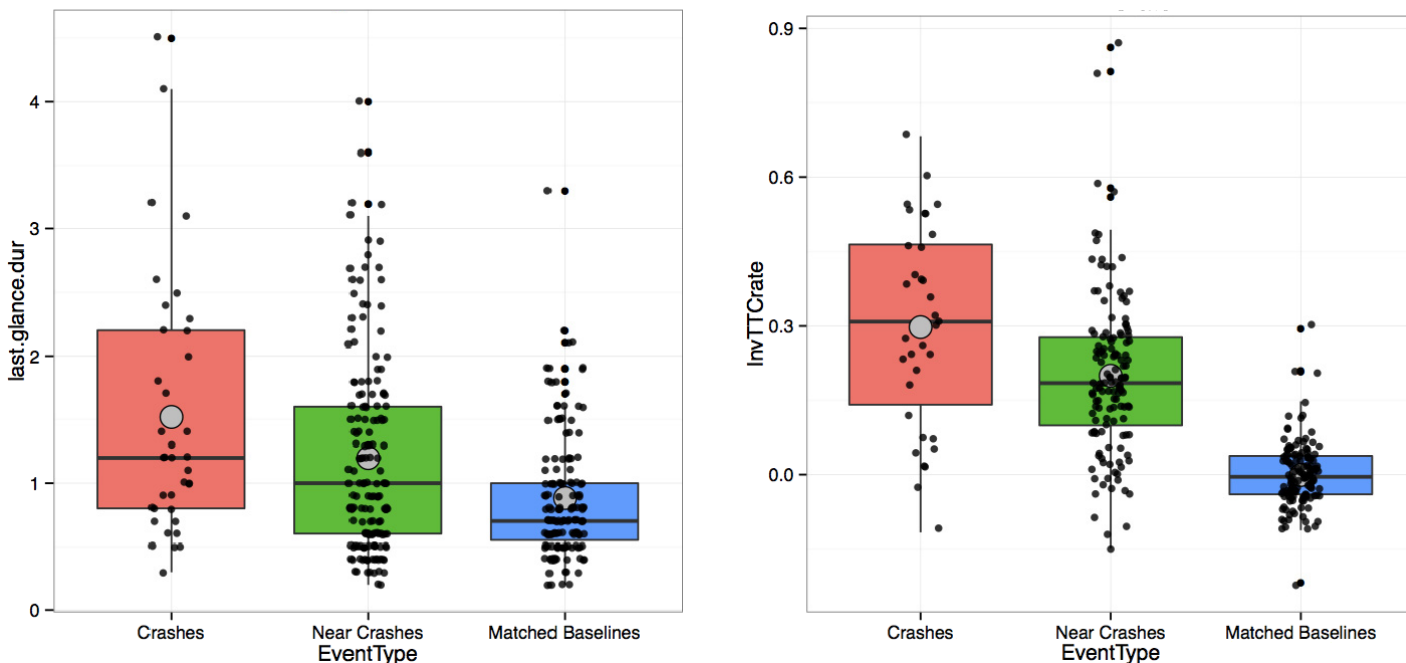


Figure 7.7. Distribution of last glance duration (left) and invTTC change rate (right) for the three event types.

the mean LG duration and invTTC change rate are both higher for crashes than for near crashes although the distributions overlap considerably.

The multivariate logistic regression analysis assesses the effect of last glance duration and the invTTC change rate on the likelihood of a crash/near crash relative to the matched baselines. It should be kept in mind that this analysis excludes cases with no off-path glances. Hence, the models presented here represent the crash/near-crash likelihood only for cases in which the driver looked away at least once in the 8 seconds before the crash/minTTC. Due to the relatively large number of missing cases in the matched crash/near crash and matched baselines pairs, a mixed effect model, rather than conditional logistic regression model, was used.

Table 7.3 summarizes the AIC criteria for six estimated models. The models are discussed in order, beginning at the bottom of the table. The first model is a null model that includes only the intercept. The second model includes only the LG duration (LGD), and the third includes only the invTTC change rate (CR). The fourth model includes a linear combination of LGD and CR, while the fifth model includes the interaction. The final model includes the linear combination of CR and LG and the interaction term.

The results show that all models are superior to the null model, but that LGD does not improve predictions beyond the effect of CR. The linear combination of CR and LG was not significantly better than the model including only CR. However, the model that includes the interaction LGD and CR was substantially better than the others. The obtained difference in AIC of 14 between this and linear combination was

relatively large. As a rule of thumb, models that have an AIC that is 10 units higher than the others can safely be removed from consideration (Burnham and Anderson 2004). The full model that included both the individual contributions of LGD and CR along with the interaction term had a slightly lower AIC (Delta AIC = 2.65). However, the difference was relatively small.

Based on this analysis, it may be concluded that invTTC change rate during the last glance had a strong effect on crash/near-crash risk while the individual effect of the glance duration was much weaker. Moreover, invTTC change rate and glance duration interacted strongly—to the degree that additional contribution of the individual invTTC rate and LG duration factors is marginal. What the present analysis essentially

Table 7.3. General Results from Multivariate Regression Analysis of the Effect of Last Glance Duration (LGD) and invTTC Change Rate (CR) on Crash/Near-Crash Risk

Model	AICc	Delta AICc
LGD.CR.LGD X CR	226.12	2.65
LGD X CR	228.77	14.08
CR.LG	242.85	1.72
CR	244.57	206.61
LGD	451.18	265.38
Null model	716.56	

shows is that, given that the driver looks away from the road within the 8 seconds before the crash, the risk that the event develops into a crash or near crash is mainly determined by the interaction of invTTC change rate and last glance duration.

To gain further insight into this interaction between LG duration and the invTTC change rate during the last glance, the two variables were plotted against each other, as shown in Figure 7.8. It can be observed that the crashes, near crashes, and matched baselines are relatively well separated in this state space. In particular, the majority of the crashes and a subset of the near crashes are approximately linearly organized with a negative slope. This is clearly the source of the strong interaction in the logistic regression analysis above.

The key implication of this result is that the majority of the rear-end crashes in the present sample can be characterized in terms of a particular combination of LG duration and invTTC change rate. For a short glance away from the road, the change rate needs to be higher for a crash to occur. Conversely, for a long glance, a lower change rate is sufficient to produce a crash. If the required combination of glance duration and change rate is not present, the situation normally results in a near crash, as indicated by the large cluster of near crashes below the hypothetical boundary in Figure 7.8.

However, a number of crashes do not fit this pattern. In particular, several crashes with low change rates cluster with

the matched baselines and a significant portion of the near crashes. Moreover, some cases have moderate to high change rates but very short LG durations that tile up vertically to the left in the figure. To better understand the characteristics of these different clusters of crashes, the forward video recordings for each crash were inspected together with corresponding time-series plots of glances and kinematics. This analysis suggests that the present crashes can be roughly divided into three main categories, also indicated in Figure 7.8 and further described below.

Category 1: Inopportune Glance

These crashes are the prototypical cases for the general mechanism suggested by Tijerina et al. (2004) and constitute the bulk (about 60%) of the crashes in the subset analyzed here. In these cases, the driver does not expect the lead vehicle to brake and thus looks away from the road while the situation is not yet critical (when invTTC is close to zero). During the glance away, the lead vehicle initiates braking. The level of criticality the driver faces when looking back depends on the interaction between the duration of the glance and the rate at which the situation develops, yielding the linear organization with a negative slope in Figure 7.8.

Inspection of videos and time-series plots indicated that the driver typically looked away just before the invTTC started to

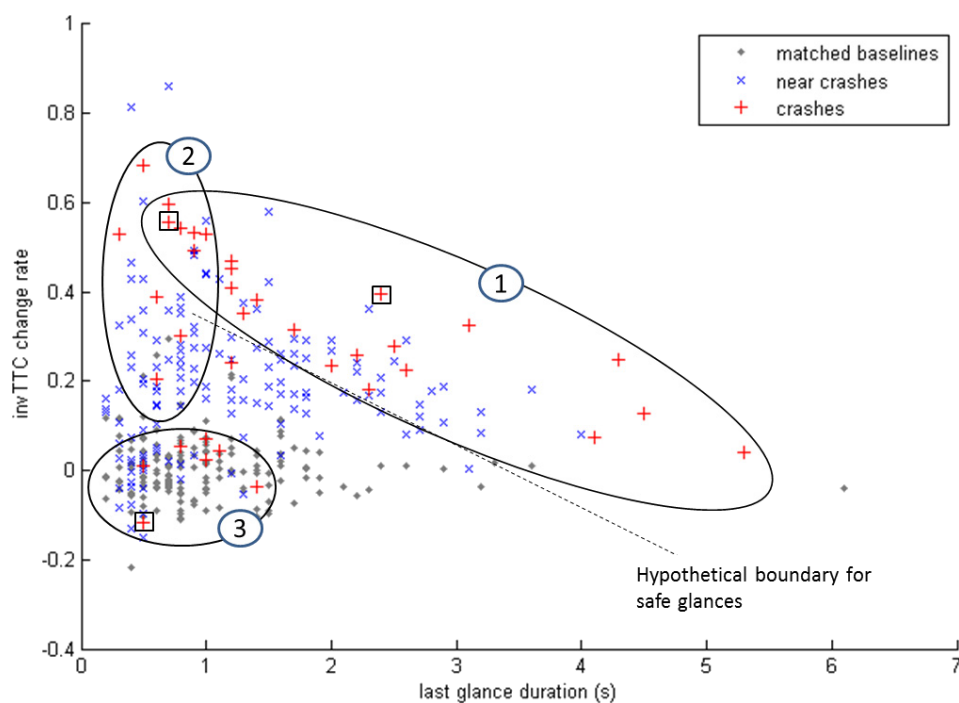


Figure 7.8. Last glance duration versus invTTC change rate. The ovals mark the three main categories of crashes identified through video inspection. The cases marked by squares are described in the text. The dashed line represents the hypothetical boundary for safe glances.

grow above zero. There was most often a strong violation of expectations; these events often occurred at junctions when the principal other vehicle (POV) would normally continue ahead but instead stopped suddenly and unexpectedly. The last glance was in some cases preceded by other glances that may have impaired the detection of visual cues that could have predicted the lead vehicle's action. When the driver looked back the second-to-last time (i.e., at the end of the glance preceding the last glance), the invTTC was generally close to zero or negative (in the latter case the lead vehicle accelerated away, which may have further enhanced the false expectation). The lead vehicle's brake lights were often salient and, as indicated by the analysis in Table 7.1, often illuminated while the driver looked forward. However, as also shown above, these brake light onsets generally failed to influence the driver's decision to take his or her eyes off the road. In the upper left region of Figure 7.8 (short glances, high change rate), there is some overlap with Category 2, in which the driver looked away when invTTC had already risen significantly above zero (see below). The cases at the lower right end of Category 1 of Figure 7.8 (extreme LG duration, low change rate) are typically low-speed scenarios in which the driver looks away for an extensive period while the vehicle is moving very slowly toward a stationary POV (e.g., in stop-and-go traffic).

An example of a representative Category 1 crash is given in Figure 7.9. This case is also marked in Figure 7.8.

Category 2: Looking Away in an Already Critical Situation

These cases represent situations in which the driver looks away at a point when the situation is already critical—that is,

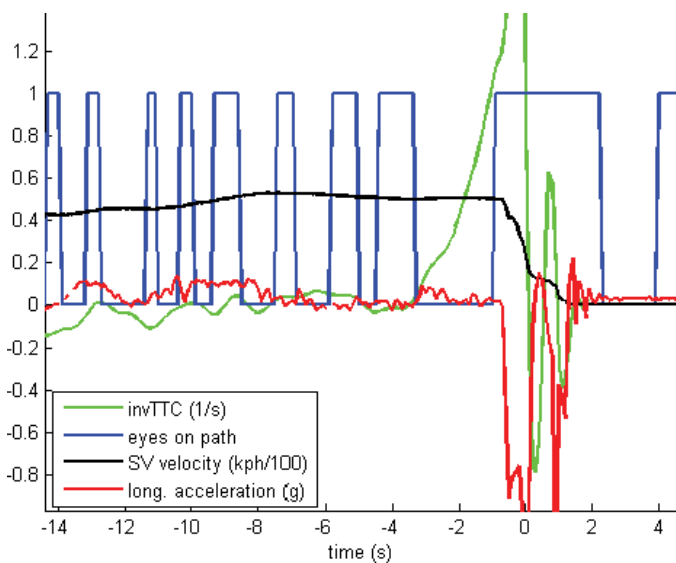


Figure 7.9. Example of a Category 1 crash (event ID 19147492).

the vehicles are already closing and the invTTC has already risen significantly above zero. This typically involves a very brief glance (around 0.5 second) before the gaze is presumably redirected to the road by the strong looming cues. These cases constitute about 20% of the cases in Figure 7.8 (as mentioned above, some of these cases overlap with Category 1).

Based on the video inspection, there seem to be several potential reasons (which sometimes combine) for why the last glance was initiated even though the POV was closing. These include

- Reduced visibility due to rain, darkness, or glare;
- A fast approach while time sharing, leading to a small angular rate (θ -dot) when looking back before the last glance;
- Intense visual time sharing with a short gap between the second-to-last and the last glance; and
- A search for escape: The driver knows that he or she is on a collision course and looks to the sides/mirrors for an escape path.

An example of a Category 2 crash is given in Figure 7.10.

Category 3: Looking Away and Back Again Before the Situation Has Turned Critical

Here the driver looks away and back again before the situation has turned critical, leading to a small change rate during the last glance and varying glance durations. Here the off-path glance(s) most likely did not interfere with the reaction to the event (although it may possibly have affected the detection of available predictive cues). Thus, these events can be regarded as functionally similar to crashes in which the drivers did not

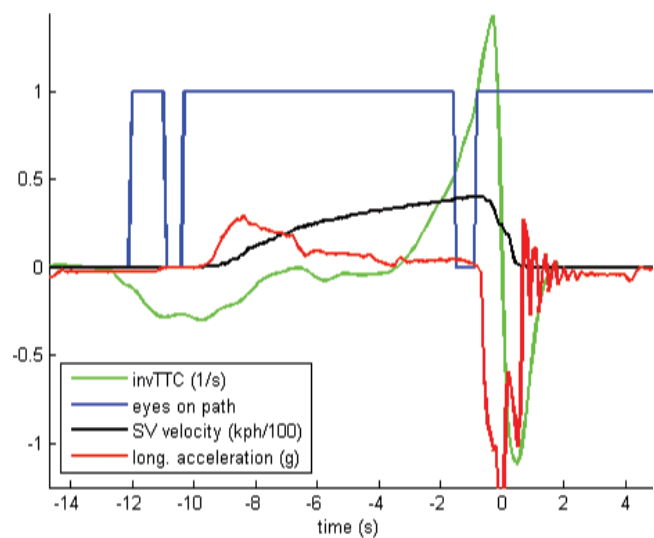


Figure 7.10. Example of a Category 2 crash (event ID 19147617).

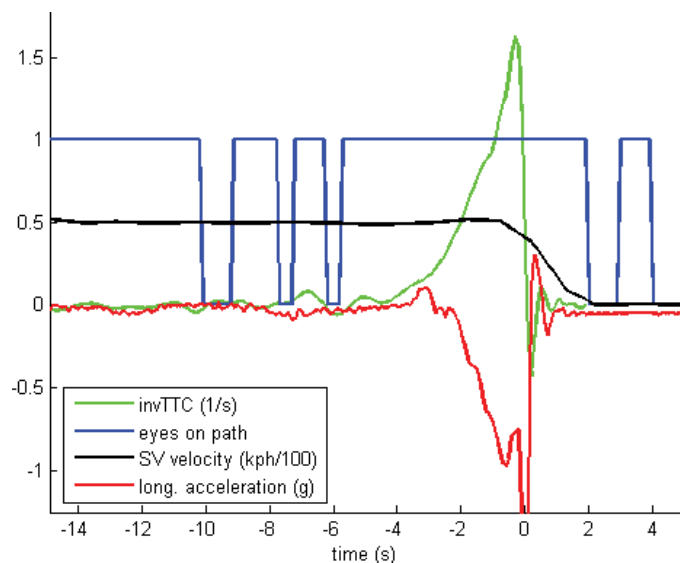


Figure 7.11. Example of a Category 3 crash (event ID 19147493).

look away at all within the 8-second window (these were excluded in the present analysis, as explained above).

Video inspection revealed that Category 3 events typically involved a strong violation of expectation (e.g., the lead vehicle stops late at yellow light, or a traffic queue builds in front of the POV in an unexpected location). The driver's reaction to the closing vehicle does not appear to be markedly delayed. Rather, an insufficient safety margin and/or a strong lead-vehicle deceleration rate seem to be key mechanisms behind these crashes. Moreover, the effectiveness of the avoidance maneuver may be a key factor separating crashes from near crashes in these events. A more detailed quantitative analysis is needed before any safe conclusions may be drawn. An example of a Category 3 crash is given in Figure 7.11.

Summary

The analysis in this section demonstrates that the majority of the rear-end crashes in the present subset are well explained by the general hypothesis stated above (based on Tijerina et al. 2004). These Category 1 crashes can be explained in terms of the co-occurrence of an off-path glance and a change in situation kinematics (normally the lead vehicle initiating braking) that strongly violated the driver's expectations. In line with Tijerina et al., the situation was generally kinematically non-critical at the moment when the driver looked away and then changed rapidly just after the driver looked away. Crashes in this category are generally distinguished from near crashes by the combination of last glance duration and the rate at which the situation changes during the glance away (here operationalized as invTTC change rate). Thus, these crashes happen largely due to a "perfect mismatch" between the visual

attention to the forward roadway and the kinematics of the traffic situation, in line with the general mismatch model of driver inattention suggested by Engström, Monk et al. (2013). For a given glance duration, a certain minimum change rate is needed to produce a crash. Conversely, for a given change rate, the glance has to be sufficiently long for a crash to happen. This leads to the strong interaction between last glance duration and invTTC change rate in influencing crash/near-crash risk observed in the multivariate logistic regression analysis.

However, a number of crashes did not entirely fit this pattern. Category 2 crashes are characterized by the driver looking away for the last time at a moment when the situation was already kinematically critical (i.e., the distance between the two vehicles was already closing at LG start). This indicates that other factors than off-path glances affected the driver's ability to detect the hazard. Video inspection suggested that, in particular, reduced visibility might be a key factor in this type of crash. This seems to be in line with the finding in Chapter 3 (Figure 3.6) that visual obstructions (in particular sunlight, precipitation, curve/hill, and broken or inappropriately cleaned windshield) are overrepresented in crashes. However, a more detailed and systematic analysis of these factors is needed before any safe conclusions may be drawn.

Finally, in the Category 3 crashes, drivers looked back before the situation had turned critical, and thus, the last glance did not directly contribute to the crash. In these crashes, an insufficient safety margin (headway) in combination with a strong violation of expectation seems to be the key mechanism that led to the crash.

This analysis thus provides one answer to what constitutes safer glances: As long as the combination of glance duration and change rate remains in the safe region under the hypothetical boundary indicated in Figure 7.8, the situation normally does not result in Category 1 crashes. Minimizing the duration of off-path glances is naturally one way to achieve this. However, the present data show, in line with previous studies, that excessive glance durations are infrequent, even in crashes. The extreme glance durations (>4 seconds) in the present sample typically occurred at close to zero speed in stop-and-go situations. Of the crashes in Category 1, 50% occurred for glances shorter than 2 seconds, combined with a high change rate (there are also a number of similar cases in Category 2). Thus, an efficient strategy to protect oneself from Category 1 crashes is to ensure that the headway when looking away is sufficient while, at the same time, avoiding extreme glance durations. As can be observed in Figures 7.3 and 7.4, rear-end crashes with a time headway above 2 seconds at LG start were rare, and the average headway adopted at LG start was generally small, also in the baseline events. Therefore, a shift toward a more defensive driving style with larger adopted headways would have a very strong potential for preventing these types of crashes. Note that this strategy

does not apply to cut-in scenarios, which were excluded from the present analysis.

What determines the location of the critical boundary for the Category 1 crashes? First, it is largely determined by vehicle's braking capacity (given road surface conditions). The single crash not included in any of the categories in Figure 7.8 followed the general pattern of a Category 1 event. The invTTC consumed during the last glance would normally not have been sufficient to produce a crash; however, video inspection as well as the video annotation revealed that the driver was skidding with brake lockup (due to wet road surface), so the stopping distance was longer than usual. With a normal stopping distance, this crash would have ended up a near crash (like the other events that surround it). Thus, improvements in vehicle braking systems and roads that reduce stopping distances would shift the boundary upward (i.e., requiring a greater change rate for a given last glance duration to produce a crash).

Second, the boundary also depends on what the driver does after looking back to the forward path the last time. For example, did drivers that successfully avoided the crash react faster to the impending hazard after looking back than those who crashed? This topic is addressed in the following section.

7.5 What Triggers Drivers' Responses After the Last Glance?

So far, the focus has been on what happens before and during the final off-road glance, and how this differs between crashes, near crashes, and normal driving. A main insight has been that in many crashes (Category 1 in Figure 7.8) the amount of change in situation kinematics during the final off-path glance (as determined by the interaction between glance duration and kinematics change rate) seems to be a main factor separating these crashes from near crashes. However, there could also be differences between near crashes and crashes in what happened after the final glance, a possibility that applies to all three categories of crashes in Figure 7.8. Investigating this possibility seems relevant, not the least for the crashes in Category 3, for which the analyses so far in this chapter have not shed any light on potential causes (other than some preliminary suggestions based on video inspection). This section looks specifically at the question of *when* drivers reacted to the rear-end situation, with the aim of answering the following questions:

- When, in relation to the situation kinematics, did drivers react? Were there differences between near crashes and crashes in this respect?
- Do POV brake lights predict timing of SV driver reaction?

One tool used to answer these questions will be parameter-fitting and comparison of reaction timing models. The test of these models is in itself an additional aim here, since it is envisioned that they can be useful in future analyses. For example, they may be used in Monte Carlo simulations to extrapolate from the findings in this chapter by studying a wide range of hypothetical rear-end situations, or to address “what if” questions about the SHRP 2 events.

Throughout this section, *driver reaction point* refers to the manual annotation of “the first visible reaction of the SV driver to the POV [such as a] body movement, a change in facial expression, etc.” This point of driver reaction does not necessarily coincide exactly with the initiation of an evasive braking or steering maneuver; it was adopted here due to difficulties in identifying the exact point of maneuver onset, partially caused by the lack of reliable data on pedal use (see Section 2.9). From manual inspection of the driver reaction point annotations, it is clear that in a great majority of cases this annotation is followed within some tenths of a second by signs of subject-vehicle deceleration (although there are some exceptions to this rule).

The inclusion criteria adopted here (see Table 7.4) targeted the same type of scenarios as described above in this chapter, but they were stricter to allow parameter-fitting of models in the time plane. Matched baseline events were not included at all, since they did not have any annotated driver reaction points.

The difference in exclusion rate between crashes and near crashes was mainly due to three criteria: (1) greater prevalence of events with >8 seconds driving with Eyes on Path before reaction among near crashes than crashes (Criterion 2), (2) lack of optical data all the way up to the point of extrapolated collision (see next section) in 21 near-crash events (Criterion 3), and (3) a manual effort to inspect the quality of GPS speed data in crashes without CAN speed data, allowing inclusion of three crash events that would otherwise have been programmatically excluded (Criterion 4).

Driver Reaction Timing, Situation Kinematics, and Brake Lights

Figure 7.12 provides a first look at the extracted data, representing each event as a vertical gray line. Each event line starts on the *x*-axis, at the event's invTTC at end of last off-path glance (here and below denoted invTTC_{ELG}); passes through a black cross, showing the time from end of last glance to annotated driver reaction point; and ends at a blue dot, showing the time when a collision would have occurred, assuming the driver did not react at all and, in practice, defined as a constant SV speed from the annotated driver reaction point (same approach as in Chapter 8).

Table 7.4. Exclusion of Crashes and Near Crashes for the Analysis of Driver Reaction Timing

Exclusion Criterion	Crashes Excluded (% of total 46)	Near Crashes Excluded (% of total 211)
1. No annotated reaction before collision	5 ^a (11%)	0
2. Time from last off-path glance to reaction >8 seconds, or no off-path glances in event	3 (7%)	35 (17%)
3. Optical data not complete from end of last glance to extrapolated point of collision	3 (7%)	32 (15%)
4. No usable CAN or GPS SVspeed data (missing or with apparent synchronization issues)	1 (2%)	14 (7%)
5. Annotated reaction with driver's eyes still off-path	0	9 (4%)
6. Other apparent problems with the optical angle data	0	3 (1%)
7. Annotated reaction after minimum distance point	0	1 (<1%)
Total number of excluded events	12 (26%)	94 (45%)
Total number of included events	34	117

^aIn four of these five crash events, the driver's eyes were still off-path at collision.

First, consider the actual driver reaction points (the black crosses). For both crashes and near crashes, two approximate regimes of behavior are discernible in this figure, to the left and right of an $\text{invTTC}_{\text{ELG}} = 0.2 \text{ s}^{-1}$ threshold:

1. A clear majority of the long times to reaction >1 second occurred for $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$ (seven out of eight for

crashes; 27 out of 28 for near crashes). This is consistent with the observation in the previous section that in some events, more specifically those in Category 3 of Figure 7.8, the driver did not find anything to react to at the end of the last off-path glance. Indeed, all the crashes in Category 3 of Figure 7.8 have $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$. As a shorthand throughout this section, events with $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$ will be

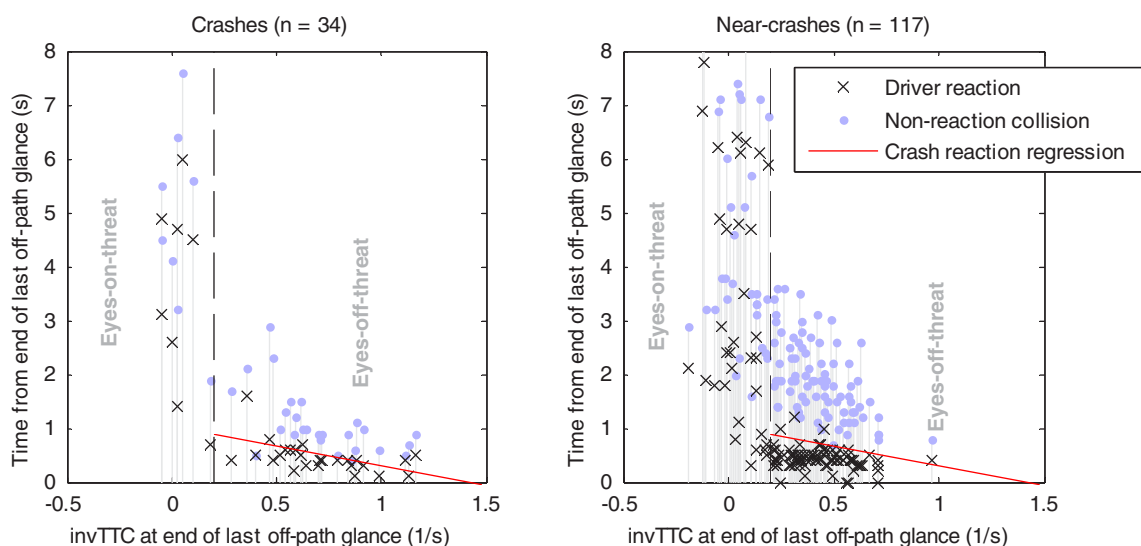


Figure 7.12. Inverse TTC at end of last glance ($\text{invTTC}_{\text{ELG}}$) versus time from end of last glance to the driver reaction point and to extrapolated collision. Threshold $\text{invTTC}_{\text{ELG}} = 0.2 \text{ s}^{-1}$ is shown as a vertical dashed line; the regression line, fitted to reactions in crash events with $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$, is shown as a red line in both panels. Eyes-off-threat crashes correspond to Categories 1 and 2 in Figure 7.8; eyes-on-threat crashes correspond to Category 3.

referred to as *eyes-on-threat* events, in line with the conclusion above in this chapter that in the Category 3 crashes, the rear-end threat arose *after* the last off-path glance.

2. A clear majority of all short times to reaction, ≤ 1 second, occurred for $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$ (25 out of 26 for crashes; 82 out of 89 for near crashes), suggesting situations in which a threat arose sometime before the end of the off-path glance, such that the driver found something to react to more or less immediately after the glance. Consistent with this idea, all the crashes in Categories 1 and 2 of Figure 7.8 have $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$; throughout this section, events with $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$ will be referred to as *eyes-off-threat* events. For these events, there are significant decreases in time to reaction with increasing $\text{invTTC}_{\text{ELG}}$ for both crashes [$r = -0.52$; $t(24) = 2.96$; $p = 0.007$; regression line shown in both panels of Figure 7.12] and near crashes [$r = -0.25$; $t(81) = 2.30$; $p = 0.024$; regression line not shown in Figure 7.12].

Given the aims of this section, it is interesting to note that for eyes-off-threat near crashes (i.e., the near crashes with $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$), driver reaction points seem to group *below* the regression line for eyes-off-threat crashes (the red line in both panels of Figure 7.12). To verify this impression, deviations from this regression line were compared between crashes and near crashes; they were found to have significantly different averages [$t(107) = -4.020$; $p = 0.0001$], with near-crashing drivers reacting, on average, 0.19 seconds faster than what is predicted by the regression line for crashes.

Next, consider the blue dots, showing the time after end of last off-path glance, of nonreaction collisions. This time duration can be regarded as a crude estimate of situation urgency at end of last off-path glance, and there are two observations to be made here. First, the times to nonreaction collision seem shorter in crashes than in near crashes. If so, this would mean that not only was $\text{invTTC}_{\text{ELG}}$ at end of last glance higher, on average, for crashes than for near crashes (as shown in Figure 7.5), but also for a given $\text{invTTC}_{\text{ELG}}$ the situation grew worse faster for crashes (e.g., due to larger POV decelerations). As a crude test of this possibility, times to nonreaction collision in the $\text{invTTC}_{\text{ELG}}$ interval $[0.4, 0.7] \text{ s}^{-1}$ (where there is a reasonable coverage of both crashes and near crashes) were compared and found to be lower for crashes (1.4 seconds) than for near crashes (1.7 seconds), but this difference is not statistically significant [$t(48) = -1.268$; $p = 0.21$]. A similar test for the eyes-on-threat crashes (with $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$) also comes up nonsignificant [average times to extrapolated collision are 4.9 seconds for crashes and 4.7 seconds for near crashes; $t(40) = 0.188$; $p = 0.85$].

Second, it should be noted that in most crash events, there are time margins *after* the observed reaction point within which reaction *could* have occurred and still precede a collision,

in some cases up to 2 seconds. This observation—as well as the observation of only one nonreaction collision with Eyes on Path among the 46 crashes in the total data set (see Table 7.4)—suggests that if a driver looks forward, he or she will generally react (at least in the sense of a first visible reaction) to a rear-end threat before the actual crash. This makes a very strong case for the hypothesis that situation kinematics (e.g., mediated by visual looming) have an effect on the timing of driver reactions.

The analysis in Table 7.1 indicated that drivers in crashes and near crashes generally tended to ignore the onset of brake lights as a cue that the lead vehicle was likely to become a threat in the near future. Nonetheless, it is still possible that lead-vehicle brake lights influenced driver reactions once the situation became critical (i.e., after the end of the last glance). However, in most crashes (74%) and near crashes (79%), POV brake lights were on all the way from end of last glance to the driver reaction point, so it is clear from Figure 7.12 that, in general, drivers did not react within some fixed, situation-independent reaction time to the sight of already illuminated brake lights. Figure 7.13 shows driver reaction points in the (rather few) events in which one or more brake light *onsets* occurred between end of last glance and the driver reaction point; the figure also shows when in time the last brake light onset occurred (the start of the red lines). One interesting possibility regarding the difference between crashes and near crashes starting at $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$ (i.e., the eyes-on-threat events, corresponding to Category 3 of Figure 7.8) would have been that near-crashing drivers in these events were more successful than crashing drivers at responding to brake light onsets. However, the data shown in Figure 7.13 do not provide any strong support for this idea. Among the five eyes-on-threat crashes, driver reaction came within 1 second after brake light onset in one case (20%). For near crashes, the same figure was seven cases out of 20 (35%), a difference that was not statistically significant ($p = 0.47$; Fisher's exact test). In the other crashes and near crashes shown in Figure 7.13, reaction came any time up to 6 or 7 seconds after the last brake light onset. This leaves the general impression that brake light onsets had rather little to do with the timing of driver reactions in the present crashes and near crashes.

Thus, so far the results indicate that brake lights had a limited effect on reaction timing but that reactions were instead strongly related to kinematics, at least in the sense that driver reaction occurred (with only one exception) before the actual crash, and typically with quite some time margin left to when a nonreacting driver would have crashed. Figure 7.14 provides further insight into the relationship between kinematics and reactions, by showing both invTTC at end of last glance (on the x -axis) and invTTC at the driver reaction point, referred to here as invTTC_R (on the y -axis). A diagonal $y = x$ line is shown; a reaction on this line implies an event in which

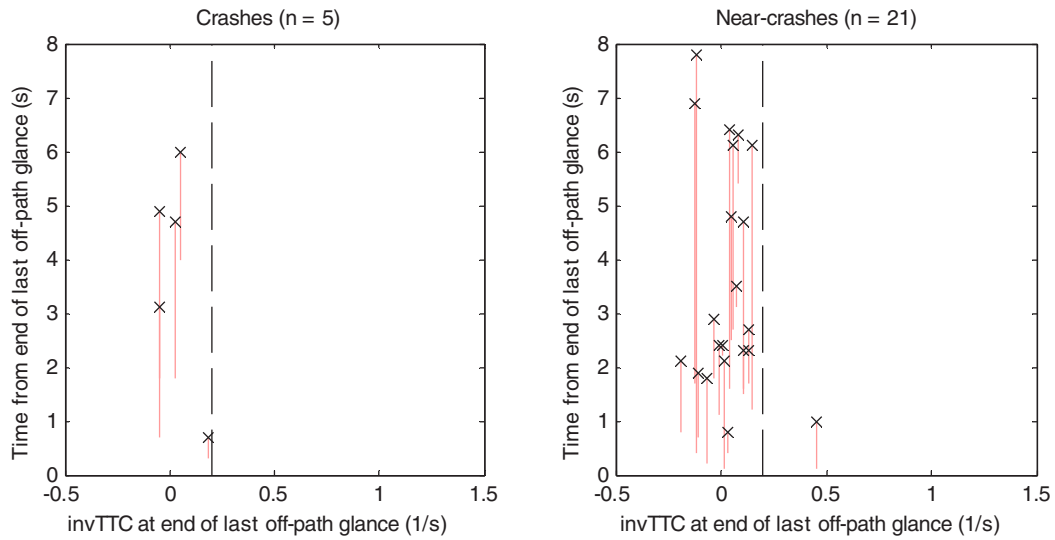


Figure 7.13. As in Figure 7.12, but showing only events with one or more brake light onsets between end of last glance and the driver reaction point. The red stripes begin at the time of last brake light onset and, for clarity, end at the driver reaction point (regardless of whether or not the brake lights remained illuminated up to this point).

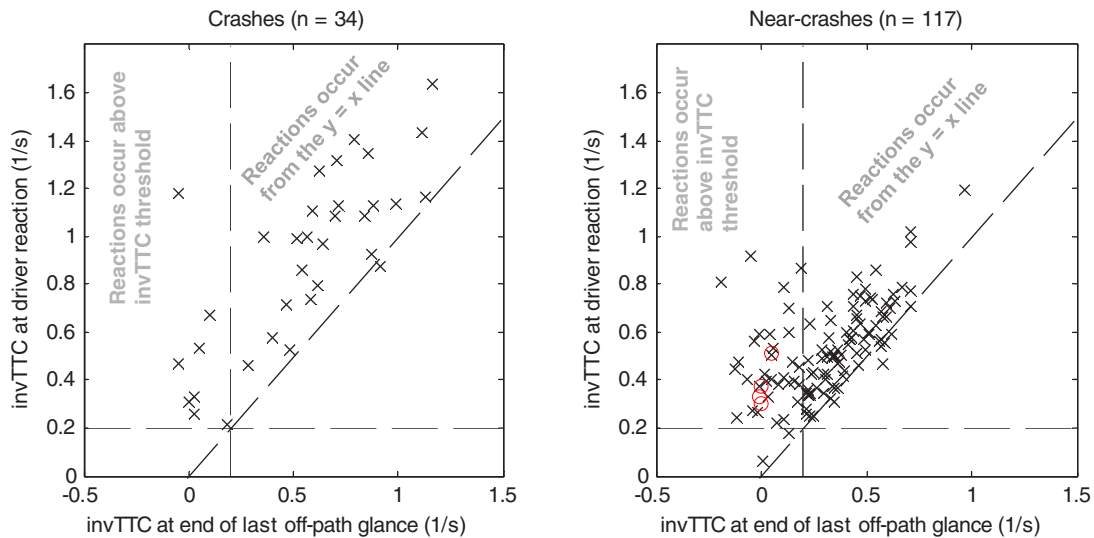


Figure 7.14. $invTTC$ at end of last off-path glance ($invTTC_{ELG}$) versus $invTTC$ at the driver reaction point ($invTTC_R$), for crashes and near crashes. Four red rings show driver reactions in the four near crashes when the driver talked/listened on cell phone (right panel): one cell phone event (at $invTTC_R \approx 0.5$) was included in the other analyses of this section; the other three were originally excluded (see Table 7.4) due to time to reaction over 8 seconds (one case), or to no optical cues available at the end of the last off-path glance (two cases; at $invTTC_{ELG} = 0$ since both were clear eyes-on-road Category 3 events).

invTTC was the same at end of last glance and reaction. As in Figure 7.12, there are signs of qualitative differences between eyes-on-threat and eyes-off-threat events, and there are traces of the same 0.2 s^{-1} threshold for invTTC_R . In the figure, both of these thresholds are shown, as one vertical and one horizontal line.

1. To the left of the vertical line in the figure—that is, for the eyes-on-threat events (with $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$)—there is a vertical gap from the diagonal $y = x$ line up to the horizontal line, above which almost all reactions occur, with some variability. This signifies that in both crashes and near crashes, reactions generally did not occur before the kinematics had evolved to at least a level of 0.2 s^{-1} invTTC. Specifically, for these crashes and near crashes, average invTTC_R was 0.49 s^{-1} and 0.45 s^{-1} , respectively, a non-significant difference [$t(40) = 0.479$; $p = 0.63$].
2. To the right of the vertical line—that is, for the eyes-off-threat events (with $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$)—driver reactions are present directly from the diagonal $y = x$ line, again with variability, creating a diagonal band of points in the plot both for crashes and near crashes. This band seems to have a larger vertical spread for crashes than for near crashes. Indeed, the average of $\text{invTTC}_R - \text{invTTC}_{\text{ELG}}$ —that is, the height of reactions over the $y = x$ line—was significantly larger [$t(107) = 6.182 < p 0.0001$] for crashes (0.32 s^{-1} average increase) than for near crashes (0.13 s^{-1} average increase). In other words, even for comparable situation kinematics at end of last glance, crashing drivers reacted, on average, at a point in time with more severe kinematics than near-crashing drivers.

Another way of formulating this last result is that, on average, in eyes-off-threat events, the situation changed more for the worse in crashes than in near crashes during the time interval from end of last glance to the driver reaction point. This is analogous to what was found in the previous section regarding changes in kinematics during the last off-path glance, and again both time (here, time to reaction) and kinematics change rate could play a role. Here, it has already been observed, in relation to Figure 7.12, that for eyes-off-threat events, driver reactions were, on average, significantly slower in crashes than in near crashes and that there was a possible nonsignificant trend of times to extrapolated collision being shorter in crashes than in near crashes (implying a faster kinematics change rate). Both of these observations align with the observed difference in total change in invTTC from end of last glance to the driver reaction point.

Driver Reactions When Talking/Listening on a Cell Phone

Several naturalistic driving studies have found cell phone conversation to have a protective effect (Olson et al. 2009;

Hickman et al. 2010). The present study found an even stronger protective effect, with an odds ratio for Talking/Listening on Cell Phone of 0.1 (see Chapter 4). To investigate to what extent this effect is related to changes in driver reactions induced by phone conversation, the four near-crash events in which the driver was coded as Talking/Listening on Cell Phone are plotted in the right panel of Figure 7.14 along with the other events in which the driver was not in a phone conversation. (As described in Chapter 4, there were no crashes in the present sample coded as Talking/Listening on Cell Phone.)

First, it may be noted that all four talking/listening near crashes are of the eyes-on-threat type (i.e., Category 3). Second, as can be observed in Figure 7.14, there are no indications that the cell phone conversation affects reactions to the rear-end threat; these drivers react at about the same kinematic severities as the other nearly crashing drivers. Average invTTC_R for the four talking/listening drivers was 0.38 s^{-1} , which is actually lower than the average 0.45 s^{-1} for the other eyes-on-threat near crashes. However, the difference was nonsignificant [$t(35) = -0.708$; $p = 0.48$].

Underlying Mechanisms and Model-Fitting

Driver reactions in the SHRP 2 crashes and near crashes are strongly associated with situation kinematics. Reactions are almost never observed for invTTC below 0.2 s^{-1} , but above this threshold, reactions almost always occur before collision. In practice this means that at progressively higher $\text{invTTC}_{\text{ELG}}$, the reactions are progressively faster.

A candidate mechanism that could account for this set of observations is called *evidence accumulation*. In psychology and neuroscience, some models assume that overt actions are triggered once evidence for their suitability has accumulated to a threshold (also known as *diffusion* or *race* models). These models have been found to account well for reaction-time distributions in a wide variety of tasks (Gold and Shadlen 2007; Ratcliff and Van Dongen 2011), including brake reactions to expected activations of lead-vehicle brake lights (Ratcliff and Strayer 2013). Potential neural correlates of such processes have also been identified (Gold and Shadlen 2007; Purcell et al. 2010). Markkula (2014) hypothesized that timing of brake responses in driving could be driven by accumulation of the various cues that signal the possible need for deceleration (e.g., contextual, augmenting, and primary cues, in the terminology of Tijerina et al. 2004). Here, using the same type of accumulator as Markkula (2014) and, for simplicity, assuming accumulation of invTTC, driver reaction could be hypothesized to occur when an activation $A(t) \geq 0$, changing over time as

$$\frac{dA(t)}{dt} = \text{invTTC}(t) - M + \varepsilon(t) \quad (7.1)$$

has risen above a threshold A_r . Here invTTC is used, but inverse Tau could equally be used. (Here, these two are the same; see above in this section. Also see, for example, Flach et al. 2004, Kiefer et al. 2005, and Fajen 2007 for alternative visual cues to consider.) Markkula (2014) suggested that the model parameter M could be regarded as the sum of the influence from all other cues (e.g., contextual cues) and that it therefore could be affected by factors such as attention or expectancy. $\varepsilon(t)$ is a noise term (e.g., normally distributed) that relates to inherent variability in underlying neural activity. For a given parameterization of the model as formulated above:

- No reactions will be generated as long as invTTC is sufficiently below M [sufficiently below given the variability of $\varepsilon(t)$]; and
- Above M , larger values of invTTC will cause activation to reach threshold faster.

In other words, qualitatively, the model is completely in line with what has been observed here.

To test these ideas in practice, the model in Equation 7.1 was parameter-fitted to the crash and near-crash data separately, by means of a genetic algorithm (GA) optimizing parameters to minimize Δ_{RMS} , the root mean square deviation between observed and predicted times of reaction (Wahde 2008). $\varepsilon(t) = 0$ to allow this type of deterministic simulation and model-fitting (rather than, for example, maximum likelihood model-fitting). This approach can provide a first idea of the usefulness of the model, but perfect fits should not be expected. A deterministic model with one shared parameterization for all events cannot at all account for natural variability in reaction times [nonzero $\varepsilon(t)$] or for variations between events in driver attention or expectancy (varying M).

For each event, the model was fed the invTTC history starting from end of last glance. To allow meaningful fitting of model reactions occurring later than the observed reactions, the effect of driver avoidance maneuvering on invTTC was removed, as mentioned above, by assuming a constant SV vehicle speed after the annotated point of driver reaction. To reduce the risk of obtaining local optima, each optimization was repeated three times, with 500 GA generations in each repetition, and reasonable optimization convergence was subjectively verified by inspection of model-fit time histories.

Figure 7.14 shows the fit of the model to the crash and near-crash data, together with the coefficients of determination R^2 , interpretable as the amount of variance explained by the model, computed as

$$R^2 = 1 - \frac{SS_E}{SS_T} = 1 - \frac{\sum_i (T_{i,\text{model}} - T_{i,\text{observed}})^2}{\sum_i (T_{i,\text{observed}} - \bar{T}_{\text{observed}})^2}$$

where $T_{i,\text{observed}}$ are the observed times to reaction, with average $\bar{T}_{\text{observed}}$, and $T_{i,\text{model}}$ are the corresponding model predictions. Negative values for R^2 thus imply that the model produces larger prediction errors than what would be obtained for a fixed prediction $T_{i,\text{model}} = \bar{T}_{\text{observed}}$ for all events.

Figure 7.15 shows that for both crashes and near crashes, the accumulator model is rather successful at predicting times to reaction ($R^2 = 0.95$ and $R^2 = 0.93$, respectively, root mean square error of predicted reaction timing $\Delta_{\text{RMS}} \approx 0.4$ second) when considering the entire sets of data, in which the variability is dominated by the long times to reaction of the eyes-on-threat crashes. If singling out only the shorter times to reaction of the eyes-off-threat crashes ($\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$; bottom left panel of Figure 7.15), the coefficient of determination is more modest ($R^2 = 0.24$), but note that it is comparable to what was obtained for the linear correlation in Figure 7.12 ($R^2 = 0.27$). This can be interpreted as the model indeed providing a possible underlying mechanism behind that linear correlation, but not having any further explanatory power beyond it (and, as mentioned above, no means of accounting for, for example, variations in attention or expectancy). When fitting the model only to the eyes-off-threat events, a slightly better fit, with $\Delta_{\text{RMS}} = 0.24$ seconds and $R^2 = 0.28$, was obtained.

For the eyes-off-threat near crashes, the linear correlation in Figure 7.12, was, although statistically significant, even weaker than for the crashes ($R^2 = 0.06$). As is clear from Figure 7.14 (bottom right panel), this weak correlation was not recreated by the accumulator model. Also, fitting only to the $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$ subset yielded an improved model fit, $\Delta_{\text{RMS}} = 0.20$ seconds, though still with a negative coefficient of determination ($R^2 = -0.04$).

That the accumulator model was less able to fit the times to reaction in eyes-off-threat near crashes than in eyes-off-threat crashes could imply there were some differences in mechanisms between these crashes and near crashes which the model doesn't cover. Another possibility might be that a type of selection bias comes into play, making any signs of evidence accumulation difficult to discern. Driver reactions in the crash events did not seem tightly constrained by the need to lead to collisions to be included in the data set (as discussed in relation to Figure 7.12). However, reaction timing in near crashes was constrained both from above (must be early enough to avoid crash) and from below (must be late enough to generate a near crash). In other words, the SHRP 2 vehicles may have been involved in many driving events with similar kinematics to the near-crash events, but those did not register as near crashes because the driver happened to react slightly faster (in the terms of the model, due to favorable ε , or a lower M), or they registered as a crash because of a slightly later reaction. If so, this could mean that variability in observed near-crash driver reactions may be dictated more by the kinematic constraints of near-crash-detecting triggers and crash-avoidance feasibility, than by actual driver behavior phenomena.

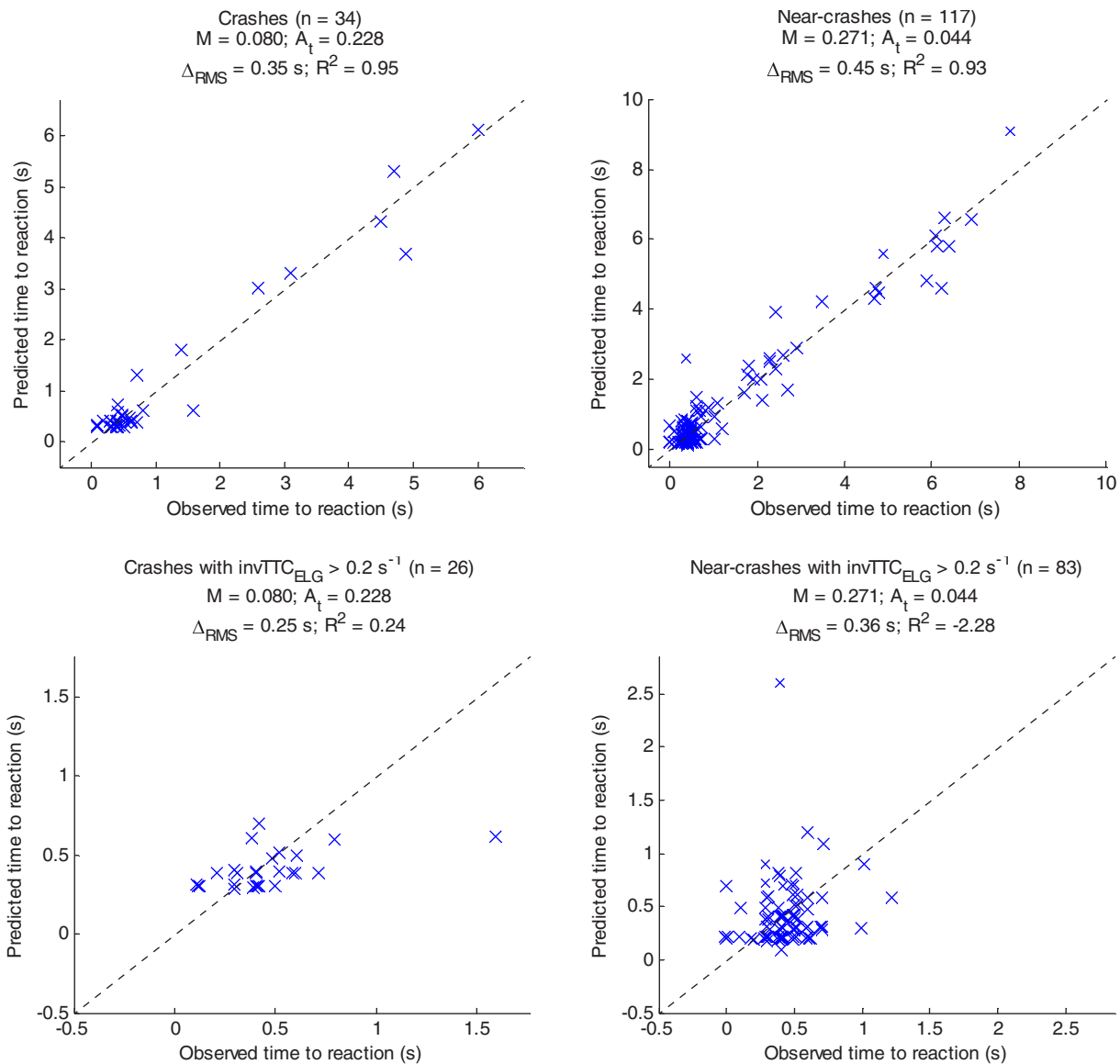


Figure 7.15. Fits of the accumulator model to observed reactions, in crashes and near crashes. The top two panels show full sets of data used for model-fitting. The bottom two graphs provide a zoomed-in view of the events with $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$.

As a contrast to the accumulator model, another two-parameter model was also fitted that predicts a driver reaction and a fixed reaction-time delay T_R after passing an invTTC threshold. At long times to reaction, this model closely approximates the accumulator model (with M as the invTTC threshold, and accumulation to A_t as a delay). As could therefore be expected, this simpler model also worked well for the eyes-on-threat events, with long times to reaction (overall $\Delta_{\text{RMS}} = 0.38$ seconds and $R^2 = 0.94$ for crashes; $\Delta_{\text{RMS}} = 0.43$ seconds and $R^2 = 0.94$ for near crashes). However, for the shorter times to reaction of the eyes-off-threat events, this model will almost always predict a time to reaction of T_R , yielding poor fits ($\Delta_{\text{RMS}} = 0.29$ seconds and $R^2 = -0.04$ for

crashes; $\Delta_{\text{RMS}} = 0.33$ seconds and $R^2 = -1.74$ for near crashes) and reinforcing the idea that something akin to evidence accumulation is needed to explain the effect of situation kinematics on times to reaction in eyes-off-threat events.

Finally, consider the parameter values obtained for the accumulator model when fitted to crashes and near crashes. The mere observation that the parameter values differ does not provide much information, since M and A_t are to some extent redundant (a higher M can be partially compensated for by a lower A_t , and vice versa). Therefore, analogously to what was done for the linear correlation in Figure 7.12, Figure 7.16 shows the results of applying the accumulator model obtained for near crashes to the crash events. For the eyes-off-threat crashes,

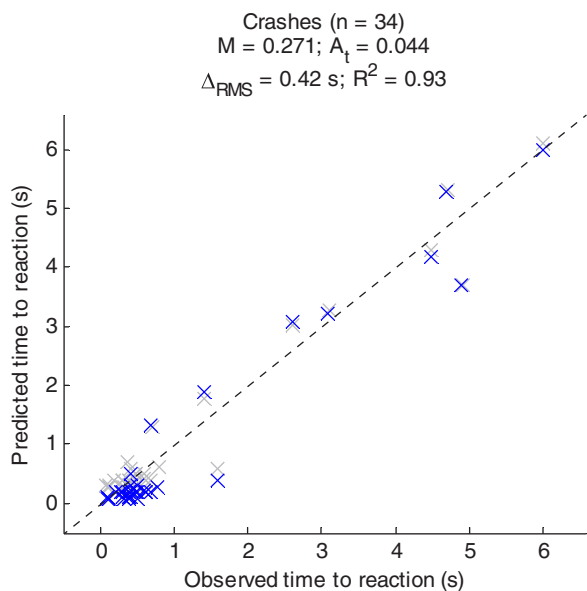


Figure 7.16. Comparison of fits of crash data for the crash model (gray crosses, same as in top left panel of Figure 7.15) and the near-crash model (blue crosses, same parameters as in top right panel of Figure 7.15).

with short times to reaction, the model fitted to near crashes predicted faster reactions than the model fitted to crashes, and the average difference of 0.22 seconds is well in line with the 0.19 seconds difference observed in relation to Figure 7.12. For the eyes-on-threat crashes, with longer times to reaction, prediction deviations went in both directions, adding up to the near-crash model predicting, on average, 0.01-second shorter times to reaction. This is in line with the apparent lack of difference in reaction timing between eyes-on-threat crashes and near crashes observed in Figure 7.14.

Summary

In conclusion, it has been shown that driver reactions in the SHRP 2 crashes and near crashes were not notably affected by POV brake lights but were instead strongly coupled to situation kinematics. It was found that the categories of crashes in Figure 7.8 could be neatly separated by a threshold of $\text{invTTC}_{\text{ELG}}$ at end of last off-path glance: the eyes-off-threat crashes (Categories 1 and 2) all had $\text{invTTC}_{\text{ELG}} > 0.2 \text{ s}^{-1}$, and the eyes-on-threat crashes (Category 3) all had $\text{invTTC}_{\text{ELG}} < 0.2 \text{ s}^{-1}$. For eyes-on-threat events (both crashes and near crashes), very few reactions occurred before reaching an invTTC of at least 0.2 s^{-1} . This means the reaction could occur an arbitrarily long time after the last off-path glance. In contrast, for eyes-off-threat events (again, both crashes and near crashes), the driver reactions almost always came within a second, and almost

always before the crash, in practice implying that reactions were faster in situations with high $\text{invTTC}_{\text{ELG}}$.

It has been explained that an accumulator model of reaction timing, accumulating invTTC once invTTC has reached a minimum threshold, would, qualitatively, predict exactly these observations (no reactions below an invTTC threshold, and progressively faster reactions above it). In actual model-fitting to the observed reactions, a simple two-parameter accumulator was found to account acceptably well for reaction variability in crash events (both eyes-off-threat and eyes-on-threat) and in eyes-on-threat near-crash events, but not in eyes-off-threat near crashes. This could possibly relate to issues of selection bias, which make model-fitting to this type of naturalistic data challenging in general.

There are clear signs that, for eyes-off-threat events, near-crashing drivers reacted, on average, about 0.2 second faster than crashing drivers, and there are possible indications that the crash events in this regime also evolved to higher severity faster than comparable near crashes. This implies that causation of eyes-off-threat crashes could be further understood as involving (a) kinematics that changed faster than in similar near crashes *after* the end of the last off-path glance (not statistically proven here), and (b) drivers that for some reason had slower reactions (statistically significant). These slower driver reactions could be a result of natural variability in reaction timing, such that slightly slower reactions happened to lead to crashes, and slightly faster reactions did not. However, the descriptive data analysis (Chapter 3) identifies a number of factors that were overrepresented in crashes, such as young age, rain, and visual obstructions—factors that could be hypothesized to be associated with slower reactions in critical situations. Another factor that could be expected to influence driver reactions is the degree to which the driver's expectancy was violated (Green 2000); it is possible that crashes on average involved situations in which the driver was more certain that the lead vehicle would not brake, leading to a longer time to reaction. Finally, one aspect which has not been considered in the analyses presented here is the possibility of drivers acquiring some information about the impending rear-end situation via peripheral vision (Lamble et al. 1999; Markkula, 2014). This could be needed to convincingly explain some of the very short and even zero times to reaction occurring in some eyes-off-threat events, especially in near crashes.

For the eyes-on-threat crashes, the analyses in this section did not identify any specific differences from comparable near crashes that could serve as clues regarding crash causation. No clear signs were found of slower reactions from crashing drivers or of situation kinematics evolving faster in crashes than in near crashes. Moreover, drivers involved in cell phone conversation did not respond at higher invTTC (looming) values than the other near-crash-involved drivers. Overall, these results suggest that what separates eyes-on-threat crashes

from comparable near crashes may be related to failures to apply crash-avoidance braking or steering maneuvers after the point of driver reaction. This could involve differences in the time from observed driver reaction (such as studied here) to initiation of actual maneuvering, but also differences in factors such as actual maneuvering capacity of the vehicle on the road (e.g., relating to vehicle brakes, road surface friction), space available for lateral maneuvering, or the extent to which the drivers used the full maneuvering capacities of the vehicle.

7.6 Conclusions

The present analysis has yielded several novel insights on the role of glance timing relative to external events in rear-end crashes. The main conclusions are summarized and discussed below.

Conclusion 1: Brake Lights Have a Limited Impact on Driver Behavior in Rear-End Situations

The present results indicate that the timing relationship between brake light onsets and off-path glances does not have any impact on whether the situation develops into a safety-critical event. In fact, co-occurrences between Eyes off Path and brake light onsets were *less* prevalent in crashes compared with near crashes and matched baselines. Moreover, brake light onsets occurring while the driver looked forward were generally ignored and do not seem to have influenced the willingness of the driver to take his or her eyes off the road. Finally, as further discussed below, there was no indication that drivers reacted to brake light onsets after looking back to the road for the last time.

One possible explanation for why many drivers in the present sample seem to have ignored brake light onsets is based on the notion that their predictive value could be limited. Brake light onsets are very common in noncritical situations; as indicated in Table 7.1, 32% of the matched baselines in the present sample included brake light onsets. Thus, the great majority of brake light onsets that drivers are exposed to are not associated with any real threat. This may lead to a “cry-wolf” effect such that evidence from brake lights is taken more lightly than, for example, the detection of a closing lead vehicle. In the present crashes and near crashes, strong expectations that the lead vehicle would not brake may thus have overridden the relatively weak evidence from the brake light onset that the lead vehicle might become a threat in the near future.

Drivers about to crash were more likely than near-crash and baseline drivers to look ahead when the brake lights illuminated, and also more likely to look away in the next moment. One possible explanation for this somewhat counterintuitive finding is that the phenomenon occurs as an indirect consequence of the way rear-end crashes typically

happen. As described above (and further discussed below), a large portion of rear-end crashes (Category 1) occur because of a particular combination of glance duration and the rate at which the criticality changes (measured here in terms of invTTC change rate). For this to happen, the driver must often look away precisely at the wrong moment, that is, just after the invTTC has started to rise. Since the last brake light onset often occurs just before the rise in invTTC, it will often also occur at a moment when the driver looks ahead. Figure 7.1 provided two examples, and there were many similar cases among the Category 1 crashes.

It should be noted that this does not mean that drivers never use brake lights as a cue for initiating braking. On the contrary, early responses to brake lights may have been a key reason that many potentially critical scenarios did not end up as crashes and near crashes in the present sample. However, as suggested by the cry-wolf effect described above, strong expectations induced by other cues and/or a strong motivation to engage in a secondary task may easily override evidence from brake light onset that the lead vehicle is about to close.

An issue that has not been systematically addressed in the present analysis is the saliency of the brake lights. Here it was generally assumed that the brake light onset was perceived when the driver was looking ahead and missed when looking away. However, this may not always be the case since detection also depends on the saliency of the brake lights, which may be strongly reduced, for example, due to strong sunlight. As mentioned above, video inspection of the Category 1 crashes indicated that the driver often looked away despite a very salient brake light onset. However, a more systematic analysis is needed to better understand the role of brake light saliency in this context.

Conclusion 2: Most Rear-End Crashes Are Characterized by a Mismatch Between Duration of the Last Glance and the Change Rate of the Situation Kinematics

The present analysis revealed, for the first time, how the driver’s visual behavior and the situation kinematics interact to produce rear-end crashes, yielding a distinct pattern that characterizes the majority of crashes in the present sample (i.e., those belonging to Category 1 in Figure 7.8, and exemplified in Figures 7.9 and 7.12). These crashes happen because of a rapid change in situation kinematics, often occurring just after the driver has taken his or her eyes off the road. The crash mechanism is constrained by the fact that drivers normally do not take their eyes off the forward roadway if they detect that the lead vehicle is closing (Tijerina et al. 2004). Thus, the kinematic situation is perceived as normal when the driver looks away but has turned critical when the driver looks back. This can thus be understood in terms of a mismatch model of driver inattention (Engström, Monk et al.

2013), in which the duration of the last glance and the invTTC change rate combine into a “perfect mismatch” that produces the crash. If one of the two constraints is not met (e.g., the glance is too short or the change rate is too low), the situation will end up in a near crash or may not turn critical at all.

This mechanism results in the linear organization of Category 1 crashes in Figure 7.8. One way to look at this phenomenon is as the result of a natural variability in situation kinematics in vehicle-following situations and the driver’s (learned) ability to control it. The driver’s decision to take his or her eyes off the road is largely guided by expectation. Thus, long glances are very infrequent because the driving situation normally does not permit them. Similarly, very rapidly changing kinematics in vehicle-following situations are also infrequent (because the lead-vehicle drivers are also good at controlling variability). Thus, the probability of Category 1 rear-end crashes can be understood in terms of a joint probability distribution of off-path glance durations and kinematics change rates. Long off-path glances require only a low change rate for a crash to happen, while short glances require high rates. The pattern observed in Figure 7.8 emerges because long glances and fast change rates are both rare, and the points along this line represent the combinations with the highest joint probability. The present limited sample of crashes mainly contains low-severity crashes on the border of the near-crash region. With a larger sample, containing more severe cases, the crashes would be expected to be less linearly organized, featuring the more rare—and severe—combinations of long glances and fast kinematics.

The present data suggest a hypothetical boundary for what characterizes safe glances (see Figure 7.8). Off-road glances and change rates below this line are unlikely to produce a crash. However, the key problem is that the variability in situation kinematics is only partially controlled by the driver. One important implication of the present results is that the majority of Category 1 and Category 2 crashes are produced by relatively short glances (<2 seconds). Thus, even in the hypothetical situation in which all glances longer than 2 seconds are eliminated, the majority of crashes directly caused by off-path glances would remain (all other things being equal).

A simple and efficient strategy for counteracting these categories would be to increase headway; very few Category 1 or 2 crashes happened at initial headways (at LG start) larger than 2 seconds. Moreover, the present analysis showed that the lead vehicle often initiated braking just before the driver looked away, as indicated by the frequent occurrence of brake light onsets while the driver was still looking forward (e.g., the cases plotted in Figure 7.16). However, the driver often ignored the brake lights and looked away just before strong looming cues (indicating closing of the lead vehicle) started to appear. Thus, if the driver could be reliably alerted already at the point when the lead vehicle initiates braking (in some way other than by the lead vehicle’s brake lights, which seem

to have lost their predictive value due to the cry-wolf effect), many of the critical off-path glances could likely be eliminated. Collision warnings enabled by V2X technology should have a great potential in this context.

Although the majority of the present crashes could be explained by the mechanism just discussed, the results also pointed to other mechanisms behind rear-end crashes. In particular, in the Category 2 crashes, drivers typically failed to detect that the lead vehicle was already closing and eventually looked away from the road, thus further delaying their reaction. The preliminary video inspection pointed to reduced visibility as a key factor in these cases, but a more systematic analysis is needed to establish this.

Finally, in a significant portion of the present crashes, grouped as Category 3 and characterized as *eyes-on-threat*, the off-road glance did not have anything to do with the driver’s reaction. These crashes are thus functionally similar to crashes in which the driver did not look away at all before the crash. Further analysis is needed to determine the key factors behind these crashes, although some initial speculations were offered above.

Conclusion 3: Driver Reactions Are Coupled to the (Perceived) Situation Kinematics

A key insight from the analysis of driver reactions is that reactions in critical situations are strongly coupled to the situation kinematics. As mentioned above, this analysis further demonstrated that neither the drivers who crashed nor those ending up in near crashes appeared to have responded to brake light onsets that occurred after looking back. (Note, however, that the number of cases with a brake light onset occurring after the last glance back was relatively limited.) Rather, the present results indicate that the moment when the driver reacts is mainly determined by the presence of sufficiently strong optical cues indicating that the lead vehicle is closing. The analysis indicates that drivers with their eyes on the road did not react until the criticality of the situation was sufficiently high, as mediated by visual looming. The present data for crashes and near crashes indicate an invTTC (or $1/\tau$) threshold of roughly 0.2, below which drivers did not seem to react. While both this finding and the lack of reaction to brake lights can possibly be explained in terms of selection bias (drivers ended up in these crashes and near crashes precisely because they did not react earlier), a key further finding, not affected by selection bias, was that all but one driver did react after passing the 0.2 invTTC threshold.

This last result has important consequences for how to deal with the concept of *reaction time* in naturalistic data. In previous studies of near-crash and crash events (e.g., in simulation models), many researchers have assumed a constant, situation-independent distribution of driver reaction times to the situation itself (Sugimoto and Sauer 2005; Kusano and Gabler

2012). The present results indicate that such an assumption is inadequate. Rather, a model of driver reactions in critical rear-end situations must account for the fact that drivers react when the situation is perceived as sufficiently critical (e.g., when looming information has accumulated above a threshold). In the present eyes-on-threat situations (Category 3), the reaction time largely depended on the moment when the driver looked back to the road for the last time and the way the kinematics developed, rather than on a driver-inherent reaction time. Thus, the concept of reaction time is generally meaningless in naturalistic driving analysis—except in specific types of situations (such as the current eyes-off-threat cases in Categories 1 and 2) in which the driver looks back at a moment when *invTTC* has risen above the critical threshold.

Another key finding was that reactions in eyes-off-threat situations were generally faster for near crashes than for crashes. It is not possible to determine whether this reflects an actual difference in reaction performance between crash- and near-crash-involved drivers or just a selection bias operating on a natural variability in time to reaction; however, this result at least indicates that small differences in the time to reaction after looking back to the road sometimes determine whether the event results in a crash or a near crash.

Finally, the specific analysis of reaction timing in the four near crashes in which the driver was Talking/Listening on Cell Phone did not indicate any significant difference in reaction performance to the other near crashes. If, as suggested by experimental studies (e.g., Brookhuis et al. 1991; Alm and Nilsson 1995; Strayer et al. 2003; Strayer and Drews 2004; Strayer et al. 2006), cell phone conversation induces reaction delays critical for road safety, drivers on the phone would be expected to react markedly slower (i.e., at higher *invTTC*) than the average near-crash driver. It is of course difficult to draw any safe conclusions on the basis of just four cases, but there is no sign of such an effect in these data. If anything, the *invTTC* values at which these drivers reacted were slightly lower than average.

However, the general results from the reaction analysis have further implications for the generalizability of results from experimental studies on cell phone conversation to the real world. Most of these studies have used reactions to the lead-vehicle brake lights as the key performance measure. However, as demonstrated by the present analysis, drivers do not seem to react to brake lights in naturalistic rear-end situations but rather to the situation kinematics, mediated by visual looming. Thus, whether the cognitive load induced by cell phone conversation delays reactions to brake lights might be irrelevant for understanding reactions to looming in real-world situations. In fact, the few experimental lead-vehicle braking studies on cognitive load in which the brake lights were turned off (Muttart et al. 2007) or using other looming stimuli (Baumann et al. 2008) have generally found a null effect of cognitive load on driver reaction performance. This

does not explain the protective effect found in the present study (Section 4.1) as well as previous naturalistic driving studies. But it may at least suggest a reason why talking/listening does not increase crash risk in naturalistic rear-end crashes, as would be predicted by the experimental results.

Conclusion 4: Modeling Driver Reactions on the Basis of Naturalistic Data Is Feasible

Initial attempts to model driver reactions based on evidence accumulation were partly successful. First, such a model conceptually accounts for the general observed patterns: reactions do not occur while there is no looming (as observed in the eyes-on-threat cases), but reactions nevertheless almost always occur before crash, that is, faster in more severe situations (as observed in the eyes-off-threat cases). Thus, this type of model is clearly superior to naïve models that assume a constant reaction time to the situation as such, or to brake lights. The model also did a reasonably good job in capturing the fine-grained variance in eyes-off-threat cases in which the driver looks back to the road when looming cues are already present. However, the model did not capture all the variance in these reactions; this is not surprising given the multitude of factors that possibly influence time to reaction at this scale (e.g., visibility, the eccentricity of the off-path glances, individual variation). The proposed model is still potentially useful for simulating driver reactions in computer simulations of the phenomena investigated here. A particularly promising application area is what-if simulations, such as those described in Chapter 8, or the evaluation of active safety systems [e.g., forward collision warning (FCW) and autonomous emergency braking (AEB) systems].

Further Work

While the present analysis has yielded several new insights on the relationship between the last off-path glance and situation kinematics/visual cues, a fundamental question remains: Why did the driver take his or her eyes off the road at that inopportune moment in time? This decision might be governed by a balance between (1) the motivation to perform a secondary task and (2) expectations on how the situation will develop. Expectations derive from the driver's current understanding of the situation, which, in turn, depends on the perception of relevant contextual cues (such as a traffic queue building up ahead or a red light). Glances away from the forward path very likely impair the detection of such contextual cues, leaving the driver with an inadequate understanding of the situation and possibly increasing the risk that an inopportune glance will coincide with sudden braking by the lead vehicle. One way to address this issue is through video-based analysis using a dedicated coding scheme. See Engström, Werneke et al. (2013) for the first step in this direction.

CHAPTER 8

Actual and Potential Severity

The previous analyses have focused on crash-contributing factors in Lead-Vehicle Precrash Scenarios, including descriptive variables, distracting activities, glance behavior, situation kinematics, and visual cues. The focus has been on quantifying *crash risk* rather than *injury risk*. By developing methods to estimate both the probability of crashing and injury risk, this chapter focuses on the research question, What crash severity scale is best suited for analysis of risk?

Here, we propose a method that estimates potential outcome severity (crash probability and injury risk) by using a model to simulate the effect of applying different glance durations on the actual kinematics of the crashes and near crashes. These potential outcome severity scales, Model-estimated Injury Risk (MIR) and Model-estimated Crash Risk (MCR), are indices that are output as continuous values, in contrast to the approach used in previous chapters, which has two broad crash and near-crash categories.

According to current common practice, safety-critical events in naturalistic driving data are grouped into categories such as crash or near crash in the SHRP 2 Event Severity variable. This approach has been used extensively in naturalistic driving studies (see Fitch et al. 2013; Klauer et al. 2010; Olson et al. 2009). However, such an approach has significant limitations. For example, does the categorization always treat a crash as more severe than a near crash? Why should an Event Severity variable value a very-low-velocity, stop-and-go crash (e.g., <1 mph) as more severe than a high-speed near crash on a motorway, in which the driver is just barely able to stop with full braking from 70 mph? The categorization approach cannot provide a continuous outcome variable for risk analyses across crashes and near crashes. MIR and MCR are two continuous variables that can be calculated for near crashes and crashes alike. The potential severity scales developed here were compared with actual outcome severity scales: (1) DeltaV, the estimated change in velocity for the vehicles in a crash (Kusano and Gabler 2010), and (2) minimum time to collision (minTTC) (Lee 1976). These outcome scales provide information about

what actually happened in an event, are well established, and are described more in detail in Appendix A. We also compared the crashes and near crashes in the SHRP 2 sample with accident statistics, including the use of extreme value analysis (EVA) (Jonasson and Rootzén 2014).

As shown in previous chapters, the mismatch between Eyes-off-Path glances and event kinematics is central to an event becoming a crash. Thus, it makes sense to ask these questions: What if the last glance duration was different in a particular event? What if the driver in the subject vehicle started his or her glance at a different point in time? Would there still be a crash? Would it turn into a near crash? Given a specific off-path glance behavior, what is the risk that this particular driving situation's kinematics would end in a crash or result in an injury?

The basic idea behind potential (model-based) severity scales is the use of mathematical simulations to provide insight into what could have happened in a specific event if the driver had behaved differently (i.e., different glance behavior). These can be called *what-if* simulations because they make it possible to study how a change in driver glance behavior would have influenced the outcome of an individual event. An example of what-if simulations using naturalistic driving data is McLaughlin et al. (2008) in which the safety benefit of forward collision warning (FCW) systems was evaluated by applying FCW algorithms to the kinematic data of 60 near-crash events and 13 crash events in lead-vehicle conflicts. In the what-if simulations presented here, the kinematics of the subject vehicle are changed depending on driver off-path glance behavior to determine the effect that different glance distributions could have on the crash/near-crash outcome. These what-if simulations are used to calculate the following three potential severity scales: (1) Maximum Severity Delta Velocity (MSDeltaV), (2) Model-estimated Injury Risk (MIR) index, and (3) Model-estimated Crash Risk (MCR) index.

A primary objective of this chapter is to demonstrate the usefulness of what-if simulations and potential (model-based) severity scales as tools for analyzing driver behavior in

naturalistic driving data. The aim is not to provide definitive answers but rather to show a proof of concept. First, we describe and show how to calculate the potential severity scales and compare them with the actual severity scales (DeltaV and minTTC). Then we present how these methods can be used to perform three types of analyses: (1) glance duration analysis, (2) secondary-task analysis, and (3) generalization analysis. The what-if method and potential severity scales are primarily demonstrated through examples.

The first example, glance duration analysis, presents an application of potential severity scales to evaluate the effect of the duration of the last glance, when applied to the crashes and near crashes. The second example, secondary-task analysis, presents an evaluation procedure that can facilitate relative-risk estimates of secondary tasks (e.g., navigation entry or texting) with different off-path glance distributions. Two hypothetical tasks are evaluated. The final example, generalization analysis, evaluates the selection of near crashes and crashes in the sample, with respect to accident statistics, and explores the use of extreme value theory. The what-if method is in early-stage development and needs to be validated, and the underlying assumptions and limitations need further scrutiny.

A brief description of the method and results are given below. Detailed descriptions of the what-if simulations and the potential severity scales can be found in Appendix A.

8.1 The Three Potential Severity Scales

Maximum Severity Delta Velocity (MSDeltaV) is the estimated (mass-adjusted) DeltaV of an event had the subject vehicle's driver not performed an evasive maneuver. MSDeltaV is calculated by running a what-if simulation in which any evasive braking maneuver by the driver in the subject vehicle is "removed." This removal includes the replacement of the SVspeed after the evasive maneuver with a constant speed equal to the speed just before the evasive maneuver. For crashes in which the driver did not perform an evasive maneuver, MSDeltaV is equal to the actual (original event) DeltaV.

The Model-estimated Injury Risk (MIR) index is a potential severity metric that extrapolates from any event in naturalistic driving data with an evasive maneuver (e.g., crash or near crash) to a continuous injury-risk value (called MIR) of the event, given a model of driver glance-off-path behavior. This is not the risk of an injury in the actual event as it happened, but rather the risk of a serious injury in the event had it played out differently according to the simulation. According to the Abbreviated Injury Scale, serious injury in this context is defined as MAIS3+ injury (Gennarelli and Wodzin 2005). The possible glance behaviors are assumed to be a sample from a probabilistic distribution that can be either generic or estimated from available data. The calculation of MIR presented here is equivalent to

applying all glances in a glance-off-path distribution to the kinematics of a specific event and estimating the injury risk given that distribution. That is, MIR is acquired via simulation and is related to an estimate of MAIS3+ injury risk, given the underlying assumptions. The higher the MIR index, the higher the risk of injury.

The Model-estimated Crash Risk (MCR) index is based on the same concept as MIR, but the index represents the probability of a crash. Here, the what-if simulation classifies an event as crash or no-crash for a specific glance duration. It is equivalent to each glance duration in the glance-off-path distribution being simulated, and the outcome is classified as crash or no-crash. This is different from MIR, for which the injury risk of those crashes is calculated as well.

One use for both MIR and MCR is to apply them to a sample of crashes and near crashes (e.g., the data set used in this study). This is equivalent to performing all permutations of glance-off-path (in a chosen distribution) on all near crashes and crashes in the sample, producing a distribution of MIR and MCR indices for that sample.

8.2 What-If Simulation Basics and the Calculation of MIR and MCR

The what-if simulations and calculations of MIR and MCR indices are based on a set of assumptions and a procedure that are briefly described below. For details and the reasoning around the choices, see Appendix A.

Prerequisites

- The extraction of both the subject- and lead-vehicle kinematics.
- The choice of a brake profile (how the driver brakes) to be used as a hypothetical brake response in the simulations. We use a constant 8 m/s^2 . However, the brake profile does not have to be constant and the same across events. Future implementations should consider using (1) different brake profiles depending on scenario-specific parameters, such as the estimated coefficient of friction; and (2) different brake profiles depending on the urgency of the situation (e.g., low or high looming or looming rate). The former may use estimates of the coefficient of friction from video or quantitative data [actual acceleration and, for example, antilock braking system (ABS) engagement]. Including the coefficient of friction on the results will provide higher-fidelity results that minimize the effect of road conditions as a confounding factor. The latter (urgency-based brake response) may attenuate the effect of looming rates on the outcome, but it depends on which urgency/brake response relationship is established and used.

- The choice of a driver reaction time—that is, time from looking back on the road until applying full brake. Conclusion 3 under Section 7.6 indicated that the results show that a fixed reaction time is not correct. However, we choose a fixed reaction time (0.4 second) since it produces conservative estimates of risk and shows proof of concept. The value 0.4 second is the median of the reaction time for crashes in which the reaction is made after $\text{invTTC} \geq 0.1 \text{ s}^{-1}$ is fulfilled. That is, the median reaction time for drivers when the invTTC reached at least 0.1 s^{-1} before the driver reaction (brake response) is 0.4 second. Alternative reaction models can be integrated into the current simulation. One implication of using a short and constant reaction time is that the MIR and MCR estimates will be lower on a sample level. Similar to the use of urgency-based brake profiles, if a looming-based reaction time were used (e.g., based on the results in Chapter 7) in the what-if simulation, the effect of high looming rate might be somewhat attenuated due to faster responses at high looming.
- The choice and extraction of the off-path glance distribution that should be used in the simulations. We choose the glance distribution from matched baseline events for most analyses but when comparing tasks, we also used the glance distributions of the individual tasks (as well as the total task time).
- The choice of where (an anchor point) and how to place the glance-off-road distribution in time, in the simulation.

- This choice is very important for the actual outcome severity estimates. We choose an anchor point at the threshold of the $\text{invTTC} = 0.1 \text{ s}^{-1}$ close to the crash or minTTC of the event. This is based on the assumption that the driver’s glance behavior (glance-off-road distribution) is the same as in normal driving (matched baseline) up until that point.
- A choice of injury-risk function, transforming ΔV into injury risk that is relevant for rear-end crashes. We created an injury-risk function from NASS Crashworthiness Data System (CDS) data.
- Identification of the time point of start of evasive maneuver in the original events. We use the time of the first negative derivative (deceleration) of the SVspeed after the driver reaction point.

What-If Procedure

The method of what-if simulations starts with the removal of the evasive maneuver in the original event from the SVspeed, substituting SVspeed at all times after the start of evasive maneuver with the speed just before the evasive maneuver.

Second, a simulation is run to get the outcome of “all” possible starts of an evasive maneuver by braking (Figure 8.1, Panel 1). The result is the impact speed related to the initiation of an evasive maneuver at “all” times in the event. The cyan curve in Figure 8.1, Panel 1, is the original event’s LVspeed. The red curve is the original event’s SVspeed. The green lines

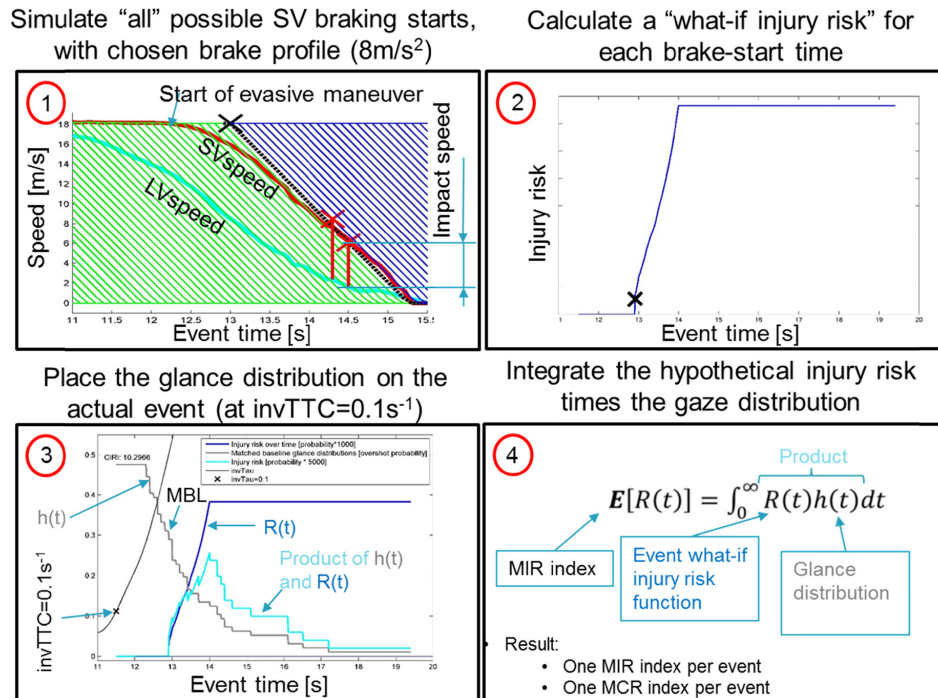


Figure 8.1. A short description of the main steps for calculating MIR and MCR.

(slopes) represent successful evasive maneuvers (where there was no crash) in the SVspeed simulations up until the first simulation ending in a crash, based on different starting points of the simulated evasive maneuvers. The blue lines (slopes) represent simulated SVspeeds where the outcome was a crash. The blue horizontal line is the simulated SVspeed until the start of each simulated evasive maneuver. The dashed black line is the evasive maneuver part of the SVspeed for the first simulation resulting in a crash. The start of the evasive maneuver corresponding to this first simulated crash is marked by a black X. The red Xs show the time instance and SVspeed value for the first and second simulations that resulted in a crash. The difference between the SVspeeds for the simulated crashes and the original LVspeed are the impact speed (shown as vertical red lines). For example, for the first crash, follow the original SVspeed, then the simulated (horizontal) SVspeed, until the black X. At that time the evasive maneuver starts. Follow the dashed line down to the red X. That is the crash point. The crash point is defined as the first time the relative distance goes below zero (integration of SVspeed and LVspeed with an initial distance).

As a third step, the injury risk for each start of evasive maneuver is calculated (Figure 8.1, Panel 2), based on (1) the estimated impact speed in the previous step, (2) the chosen injury-risk function, and (3) estimates of SV and POV masses. That is, each simulated start of evasive maneuver has a corresponding risk of injury. The black X corresponds to the black X in Figure 8.1, Panel 1—that is, the start of the evasive maneuver for the first simulated event that became a crash.

As a fourth step (Figure 8.1, Panel 3), we place the glance distribution at the chosen anchor point (in this implementation, $\text{invTTC} = 0.1 \text{ s}^{-1}$; see Appendix A). Now both the injury risks and the glance distributions are in the time domain, ready for calculating estimated injury (and crash) risk.

Finally, by integrating the product of the injury risks and the glance distribution at each time point over time, an estimate of the injury risk for this event can be obtained, given (1) the glance behavior, and (2) the original lead-vehicle kinematics and simulated subject-vehicle behavior (Figure 8.1, Panel 4). This yields a value of the MIR index. The MCR index is derived by counting instances of the simulation for an event that results in a crash and relating this to the total number of instances rather than calculating the injury risk that corresponds to each such instance (i.e., MIR).

This procedure to calculate MIR and MCR can now be applied to the crash and near-crash data to address different questions. In the following section, actual and potential outcome severity scales are compared as applied to the events in the present sample. Then, three analyses that may be performed using this approach are briefly described and results are shown.

8.3 Actual Outcome Severity Versus Potential Outcome Severity

The comparison of actual and potential outcome severity scales is made by calculating each scale value for each of the crashes and near crashes in the present sample. Figure 8.2 shows six different outcome severity scales. When comparing the actual and potential severity scales, it is apparent that the *actual* severity scales are difficult to work with across crashes and near crashes because they cannot be used for both crashes and near crashes (see the three left panels in Figure 8.2). The three left panels show actual outcome severity (what actually happened) in this study's data set. The three right panels show potential severity scales (what could have happened, created using what-if simulations) in the data set. The six scales are described in turn.

The dichotomous categorization of crashes and near crashes (leftmost panel in Figure 8.2) has so far been used extensively in analysis in naturalistic driving data, but it does not provide a way to compare the two event categories (crash and near-crash) or make comparisons within each category. The minimum time to collision (second panel from the left) is well established, and although it has some drawbacks, it is one of the most readily used scales of severity for near crashes, especially as a safety-critical event trigger in naturalistic driving studies (Rootzén and Jonasson 2014). However, even though minTTC is defined for crashes, it is not very helpful because the minTTC for crashes is by definition zero. The ΔV (Figure 8.2, third panel from the left) is also a well-established metric of actual outcome severity (Buzeman et al. 1998; Kusano and Gabler 2010; Viano and Parenteau 2010), but it is only defined for crashes, since there is no actual crash in a near crash. Of the scales presented here, the ΔV metric is the most relevant metric for actual outcome injury estimations.

The third panel from the right in Figure 8.2 shows Maximum Severity Delta Velocity ($\text{MS}\Delta V$), which is an estimate, using what-if simulations, of the ΔV had the driver not performed an evasive maneuver. Although this is a continuous potential severity metric, it does not account for any driver reaction; rather, it plays out each event to the maximum possible ΔV (excluding the following vehicle's driver accelerating into the crash). $\text{MS}\Delta V$ may still be used for evaluation of sample selections and for analyses that do not involve driver behavior explicitly. The difference between ΔV (third panel from left) and $\text{MS}\Delta V$ (third panel from right) is that ΔV takes into account the braking of the subject vehicle after the start of the evasive maneuver, while $\text{MS}\Delta V$ removes it. This difference is primarily created by the time headway at the start of evasive maneuver and the amplitude (brake profile) of subject-vehicle deceleration.

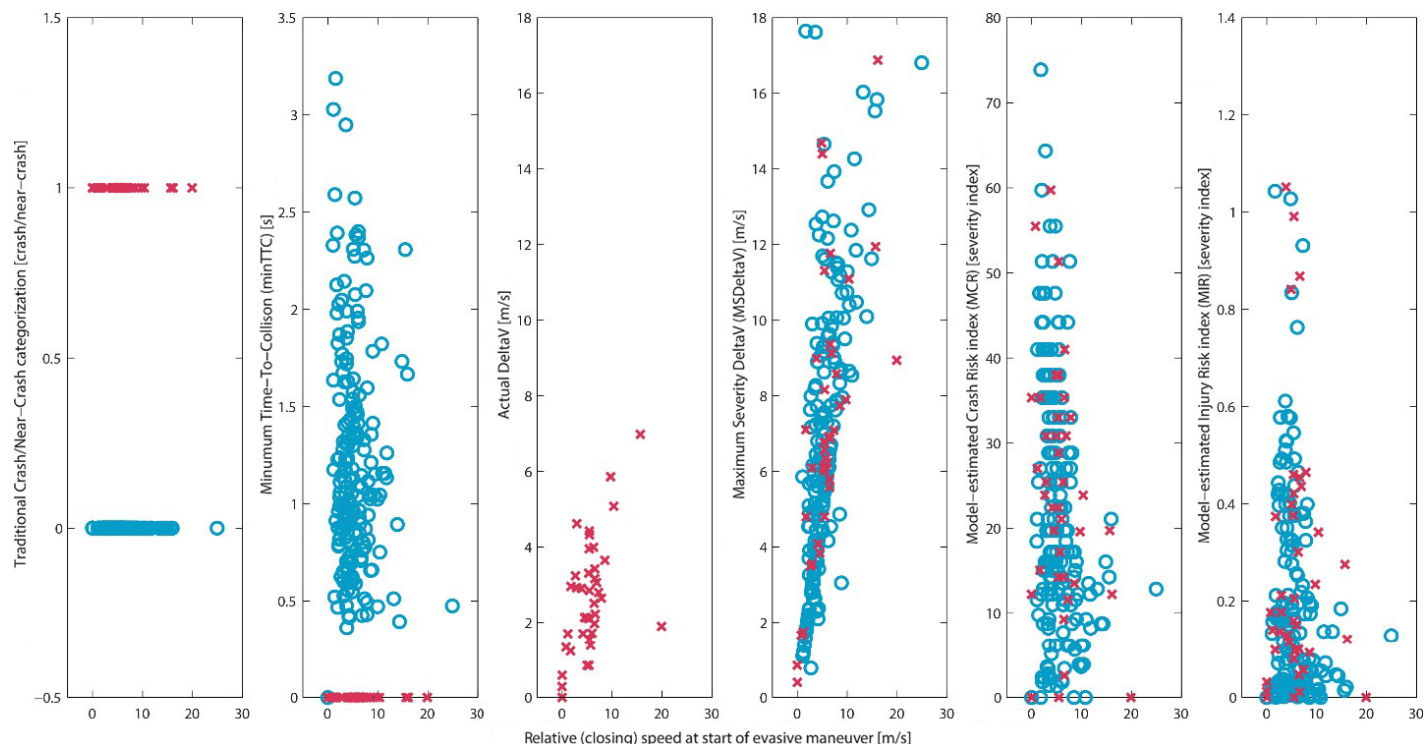


Figure 8.2. Application of six different severity scales on the crashes and near crashes used in this report. The three left plots show actual severity scales; the three right plots show potential severity scales. Left to right: dichotomous classification into crashes and near crashes, minTTC (crashes equal zero), DeltaV for crashes (no near crashes shown since DeltaV is undefined for near crashes), MSDeltaV, MCR, and MIR.

In the second panel from the right, MCR values for the individual crashes and near crashes are shown. The scale is clearly continuous for both crashes and near crashes. Thus, a high-speed near crash is rated higher than a low-speed stop-and-go crash. However, this is not what actually happened; it is what might have happened given an underlying driver behavior model. In this way, MCR is most applicable to analysis of precursors of contributing factors in safety-critical events, as opposed to analysis of how drivers avoid crashes once a safety-critical event is under way. The resolution depends on the granularity of the glance distribution (fewer glances in the creation of the distribution mean lower resolution).

The rightmost panel in Figure 8.2 shows the MIR values. This scale is continuous as well, for both crashes and near crashes. Although difficult to judge, comparing MIR and MCR, there seem to be only a few crashes and near crashes with high injury risk, while the probability of crashing is more uniformly distributed. This results, in part, from the matching of the matched baseline glance distribution and the specific crash and near-crash events in the sample; a different sample might produce different results. However, the results in our study seem reasonable since we would generally expect a low probability of serious injury and a higher and more uniform probability of crashing for any safety-critical event.

8.4 Glance Duration Analysis

To evaluate the injury risk related to a last glance of a different duration, the MIR and MCR indices can be calculated using different glance durations. A calculation of MIR was made for each last glance duration between 0.1 second and 4.0 seconds, in steps of 0.1 second. That is, instead of using the matched baseline distribution in the MIR calculations, a glance “distribution” with glances of only one specific duration was used for each simulation. These completely artificial distributions contained 100 glances (events) of the same duration (e.g., 0.7 second or 1.8 seconds). We call these *distributions* just to be coherent with the method descriptions. The single-duration distribution was applied to all crash and near-crash events respectively, producing a MIR index distribution for all near crashes and crashes (separately) for each 0.1-second step. Based on this distribution, the standard error could also be calculated. Each one-duration distribution was applied, conditioning it on overlapping the $\text{invTTC} = 0.1 \text{ s}^{-1}$ (see Figure 8.1). Note that in this and subsequent analyses, a number of events (crashes and near crashes) were excluded. Since this is a proof of concept, details of the exclusion criteria are not provided, but the majority were excluded because they were very-low-speed events or because there were some problems with data quality

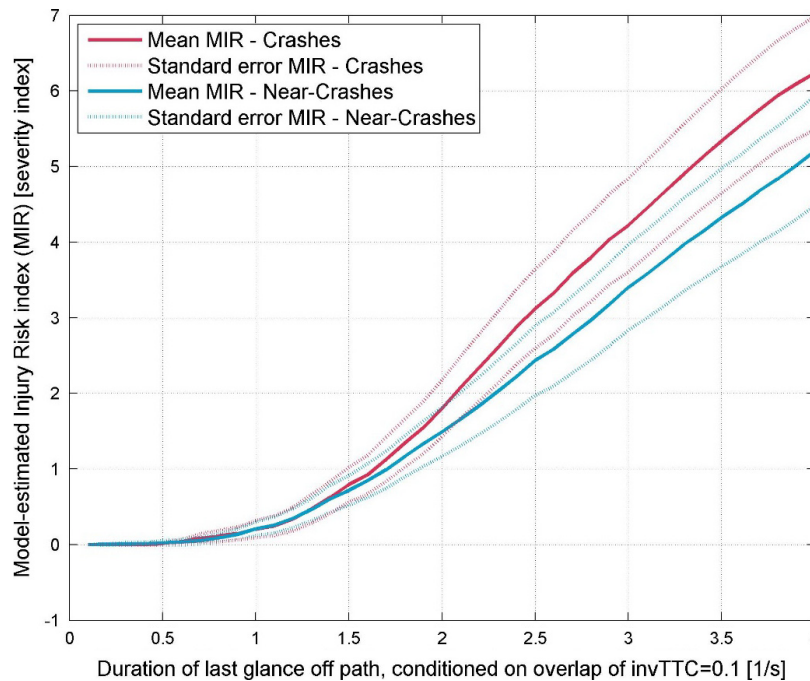


Figure 8.3. The mean MIR value for all crashes (red) and near crashes (blue) in the sample, \pm the standard error (dashed lines).

(e.g., availability of speed). The exclusion of very-low-speed events may affect the results, but since all analyses are relative (i.e., using the same sample of crashes and near crashes when comparisons are made), the effect is likely minor.

Results from Glance Duration Analysis

The MIR starts to increase more rapidly around a last glance duration of 1.25 seconds and after that is practically linearly increasing (Figure 8.3). On average, MIR for crashes seems, at least for longer durations, to reflect more severe kinematics than for near crashes, though the confidence intervals overlap. The glance anchor point ($\text{invTTC} = 0.1 \text{ s}^{-1}$) can be seen as aligning the application of the glance for both crashes and near crashes to a common “start” of critical kinematics. Then, since for the same glance duration crashes have a higher MIR than near crashes, what is different is the rate at which the event is unfolding. These results indicate that crashes in the sample are, on average, developing faster than near crashes, which is consistent with the results in Chapter 7.

8.5 Secondary-Task Analysis

The crash risk related to a visual-manual task—such as radio turning, navigation entry, or texting—can be evaluated by studying the effect of glance behavior related to these tasks (such as glance histograms collected in a separate experiment)

on actual crashes and near crashes in naturalistic data (e.g., the distributions found in NHTSA 2013). Here we introduce a method that may be used to complement to such analyses. It uses what-if simulations to assess potential (model-based) injury risk, given the assumptions for the MIR index construction described above. This section describes the method and exemplifies its use with two hypothetical task-glance distributions (Eyes off Path) with corresponding task durations (total task time). The method is based on performing simulations of how the duration of the last glance off path affects MIR when applied to our sample of crashes and near crashes—that is, what would happen had the glance distribution in the event been similar to the one described by the glance distribution of the evaluated task. We only calculate MIR, but the same methodology can just as well be applied to MCR.

In this analysis (but not all what-if analyses) it is important that the on-path glances be taken into account in the calculations. In the matched baseline distributions in SHRP 2, drivers are looking on the road approximately 79% of the time. When performing a visual-manual task, however, the time of gaze on road is much smaller, say 30% of the time (NHTSA 2013). We want to compare a task of a specific length (total task time)—for example, 20 seconds—with an alternative use of that same amount of time, as in baseline driving. The top panel in Figure 8.4 shows the matched baseline distribution with what is called a point mass at a glance duration of zero. This point mass corresponds to the time looking

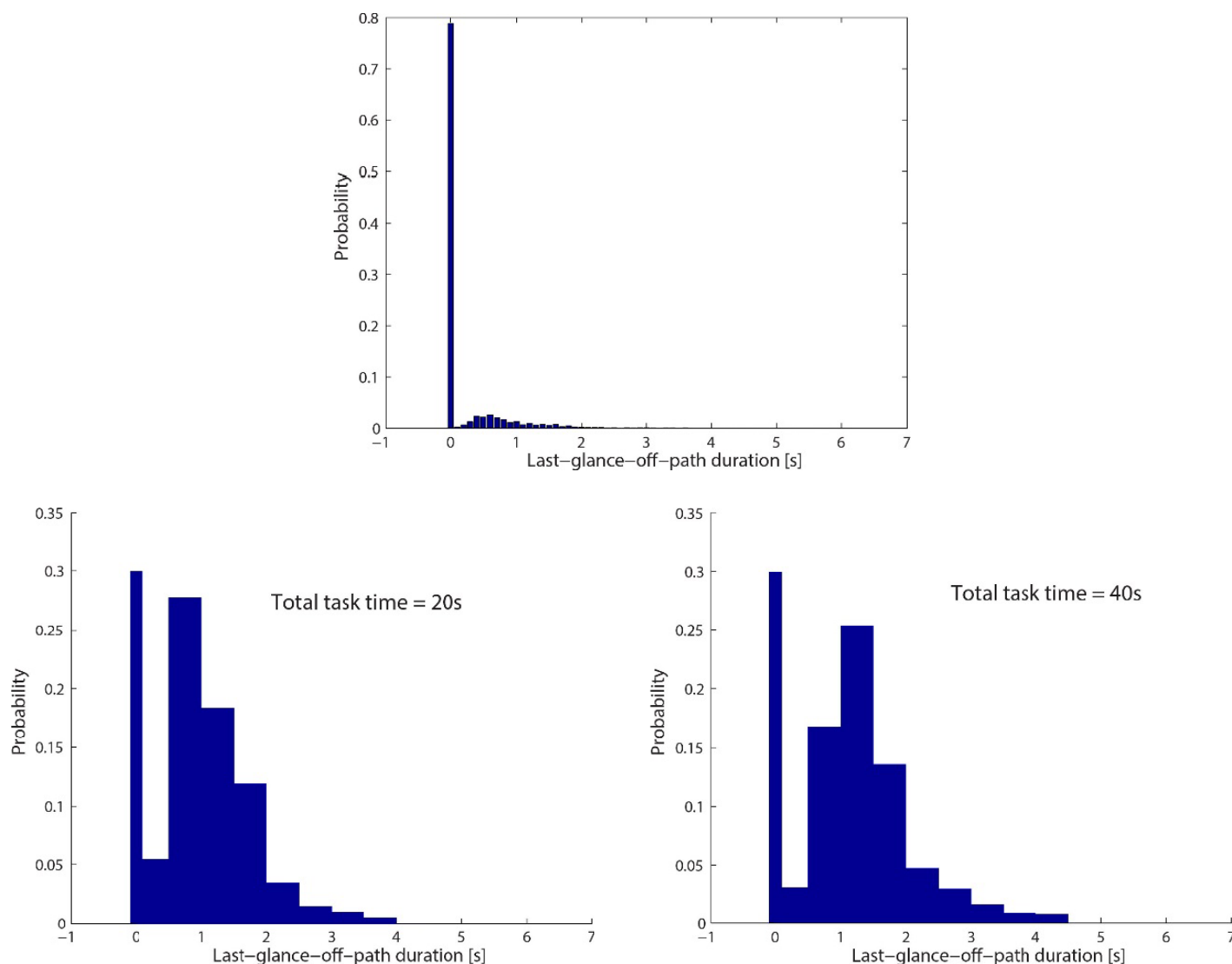


Figure 8.4. Matched baseline glance distribution with a point mass at zero (78.83%) (top), the glance distribution of a hypothetical easy task with a point mass at zero (30%) (bottom left), and the glance distribution of a hypothetical difficult task with a point mass at zero (30%) (bottom right). Point masses correspond to the portion of the time looking on the roadway for the respective task (e.g., 0.3 = 30% glances on forward roadway).

on the road. The bar at zero is 79% of the total distribution (histogram). That is, there is a 79% chance (probability of 0.79) that the driver will be looking on the road at some critical point (e.g., $\text{invTTC} = 0.1 \text{ s}^{-1}$). The bottom left panel in Figure 8.4 shows an example of a (hypothetical) “simple” task, off-road glance distribution. Here the point mass at zero is 30% of the total of the distribution (histogram); thus, while performing this task, there is a 30% chance that the driver is looking at the road when something occurs.

To get the relative risk of engaging in different tasks, an MIR index is first calculated for each of the tasks to be compared, by applying the corresponding glance distribution to the kinematics of all crashes and near crashes in the sample. The same is done for the matched baseline glance distribution. All the

glance-off-path distributions include point masses at duration zero (0) to account for the time when the driver is looking on the road (Victor et al. 2009). The resulting MIR indices for the application of each task’s glance distribution (conditioned on overlapping $\text{invTTC} = 0.1 \text{ s}^{-1}$) to the kinematics of each crash and near crash in the SHRP 2 sample can be compared with the corresponding distribution that results from application of the matched baseline glance distribution to the same set of crashes and near crashes. This can be done using the method outlined in Figure 8.1.

Since the tasks take different amounts of time to complete, the total duration of the individual tasks is needed to calculate relative risk. Let us assume that the easy task takes, on average, 20 seconds to complete, while the difficult task takes

40 seconds to complete. The $\text{RelativeRisk}_{\text{Task_vs_task}}$ of the two tasks can be calculated using the following equation, where the mean MIR of the matched baseline glance distribution is subtracted from the easy and difficult tasks' mean MIRs, and the relative risk is scaled by the difference in Total Glance Time. This equation effectively assumes an alternative use (glance behavior) for the difference in total task time between the easy and difficult tasks (20 seconds), equivalent to that of the matched baseline. That is, it takes into account the MIR for the 20-second matched baseline behavior that is the difference between the two tasks (total task time).

$$\text{RelativeRisk}_{\text{Task_vs_task}} = \frac{(\overline{\text{MIR}}_{\text{DifficultTask}} - \overline{\text{MIR}}_{\text{MatchedBaseline}})}{(\overline{\text{MIR}}_{\text{EasyTask}} - \overline{\text{MIR}}_{\text{MatchedBaseline}})} \cdot \frac{\text{TotalTaskTime}_{\text{DifficultTask}}}{\text{TotalTaskTime}_{\text{EasyTask}}}$$

Observe that this equation would have a population interpretation if the distribution of the sample of (near) accidents was representative of all the possibly dangerous situations. Since this is not entirely correct because of selection bias, a better procedure should incorporate weighting. Such weighting is not considered here, but research on how this should be implemented would be a good next step in the method development.

If only the relative risk between the task and matched baseline is desired, a simple division of mean MIRs can be performed ($\text{RelativeRisk}_{\text{Task_vs_MBL}}$). This risk includes the point mass at zero.

$$\text{RelativeRisk}_{\text{Task_vs_MBL}} = \frac{\overline{\text{MIR}}_{\text{Task}}}{\overline{\text{MIR}}_{\text{MatchedBaseline}}}$$

Results from Secondary-Task Analysis

The difference between the MIR index for the matched baseline glance ($M = 0.267$, $SD = 0.372$) and the simple task ($M = 0.776$, $SD = 1.194$) is significant, $t_{256} = 9.76$, $p < 0.001$. Similarly, the difference between the MIR for the matched baseline glance and the difficult task ($M = 0.856$, $SD = 1.150$) is significant, $t_{256} = 11.91$, $p < 0.001$ (see Figure 8.5).

The relative risk of the difficult task and matched baseline (ratio of MIR index means; $\text{RelativeRisk}_{\text{Difficult_task_vs_MBL}}$) is 3.2. The relative risk of the simple task and matched baseline ($\text{RelativeRisk}_{\text{Easy_task_vs_MBL}}$) is 2.9. Now assume the difficult task's total task time is 40 seconds, and the easy task's total task time is 20 seconds. Using the equation for relative task risk, the relative risk is calculated to be 2.31 [$\text{RelativeRisk}_{\text{Difficult_task_vs_MBL}} = (0.856 - 0.267)/(0.776 - 0.267) * (40/20)$]. This is the relative risk of engaging in the difficult task (difficult task off-path glance distribution with a total task time of 40 seconds), compared with engaging in the easy task (with a total task time of 20 seconds).

This relative task risk is almost the same as the relative risk that corresponds to two tasks with exactly the same glance-off-path distribution but with different durations (i.e., total task time 20 seconds and 40 seconds but same glance distribution), for which the relative risk would be 2.0. The small increase in relative risk (2.31 compared with 2.0) is due to the relatively minor difference in glance distributions between the two tasks. Comparing the off-path glances for the two tasks (Figure 8.4 bottom left and right), the difficult task has a few longer (>2.5-second) off-path glances than the easy task. There is also a relatively large difference in glance probability in the 0.75-second and 1.25-second bins, with a higher

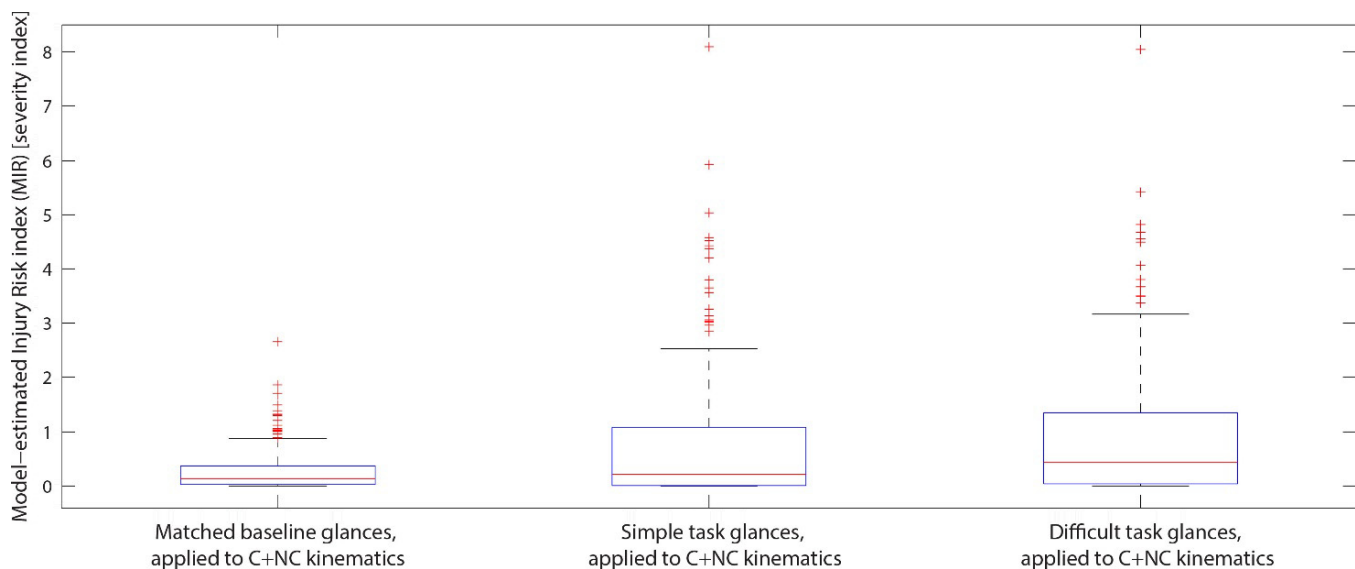


Figure 8.5. The MIR when all the glances (glance-off-path distribution) from matched baseline (left), a hypothetical simple task (middle), and a hypothetical difficult task (right) are applied to all crash and near-crash event kinematics in the SHRP 2 data set, using what-if simulations.

probability of glances of 1.25-second duration in the difficult task compared with the easy task, and vice versa for 0.75 seconds. Longer glances in either task would increase the MIR for that task (compare with Figure 8.3).

Another key component affecting the task risk is the portion (ratio) of time the driver looks at the forward path during task execution. In the MIR calculation this is represented as a point mass at zero duration in the glance distribution (Figure 8.4). If the two tasks had different point masses at zero, that would have had additional effects on the relative risk, increasing the risk for the task that had a lower portion of glances on road during the task. To illustrate how to evaluate the influence of the portion of time looking at the forward roadway, calculations of relative task risk were done for the hypothetical easy task with 11 different point masses. The point masses used were 0% to 100% glances to the forward roadway during the task, in 10% steps. Obviously, 0% and 100% glances off road during the task may not be relevant.

The relative risk for the glance-off-road ratio of the matched baseline (78.83%; point mass in Figure 8.4, top) compared with the easy task with point mass of the same value (78.83%) is approximately 1.6. This is the same relative risk as if the matched baseline off-path glances had been compared with the easy tasks off-path glance distribution, without taking the glances on the forward roadway into account. Further, by simulating different glance-on-forward-roadway ratios it is possible to identify the percentage of gaze on the forward roadway that would create a risk equal to that of driving without doing the task. In our hypothetical easy task, with linear interpolation between 80% and 90%, this point is approximately 87% on-road glances during the task (as in the matched baseline).

In summary, the two hypothetical tasks' off-path glance distributions shown in Figure 8.4 are similar, with a somewhat higher proportion of longer glances in the difficult task, while the total task time is longer for the difficult task. This results in a relative risk close to the one that would be obtained had only the total task time been taken into account. Note that this analysis assumes that drivers have the same glance behavior (1) up until $\text{invTTC} = 0.1 \text{ s}^{-1}$, and (2) in all contexts in our sample of crashes and near crashes. These assumptions need to be discussed and the method developed further. Specifically, focus should be placed on identifying means to get the context dependency in the task-glance-off-path distributions sorted out. That is, there are likely different matched baseline glance distributions for different subscenarios and also for rear-end scenarios. Subscenarios may include highway driving with heavy and light traffic, respectively, or rural close-to-intersection scenarios. When calculating MIR for the crashes and near crashes for different tasks and baseline, to calculate relative task risk, it is likely more correct to use different matched baseline glance distributions for different scenarios. It would also be

important to know if drivers would start engaging in the specific task for each of the different scenarios.

8.6 Generalization Analysis: Comparison of DeltaV Metrics

In accident statistics, the DeltaVs of crashes are recorded. To evaluate how representative the selection of crashes is in a sample (e.g., our SHRP 2 data set), a comparison of distributions of DeltaV between accident statistics and the sample of crashes can be made. Since near crashes by definition did not result in a crash, they do not have DeltaVs. Therefore, we also compare MSDeltaV for both crashes and near crashes to a DeltaV distribution from accident statistics. We use the National Automotive Sampling System–Crashworthiness Data System (NASS-CDS) crash database (NHTSA 2010c) to construct a distribution of DeltaV for rear-end crashes for this evaluation of representativeness. NASS-CDS is a probability sample of approximately 3,300–4,000 tow-away crashes involving a light vehicle per year. Each crash is investigated, and, when possible, DeltaV is reconstructed from measurements of damage to the vehicle. We used weights and survey techniques (Taylor Series) to estimate the distribution of DeltaV for rear-end striking crashes (frontal impacts) (see Appendix A). The distributions of DeltaV and MSDeltaV were plotted as cumulative distribution functions (CDFs), and the sample means were compared with simple *t*-test statistics.

Results from Comparison of DeltaV Metrics

The actual DeltaVs in the crashes in the sample are substantially lower compared with the DeltaVs in the CDS accident statistics (Figure 8.6). However, this is expected, since the CDS samples tow-away crashes, which are generally the more severe 40% of police-reported crashes. The SHRP 2 sample includes crashes with very low DeltaV (even near zero), which in many cases would not be severe enough even to meet police-report criteria. These crashes have very low risk of injury and even limited property damage. There is no significant difference ($t_{227} = 0.606$, $p > 0.05$) between the mean MSDeltaV for crashes and near crashes in the SHRP 2 sample. This means that without the just-in-time evasive maneuver, near crashes in this sample have the same potential for injury as the crashes. It is interesting that at their maximum severity, these crashes fall near the DeltaV distribution for tow-away crashes. The CDS crash severity is a notable landmark, though there is no reason why these crashes should necessarily fall near that line. Interestingly, given the low actual severity of the SHRP 2 crashes, a larger sample that includes higher-severity crashes would be expected to include some very high MSDeltaV values.

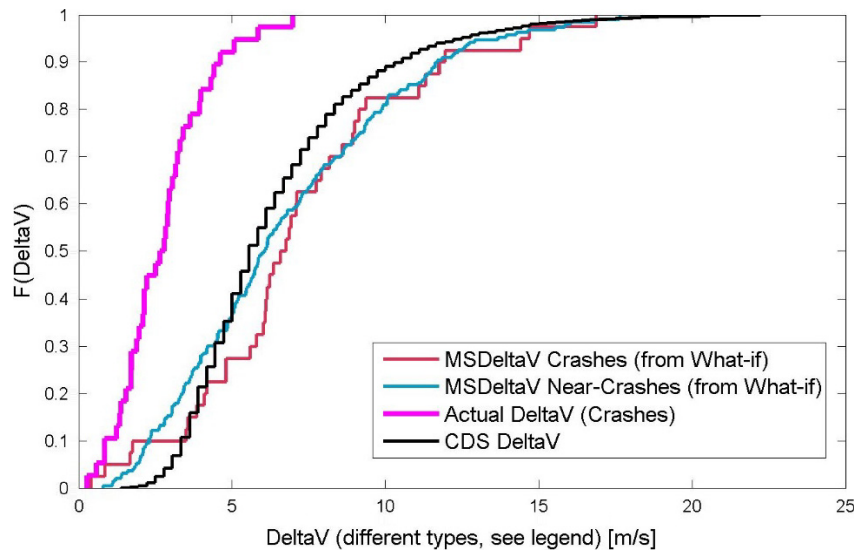


Figure 8.6. Cumulative density functions (distributions) of different DeltaV scales.

8.7 Generalization Analysis: Extreme Value Analysis

This section discusses results of models using extreme value theory to extrapolate from crashes to high-severity (extreme) DeltaV values and from near crashes to crash risk. Like the severity modeling in Sections 8.3–8.5, this approach tries to evaluate how the sample of crashes and near crashes relates to those that appear in crash databases.

Following Jonasson and Rootzén (2014), we modeled the minimum time to collision (= $\max\{-TTC\}$) from the set of near crashes using a Generalized Extreme Value (GEV) distribution. We removed TTC values of less than 1.5 seconds, and used L-Moments estimation to obtain a fit from which we could estimate the rate of $\minTTC = 0$ per near-crash event.

The parameter estimates were $\hat{\mu} = -1.058$, $\hat{\sigma} = 0.291$, and $\hat{\xi} = -0.244$. The model fit is shown in Figure 8.7. The points generally fall on the 45-degree line, indicating reasonably good fit.

The return period plot is shown in Figure 8.8. Note that the observed values lie inside the confidence intervals but are tending toward the lower bound at the higher return levels. When the fit line crosses a return level of 0.0, the corresponding return period is the number of near crashes expected before a crash would occur. This occurs at 7,815 crashes, indicating a probability of 0.00013 of \minTTC reaching zero. Interestingly, this value is below the confidence interval from Jonasson and Rootzén (2014), who used data from the 100-car study. Thus, using this set of near crashes, we estimated a greater risk of crashing than they did.

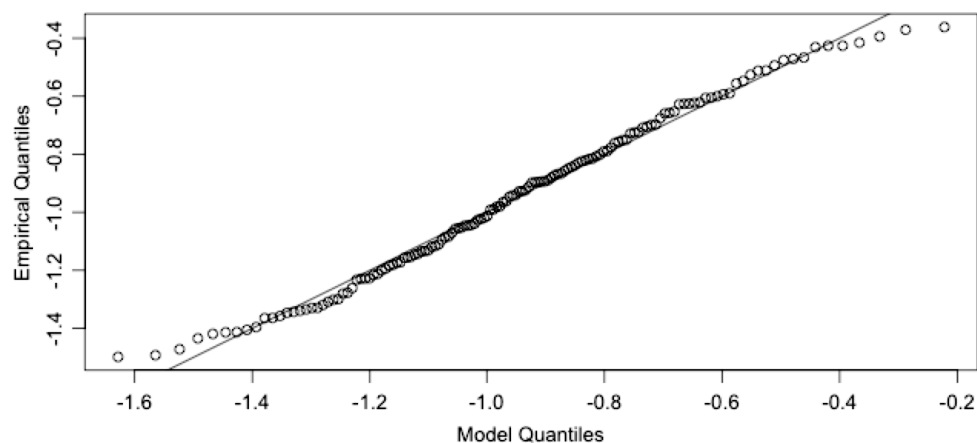


Figure 8.7. Empirical versus model quantiles for Generalized Extreme Value (GEV) fit to \minTTC data from near crashes. Points lying on the 45-degree line indicate good fit.

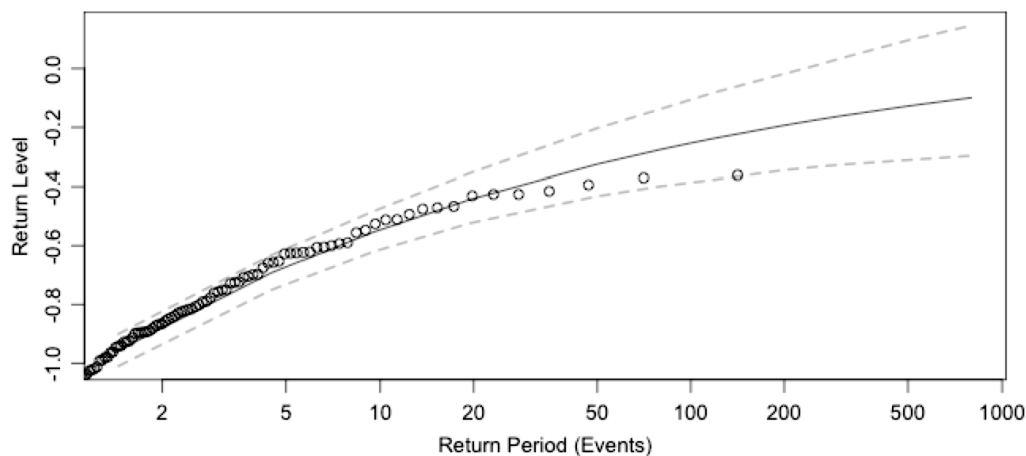


Figure 8.8. Return level versus return period for near-crash GEV fit.

We also used extreme value analysis (EVA) to estimate the tail of the impact-speed distribution for crashes. Since impact speed is not an extreme value, we used the points-over-threshold, or exceedance, model. This approach involves selecting a high threshold and modeling only the observations above that threshold using a Generalized Pareto (GP) distribution. The threshold was selected to be 4 m/s, which maximizes the sample size of the exceedances while still remaining in the tail of the distribution. This is necessary because the GP model only applies to distribution tails, and thresholds that are too low tend to produce bias in the estimates.

The GP model fit is shown in Figure 8.9. The points do not fall entirely on the 45-degree line, but seem to indicate that the empirical quantiles are higher than the model quantiles. This was the best fit of the available methods but indicates the weakness of trying to model a tail with such a small sample of points. To generalize a reasonable fit to the tail, a sample of 200 or more crashes would likely be necessary so that the tail sample (generally <1.5% of the sample) is large enough (Coles 2001).

Using this GP model, we looked at the return level for impact speed, shown in Figure 8.10. Here, the return level climbs slowly but steadily (in the log of event count). Note that return levels only make sense for a return period large enough to be above threshold. Thus, only return levels of 100+ crashes are likely to be interpretable.

To put these values in context, we computed the return level for return periods of 100, 200, 300, 400, and 500 events. These correspond to impact speeds of 14.4, 15.2, 15.7, 16.1, and 16.3 m/s. The CDS return periods for these impact speeds are plotted in Figure 8.11 against the GP return periods for comparison. In general, the GP return periods are more spread out than those from CDS (i.e., more events are needed to see values at the next level based on the GP model compared with the CDS estimates). However, these values are generally comparable to the upper tail from CDS. In general, since CDS is only tow-away crashes, we would expect the true return period to be greater (approximately double).

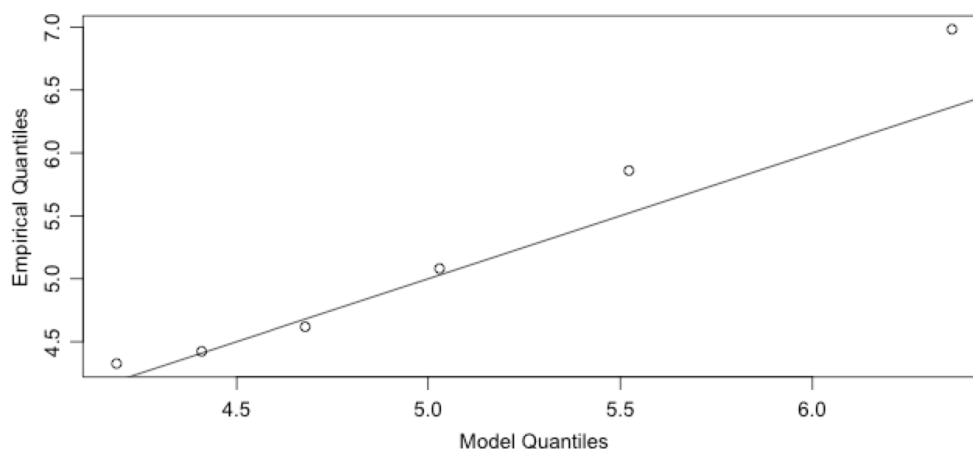


Figure 8.9. Model fit for Generalized Pareto model of impact-speed exceedances.

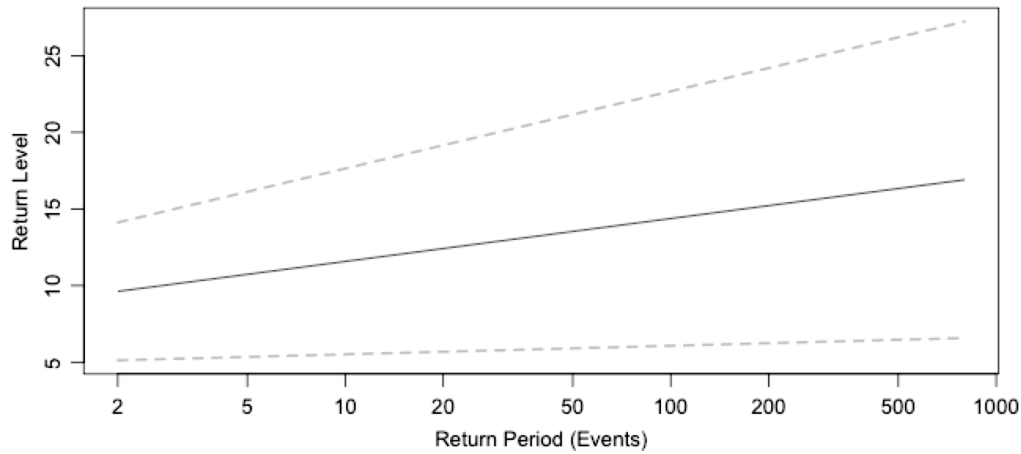


Figure 8.10. Return level graph for Generalized Pareto model of impact speed in crashes.

The EVA results demonstrate that crashes in this set are reasonably comparable to CDS crashes of the same type. Crashes from SHRP 2 form a small set of lower-speed events, but higher-impact-speed events would not be expected with a small sample in general. The EVA approach allows us to use the lower-speed events to estimate how many higher-speed events would be expected to occur if we had a larger sample of crashes. In addition, EVA makes it possible to estimate the correspondence between near-crash and crash events. We expect a crash to occur once per 7,815 near crashes, a number that is lower than was estimated from the 100-car study. Unlike the 100-car study, these near crashes appear to be more similar to crashes. At a minimum, the selection of rear-end-striking crashes creates a more uniform sample that might begin to correspond to a set like that described in Wu and Jovanis (2012).

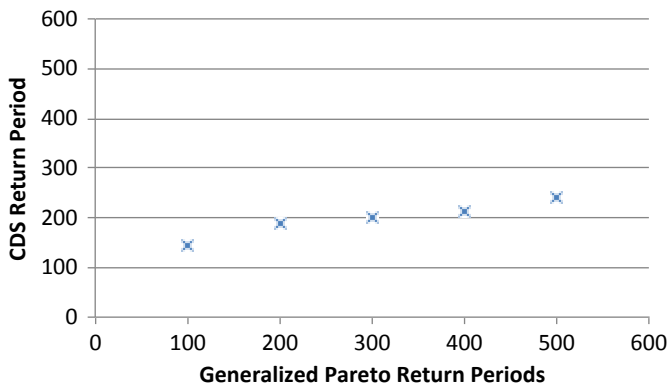


Figure 8.11. Return periods for the Crashworthiness Data System (CDS) and GP models of SHRP 2 crashes for a sample set of impact speeds.

8.8 General Discussion on Actual and Potential Severity

The what-if simulations introduced in this chapter can be used to create potential severity scales that are continuous and common across crashes and near crashes (i.e., the MIR index and the MCR index), given a model of driver behavior and a set of assumptions for the simulations. These scales can, in turn, be used for many different types of analysis. We used three examples to demonstrate proof of concept but did not aim to provide definite results.

Potential (Model-Estimated) Severity and Example Analyses

This report introduces the MIR and MCR scales, acknowledging the need for further evaluation and adjustment. However, the main aim of MIR and MCR is to establish a methodological framework and proof of concept. In particular, there is a clear need for a continuous severity scale that can be applied to both near crashes and crashes. The work described in this report shows in many ways that near crashes are not simply a less-severe version of a critical event, as the categorical methods assume. Crashes and near crashes are different instantiations of a risk that was established earlier in the event and based on mismatches between driver behavior and the event kinematics (e.g., lead-vehicle deceleration). The scales described here provide a way to focus on the potential for damage (injury or crash) of each event, rather than the way things happened to turn out in a given case. In future analyses, this should help to better differentiate precursors to crashes and methods of prevention. As discussed earlier, crashes often arise from situations that change quickly,

resulting in higher MIR and MCR indices. It may be that remedies for these situations are what is needed. Analysis to that end would benefit from separating cases (whether crash or near crash) that have high MIR/MCR from those with a lower MIR/MCR.

The next steps in the development of MIR and MCR and the corresponding what-if simulation focus on validation strategies. The validation will likely result in refinement of the method, for example, by using different reaction models or matching glance distributions with scenarios. Two different types of validations should be performed. First is the validation of the underlying assumptions in themselves. For example, how valid is it to condition the glances to overlap $\text{invTTC} = 0.1 \text{ s}^{-1}$? Is there a need to establish different glance distributions for different scenarios (e.g., time headway) and do separate analysis for the different scenarios? The second type of validation relates to comparison of the MIR outcomes to crash statistics. For example, the MIR distributions for the present sample of crashes and near crashes can be compared with observed measures of the injury risk from accident statistics.

In the glance duration analysis, the impact of the duration of a glance was evaluated. The results are in line with the results in Chapter 7 and show the potential of applying hypothetical ideas of glance behavior (i.e., not empirical glance distribution) on existing data. In the analyses using this method, a main assumption affecting the results is/will be the anchoring of the glances as overlapping $\text{invTTC} = 0.1 \text{ s}^{-1}$. This choice of anchor point was made for a few different reasons. We did want to capture the basic idea that drivers try to avoid a critical situation by adapting to the situation. In the Tijerina et al. (2004) study of eyeglance behavior during car following, it was found that drivers under normal car-following conditions generally do not take their eyes off the road unless both the SV and lead vehicle are traveling at approximately the same speed (i.e., at range rates close to zero). Although we want to adopt a strategy based on drivers avoiding critical situations, we want a driver model that is reasonably related to the kinematics of crashes and near crashes. In Chapter 7, Figure 7.4 shows that for matched baseline, only a few drivers started to look away at an invTTC higher than 0.1 s^{-1} . At the same time the mean of invTTC for near crashes is just below $\text{invTTC} = 0.1 \text{ s}^{-1}$. This led us, for proof of concept, to choose $\text{invTTC} = 0.1 \text{ s}^{-1}$ as the gaze anchor point. Future application of the method can change this anchor point. Another obvious anchor point would be $\text{invTTC} = 0.2 \text{ s}^{-1}$ as described in Chapter 7 (e.g., Figure 7.3). Appendix A also includes a description of how to apply the glance distributions at the original start of last glance off path instead of conditioning on an overlap of, for example, $\text{invTTC} 0.1 \text{ s}^{-1}$ or $\text{invTTC} 0.2 \text{ s}^{-1}$. That is, the glances start at the actual start of each last glance in the original event. Further development is needed on the choice of anchor point. Should lower-value anchor points be chosen

instead, in line with Tijerina et al. (2004)? Or should thresholds such as $\text{invTTC} = 0.2 \text{ s}^{-1}$ be used? If a lower-value approach is chosen, data quality may also be a limiting factor (noise at longer ranges; see Appendix A).

The second example addressed the calculation of relative risk by calculating MIR for two hypothetical tasks. That is, there is a need to measure the potential risks from eyeglance characteristics of tasks that have different glance distributions, total task time, and Total Eyes off Road Time (TEORT). The scales developed here present one way to incorporate these different elements of a complex glance pattern into a risk scale (MIR/MCR). More work is needed to understand whether the risks of different glance patterns are fully characterized by this approach. However, MIR was calculated for all crashes and near crashes ($N = 256$) with the two (hypothetical) task-glance-off-road distributions and matched baselines. Results showed a relative risk that was only slightly higher than the risk that only took into account exposure (20-second task versus 40-second task). However, the off-path glance distributions were only slightly different with the same ratio of eyes on road. Although this is just an example, it does show how exposure (total task time) contributes to relative task risk. The longer the total task time, the higher the risk of exposure is. Only a very large shift in the glance distribution toward longer glances for a task, or a different ratio of glances on the forward roadway between tasks, would create a similar risk. Further analysis should include

1. Real tasks (a larger set of task-glance distributions with real data);
2. Evaluation of how the glance anchoring affects the relative risks;
3. Evaluation of how different driver reaction models, including how the glance durations on path (between glances off path), would affect the results;
4. Categorizing events into subscenarios to extract a matched baseline for each subscenario and used it for the respective events MIR calculations; and
5. Further investigation of driver adaptation/self-pacing in initiation of tasks in different scenarios.

The glance anchoring analysis is practically a sensitivity analysis in which the anchor point may be, for example, (a) the original last-glance off-road start, (b) a different invTTC threshold, or (c) based on a different reaction model (e.g., what is described in Chapter 7). Also, the evaluation of reaction models and the categorization into subscenarios can be seen as sensitivity analyses—but with the focus to enhance precision in the relative-risk estimates. Finally, the question of whether a driver would initiate a specific task in a specific situation is not considered in the current model. Further work is needed to investigate how this can be integrated.

The third example addressed the representativeness of the sample of crashes and near crashes. This was done by comparing DeltaV from accident statistics (NASS-CDS crash database) with the actual DeltaV of the crashes in the sample as well as the MSDeltaV for both crashes and near crashes. The results were as expected and were further corroborated by EVA analysis.

Limitations

The potential severity metrics developed here depend on the extent to which the underlying behavior model actually represents (or is related to) driver behavior in the contexts in which it is applied. It is important to take the limitations of these metrics into account in any analysis. It is, for example, not wise to mix analysis of the behavior that actually happened in an event with the potential severity scales, unless there are strong reasons for doing so. The next step in the development of MIR, MCR, and the corresponding what-if simulations is to focus on validation strategies—that is, validation of the individual assumptions (including further refinement) and comparison with accident statistics. Since all scales rely on the underlying model, it is those that have to be validated further, in the context of use in what-if simulations.

There are 15 identified assumptions related to the what-if simulations and the creation of MIR and MCR. These are described in detail in Appendix A. Of the 15, five are in need of particular scrutiny and evaluation. We believe these five (more than the others) may affect MIR/MCR index calculations in a way that not only shifts the scale but also may affect conclusions without easily being about to assess why. The following is a list of these five assumptions (details are provided in Appendix A). Note that the first four are at different levels and violate conclusions in previous chapters. Future applications of MIR and MCR should likely revise the implementation; however, due to late data availability, parallel analysis (results from other chapters arrived late), and the aim only to show proof of concept, these assumptions stand and were kept for the current implementation:

1. Driver's glance behavior (glance-off-path distribution) is the same as that in the matched baseline (or task when performing task analysis) up until the chosen anchor point ($\text{invTTC} = 0.1 \text{ s}^{-1}$);
2. Drivers respond by braking at 8 m/s^2 in all situations;
3. Brake initiation is made a fixed reaction time (0.4 second) after the driver has looked back on the road;
4. The quality of data is not affecting results significantly; and
5. It is reasonable to assume that, had the event not become critical, the driver would have continued at the same speed as just before the evasive maneuver.

The extreme value analysis provides a glimpse into the relationship between near crashes and crashes. It would benefit from a larger sample size and might be applied to a larger number of descriptors. In addition, future analysis might try the multivariate approach described in Jonasson and Rootzén (2014). Further, crashes and near crashes result from an interplay between potentially critical kinematic situations and local glance behavior. Thus, there are typically many more similar kinematic situations present in the driving data that—combined with extreme glance behavior—would have resulted in near crashes or crashes. It is of some interest to try to develop estimation methods to weight the observed crash kinetics to better represent these potentially critical situations and to estimate their frequencies per driving distance or driving time.

8.9 Conclusions on Actual and Potential Severity

This chapter has described a novel approach to analyzing driver behavior in naturalistic driving data. Specifically, we propose two potential severity scales, created using mathematical simulations that apply a model of driver glance behavior to kinematics based on actual crashes and near crashes. The two scales (MIR and MCR) are continuous and calculable for crashes and near crashes alike. These properties may be fundamental in future analysis of naturalistic driving data, but they are not present for available actual outcome severity metrics, such as DeltaV and minTTC. We recommend that DeltaV and minTTC be calculated for all crashes and near crashes, respectively. Proof of concept of the evaluation of visual-manual task risk was established through the application of MIR to two (hypothetical) visual-manual tasks. The results of the example application of MIR (to study the effect of last glance-off-path duration between crashes and near crashes) are in line with results in Chapter 7. That is, they show that crash scenarios play out faster than near-crash scenarios—higher risks at shorter glance durations. The potential severity metrics are likely to have many uses. Those uses range from visual-manual task evaluation—by facilitating a continuous metric in advanced driver assistance systems evaluation (rather than simply counting instances of crashes and near crashes)—to providing a tool for further validation of driver models (e.g., reaction models). Given the inherent limitations in the metrics, assumptions must be evaluated extensively for each analysis use-case.

We demonstrate how a comparable, continuous metric for crashes and near crashes can allow a more nuanced analysis of the precursor conditions, which can be worse in some near crashes than in some crashes. This approach focuses on common elements of the precursor conditions and provides a way to analyze them without including the influence of actions that were taken afterwards (i.e., success or failure to avoid).

While success or failure to avoid is important for understanding avoidance itself, *the outcome of an event does not, in itself, determine the inherent risk of crashing in that event.*

Another use of the approach is to evaluate the consequences of different task-related glance distributions on a large set of crashes and near crashes. Potential consequences of tasks depend on the inherent risk in an event, which is often related to how fast it develops. These, again, are independent of what actually happened.

Finally, the EVA begins to quantify the relationship between crashes and near crashes. The similarity of precursor conditions for near crashes and crashes, combined with the very large number of EVA-estimated near crashes per crash, suggests that avoidance is common. Thus, failure to avoid may be fairly random, while avoidance of the circumstances (focus on the precursors) might be more effective in reducing crash risk.

Thus, the analyses undertaken to answer the research question, What crash severity scale is best suited for analysis of risk? resulted in the formulation and proposal of two potential severity scales: Model-estimated Injury Risk (MIR) index and Model-estimated Crash Risk (MCR) index. These

scales were created using mathematical simulations, applying a model of driver glance behavior to kinematics based on actual crashes and near crashes, and represent what might have happened had the event played out according to a specific driver model. The two scales (MIR and MCR) provide continuous values and can be calculated for actual crash and near-crash events. However, further work is necessary to validate the scales. Note that the severity scales are simulated. Actual severity scales—Delta Velocity (DeltaV) for crashes and minimum time to collision (minTTC) for near crashes—are still the most relevant metrics when analyzing actual severity (what actually happened in the event) and should be calculated for the SHRP 2 data set. The main drawback with the actual severity scales is that they cannot be used to compare both crashes and near crashes. This property—the ability to compare potential severity across crashes and near crashes—is enabled by our proposed MIR and MCR scales. It is important to note that these scales are also enabled by naturalistic data. Without the detailed time-series data leading up to crashes and near crashes, the MIR and MCR scales could not be computed.

CHAPTER 9

Conclusions and Recommendations

This chapter focuses on answering the detailed research questions first and then, the main research question.

What are the most dangerous glances away from the road, and what are safer glances? Can risk from distracting activities (secondary tasks) be explained by glance behavior?

The analysis started by replicating previous findings. The analysis shows generally similar results that are consistent with previous findings regarding distracting activities and glance metrics. In general, distracting activities occurred frequently—much more frequently in crashes, near crashes, and baselines than impairments such as drowsiness. In line with previous naturalistic driving studies (e.g., Fitch et al. 2013; Klauer et al. 2006, 2010, 2014; Olson et al. 2009), visually demanding tasks were associated with the highest risk. When considering crash and near-crash (CNC) situations combined, the results showed that the aggregate category of Portable Electronics Visual-Manual (OR 2.7, CI 1.4–5.2), and in particular, one individual activity in that category, Texting (OR 5.6, CI 2.2–14.5), had the highest odds ratios, suggesting a substantial risk.

Talking/Listening on Cell Phone was found to decrease crash/near-crash risk significantly compared with not engaging in a phone conversation (OR 0.1, CI 0.01–0.7), representing an estimated 10-fold reduction in risk compared with baseline (OR 10 if the sign of the coefficient is reversed). There were no crashes when drivers were Talking/Listening on Cell Phone.

Odds ratios for more than 50 distracting activities were examined. However, many of the activities did not occur frequently enough to achieve statistical significance. Distracting activities do not occur as frequently as glances and thus need larger sample sizes. Other individual categories (e.g., Locating/Reaching/Answering Cell Phone or Adjusting/Monitoring

Radio) or other aggregate categories (e.g., Original Equipment or Vehicle External Distraction) were not significantly risky.

To determine whether risk from distracting activities (secondary tasks) can be explained by glance behavior, it was necessary to first find the most predictive glance metrics. Many Eyes-off-Path glance behavior metrics were found to be powerful predictors of risk, much more so than the type of distracting activity (secondary task). The finding that glance behavior plays a key contributing role in crashes and near crashes is in line with existing research (e.g., Klauer et al. 2006, 2010, 2014). However, our analyses of separate glance metrics specified more strongly the benefits of using glance metrics to estimate risk. In general, the largest risk estimates were shown when crashes were analyzed separately from near crashes.

Although very strong Eyes-off-Path–risk relationships were shown in separate glance metrics, the relationship between glance behavior and risk cannot be reduced to a single metric, as there is no separate metric that fully accounts for risk on its own. The relationship is analogous to accounting for discomfort associated with heat. Temperature is a good metric that accounts for much of the variance, but including humidity would result in better predictions, as would including wind speed. Each glance metric helps inform the risk estimates.

The most sensitive glance metric model was a linear combination of three-glance metrics as it was most predictive of crashes and near crashes. The first glance metric, Off3to1, represents the proportion of time the eyes were off path from 3 seconds before until 1 second before the crash or minimum time to collision. The second glance metric is the mean duration of off-path glances during the 12 seconds preceding the crash point or minTTC (mean.off). The third metric, mean uncertainty (m.uncertainty), is the mean value (in the same 12 seconds) of a composite measure based on the “uncertainty model” of the driving situation (Senders et al. 1967). However, if an individual metric is to be used, the Off3to1 metric was the second most powerful model after the linear combination of the three-glance metrics and much more powerful than the

max.off and m.uncertainty metrics used individually. Note that the Off3to1 metric is equivalent to the metric Percent Road Center (PRC) (Victor et al. 2009). The PRC metric takes the percentage of *on*-road gaze, while the Off3to1 metric takes the proportion (0–1) of *off*-road gaze; thus, they produce directly comparable values (Off3to1 being the inverse of PRC).

Thus, based on our results up to this point, the question, What are the most dangerous glances away from the road, and what are safer glances? can be answered in this way: the most dangerous and safest glances are quantified by the three-metric glance model, which combines a metric of inopportune glance, mean glance duration, and a composite measure estimating the driver's uncertainty of the driving situation.

Returning to the question of whether this most sensitive glance metric model can explain the risk from distracting activities, we found that it was substantially more predictive than the models based on distracting activities. Because the three-metric glance model was so superior, it might be expected to fully account for the effect of distracting activities (secondary tasks). However, the three-metric model could not be compared in a straightforward manner with distracting activities because the distracting activities were only coded in the 5 seconds preceding the precipitating event and 1 second after. Instead the best-performing glance model available at the precipitating event was used: the proportion of Eyes off Path in the 2 seconds overlapping the precipitating event. The aggregated category of distracting activities called Portable Electronics Visual-Manual was accounted for by the proportion of Eyes-off-Path metric. However, we also found that the risk-increasing effect of Texting and risk-decreasing effect of Talking/Listening on Cell Phone were not accounted for by that metric. This gives some indication that the crash/near-crash risk of neither Texting nor Talking/Listening on Cell Phone is fully determined by glances. Hence, properties of the activities themselves further add to the risk. The present analysis does not further indicate what these properties might be, but cognitive load and motivational factors likely play a role in both Texting and Talking/Listening on Cell Phone. However, the influences of distracting activities might be explained by the more powerful three-metric glance model. This is clearly an interesting a topic for further research.

On the basis of these results our answer to the question, Can risk from distracting activities (secondary tasks) be explained by glance behavior? is mixed and requires further research: Portable Electronics Visual-Manual was accounted for by the proportion of Eyes off Path in the 2 seconds overlapping the precipitating event, but Texting and Talking/Listening on Cell Phone were not.

The finding that Talking/Listening on Cell Phone significantly reduces risk compared with not engaging in a phone conversation (OR 0.1) is in line with previous naturalistic driving studies (Olsson et al. 2009; Hickman et al. 2010) but

shows an even stronger protective effect (lower OR). The present study extends these results in several ways. First, the number of crashes in Olson et al. (2009) was limited, and it has been suggested that the protective effect primarily occurs for near crashes and incidents rather than crashes. However, the present results point in the opposite direction. None of the crashes in the present study involved phone conversation and thus, increasing the proportion of crashes would be expected to reduce the odds ratio for combined crashes and near crashes even further. Second, previous studies found the protective effect only for commercial vehicle (mainly long-haul truck) drivers; the present results show that it also occurs for passenger-car drivers. Third, one criticism against the previous studies has been that the baselines were poorly matched with the crashes and near crashes. However, the present results demonstrate that the effect also occurs with a baseline sample of closely matched events.

One important caveat is that the present study included only rear-end scenarios, and it is unclear to what extent these results generalize to other scenarios. The cognitive load induced by phone conversation may lead to an increased crash risk in other crash scenarios involving higher cognitive or executive functions (such as planning, decision making, novel sequences of action, or inhibiting habitual responses) rather than the more automatic reaction to a looming lead vehicle. For example, cognitive load may lead to impaired detection of red traffic lights or other types of signalized information in intersection scenarios. Indeed, one possible reason for the stronger protective effect in the present study is that the protective effect is strongest in rear-end scenarios, which constitute a relatively large portion (about 30%) of all crashes. Thus, any increased risk due to cognitive load in less frequent crash scenarios may be washed out by the strong protective effect in the more frequently occurring rear-end scenarios. This hypothesis can be further investigated by examining the prevalence of cognitive load for different crash types in the SHRP 2 data set. Note that the protective effect of talking/listening found in the present data may not necessarily generalize to more severe crashes involving injuries and fatalities.

So how can this strong protective effect for rear-end crashes be explained? One common suggestion is that the cognitive load induced by phone conversation counteracts drowsiness. This explanation seems consistent with previous findings that the effect mainly occurs for commercial vehicle drivers, in particular long-haul truck operations. However, in the present study, drowsiness was relatively rare in both baselines and crash/near-crash events. Thus, this explanation does not seem to account for the present results.

Another possible explanation derives from the well-established experimental finding that phone conversation (and other cognitively loading tasks) induces a concentration of gaze toward the road center. If this effect occurs in

naturalistic driving, the chances are greater that the eyes are on the forward path when a lead vehicle brakes, thus disabling the key mismatch mechanism behind Category 1 rear-end crashes (further discussed below). Indeed, Victor and Dozza (2011) found such a gaze-concentration effect in the 100-car study data. In the present data shown in Figure 6.5, Talking/Listening was not associated with a general reduction in off-path glances. Thus, by contrast to the 100-car study, the present data do not lend strong support for a pure gaze-concentration explanation. However, if the glances to the phone associated with hanging up are excluded, the present data show at least a tendency for gaze concentration. Thus, subtle differences in the distraction coding may be one reason for the differences between these studies. Also, the 100-car analysis included all scenario types while the present analysis only included rear-end scenarios.

Another related explanation is the task displacement hypothesis. Recent naturalistic studies suggest that drivers are on the phone about 10% of their driving time (Fitch et al. 2013). In our present matched baselines sample, the prevalence of Talking/Listening on Cell Phone was about 5%. Thus, because of its prevalence, phone conversation may *displace* or reduce engagement in other more risky activities such as texting, thus reducing the overall risk. The analysis of glance locations in Figure 6.5 clearly offers some support for this idea.

A more specific version of this hypothesis is what may be called the *glance displacement hypothesis*. As shown in Figure 6.5, the proportion of off-path glances was similar for matched baseline events with and without talking/listening coded as a distraction. Even if the phone glances are removed (as discussed above), the proportion of off-path glances in these events is still fairly high. The great majority of the glances presumably occurring during phone conversation are toward the left/right windshield and the left/right mirrors; almost no glances are to other secondary tasks (Figure 6.5). Thus, off-path glances while Talking/Listening on Cell Phone were mainly related to the driving task (e.g., road scanning and routine mirror checks while overtaking). This suggests that visual time sharing between driving-related activities is more “in pace” with the driving situation than visual time sharing with a secondary task. So, over and above a general gaze-concentration effect, replacing secondary-task glances with driving-related glances may increase the chance that the driver looks ahead at the critical moment when the lead vehicle brakes. In other words, driving-related glances may be less likely than secondary-task-related glances to combine with a sudden, unexpected, lead-vehicle closure. Therefore, the “perfect mismatch” mechanism outlined in Chapter 7 is more likely to be disabled during talking/listening compared with other instances of normal driving. This hypothesized difference between driving-related and secondary-task-related glances may be further exacerbated by the fact that driving-related

glances usually occur at a smaller visual eccentricity relative to the forward path than secondary-task glances. A small visual eccentricity increases the chance that a looming lead vehicle will be detected early in the peripheral field of view. This explanation appears to be the one that best fits the present data. However, more detailed analyses are needed to further examine this and other potential explanations for the protective effect.

Factors other than Eyes off Path also contribute to rear-end crashes. First, factors such as age (16–17 years and 76+ years) and visibility problems (visual obstructions or rain) may influence risk. Second, the present sample contains a significant proportion of crashes and near crashes in which off-path glances were not the main contributing factor, such as when the driver looked at the road for the entire 12 seconds before the crash or only looked away at the beginning of the event. These crashes and near crashes were not systematically investigated in the present study. However, it may be that false expectations, small headways, and/or inadequately performed avoidance maneuvers may be key contributing factors. Clearly, further analysis is needed.

How does the timing of lead-vehicle closing kinematics in relation to off-road glances influence crash risk?

Given the present and previous findings on the importance of glance timing (e.g., Liang et al. 2012; Victor and Dozza 2011), we set out to study off-path glance timing with lead-vehicle closing kinematics and visual cues. This analysis revealed a distinct mechanism for many of the crashes. In line with Tijerina et al. (2004), we found that drivers in most cases did not look away when the lead vehicle was closing. Drivers who crashed typically looked away just before the lead vehicle started closing and did not look back until collision was unavoidable. This implies that, while drivers generally self-regulate their off-road glances based on expectations of how the situation will develop, their self-regulation is not always effective because expectations are sometimes violated. The criticality when looking back, and thus the crash risk, is largely determined by an interaction between last glance duration and the rate at which the situation changed during the glance (operationalized here in terms of inverse TTC change rate). The event outcome is also determined by the vehicle’s braking capacity and the driver’s time to react.

Thus, the key mechanism behind these types of rear-end crashes (grouped as Category 1, Inopportune glance, in Figure 7.8) can be understood as a perfect mismatch between last glance duration and situation change rate (in line with the general mismatch conceptualization of inattention suggested in Engström, Monk et al. 2013). The crashes grouped under Category 2, Looking away in an already critical situation,

followed a similar pattern. But here the driver looked away when the vehicles were already closing, often because of visibility problems that presumably impaired looming detection.

The probability for the type of mismatch characterizing Category 1 and, to some extent, Category 2 crashes depends on the joint probability distributions of glance durations and situation kinematics. Since long glances are rare, many crashes occur due to the combination of a relatively short glance and a high change rate. Thus, an important finding of the present analysis is that glances that lead to crashes may not necessarily have to be long. The majority of the crashes in the present sample were associated with glances shorter than 2 seconds.

This key finding motivates reconsideration of the question, What are the most dangerous glances away from the road, and what are safer glances? One way to think about which glances are safer than others is in terms of the boundary drawn in Figure 7.8. Under normal conditions (e.g., a dry road surface, normal braking capacity, normal visibility conditions), glances can be regarded as safe as long as they appear under this line, which is determined by the interaction of glance duration and kinematics change rate.

Thus, the answer to the first part of the question can be reformulated like this: Dangerous glances are those during which the driver is exposed to the risk of a rapidly changing situation. This is naturally partly related to the glance duration; the longer the glance, the greater the probability that the kinematics will develop in such a way that the perfect mismatch occurs. However, the second part of the equation is the natural variability in vehicle-following situation kinematics. Drivers are normally successful in controlling this variability by means of anticipation. However, as shown in the present analysis, the safety margins adopted by drivers when looking away are often insufficient to protect them from unexpected rapid changes in situation kinematics. A reformulated answer to the second part of the question can be stated as follows: *An off-road glance is only perfectly safe when the safety margins adopted are sufficient to protect the driver if the situation changes rapidly during the glance.*

An important further question is this: What made the driver look away at that critical moment? It is likely that off-path glances further “upstream” in the chain of events leading to the crash may induce misunderstandings of the situation that influence the decision to initiate the critical last glance. These types of upstream effects of off-path glances have not been addressed in the present analysis and constitute an important area of further research.

What crash severity scale is best suited for analysis of risk?

The analyses to answer to this research question resulted in the formulation and proposal of two potential severity

scales: Model-estimated Injury Risk (MIR) index and Model-estimated Crash Risk (MCR) index. These scales were created using mathematical simulations, applying a model of driver glance behavior to kinematics based on actual crashes and near crashes, and they represent what might have happened had the event played out according to a specific driver model. The two scales (MIR and MCR) provide continuous values and can be calculated for actual crash and near-crash events. However, further work is necessary to validate the scales. Note that the severity scales are simulated. Actual severity scales Delta Velocity (DeltaV) for crashes and minimum time to collision (minTTC) for near crashes are still the most relevant metrics when analyzing actual severity (what actually happened in the event), and analyses of the SHRP 2 crashes and near crashes should use them. The main drawback with the actual severity scales is that they cannot be used to compare both crashes and near crashes. This property—the ability to compare potential severity across crashes and near crashes—is enabled by the proposed MIR and MCR scales. It is important to note that these scales are also enabled by naturalistic data. Without the detailed time-series data leading up to crashes and near crashes, the MIR and MCR scales could not be computed.

How can we change glance behavior to be safer, and how do the results of this research translate into countermeasures?

The findings of this research have several implications for countermeasures. Based on the general mismatch mechanism identified in the present analysis, countermeasures for rear-end crashes may be considered in terms of two general aims: (1) reduce the risk for the occurrence of mismatches between off-path glances and changes in situation kinematics and (2) if such mismatches still occur, maximize the chance of recovery.

Human-machine interaction design, distraction guidelines, and other regulatory agency countermeasures

HMI design and performance guidelines, such as the ESoP, AAM, and JAMA guidelines, and standards such as ISO (see Regan, Lee, and Young 2008) are important tools that should be used at different stages in the user-centered design process to support the safe design and evaluation of vehicle human-machine interfaces for driving-related systems. HMI design guidelines provide design specifications for installation, information presentation, interaction with displays and controls, system behavior, and information about the system. HMI performance guidelines set out the minimum level of performance that a system must meet when tested in accordance with a prescribed test method.

Current HMI guidelines provide a mix of design and performance guidelines. Problems associated with current guidelines, as well as standards developed around the world, were reviewed in Regan, Lee, and Young (2008). Regan, Victor et al. (2008) indicated that the main concern with current guidelines and standards is a lack of scientific knowledge to provide unequivocal assessment and robust compliance criteria for performance testing. Ideally, the approach to develop and implement performance standards for vehicle electronic devices would prescribe “practical, repeatable methods to measure the distracting effect of these devices and reliable benchmark levels of unacceptable performance” (Regan, Victor et al. 2008). These should be consistent for original, aftermarket, and portable devices and should not stifle product innovation. An aim of this project was to address that lack of scientific knowledge.

The main recent development regarding HMI guidelines is the NHTSA Visual-Manual Driver Distraction Guidelines for In-Vehicle Electronic Devices, released in 2013. It contains a set of design guidelines and acceptance criteria for performance testing with the aim of minimizing visual-manual distraction and promoting nonvisual means for interaction. The evaluation methods in these guidelines are based on previous naturalistic driving study reports, such as Klauer et al. (2006) and Olson et al. (2009). In particular, they argue that in-vehicle systems which cannot be used without taking the eyes off the road for more than 2 seconds at a time are inappropriate for use while driving. The 2-second limit is included in several of the guideline performance criteria that must be met by in-vehicle systems to be considered safe to use while driving. The 2-second limit for what constitutes unsafe off-road glances is also central to the Alliance of Automobile Manufacturers design guidelines.

Note that the present results are based on Lead-vehicle pre-crash scenarios and may not transfer to other pre-crash types. However, given these results, some observations can be made that may have relevance for distraction guidelines, as follows:

- The results clearly emphasize the importance of designing interfaces that minimize the need for visual interaction. Eyes-off-Path glances are strongly associated with crash risk, near-crash risk, and the combination of both.
- The results show that off-path glances leading to rear-end crashes are most often due to visual interaction with portable electronic devices rather than vehicle-integrated systems. Thus, efforts should focus on minimizing Eyes-off-Path glances with portable electronic devices.
- The risk-reducing effect found for Talking/Listening on Cell Phone seems to support the potential for nonvisual interfaces to enable safe interaction. Future research is needed to investigate whether the present findings generalize to other scenarios and to other nonvisual, but cognitively loading

tasks, such as voice interaction. In addition, the present results emphasize the need to confirm that such interfaces are indeed nonvisual.

- The results show that the majority of crashes were associated with relatively short glances. This is likely due to their higher frequency; thus, based on the present results, there is a higher likelihood of mismatch with external events. These results indicate that eliminating long glances (e.g., glances above a limit of 2 seconds) will not eliminate the problem. Rather, the results clearly demonstrate that inopportune glances of normal duration with the wrong timing relative to high lead-vehicle closure rates often produce rear-end crashes. HMI design should thus also minimize occurrence of shorter glances.
- The present analyses were not specifically designed to answer the question of whether or not the NHTSA 12-second Total Eyes off Road Time (TEORT) limit for distracting activities (secondary tasks) is supported. Fully addressing this issue would require coding each distracting activity from start to end. The present analysis used fixed 6-second or 12-second windows; thus, the coded data excludes cases that would violate the 12-second NHTSA limit. However, the present data can be examined to see if they support the general notion of the NHTSA 12-second TEORT limit, or if crashes are associated with more TEORT. Several sources of results need to be examined.

First, the analysis in Section 6.2 showed that odds ratios are highest for the proportion of time the eyes are off the forward path during the window from 3 seconds to 1 second before the crash point (Off3to1), but the odds ratios in the two preceding windows (5 seconds to 3 seconds, and 7 seconds to 5 seconds) also achieved statistical significance. Note that significance in those two preceding windows can be present even if they do not provide a significant contribution *beyond* that of the Off3to1 (the extreme case would be if these variables were perfectly correlated with Off3to1). The research team analyzed whether extended periods of eyes off the road in preceding windows might add to the risk. The results showed that there was no significant cumulative effect from the proportion of Eyes off Path in the windows preceding the Off3to1 variable. Thus, this analysis showed that risk was *not* associated with more Total Eyes off Path Time (TEOPT) than the 3 seconds to 1 second before the crash point.

Second, the analysis of glance characteristics showed that in addition to the Off3to1 variable, the mean single glance duration during the 12-second window (mean.off), and the mean level of uncertainty (m.uncertainty) during the 12-second window were together the best predictors of risk from glance data. Thus, although cumulative TEORT (in the time period before 3 seconds before the crash) was not supported as a more predictive indicator of risk, other characteristics within

the 12-second window (mean single glance duration and mean level of uncertainty) were supported.

Third, when examining the joint probability of lead-vehicle closure change rate and eyes off road (Chapter 7), a strong relationship was shown in the mismatch mechanism. The main determinant of risk appears to be the probability of mismatch, because fast change rates and short glances are associated with crashes, as well as long glances and slower change rates. Thus, although there does not appear to be a risk contribution from an accumulation of TEORT and the risk can be pinpointed in the mismatch mechanism, it can be argued that risk increases with a total exposure from the amount of eyes off road over time (as an increase in joint probability). Exposure to the joint probability of mismatch is affected by a number of factors, such as the driver's choice to frequently perform distracting tasks (e.g., texting), the type of traffic, and whether or not active safety systems are reducing the lead-vehicle closure change rate.

These results indicate that the conclusions drawn here would not have been different if the entire lengths of secondary tasks had been coded from start to finish.

Vehicle design and driving support

The results provide strong support for the potential of active safety systems—such as autonomous emergency braking (AEB) systems, forward collision warning (FCW), autonomous cruise control (ACC)—as main countermeasures for inattention-related crashes. Active safety systems provide the safety margins needed to protect the driver if the situation changes rapidly during an off-path glance by creating more time headway, issuing warnings, and actively braking.

As shown in Figures 7.3 and 7.4, drivers often adopt small headways in vehicle-following situations and do not seem to adapt the headway much when looking away from the road. Figures 7.3 and 7.4 also show that drivers looking away from the road almost never crash if the time headway at the beginning of the last glance is larger than 2 seconds. Thus, in theory, a simple way to prevent the crashes in the present sample is to increase the time headway. The European Field Operational Test (euroFOT), an EU-funded project, demonstrated that adaptive cruise control has the potential to significantly increase the average headway adopted by drivers. In terms of the present mismatch framework, this would reduce the risk of unexpected, high closure rates. Given the present results, such an increase in headway would be expected to have strong safety benefits (as long as the situations in which the adaptive cruise control is used overlap with those in which crashes occur).

As discussed in Chapter 7, the boundary suggested for safe glances (Figure 7.8) depends critically on the braking performance of the lead vehicle. In many situations, a slight difference in the vehicle's braking performance may distinguish a

crash from a near crash. A short glance may be perfectly safe under normal road surface conditions but may induce a crash if the stopping distance is increased due to a wet road surface or an ineffective braking system. As mentioned above, this was precisely the mechanism behind the single crash in Figure 7.8 not assigned to any of the three categories. Thus, improving vehicle braking systems should have great potential for mitigating the effects of inopportune glances. The same holds for AEB systems.

The results on driver reactions show that drivers react to progressively faster invTTC values above 0.2 and do not react to values below 0.2. An accumulator model successfully predicted driver reactions, and this model could likely be developed to improve the activation of warnings and interventions to better correspond to driver reaction times.

Systems for real-time inattention detection and mitigation have great safety potential, and development within inattention monitoring is a priority (e.g., NHTSA 2010a). Inattention sensing and support is being developed to detect drowsiness and distraction. Driver inattention sensing can be used for a wide range of functions and driver feedback (for a review, see Engström and Victor 2008). Driver assistance can be provided either by information and warnings or by adapting vehicle collision avoidance functionality, depending on detection of the risky inattention mismatch situations that were identified in the present research (see Figure 7.8). The project results are directly relevant for and have the potential to greatly improve real-time algorithms used for distraction and inattention detection (e.g., NHTSA 2013).

The results are very relevant for the design of forward collision warning (FCW) algorithms. Most FCW algorithms in use are based on a kinematic threat analysis, using some kind of time-to-collision–based threshold for when to warn the driver. Because this approach has difficulty separating late but controlled hard braking from hard braking in response to an unexpected event, nuisance alarms are common. Many researchers have therefore envisioned that the next step for FCWs in terms of increasing their hit rate (i.e., reducing the rate of nuisance warnings) would come through including in the warning algorithm assessments of driver states—that is, make it an inattention-adaptive collision warning.

The present results provide an enhanced understanding of the crash-producing mechanisms targeted by FCW, which can be used to improve the sensitivity and specificity of collision warning algorithms and to enable inattention-adaptive algorithms. An alternative approach, which is worth pursuing, is to tune FCW to warn more exactly when the risk is greatest according to the present results. For the analyzed events, it will be possible to establish how well existing FCW algorithms would have done in terms of alerting the driver. It will also be possible to devise principles for how to further optimize FCW algorithms in terms of warnings given and warning timing,

based on the driver's attention state and the traffic environment. For example, in some cases with relatively low kinematic threat level, a warning might still be warranted if the driver is very distracted; inversely, an attentive driver might not need a warning even if the kinematic threat level is high (for more information, see Engström and Victor 2008).

The present results also indicate a strong potential for vehicle-to-vehicle (V2V) communication-enabled FCW functions to prevent many of the crashes in the present sample. Video observation revealed that a common type of precrash scenario leading up to these crashes is the rapid build-up of a traffic queue in front of the lead vehicle. The traffic queue, however, is often hidden from the driver by the lead vehicle, so the driver often judges that it is safe to look away even if the threat is already present. If the driver had been alerted to the situation early by means of V2V communication with a vehicle in the traffic queue, many of these crashes would very likely have been prevented.

Education and behavioral change

As noted above, the present results indicate that a behavioral change toward longer time headway might have prevented a major portion of the present crashes. However, motivating drivers to make a sustained behavioral change is notoriously difficult. One way to address this is by means of public awareness campaigns. Another is behavior-based safety (BBS) programs, which are relatively well established in the commercial transport domain and have proven very efficient for inducing long-term behavioral improvement (e.g., Hickman et al. 2007). Such programs have also been successfully applied with teen drivers (Carney et al. 2010). BBS programs of this type are naturally not well suited to private motorists. However, one way to influence the behavior of this group is through usage-based insurance, which is a rapidly growing business linked to the general Big Data trend. For example, points or rewards could be given for keeping longer time headways.

Whatever the means for influencing drivers' behavior, a key implication of the present research is that the adoption of safe headways should be a key target in behavioral change programs for road safety. The results identify the types of glance behaviors and contexts that are particularly dangerous and also identify safer behaviors and contexts. Thus they can be used for education, outreach, training, and licensing to teach and inform drivers how to behave in a safer manner.

Road and infrastructure design

Road and infrastructure design is of key importance both for preventing glance-traffic situation mismatches and for maximizing the chance of recovery in case they occur.

First, as discussed above, drivers' glance allocation is strongly determined by expectations, and attentional mismatches

typically occur when expectations are violated. Designing the infrastructure layout in a way that supports the development of correct expectations and minimizes the risk of misunderstanding situations should have a strong potential for preventing rear-end crashes. While the present research has focused on mechanisms related to last-second reaction failures, understanding how expectations shape visual behavior and how this relates to infrastructure layout is an important topic for further research. The concept of *self-explaining roads*, coined by Theeuwes and Godthelp (1995), is a good starting point.

Second, addressing the other side of the mismatch equation, improvements in traffic control that aim to reduce disruptive traffic flows have potential for reducing the prevalence of sudden, unexpected, kinematic changes that often combine with off-path glances in producing rear-end crashes.

Third, as discussed above, the boundary for safe glances (Figure 7.8) depends critically on the stopping distance, which, in turn, depends on both the braking system and the road surface. Thus, by the same argument as for vehicle braking systems, improving road surfaces and their maintenance should have great potential for mitigating the effects of inopportune glances.

Assessing the potential efficiency of countermeasures

As described above, the present research has yielded several novel insights with respect to countermeasures for rear-end crashes. However, due to the complexity of the mechanisms involved, the potential efficiency of these countermeasures is difficult to assess.

Computer simulations based on the present type of naturalistic crash and near-crash data have great potential for obtaining more accurate estimates of the safety benefits of crash countermeasures. In particular, the level of detail with respect to crash kinematics and driver behavior available in these data makes it possible to reconstruct the crash scenario in simulation and ask the question, What if things had been different?

One variant of such what-if simulations (focusing on the effects of different last-glance distributions) was presented in Chapter 8. The SHRP 2 data were also used to develop driver reaction models for use in such simulations, as described in Chapter 7. The severity scales and simulation models described in Chapter 8 will also be very useful for addressing not just crash prevention but also the injury reduction potential of different countermeasures.

What is the relationship between driver inattention and crash risk in Lead-Vehicle Precrash Scenarios?

The answer to the main research question can be found in the general pattern of the results. They show, in line with previous

naturalistic driving studies, that some activity types significantly increase risk (such as Texting and Portable Electronics Visual-Manual). However, a strong significant decrease in risk was found for Talking/Listening on Cell Phone. Notably, there were no crashes while the driver was talking/listening on the phone. Three types of glance metrics showed the largest odds ratios: (1) the proportion of time the eyes were off path between 3 seconds and 1 second before the crash or minimum time to collision, (2) mean duration of off-path glances, and (3) the mean value of a composite measure estimating the driver's uncertainty of the driving situation. Further, when the three-glance metrics were combined in a glances model, they were more predictive of crashes and near crashes than each metric individually. However, an important limit of the glances model that included the three-glance metrics is that it assumes risk is purely a function of the driver's attention to the road (Eyes-off-Path metrics).

Risk stems more precisely from *both* the driver's attention to the road and the demands of the road. Analyses of the timing of off-path glances with lead-vehicle closing kinematics and visual cues revealed a distinct mechanism behind most of the crashes that can be understood in terms of a perfect mismatch between last glance duration and the change rate of the lead vehicle closing. Crashes occur with short glances and high closure rates, just as crashes occur with long glances with slow closure rates. These mismatches can be understood in terms of a joint probability distribution for glance durations and closure rates where the most likely combinations will show up in a crash sample like the present one. Since long glances are rare, many crashes occur because of the combination of a relatively short glance and a high change rate. Another group of crashes followed a similar pattern, but in those cases the driver looked away when the vehicles were already closing, often because of visibility problems that presumably impaired looming detection. This pattern of results, or mechanism, was further confirmed in what-if simulation and modeling of reaction time.

The main pattern is that lead-vehicle crashes can be understood as the mismatch between glance duration and the lead-vehicle closure rate. Timing matters greatly, and taken together, the analyses strongly reflect this mechanism.

Limitations

This study is very specific as it examined only Lead-Vehicle Precrash Scenarios (rear-end crashes and near crashes). These Lead-Vehicle Precrash Scenarios represent about 29% of crashes (Najm et al. 2003). Consideration should be given to several issues regarding generalizability and biases in the data.

To what extent can the current findings be generalized to the greater population of Lead-Vehicle *Precrash* Scenarios (rear-end crashes and near crashes)? To our knowledge, the

current data set, although not the final SHRP 2 data set, is the largest sample of Lead-Vehicle Precrash Scenarios used for risk estimation. Previous naturalistic data studies have had smaller samples of lead-vehicle crashes, and crash databases do not include driver behavior data (e.g., glance behavior) in the precrash phase. Clear indications of similarity and congruency with previous research are given by the replication analyses—for example, similarity in odds ratios on distracting activities and glance behavior at the precipitating event (Chapters 4 and 5) and similarity with the glance data in the 100-car data set (Figure 5.2).

Then the question can be asked, What biases in data and findings are due to the sample of data used versus what might have been the sample if the entire SHRP 2 data set? Although an estimated 20% to 30% of the expected final data set was fully surveyed through kinematic triggers, the *full* data set was “surveyed” by automatic notification processes (e.g., onboard Automatic Crash Notification algorithms, incident button presses, and site reports). Arguably, the most severe or noticeable crashes were found through the automatic notification processes. Future research on the full SHRP 2 data set is needed to determine similarity and biases in the current data set.

The question can also be asked, What is the representativeness of the current crash data sample to more serious crashes? Is it possible that the distraction risks and characteristics underlying serious rear-end crashes are not the same as those in the relatively minor crashes in the current crash data set? Figure 8.6 (and Figure 8.2) indicates that the actual DeltaVs in the crashes in the sample are substantially lower than the DeltaVs in the CDS accident statistics. This is expected, since CDS samples tow-away crashes, which are generally the more severe 40% of police-reported crashes. The SHRP 2 sample includes crashes with very low DeltaV (even near zero), which in many cases would not be severe enough to meet police-report criteria. As the present sample does not include crashes above DeltaV 8 m/s², this is a limitation of this study, and care should be taken in drawing conclusions beyond this level. Section 7.6 suggests that more severe crashes would be expected to be less linearly organized along the negative slope in Figure 7.8, featuring more rare, and severe, combinations of long glances and fast kinematics. This is clearly a topic for further research.

To what extent do the findings transfer to other crash types, for example, run-off-road crashes and intersection crashes? Some indication of transferability is given by the similarity with the 100-car data set (as in Figure 5.2), as the 100-car data set included all crashes, near crashes, and incidents found in that study. As discussed above, consideration of other crash types should be given, particularly with regard to the finding of reduction in risk from Talking/Listening on Cell Phone. The cognitive load induced by phone conversation may lead to an increased crash risk in other scenarios that involve higher cognitive or executive functions (such as planning,

decision making, novel sequences of action, or inhibiting habitual responses) rather than the more automatic reaction to a looming lead vehicle. For example, cognitive load may lead to impaired detection of red traffic lights or other types of signaled information in intersection scenarios. In run-off-road scenarios, the present methodology, which quantifies change rate of a looming lead vehicle (invTTC), would have to be modified and developed. In particular, defining the crash point in run-off-road crashes is challenging, as time to line crossings or road edge crossings may not be as imminent to the driver as hitting an object. Further, run-off-road crashes do not typically involve an unpredictable behavioral component from another driver as Lead-Vehicle Precrash Scenarios do.

To what extent are near crashes reasonable as surrogates for crashes? There were differences between crashes and near crashes in many metrics, such as eyes-off-road proportions, odds ratios, lead-vehicle-closure change rates, and driver reaction times. Near crashes are generally different than the baseline events in this sample and also generally different than crashes, emerging somewhere between the two in many metrics. Because near crashes are more numerous than crashes, there is a clear weighting effect from using proportionally more near crashes than crashes in risk estimates combining crashes

and near crashes, as can be seen in odds ratios (e.g., Figure 5.4 and Figure 6.8) and percentage of eyes off path (e.g., Figure 5.2). Combining crashes and near crashes generally dilutes the effect found in crashes but reduces the confidence intervals because of the larger sample and thus, it allows detection of more significant effects at a lower magnitude in combined crash/near-crash risk. Clearly, there is value in using near crashes, but risk magnitude estimations are lower. As more crashes become available for analyses in the SHRP 2 data set, this near-crash surrogate issue can be investigated further and perhaps modeled.

One further limitation is that we cannot compare our results with a similar data set without portable electronic devices. Portable electronic device interactions, including visual-manual interactions, texting, and talking/listening on a cell phone, are present in the current data set, but we do not know the proportions and distributions of glance behaviors *had they not been available* in society. Thus, we do not know whether their presence *displaces* other interactions and glance behaviors or if they increase Eyes-off-Path glances. Although a subset or control condition could be created, selecting drivers that do not use their cell phones, it would not be representative of drivers who would choose to use them if they had one.

Glossary

actual severity. The actual outcome severity which is the result of the actual event (e.g., DeltaV and minimum time to collision).

crash. Any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. Examples and hints: Includes other vehicles, roadside barriers, objects on or off of the roadway, pedestrians, cyclists, or animals. In the rear-end collisions in the present data set, only vehicle-to-vehicle contacts are classified as a crash.

driver distraction. Diversion of attention away from activities critical for safe driving to one or more activities that are not critical for safe driving. A type of driver inattention.

driver inattention. A mismatch between the current attention allocation (distribution) and that demanded by activities critical for safe driving. Includes driver distraction.

eyes off path. Glances away from the vehicle's path, the direction of the vehicle's travel. Includes transitions toward an off-path location and eye closures greater than $\frac{1}{3}$ second.

FCW. Forward collision warning system.

glance. Time from the moment at which the direction of gaze moves toward an area of interest to the moment it moves away from it. A glance consists of transition time toward a target plus the subsequent dwell time on that target (ISO 15007).

inopportune glance. A glance away from the forward path at an inappropriate time.

lead vehicle (LV). The vehicle preceding the subject (participant) vehicle in the same lane.

Lead-Vehicle Precrash Scenarios. A classification of the crash according to precrash Scenarios 22–26 from Najm and Smith (2007) corresponding to rear-end crashes in National Automotive Sampling System (NASS) crash databases.

near crash. Any circumstance that requires a rapid, evasive maneuver by the subject vehicle or any other vehicle, pedestrian, cyclist, or animal to avoid a crash. A rapid, evasive

maneuver is defined as steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle capabilities. Examples and hints: As a general guideline, subject-vehicle braking greater than 0.5 g or steering input that results in a lateral acceleration greater than 0.4 g to avoid a crash constitutes a rapid maneuver.

odds ratio (OR). A measure of association between an exposure and an outcome. The OR represents the odds that an outcome will occur given a particular exposure compared with the odds of the outcome occurring in the absence of that exposure. For example, the odds ratio of having a critical event (crash, near crash, or both, depending on the analysis) is calculated as a function of various predictors, such as glance characteristics or distraction types.

potential severity. The severity which can potentially result from a scenario, based on mathematical simulations.

precipitating event. The state of environment or action that began the sequence under analysis—that is, what state or action by this vehicle, another vehicle, person, animal or non-fixed object was critical to this vehicle becoming involved in the crash or near crash? This is a vehicle kinematic measure (based on what the vehicle does; an action, not a driver behavior). It occurs outside the vehicle and does not include factors such as driver distraction, fatigue, or disciplining a child.

secondary task. A task, unrelated to driving, that requires drivers to divert attention from the driving task (e.g., talking on a cell phone, talking to passenger[s], eating).

subject vehicle (SV). The participant's instrumented vehicle. That is, the following vehicle in the Lead-Vehicle Precrash Scenarios.

time headway (THW). Elapsed time between when the front of the lead vehicle passes a point on the roadway and when the front of the following vehicle passes the same point.

time to collision (TTC). The time left to crash before two vehicles collide (rear-end collision) if no evasive action is taken.

vehicle kinematics. The description of the motion of vehicles. For example, the description of the trajectories of the subject (driver's) vehicle and the lead vehicle and their differential properties, such as velocity, acceleration, and time to collision.

VTI. Virginia Tech Transportation Institute.

what-if simulations. A process of changing parameters (e.g., removing evasive maneuvers), applying alternative driver behaviors, and analyzing outcomes of such simulations.

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APPENDIX A

Actual and Potential Outcome Severity Scales

This appendix provides more details on the actual and potential outcome severity scales described in Chapter 8. It includes a description of the methods, as well as details on assumptions that were used in the construction of these methods.

First, we describe the actual outcome severity scales in more detail, including issues that were identified related to the specific implementation on the available data. Second, we describe the potential severity scales. Assumptions behind both of the methods are also discussed.

A.1 Actual Outcome Severity Scales

Crash/Near-Crash Dichotomy

The crashes and near crashes were identified by VTTI through kinematic triggers and site reports (and for some crashes, crash notifications by the drivers). Classification of these events as crashes and near crashes was done through manual reduction of video.

DeltaV

In traditional crash databases and in-depth crash investigations, the outcome severity is either directly related to physical harm (injury or death) or defined in monetary terms (cost of repairs, health care costs, loss-of-functional years, etc.). The Abbreviated Injury Scale (AIS) is a commonly used injury severity metric, used for classification of injuries for different parts of the body according to an established coding schema (Gennarelli and Wodzin 2005). AIS ranges from 1 to 6—AIS 1 is a minor injury and AIS 6 is generally not survivable. A large body of research has been aimed at establishing the risk of sustaining a specific degree of injury given some measurable variable. One such variable is the change of velocity of the involved road users during the impact, the so-called DeltaV (Buzeman et al. 1998; Viano and Parenteau 2010). The calculation of DeltaV is based on the law of momentum conservation of the

crashing road users. In this analysis we focus on lead-vehicle conflicts, thus Equation A.1 is relevant for DeltaV calculation (Kusano and Gabler 2010). Further, we assume pure rear-end collisions, thus the $\cos(\alpha)$ term becomes 1. The masses of the involved road users are m_1 and m_2 , while the speeds of the two road users at impact are V_1 and V_2 . In lead-vehicle conflicts, the sum of speeds is equivalent to the relative velocity at the time of impact.

$$\text{DeltaV} = \frac{m_2 (V_1 + V_2 * \text{Cos } \alpha)}{m_1 + m_2} \quad (\text{A.1})$$

The calculation of DeltaV in our implementation relies on the range rate between the subject vehicle (SV) and the lead vehicle (LV). That is, the range rate at impact is used to estimate $V_1 + V_2$. Also, an estimate of the subject-vehicle and lead-vehicle masses is needed.

Time to Collision and Minimum Time to Collision

The definition of *time to collision* (TTC) and *minimum time to collision* (minTTC) used in Chapter 8 as a severity metric is a simple range divided by range rate operation, where the range and range rates are calculated as described in Chapter 2. This definition of TTC and minTTC is different from the definition in Chapter 2 (used in most of the main report), and also different with respect to the inverse time to collision (invTTC) = 0.1 s^{-1} threshold used in Chapter 8. The available data produce some challenges in the TTC and minTTC calculations, described below.

Assumptions and Limitations

In the specific implementation of the actual severity scales in this project, the following main assumptions and limitations were identified.

Sampling Strategies in Naturalistic Driving Data

The crash/near-crash dichotomy is provided as is from VTTI. There are major issues with the sampling strategies in general in naturalistic driving studies. In particular, the near crashes found in the data are taken from a set of cases that meet any of a group of kinematic and other filters. The purpose of filtering is to reduce the workload of video reviewers, but this goal is not equivalent to the goal of finding a random sample of near crashes. In fact, filters for near crashes have become increasingly severe (e.g., harder braking, lower TTC) over time as naturalistic studies have been performed. This biases the collection of near crashes in ways that are not understood because false negatives are not reviewed. Furthermore, at the end of the process, non-near-crash events are filtered out in a partly subjective manner by the annotator looking at the videos.

An associated problem with this method is that the filters by which near crashes and crashes are typically found are different. Thus, near crashes, which are treated as a category of events that can serve as a surrogate for crashes, are filtered into the data set by different means. This in itself can make near crashes different from crashes in unintended and unmeasured ways.

General Problems with Estimating DeltaV

Several basic issues with estimating DeltaV pertain to several sources of data used in calculation of DeltaV and are relevant to our implementation of DeltaV calculations. First, we do not use (or have) any coefficient of restitution. That is, we are considering all impacts to be completely plastic. Second, we do not have the actual change in speed, we only have an estimate of the impact speed (that estimate may be better than what is available from many other data sources used to calculate DeltaV, however).

Estimate of Vehicle Masses for DeltaV Calculations

To perform the type of DeltaV calculations that we do, we need the masses of the involved vehicles. We do not have these. We do not have the subject vehicles' mass in any event (although likely available elsewhere); for the lead vehicles, we have the masses extracted from databases when the make and model of the lead vehicle could be determined from image data. Thus, for the subject vehicles we use a "standard" mass, and for the lead vehicles, we use either the make-and-model mass (empty) or a "standard" mass according to vehicle-type classification.

DeltaV and minTTC Based on Manual Lead-Vehicle Width Estimates

Both the DeltaV and the minTTC metrics are based on the manually annotated lead-vehicle width and an estimate of

the actual lead-vehicle width. This means that all issues related to this approach are also inherent in the DeltaV and minTTC estimates. One major issue related to this way of estimating range is this: width estimates of the lead vehicle (in meters) are needed to get range. A 10-cm width estimate error gives approximately a 6% error in the range (Bärgman et al. 2013). DeltaV and TTC use the derivative of the range, with calculation of TTC also involving the absolute range.

Note, however, that although our DeltaV estimates may have built-in errors through the impact-speed (i.e., range rate at impact) estimates, our estimates are not derived post-hoc, by studying vehicle deformation, but rather use a more direct measure of impact speed.

A.2 Potential Outcome Severity Scales

This section provides detailed descriptions of how the Model-estimated Injury Risk (MIR) severity scale can be calculated for two different gaze anchor point strategies. Details on the calculation of the potential severity scale are described, and assumptions and limitations of the what-if simulations and the corresponding MIR scale are discussed.

As stated in the main report, the severity scale is formulated as the expectation of some function describing the severity of a crash or a near-crash event with respect to the probability distribution describing time to eyes-on-road given that the glance covers some critical time point (Approach 1). We will also consider the option of conditioning on the glance starting at some particular point (Approach 2). That is, we add one option to how the severity scales may be calculated. In mathematical terms, the scale calculations can be formulated as follows.

We provide a somewhat simple description, followed by a more mathematical description.

General Description of the MIR Severity Scale Calculation

Possible what-if questions include the following:

- What if the driver looked away at a particular point (e.g., defined through $\text{invTTC} = 0.1 \text{ s}^{-1}$)?
- What if the driver glanced away during a longer/shorter time than he or she actually did?

We will attempt to answer these questions by considering the different driver behaviors (i.e., times when the driver looks back on road) that can occur in a rear-end crash scenario, what these behaviors lead to (e.g., risk of injury), and the probability of such behaviors occurring for an average driver in a particular traffic situation.

To answer the questions above, we need to obtain appropriate distributions describing glance-off-road behavior. This is more difficult than it may seem. Data usually provide the frequencies that describe how often a glance of certain length occurs in a particular driving situation, such as the matched baseline data in our data set. These frequencies give an approximation of the statistical distribution of the glance lengths, given that the driver has, in fact, glanced away from the road (even if, depending on how the data were collected, some transformations may be necessary; Rootzén and Zholud, submitted). Observe that, although below we will operate with these conditional distributions, we may very well apply similar approaches to the unconditional ones (i.e., the distributions that incorporate the possibility that the driver is not looking away from the road at the particular point of time that we are studying).

Let us assume that we have obtained the empirical probability density function (PDF) describing the off-road glance length. We also have constructed some sort of function describing the danger of late reaction—assumed to be caused by an off-road glance (e.g., the probability of an injury). We are now interested in measuring the expected risk corresponding to a situation given that certain conditions are met (e.g., the braking profile of the leading car looks a certain way, and the driver of the following vehicle had eyes off road at a crucial time point). The expected risk can be calculated by taking the expectation of the risk function with respect to the distribution describing when the driver of the following vehicle looks back on road. This distribution need not be the same as the glance length distribution obtained from the data, since both of the questions above involve conditioning: in the first the off-road glance covers a critical point, and in the second the off-road glance starts at a particular point.

Let us start by constructing the severity index corresponding to the latter approach—that is, the one conditioned on a glance starting at a particular point (see Figure A.1). Consider what we need and what we have. We need a PDF describing time to eyes on road given that a glance has started. Call it h_1 . We have the raw data from which the empirical distribution of the glance length, given that a glance occurs, can be constructed. That is, the raw data provide exactly what we want, and no further transformations of the glance distribution are necessary. We can calculate the severity index in a straightforward manner by applying the formula for expectation of a function with respect to a discrete distribution: $E[R(T)] = \sum(f_i \cdot R_i)$. Observe that, in general, h_1 can have any form. It may, for example, put all the probability mass on time points that are larger than time to collision, leading to the same $E[R(T)]$ that would have resulted if all the probability mass was concentrated at the exact moment of collision.

Constructing the severity index corresponding to the first question (Approach 1) is a bit more complicated. Again, it

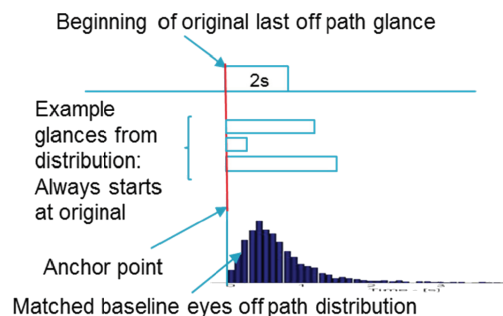


Figure A.1. Application of a glance distribution (matched baseline) as the beginning of the original last off-path glance (example with a 2-second original last off-path glance).

involves a conditioning. But now, rather than saying that a glance has to *start* at a certain point, we say that it has to *cover* this certain point. That is, we need the distribution of time to look back *given that the glance is longer than the distance between the start of the glance t_i and the critical point* (see Figure A.2). The resulting distribution will then describe the probability of looking off the road for an additional number of seconds, given that the driver has already looked away from the road for a while and missed the time point that we are interested. This distribution will be nonnegative for all time points t such that t is greater than 0 and less than the longest glance length observed in the empirical data. It will be continuous and nonincreasing. Because of the continuity, the severity index will be calculated as an integral, rather than a sum—that is, $E[R(T)] = \int(h(t) \cdot R(t)dt)$. One of the consequences of this construction will be that $E[R(T)]$, unlike in the previous case, will not become a constant if all the probability mass of f is to the right of time to collision. That is, if time to collision is 5 seconds and we have two empirical

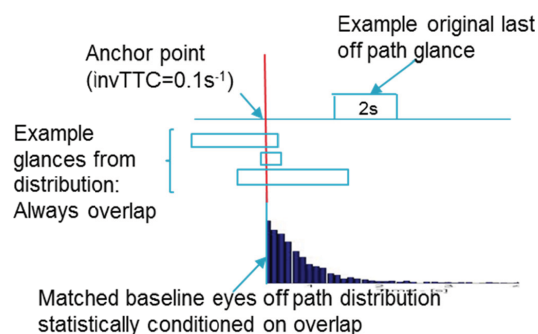


Figure A.2. Conditioning the glance distribution (matched baseline) on overlapping a fixed point ($\text{invTTC} = 0.1 \text{ s}^{-1}$, example with 2-second original last off-path glance).

$f(x)$ distributions, one placing all its mass on 10 seconds and another on 15 seconds, $E[R(T)]$ will be larger in the latter case than in the former.

Mathematical Description of the MIR Severity Scale Calculation

Let X denote the (stochastic) length of an off-road glance. We will call the corresponding PDF function $f(x)$. In our case, this function is usually obtained from the data. However, we could also use a generic PDF to, for example, assess the impact that different hypothetical glance behaviors have on the severity scale. Further details on how $f(x)$ is obtained can be found below.

Further, assume that a glance of length X covers some critical point T_{crit} and consider the difference between X and T_{crit} —that is, the remaining time of off-road glance given that T_{crit} occurred somewhere in $[0, X]$. Denote this (stochastic) length for T , with the corresponding PDF $h(t)$. In statistical terms, $h(t)$ is the overshoot distribution of $f(x)$, and the corresponding cumulative distribution function (CDF) describes $P(X - T_{\text{crit}} < t \mid 0 < T_{\text{crit}} < X)$. For further details on construction of $h(t)$, see the next section.

For each time point in a scenario, we construct a risk function $R(t)$. Theoretically, $R(t)$ may be any function, but it usually describes consequences arising from the driver glancing back at t . Examples are the impact-speed ΔV and probability of an injury; see the section on construction of the $R(t)$ below.

A severity scale is constructed by combining either $R(t)$ and $h(t)$ (Approach 1) or $R(t)$ and $f(x)$ (Approach 2). Explicitly, in Approach 1 we calculate

$$E[R(t)] = \int R(t) \cdot h(t) dt$$

and for Approach 2

$$E[R(t)] = \int R(t) \cdot f(t) dt \quad (\text{alt } E[R(t)] = \sum R(x_i) \cdot f(x_i))$$

if f is discrete, as is the case when it is obtained from empirical data).

Note that the second approach uses the distribution corresponding to the actual glance lengths, while the first approach uses the overshoot distribution. The logic behind this can be most easily understood by considering the difference in conditioning in the first and the second approach. In the second approach, we are interested in the length of a glance given that it starts at a particular point, which is exactly what we obtain by considering the possible glance length in some population. In the first approach we are interested in the glance length given that it covers a particular point. The $f(x)$ distribution is no longer applicable, but, rather, has to be transformed into $h(t)$.

Construction of the Overshot PDF $h(t)$

To begin with, let us introduce some notation. For calculations, we operate with two probabilistic distributions: $F(x)$, which is the CDF (cumulative distribution function) corresponding to the distribution of the glance lengths in a population, and $H(t)$, which is the CDF of the so-called overshoot distribution of $F(x)$, defined as $H(t) = P(X - T_{\text{crit}} < t \mid 0 < T_{\text{crit}} < X)$. We also have the corresponding PDF distributions $f(x)$ and $h(t)$. Below, we describe in detail how we may obtain $h(t)$ from $f(x)$.

Observe that in the expression for $H(t)$ above we have two random entities: the length of an off-road glance X , and the exact time at which T_{crit} occurs. We also have a conditioning, namely that T_{crit} should occur during an off-road glance. We also have $h(t) = H'(t)$ (i.e., the PDF function is the derivative of the CDF function with respect to t). Last, to simplify calculations, we assume that $f(x)$ is discrete, as is the case if it is obtained from the real data. The approach can be easily generalized to the case where $f(x)$ is a generic continuous distribution by, essentially, replacing summation with integration.

Keeping this in mind, we rewrite the expression for $H(t)$ as

$$H(t) = \sum_x \{x\} P(T_{\text{crit}} > x - t \mid X = x, 0 < T_{\text{crit}} < X)$$

$$P(X = x \mid 0 < T_{\text{crit}} < X) = \sum_x \{x\} s(t) \cdot g(x)$$

That is, we condition on X taking on a particular value x and sum over all possible x . Let us now consider the two terms within the sum, $g(x)$ and $s(t)$, separately.

The $g(x)$ term reflects the probability that we will see a glance of a certain length in a population, given that this glance contains some critical point. Observe that, if we assume that T_{crit} can occur at random (i.e., as a Poisson process) during driving, then we are more likely to see a T_{crit} within a longer glance than within a shorter glance. So, to obtain $g(x)$ we need to perform a so-called size-bias correction of $f(x)$ that reflects this property. Explicitly, we calculate $g(x)$ through

$$g(x) = f(x) \cdot x / \sum_x \{x\} (f(x) \cdot x)$$

so that the probability that T_{crit} is inside a longer glance increases proportionally to glance length x .

The $s(t)$ term describes the probability that, given that we have a glance of a certain length x and that T_{crit} is within this glance, the critical point is to the right of some time point t , $0 < t < x$. To derive this probability, we make the assumption that, under these conditions, T_{crit} is distributed according to Uniform(0, t) distribution—that is, it can occur anywhere within the glance with equal probability. Given this assumption, we have $s(t) = t/x$ if $x > t$ and $s(t) = 0$ if $x < t$, and we arrive at the expression

$$H(t) = \sum_x \{x: x > t\} (t \cdot f(x) / \sum_x \{x\} (x \cdot f(x)))$$

Finally, using $h(t) = H'(t)$, we can differentiate the sum with respect to t to obtain

$$h(t) = \text{sum}_{\{x : x > t\}} (f(x) / \text{sum}_{\{x\}} (x \cdot f(x)))$$

In words, $h(t)$ for a certain t is basically the (normalized) sum of probabilities of the glances that correspond to x that are larger than t . One thing to note here is that $h(t)$ is defined for all t and not just t such that $t = x$. This means that, although $f(x)$ is discrete, $h(t)$ is continuous.

Construction of $R(t)$

The construction of $R(t)$ is less mathematical. The following is just an enhancement of the description in the main report (Chapter 8). Figure 8.1 in the main report is advantageously used in combination with this description.

1. Vehicle kinematics are extracted. The subject-vehicle speed (SVspeed) is the interpolation (usually up-sampling) of the CAN speed to match event time. The lead-vehicle speed is the sum of the SVspeed and the range rate.
2. Start of evasive maneuver is identified by using the manually annotated reaction point (reduction by VTTI) and set to the first time after the reaction point when the derivative of the SVspeed is negative (deceleration).
3. The evasive maneuver is “washed away” (removed) by setting all SVspeeds after the start of evasive maneuver to the SVspeed at the start of evasive maneuver.
4. A brake profile is chosen. We have chosen 8 m/s^2 (see the assumptions section below for the reasoning).
5. A braking rate corresponding to a constant 8 m/s^2 is applied at each time in event time (each 0.1 second), simulating different SV driver responses.
6. The simulated SVspeed and the lead-vehicle speed (LVspeed) are integrated for each simulation to get changes in distance.
7. Using the SV and LV distances from speed integration and the initial range between the two, each simulation is checked for ranges below zero (crash).
8. For the simulations resulting in a crash, the impact speed is calculated by extracting the relative speed between SVspeed and LVspeed at the first time the range goes below zero.
9. A hypothetical impact-speed profile is created in event time. That is, for each simulated start of evasive maneuver there is a corresponding impact speed. The impact speed is zero for all no-crash simulations, and it is the impact speed calculated in the previous step for all crash simulations.
10. The masses of the lead vehicle and the subject vehicle are estimated. The SV mass was set the same for all events; the LV mass was either retrieved from databases after identifying the make and model from video, or a mass per vehicle category was applied.

11. An injury-risk function is chosen. We created an injury-risk function for rear-end events based on National Automotive Sampling System–Crashworthiness Data System (NASS-CDS) rear-end-striking crashes, using logistic regression. The function used was $\text{injury_risk} = 1 / (1 + \exp(-(-10.31316311 + 0.33308 * \text{DeltaV})))$; it relates DeltaV to MAIS3+ injuries, with an intercept adjustment. The CDS data set contains only tow-away crashes, which are more severe than the average police-reported crash. This biases the intercept term in the relationship between DeltaV and injury, but, unfortunately, there is no police-reported crash data set that includes DeltaV. To remedy this, we adjust the intercept according to the Breslow (1996) formula. The formula requires a base risk of injury, which is estimated based on the National Automotive Sampling System–General Estimates System (NASS-GES) data set, a data set of police-reported crashes.
12. The hypothetical impact-speed profile is converted to a hypothetical injury-risk profile by applying the injury-risk function. Now there is an injury risk associated with each start of evasive maneuver. This is one example of $R(t)$, used in the current implementation. However, $R(t)$ can be any function describing the severity of an individual event as a time series.

Using *invTTC* Instead of *invTau*

The what-if simulation development has been run in parallel with other parts of the project. Until late in the project, inverse Tau (*invTau*) was used instead of *invTTC* in most analysis. Since the two metrics are similar, but *TTC* is understandable by more people, the decision was made to change to *invTTC* in most places in the project and to describe the difference in Chapter 3. Specifically for the MIR/MCR development, it was the difference at $\text{invTau} = 0.1 \text{ s}^{-1}$ that mattered. In analyzing the difference between *invTau* and *invTTC* at $\text{invTau} = 0.1 \text{ s}^{-1}$, it was found that the difference is practically negligible (difference: $M = -0.000526 \text{ s}^{-1}$, $SD = 0.000859 \text{ s}^{-1}$, $\text{max} = -0.000019 \text{ s}^{-1}$, $\text{min} = -0.00081 \text{ s}^{-1}$). The equation for calculation of the difference between optically defined *invTau* and optically defined *invTTC* at $\text{invTau} = 0.1 \text{ s}^{-1}$ is

$$\text{Diff} = \tau_{|\tau^{-1}=0.1}^{-1} - \text{TTC}_{|\tau^{-1}=0.1}^{-1} = 0.1 - \frac{\dot{\theta}_{|\tau^{-1}=0.1}}{\sin(\theta_{|\tau^{-1}=0.1})}$$

Note that the *invTTC* used in the project is calculated at the camera position and not at the vehicle bumper. Thus, it is optically defined *invTTC* at the camera.

Maximum Severity DeltaV Severity Measure

The Maximum Severity Delta Velocity (MSDeltaV) is the severity that would result if the subject vehicle’s driver performed

no evasive maneuver. DeltaV is the most common approach for measuring crash severity in traditional accident investigations and correlation with injury risk (see the DeltaV section above); we calculate what DeltaV would result if no evasive maneuver was made by the SV driver. The MSDeltaV severity requires the identification of the SV evasive maneuver (see Chapter 3, variable definitions). We define MSDeltaV as the relative velocity at impact if the subject vehicle continues with the same speed as just before the evasive maneuver, multiplied with the mass ratio $m_2/(m_1 + m_2)$ as explained in the DeltaV section above. Since MSDeltaV requires an evasive maneuver (which is then “removed”), it is not defined for baseline events. However, the calculations could be applied for any chosen time point in a baseline event. This would in some events result in very high MSDeltaV values. Consider two vehicles, 1,000 m apart and both driving at a constant steady state speed of 100 km/h. Even if the lead vehicle braked softly to a stop, MSDeltaV calculated using the time point when the lead vehicle started braking as a “random” evasive maneuver would result in a 100-km/h MSDeltaV. This issue may be mitigated by adding some time window for calculations. A main advantage and disadvantage of MSDeltaV is that it does not depend on driver actions/reactions, and thus the measure may be considered orthogonal to driver behavior indicators.

Assumptions in the Creation of the What-If Simulations and Potential Severity Scales MIR, MCR, and MSDeltaV

The following subsections describe and discuss the reasoning behind the major and some minor assumptions made when creating the what-if simulations and the potential severity scales presented in the main report. They also describe limitations of the approach in general and issues with the application of the method to the SHRP 2 data set available for this project. The headings below are statements of assumptions. Note that we only aim to show proof of concept. Some of the discussions below, however, are from the perspective of the actual use of the method, while others only discuss the assumptions from the perspective of proof of concept.

The subject-vehicle driver not looking on the road ahead is the only reason for crashing, except when the driver keeps such short headway that, even with 8-m/s² deceleration, he or she cannot avoid a crash.

As described in the sections of the report focusing on analysis of mechanism, it was found that—for a majority of the crashes—drivers are looking away close to the crash. Other evidence also showed that glances seem to be a major contributing factor to the occurrence of crashes (Chapters 6 and 7).

Further, in Chapter 7 it is shown that in some crashes the headway is too small for the driver to avoid crashing (Category 3 crashes described in Section 7.4), even if he or she is keeping an eye on the road and reacting fast. However, since not all rear-end crashes can be identified as having glances as a contributing factor (a portion of the Category 3 crashes, Section 7.4), the assumption and subsequent what-if simulations will fail to address such cases. This limitation has implications for using what-if simulations as we are proposing them. Care needs to be taken with respect to interpretation of results.

The single last glance is the only reason for a delay in reaction.

This assumption is studied in Chapters 6 and 7 and is partially rejected. That is, the last glance is shown to play a large role in the occurrence of a crash, but it is not the only reason. However, since the aim of the implementation of the what-if simulations and potential severity scales was mainly to demonstrate the concept, this simpler model was chosen. A more complicated approach would be needed to also explain historical glances. Future research and applications of the what-if simulations should consider implementing more advanced and validated models of driver glance behavior. It is not unrealistic that most reaction models can be transformed into an “equivalent” last-glance distribution.

The subject-vehicle driver's glance behavior (glance off-road distribution) is the same as that in the matched baseline up until the chosen anchor point (invTTC = 0.1 s⁻¹).

We chose an anchor point of $\text{invTTC} = 0.1 \text{ s}^{-1}$ for several reasons. We wanted to capture the basic idea that drivers try to avoid critical situations by adapting to the situation. In the Tijerina et al. (2004) study of eyeglance behavior during car following, it was found that drivers under normal car-following conditions generally do not take their eyes off the road unless both the subject vehicle and lead vehicle are traveling at approximately the same speed (i.e., at range rates close to zero). Although we want to adopt a strategy based on drivers avoiding critical situations, we want a driver model that is reasonably related to the kinematics of crashes and near crashes. In Chapter 7, Figure 7.5, it is shown that for the matched baseline, only a few drivers started to look away at an invTTC higher than 0.1 s^{-1} . At the same time the mean of invTTC for near crashes is just below $\text{invTTC} = 0.1 \text{ s}^{-1}$. This leads us, for proof of concept, to choose $\text{invTTC} = 0.1 \text{ s}^{-1}$ as the gaze anchor point. Future applications of the method can change this anchor point. Another obvious anchor point would be $\text{invTTC} = 0.2 \text{ s}^{-1}$ as described in Chapter 7 (e.g., Figure 7.3). Previously in this appendix we also included a description of how to apply the

glance distributions at the original start of last glance off road instead of conditioning on an overlap with, for example, $\text{invTTC} = 0.1 \text{ s}^{-1}$ (or 0.2 s^{-1}). Further development is needed on the choice of anchor point. Should lower-value anchor points be chosen instead, in line with Tijerina et al. (2004), or should thresholds such as $\text{invTTC} = 0.2 \text{ s}^{-1}$ be used? If a lower-value approach is chosen, data quality may also be a limiting factor (noise at longer ranges).

For task analyses, driver's glance behaviors are the same as the original task distribution up until the chosen anchor point. This has the same issues as for the matched baseline, but in addition, the initiation of a task is likely dependent on context. Thus, if analysis of task risks is to be performed using our method, it is advisable to do an extended scenario selection. That is, if the analyst can identify the contexts in which drivers are (not) engaging in the tasks to be evaluated, then only crashes and near crashes matching those contexts should be selected for the analysis. In that way the context bias is minimized.

Drivers respond by braking at 8 m/s^2 in all situations.

In the simulation framework any brake profile can be used, including dynamic brake responses that depend on context. However, in our work we chose 8 m/s^2 as a conservative (hard) brake response. By choosing a relatively aggressive brake profile, estimates of risks are lowered. The brake profile choice has a pronounced effect on the outcome scale, and this choice needs to be an informed one, depending on the application of the method.

The braking is initiated after a fixed reaction time (0.4 second) after the driver looks back on the road.

Conclusion 3 of Section 7.6 states that the results from the analysis in Chapter 7 show a fixed reaction time is not correct, for several reasons. However, we chose a fixed reaction time of 0.4 second because it produces conservative estimates of risk. The value 0.4 second is the median of the reaction time for crashes when the reaction is made after $\text{invTTC} \geq 0.1 \text{ s}^{-1}$ is fulfilled (Figure A.3). That is, the invTTC has reached at least 0.1 s^{-1} before the driver reaction. Alternative reaction models can be integrated into the current model.

Peripheral vision does not help the driver react earlier (by moving the eyes back to the road).

In this approach we are not considering glance-off-road eccentricity and potential effects of looking back earlier due to peripheral vision. To allow for inclusion of such effects, data on glance-off-road eccentricity are needed, together with a model of the effects as a function of context (e.g., looming).

The quality of data is not affecting results significantly.

Data in the available data set have several quality issues. The following issues have been identified as directly influencing what-if simulation results, but others may not have been found.

The SVspeed signal is, for many events, not synchronized with other data, especially range rate. This quality issue has major implications in the what-if simulations. Since the LVspeed is

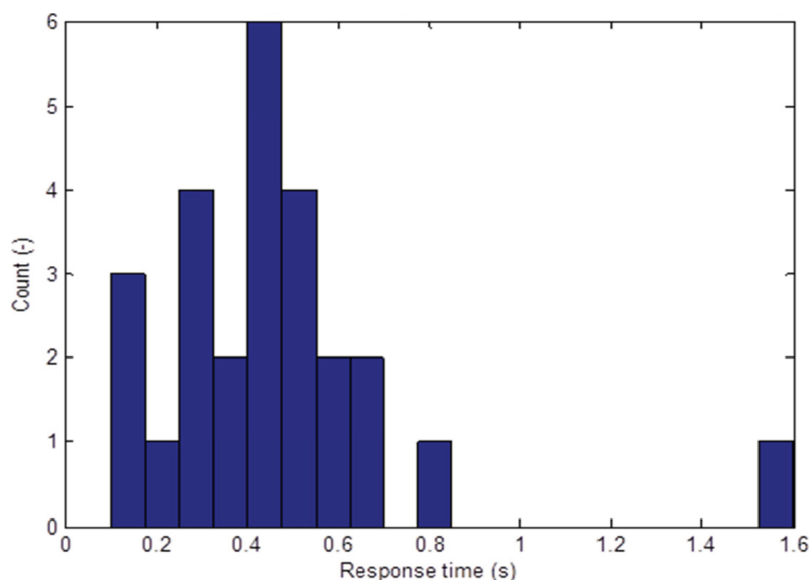


Figure A.3. Driver response time between last glance on path and the driver reaction in crashes with $\text{invTTC} \geq 0.1$ at glance on-road onset ($n = 26$; mean 0.458 second; median 0.400 second).

a major component (kept constant in all simulations of an individual event) in the what-if simulations, the creation of LVspeed is crucial. Since LVspeed is calculated by adding SVspeed and range rate, the synchronization of those two signals is important. If the SVspeed is a few hundred milliseconds late (delay) in an event, a hard deceleration by the following vehicle—seen in the range rate—will be seen as a fast increase in LVspeed (acceleration). This lead-vehicle acceleration is then just an artifact, creating delays in the crash point in what-if simulations. It may be possible to address the synchronization issues per event, but we treat such artifacts as noise in the data.

The SVspeed signal has a sample frequency of only 1 Hz for some events (vehicles). This issue is similar to that of synchronization, since 1 second between samples is effectively a delay when there are fast deceleration responses.

The range, range rate, and invTTC signals are noisy at larger ranges between the SV and LV. Both LVspeed and invTTC are major components in the what-if simulations. Both are based on the manually annotated lead-vehicle widths. To understand the implications of data quality, sensitivity analysis would have to be run.

Glance-off-path distributions from the matched baseline events in our sample are representative for car-following scenarios.

Sample selection bias is an issue because the matched baselines are matched to crashes and near crashes. It is not unlikely that these crashes and near crashes are created by drivers who have longer glances away from the roadway (since they actually got into the events in the first place) or who are close followers (tailgaters). It would be interesting to compare matched baselines in which the situation, but not the driver, was matched, with the matched baseline. Such analysis would confirm or reject the potential bias concerns. Also, a methodological enhancement would be to match events of particular scenario types with the glance-off-road distributions for each respective type.

The choice of injury-risk function and transforming DeltaV into injury risk are relevant for our events.

Calculation of injury risk is often difficult. Calculation of hypothetical injury risks may be controversial. The steps used to get to injury risk are crucial. We use an injury-risk function based on NASS-CDS data on rear-end collisions, with an intercept adjustment to account for the lower-severity event in our sample (see Chapter 8). Researchers implementing MIR or MCR should take care in using the impact-speed to injury-risk transformation most appropriate to the specific analysis at hand.

Identification of the time point of start of evasive maneuver in the original events is correct.

Our implementation of start of evasive maneuver is relatively crude. It uses manual annotation of the first driver reaction to the event as a basis for the definition of start of evasive maneuver. There are many approaches to extracting the start of evasive maneuver. However, implementing a pure mathematical definition is problematic, since events play out in very different ways in naturalistic data. It may be wise in future studies to evaluate the choice of start of evasive maneuver through sensitivity analyses. If an incorrect evasive maneuver is implemented, the initial conditions for the simulations will be wrong. Specifically, the initial SVspeed will be wrong.

It is reasonable to assume that, had the event not become critical, the driver would have continued at the speed he or she was maintaining just before the evasive maneuver.

This assumption is likely valid in many contexts, but there are definitely contexts in which this does not hold. When a driver is approaching an intersection with a red traffic light or is already turning, he or she may look away for a short period of time (for some reason), but that driver is not likely to take the long glances off path that drivers in car-following situations on a freeway do. That is, glance distributions are contextually dependent. To perform more detailed and contextually correct MIR and MCR calculations, different glance distributions may have to be used for different contexts (e.g., use freeway-driving matched baselines for freeway near crashes and crashes and identify other scenario types for other contexts). This may be difficult, and thus, future application of MIR and MCR may have a limitation in use.

The assumptions necessary to be able to perform the what-if simulations, with respect to the lead-vehicle actions, are reasonable.

When creating what-if simulations for near crashes, the LVspeed (SVspeed + range rate) is available from the original event. For crashes, however, LVspeed is not available after the crash. This means that for simulations extending after the crash point (higher-severity), assumptions must be made. We assume that the lead vehicle would have continued with the same deceleration as just before the event, until it was standing still. If the lead vehicle was accelerating, we set the LVspeed for all times after the original crash point to the LVspeed observed in the sample before the crash point. The implications of this approach are not easily understood and have to be investigated further.

The exclusion of events in the MIR/MCR calculation does not bias results significantly.

In our MIR and MCR analysis we excluded events that did not complete the what-if simulations for a number of reasons. One of these reasons was that the event did not become a crash even in the 5 seconds available after the event. That is, the relative velocities and the initial distance were such that there was not a crash for 5 seconds. This, and other outliers in the data that are excluded, may produce bias in results. However, if MIR/MCR are used to compare a distribution of MIR/MCR between, for example, two tasks, this is likely negligible. Also for other applications it is likely a minor issue.

Individual drivers' glance behavior and driving style are independent.

It is clearly not the case that individual drivers' glance behavior and driving style are independent. The frequency at which the critical situations are occurring should, to some extent, depend on the driver. Also, it could well be the case that the glancing behavior, reaction times, and so on are different for different drivers. The current approach does not take such dependencies into account. Potentially, there may be a clear correlation between a driver's glancing behavior and his or her driving style—for example, a driver who knows himself or herself to be easily distracted may tend to keep at a longer distance from the leading vehicle.

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Related SHRP 2 Research

Naturalistic Driving Study: Development of the Roadway Information Database (S04A)

Design of the In-Vehicle Driving Behavior and Crash Risk Study (S05)

Naturalistic Driving Study: Technical Coordination and Quality Control (S06)

Naturalistic Driving Study: Collecting Data on Cell Phone Use (S06)

Naturalistic Driving Study: Field Data Collection (S07)

Analysis of Naturalistic Driving Study Data: Offset Left-Turn Lanes (S08B)

Analysis of Naturalistic Driving Study Data: Roadway Departures on Rural Two-Lane Curves (S08D)

Naturalistic Driving Study: Descriptive Comparison of the Study Sample with National Data (S31)

Naturalistic Driving Study: Alcohol Sensor Performance (S31)

Naturalistic Driving Study: Linking the Study Data to the Roadway Information Database (S31)