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Evaluating the Relationship Between Near-Crashes and Crashes: Can Near-Crashes Serve as a Surrogate Safety Metric for Crashes?

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13. ABSTRACT (Maximum 200 words)

The number of crashes observed in naturalistic driving studies is typically small; thus, there is a need to use crash surrogates. This study evaluated the use of near-crashes as a surrogate measure when assessing the safety impacts of driver behaviors and other risk factors. Two metrics, the precision and bias of the risk estimation, were used to assess whether near-crashes could be combined with crashes. The principles and exact conditions for improved precision and unbiased estimation were proposed and applied to the 100-Car data. The analyses indicated that, in general, there is a strong relationship between the frequencies of contributing factors for crashes and for near-crashes. The study also indicated that analyses based on combined crash and near-crash data consistently underestimate the risk of contributing factors compared to using crash data alone. At the same time, the precision of the estimation will increase. This consistent pattern allows investigators to identify the truly high risk factors while qualitatively assessing the potential bias. In summary, the study concluded that there is a benefit to the use of near-crashes as a crash surrogate for risk assessment when naturalistic studies are not large enough to generate sufficient numbers of crashes.

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EXECUTIVE SUMMARY

Naturalistic driving is an innovative method for investigating driver behavior and traffic safety. The 100-Car Naturalistic Driving Study provides an unprecedented opportunity for evaluating the driver behaviors and factors that significantly impact traffic safety. The power of naturalistic data is in the precise vehicle kinematic data (i.e., acceleration/velocity/position collected at 10 Hz) and driver behavior and performance (as viewed using continuous video). This continuously recorded high resolution data for crashes, near-crashes, and normal driving conditions allows for far more sensitive analyses than conducted using other crash data. While naturalistic driving studies provide unique data, there are some limitations. Although the cost per vehicle year of data collected is rapidly declining, the traditionally high expense of conducting these studies limits the number of participants used during data collection. Most existing naturalistic studies have instrumented less than 100 vehicles, and the largest naturalistic driving study in planning may use a few thousand participants; however, this large number of participants will still result in a data set with approximately 1,000 crashes. While collecting precise instrumented vehicle and driver behavior data on a few hundred crashes is groundbreaking in many respects, this number is still far smaller than the number of crashes available from crash databases or actuarial analyses. Also, when parsing several hundred crashes to answer specific research questions (e.g., analyses investigating driver fatigue in run-off-road crashes), the number of resulting crashes can be quite limited.

To help alleviate this limitation of a small number of crashes, researchers (Dingus et al. 2006) have proposed the use of near-crashes in combination with crash events. The operational definition of crash and near-crash is presented in Table 1. The near-crash may have several analytical benefits for such analyses. First, a near-crash is an event that itself should be avoided since, by definition, a successful, last-second evasive maneuver is required to avoid a crash. Second, near-crashes can provide unique insight into the elements and factors associated with successful crash avoidance maneuvers for comparison to unsuccessful or crash circumstances. Third, and the topic of this report, near-crashes, since they (by definition) have many of the same elements as a crash, may provide useful insight into the risk associated with driver behavior and environmental factors *in combination with crashes*. This third benefit, if it can be validated, can provide a powerful tool for analyzing naturalistic driving data since near-crashes occur at a rate of roughly 10 to 15 times more frequently than crashes. Thus, there is a need to better understand the relationship between crashes and near-crashes as well as the impact of using crash surrogate measures when assessing crash risk.

Table 1. Operational Definitions for the Event Severity Levels

Severity Level	Operational Definition
Crash	Any contact with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. Includes other vehicles, roadside barriers, objects on or off of the roadway, pedestrians, cyclists, or animals.
Near-crash	Any circumstance that requires a rapid, evasive maneuver by the participant 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.

The analyses presented in this report focus on assessing the conditions where near-crashes can be used as crash surrogates and the consequences thereof when analyzing naturalistic driving data. It should be clarified that crashes and near-crashes are operationally defined as different types of events, differing in the outcome of (or presence of) an evasive maneuver. The intention of this analysis is not to prove that they are identical. Instead, the focus is to assess the relationship between these two types of events and the consequence of using a near-crash as a crash surrogate for risk assessment. The use of surrogate measures is based on the premise that surrogates happen more frequently than crashes and that more precise risk assessment can be achieved with the increased number of observations (i.e., greater statistical power). The other key aspect for a crash surrogate is that minimal bias should be introduced by combining near-crashes with crashes for risk assessment. For naturalistic driving studies, a quality surrogate measure should adhere to the following two principles:

- The causal mechanism for surrogates (near-crashes) and crashes are the same or similar.
- There is a strong association between the frequency of surrogate measures and crashes under different settings.

These two principles were used to guide the analyses which focused around a thorough examination of the contributing factors for crashes and near-crashes from the 100-Car Naturalistic Driving Study. The complexity and high variability of the causal mechanisms for crashes and near-crashes make the evaluation of the identical causal mechanism assumption very difficult, if not impossible, using existing frequency data. Instead of directly addressing the causal issue, the comparison used in this report focused on the quantitative evaluation of the presence of contributing factors in crashes and near-crashes. The similarity between the frequencies of potential risk factors for crashes and near-crashes was used as an indirect measure for this causal mechanism.

Specifically, the following analyses were conducted, with the primary results summarized in the following sections:

- Sequential factor analysis
- Crash/near-crash ratio analysis
- Sensitivity analysis

SEQUENTIAL FACTOR ANALYSIS

This analysis focused on answering the question of whether the sequence of events prior to crashes and near-crashes is similar. For each crash and near-crash, a sequence of factors was recorded to capture not only the vehicle trajectory but also the relevant driver behavior and driver response to the situation. This sequence of behaviors can best be characterized as shown in Figure 1. The pre-incident maneuver captures the driver's action just prior to the beginning of the event. The precipitating factor is the action by the 100-Car driver or another driver in the near vicinity that begins the sequence. The evasive maneuver is the action by the driver performed either successfully (resulting in a near-crash) or unsuccessfully (resulting in a crash). Contributing factors can occur at any point in time or be present for the duration of the event. Contributing factors include driver factors (e.g., driver drowsiness), environmental states (e.g., icy road conditions), or mechanical problems with the vehicle (e.g., flat tire).

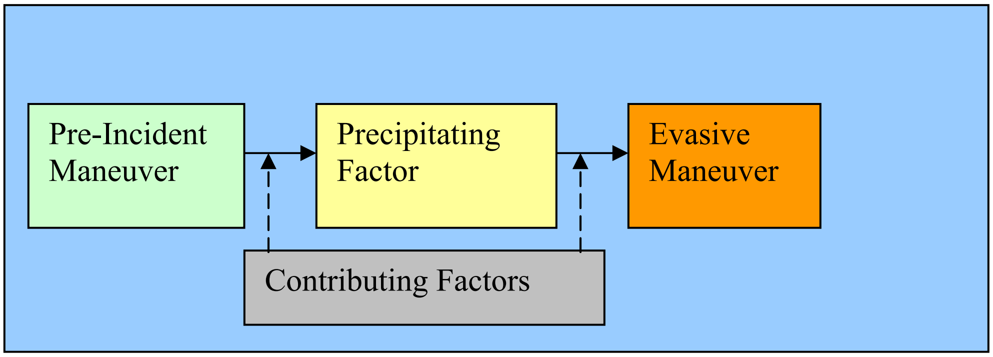

Figure 1. **Sequence of Factors of a Crash or Near-Crash**

The sequence of factors was analyzed for all conflicts and by three different conflict types (Table 2, Table 3). The percentage of no-reactions for crashes is substantially higher than that for the near-crash data. This indicates that the no-reaction response is the key factor to determine whether an event will result in a crash or near-crash (for a large proportion of events). As driver reaction is not considered a risk factor, this result does not hinder the use of near-crashes for risk assessment purposes.

Table 2. Driver Reaction to Crash and Near-Crash

	Crash	Near-Crash
Reaction	45	723
No-Reaction	23	37
Percentage Reaction	66%	95%

p-value≤0.0001

Table 3. Evasive Maneuver for Lead-Vehicle Conflict

Evasive Maneuver	Crash	Near-Crash
Reaction	5	377
No-reaction	9	0
Percentage Reaction	36%	100%

p-value<0.0001

The number of contributing factors was evaluated as an indicator of the complexity of the crash or near-crash situation. In general, there is no substantial difference between the number of contributing factors for a crash and near-crash (Table 4). As shown in Table 5, of the three types of conflict only the lead-vehicle conflict crashes shows significantly higher numbers of contributing factors than near-crashes (2.93 versus 2.27). This result implies that drivers in a lead-vehicle crash may be engaging in a more complex situation than drivers in a lead-vehicle conflict near-crash. Significant differences were not found for following-vehicle or single vehicle conflicts. No unique contributing factors were found for crashes that were not found for near-crashes, thus there is no evidence of a violation of the causal mechanism.

Table 4. Number of Contributing Factors for All Conflict Types

# of Factors	Crash	Near-Crash
0	3	25
1	21	183
2	25	311
3	11	161
4	6	62
5	1	14
6	1	4
Mean	**2.04**	**2.14**

p-value=0.46

Table 5. Number of Contributing Factors by Conflict Type

	Leading-Vehicle Conflict		Single Vehicle Conflict		Following-Vehicle Conflict	
# of Factors	**Crash**	**Near-Crash**	**Crash**	**Near-Crash**	**Crash**	**Near-Crash**
0	0	5	1	3	0	3
1	1	76	13	18	2	15
2	6	163	6	22	7	29
3	4	88	3	2	2	15
4	2	36	1	4	1	7
5	1	6			0	1
6	1	2				
Mean	**2.93**	**2.27**	**1.58**	**1.71**	**2.17**	**2.16**
P-Value for Equal Means	**0.01**		**0.58**		**0.98**	

FREQUENCY RELATIONSHIP BETWEEN CRASH AND NEAR-CRASH

This analysis sought to assess whether there was a correlation between the circumstances that resulted in a larger number of crashes and those that resulted in a larger number of near-crashes. For an ideal situation, it was shown that a constant crash to near-crash ratio will lead to an unbiased risk estimation; that is, the point estimate of the odds ratio using crashes only will be identical to the point estimate obtained using crashes and near-crashes combined. A number of factors were used to evaluate the correlation between a crash and near-crash. The results from the crash/near-crash frequency analyses generally indicated a positive correlation between the occurrence of crashes and near-crashes.

The analysis investigating the relationship between crash and near-crash occurrence by driver was particularly interesting. A Poisson regression model was used to assess the relationship of crash and near-crash occurrence by driver using the number of near-crashes as covariates. The model fitting is shown in Table 6.

Table 6. Poisson Regression Results

	Coefficient	Standard Error	*p*-value
Intercept	-2.31	0.25	<.0001
Near-Crash	0.21	0.04	<.0001

The coefficient for near-crashes is highly significant. This coefficient implies that for every additional near-crash a driver is involved in, the frequency of crash involvement will increase by a factor of exp(0.21)=1.23. This result indicates that there is a positive relationship between the frequency of crash and near-crash involvement.

Generally, the frequency of crashes and near-crashes shows a quality linear relationship as measured by the R-squared value (Table 7). The analyses also indicate that the crash to near-crash ratio depends upon contributing factors. In summary, the analyses confirm that a positive relationship exists between the crash and near-crash frequencies. Therefore, the near-crashes contain valuable information about crash risks and can serve as a surrogate.

Table 7. Summary of the Testing Results for Constant Crash to Near-crash Ratio

	Test for Constant Crash to Near-Crash Ratio		Measure for Association	
Factors	**p-value**	**Significant**	**R-squared**	**Adjusted R-squared**
Gender	0.26	NO	NA	NA
Age Group	0.23	NO	0.91	0.87
Level of Service (LOS)	<0.001	YES	0.5 (0.72*)	0.33 (0.45*)
Lighting Conditions	0.414	NO	0.97	0.95
Road Alignment	0.02	YES	0.99	0.99
Road Surface Condition	0.02	YES	0.99	0.99
Weather	0.32	NO	0.99	0.99

**the R-squared value using polynomial regressions*

SENSITIVITY ANALYSIS

The bias and precision are the most critical criteria in quantitatively evaluating a risk factor. The precision is directly related to the sample size; thus, improved precision can be obtained by combining surrogates with crashes. The bias, introduced by combining the surrogate measure with crashes, is thus the key to assessing a proper crash surrogate and is directly related to the validity of these analyses.

For this analysis, the risk estimation based on crashes alone is considered an unbiased estimation. If a near-crash is a proper surrogate, the risk estimation (odds ratios in the current analysis framework) achieved by combining crashes and near-crashes will be either unbiased or have a consistent bias direction. Because of the strong linear-relationship but non-constant crash to near-crash ratios, it is expected that using near-crashes as surrogates will provide valuable information about risk though a certain level of bias will be introduced. The primary question is whether the benefits of combined analysis outweigh whatever bias may exist. The analyses presented here are thus focusing on evaluating the magnitude and direction of the potential bias, and this is conducted through a sensitivity analysis.

The sensitivity analysis consists of two components: the estimation of risk for crashes only and crashes/near-crashes combined and the comparison of the estimated risks for these two cases. The sensitivity analysis produced consistent results. First, in terms of bias, the point estimates for the odds ratios using combined data were always smaller than for using crash data alone. Secondly, the precision of the estimator, as expected because of the increased sample size, was always better than that of using crashes alone. The results are illustrated in Figure 2. As can be seen, the precision of the odds ratio estimation improves substantially by combining crashes and near-crashes as measured by the reduced length of the confidence interval. Similar patterns hold for all the factors assessed. The consistency of the results has a significant implication: using surrogate measures tends to provide conservative risk estimates, yet with statistically significant test results. Therefore, significant risk factors identified using crashes combined with near-crash surrogates will be at least as dangerous as the analysis indicated. The estimated odds ratio can be considered as a lower bound of the mean of a "true" odds ratio by using crashes alone (if there are sufficient data). This suggests that assessing the risk of various contributing factors using near-crashes as surrogates will provide conservative results as compared to calculating the risk using crashes alone.

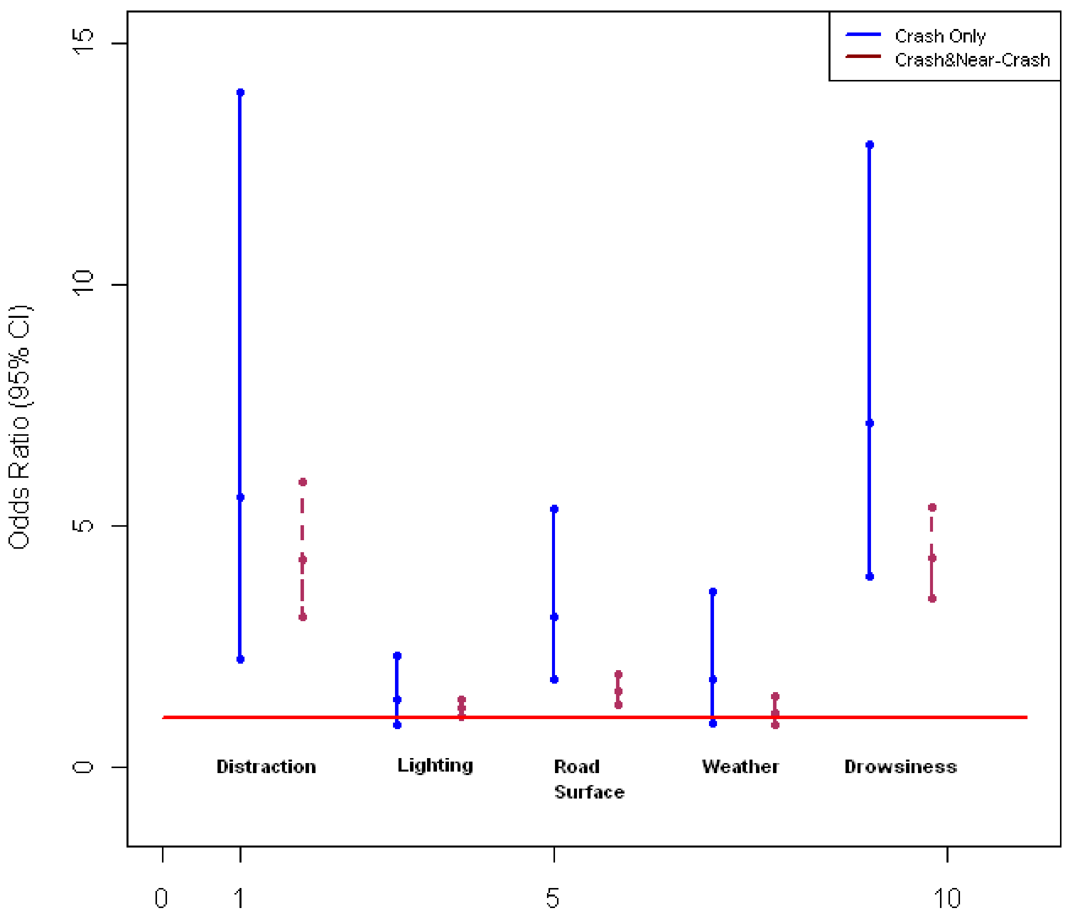

Figure 2. Sensitivity Analysis: Odds Ratio and 95 Percent Confidence Interval

CONCLUSIONS

In summary, the relationship between crashes and near-crashes is complex and context dependent. There are no simple or absolute criteria to prove near-crashes can be used as crash surrogates for general purpose. The empirical study using 100-Car data indicates the following main conclusions: 1) there is no evidence suggesting that the causal mechanism for crash and near-crash are different; 2) there is a strong frequency relationship between crash and near-crash; 3) using near-crashes will have biased results; however, the direction of the bias is consistent based on this empirical study, and 4) using near-crashes as surrogates can significantly improve the precision of the estimation. This result is analogous to the trade-off between bias and precision in many statistical estimation problems. For small-scale studies with limited numbers of crashes, using near-crashes as surrogate measures is informative for risk assessment and will help identify those factors that have a significant impact on traffic factors.

ACRONYMS

AADT – Annual average daily traffic

DAS – Data Acquisition System

GES – General Estimates System

GPS – Global Positioning System

FARS – Fatality Analysis Reporting System

LOS – Level of service

SUV – Sport Utility Vehicle

TTC – Time to collision

VMT–Vehicle miles traveled

VTTI – Virginia Tech Transportation Institute

GLOSSARY OF TERMS

Contributing factors – Any circumstance that leads up to or impacts the outcome of the event. This term encompasses driver proficiency, willful behavior, roadway infrastructure, distraction, vehicle contributing factors, and visual obstructions.

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

Conflict Type – All crashes, near-crashes, crash-relevant conflicts and proximity conflicts were categorized based on the initial conflict that led to the crash that occurred or would have occurred in the case of near-crashes and incidents (crash-relevant conflicts and proximity conflicts were combined to form *incidents*, as used in this report). There were 20 types of conflicts used which are as follows: conflict with lead-vehicle, following vehicle, oncoming traffic, vehicle in adjacent lane, merging vehicle, vehicle turning across subject vehicle path (same direction), vehicle turning across subject vehicle path (opposite direction), vehicle turning into subject vehicle path (same direction), vehicle turning into subject vehicle path (opposite direction), vehicle moving across subject vehicle path (through intersection), parked vehicle, pedestrian, pedalcyclist, animal, obstacle/object in roadway, single vehicle conflict, other, no known conflict, unknown conflict. This list is primarily derived from National Automotive Sampling System: General Estimates System (NASS GES) Accident Types.

Data Reduction – Process used by which trained Virginia Tech Transportation Institute (VTTI) employees reviewed segments of driving video and recorded a taxonomy of variables that provided information regarding the sequence of events leading up to the crash, near-crash, incident, environmental variables, roadway variables, and driver behavior variables.

Driver Reaction – The evasive maneuver performed in response to the precipitating event.

Epoch – Typically, a short period of time (6-second for baseline) in the data

Event – a term referring to all crashes, near-crashes, and incidents. The ‘event’ begins at the onset of the precipitating factor and ends after the evasive maneuver.

Event Nature – Classification of the type of conflict occurring in the event (e.g., conflict with lead vehicle, conflict with vehicle in adjacent lane).

Event Severity – Classification of the level of harm or damage resulting from an event. The five levels were crash, near-crash, crash-relevant, proximity, non-conflict.

Exposure – The observed status of being exposed to a contributing factor.

Naturalistic – Unobtrusive observation; observation of behavior taking place in its natural setting.

Near-Crash – Any circumstance that requires a rapid, evasive maneuver by the participant 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.

Onset of Conflict – Sync number designated to identify the beginning of a conflict; also known as the beginning of the precipitating factor.

Precipitating Factor – The action by a driver that begins the chain of events leading up to a crash, near-crash, or incident. For example, for a rear-end striking collision, the precipitating factor most likely would be "lead vehicle begins braking" or "lead vehicle brake lights illuminate".

Pre-Incident Maneuver – The maneuver that the driver was performing immediately prior to an event.

Secondary Task – Task, unrelated to driving, which requires drivers to divert attention from the driving task (e.g., talking on a cell phone, talking to passenger[s], eating, etc.).

Trigger/Trigger Criteria – A signature in the data stream that, when exceeded, results in 90 s of video and corresponding driving performance data being copied and saved to a database (60 s prior and 30 s after the data exceedence). Trained data reductionists assess these segments of video and driving performance data to determine whether or not this segment of data contains a safety-relevant conflict (i.e., crash, near-crash, or incident). Examples of triggers include a driver braking at 0.76 *g* longitudinal deceleration or swerving around an obstacle with 0.8 *g* lateral acceleration.

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CHAPTER 1. INTRODUCTION

Naturalistic driving is an innovative method for investigating driver behavior and traffic safety. In a naturalistic study, multiple video cameras and various sensors are installed on the participating vehicles. The participants drive the instrumented vehicles for an extended period of time with limited interventions from investigators. Typically, the driver's behavior and driving conditions are continuously monitored by the video cameras and sensors. The 100-Car Naturalistic Driving Study provides an unprecedented opportunity for investigating the driver behaviors and factors that significantly impact traffic safety. Compared to traditional crash database studies or simulation-based studies, the naturalistic data provide detailed information about a driver's everyday driving behavior. In the cases of crashes and near-crashes, the video cameras and sensors provide an opportunity to investigate driving behavior in the seconds leading up to the crash or near-crash. Information about driver behavior and roadways (such as inattention, drowsiness, and real-time traffic conditions) has been impossible to collect using traditional accident report-based methods.

While naturalistic driving studies provide unique data, there are some limitations in using this research method. The costs of naturalistic studies are typically higher than for traditional research methods. This in turn limits the number of participants included in the study. The number of instrumented vehicles is small relative to the number of vehicles that are potentially at risk for crashes. The upcoming SHRP 2 naturalistic driving study may include more than 2,000 vehicles nationwide. However, the number of crashes collected during data collection for the SHRP 2 project will still be much smaller than the number of crashes available from crash database records. Furthermore, the duration of naturalistic data collection is usually limited (typically less than two years). For these reasons, the number of crashes that can be observed from a naturalistic study is usually limited.

In the 100-Car Naturalistic Driving Study (Dingus, Klauer, Neale, Petersen, Lee, Perez, et al., 2006), 100 instrumented vehicles collected continuous data for one year, resulting in only 69 observed crashes (and 13 additional crashes that were not captured on video). This relatively small number of crashes results in several challenges to data analyses. First, statistically significant conclusions could not be reached with a sample size this small. This is especially true for a stratified analysis investigating the contributing factors for different types of crashes (e.g., rear end, single vehicle, and parking lot crashes). Second, rare crash conditions (e.g., icy roads at night) are even less frequent, and thus crashes associated with these rare conditions are even less frequently observed. Therefore, it is desirable to use safety outcomes beyond crashes.

One major advantage of naturalistic studies is the continuous nature of the data collection. Continuous data collection allows researchers to perform detailed data analyses on safety-relevant events other than crashes. Through the analysis of continuous vehicle kinematic data and video, a relatively large number of events are identified that do not fit the exact definition of a crash but are very similar to crashes. Some of these could have resulted in severe or fatal crashes if one or two factors had been slightly different. These safety-relevant events are classified as near-crashes and/or incidents. The information contained in near-crashes and incidents provides valuable insight into the risk factors associated with traffic safety and are thus worth investigating. The near-crash is especially important for its similarity to crashes. Using near-crashes or incidents can help overcome the small sample size problem that exists when using crashes alone. Combining these safety-relevant events can help make maximum use of the detailed driver behavior information that is collected in naturalistic studies. This report focuses on the appropriateness of using near-crashes as a safety surrogate measure for crashes.

BACKGROUND AND LITERATURE REVIEW

The objective of most safety studies is to identify risk factors that have a significant impact on traffic safety. For example, evaluating the safety impact of highway design features has been a focus of many traffic safety studies. The conclusions from those studies can help improve the overall safety of the roadway infrastructure and result in the development of new, safer design standards.

One objective measure used in traffic safety research is the frequency of crashes at specific locations. However, crash frequency data are not universally available or useful for the following conditions and reasons.

- When crash data cannot be collected directly; for example, the safety performance of a proposed new infrastructure.
- When crash data are too sparse given that traffic accidents are rare events. Under these situations, there are not enough observations to reach statistically significant conclusions.

Therefore, alternative measures of safety (e.g., surrogate metrics) have been proposed and used in traffic safety evaluation. Surrogate measures represent an indirect measure of safety. Commonly used surrogate measures include operational and nonoperational characteristics (e.g., annual average daily traffic [AADT] and vehicle speed). Note that some of these measures are confounded; for example, those highway segments with higher AADT also tend to have more crashes. Thus, higher crash frequency does not necessarily mean that this road segment is also more dangerous. The number of crashes per unit of traffic volume is the more appropriate surrogate measure. In general, surrogate measures can alert traffic safety experts to hazardous roadway conditions because an increase in the possibility of crashes is observed.

The most widely used surrogate measure technique, the "traffic conflict technique," was originally developed to evaluate vehicle safety (Perkins and Harris, 1968). Using this technique, a traffic conflict was operationally defined as an event involving two or more road users in which the action of one user causes the other user to make an evasive maneuver to avoid a collision (Parker and Zegeer, 1989). The reliability and validity of the traffic conflict have been a major concern, and there are a number of studies that have tried to address this issue (Williams, 1981; Hauer, 1982; Migletz, Glauz, and Bauer, 1985; Hauer and Garder, 1986). Some empirical studies found that there were clear relationships between traffic conflicts and crashes (Glauz, Bauer, and Migletz, 1985; Hydén, 1987). Despite the concerns about those issues, traffic conflict techniques have been used in various studies to evaluate safety (Katamine and Hamarneh, 1998; Rao and Rengaraju, 1998; Retting and Greene, 1997; Tiwari, Mohan, and Fazio, 1998; Spicer, 1973).

Surrogate measures are especially useful for evaluating the performance of new roadway designs. The surrogate measures are used in computer simulation models in which the number of conflicts for different designs is compared to evaluate the overall safety of the new roadway. In the report "Surrogate Safety Measures from Traffic Simulation Models" (Gettman and Head,

2003) and the report “Surrogate Safety Assessment Model and Validation” (Gettman, Pu, Sayed, & Shelby, 2008), the following conflict types were considered:

- Time to collision (TTC)
- Encroachment
- Vehicle delay or travel time
- Approach speed
- Percentage of stopped vehicles
- Queue lengths
- Stop-bar encroachments
- Red-light violations
- Percentage of left turns
- Speed distribution
- Deceleration distribution

The reports found that the rate of traffic conflicts to actual crashes was approximately 20,000 to 1.

There are disadvantages for both traffic conflict techniques and simulation-based studies. The traditional traffic conflict technique relies on the subjective judgment of observers to decide the severity of the crash or traffic conflict, and inter-observer variability can distort the true situation. Objective measures such as TTC are difficult to obtain in the field. While TTC is relatively simple to obtain in simulation studies, the studies themselves rely on subjective assumptions for simulation models. The traffic conflict studies typically collect data for only a few days, which makes crash data collection difficult. Single vehicle conflicts (which are difficult to evaluate in either traffic conflict studies or simulation studies) are commonly excluded from both types of analysis.

The naturalistic data collection method has several advantages over the traffic conflict technique and simulation studies. The observed safety events are real-life events under normal driving conditions without relying on simulation assumptions. The crashes and near-crashes observed in naturalistic studies are collected for the same time period, which is not available for traditional traffic conflict studies. The frequency of crashes and near-crashes thus truly reflects the relationship between safety hazardous conditions and crashes. All types of crashes can be effectively evaluated. The combination of video, radar, a global positioning system (GPS), and data from other instrumentation allows event severity to be more accurately and objectively evaluated. Therefore, the surrogates based on naturalistic driving data contain more information than single measure-based surrogates.

As discussed previously, the primary reason to use near-crashes as a surrogate measure for crashes in naturalistic driving studies is because the number of crashes observed is not large enough to evaluate safety contributing factors or draw conclusions. Surrogate measures are closely related to Heinrich’s Triangle (Heinrich, 1959), which was developed to assess injuries and accidents that occurred in industry. The basic tenet behind Heinrich’s Triangle is that less severe accidents happen more frequently than severe accidents, and the frequency of severe injuries can be reduced by reducing the frequency of minor injuries. An example is shown in

Figure 3, in which there are 29 minor injuries and one major injury for every 300 unsafe acts. The underlying assumption of Heinrich's Triangle is that the unsafe acts, minor injuries, and major injuries all share the same underlying causal mechanism.

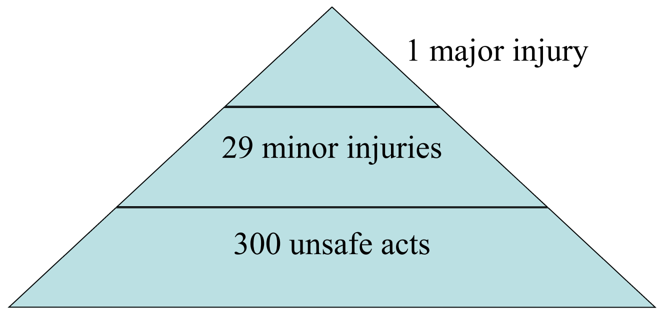

Figure 3. Heinrich's Triangle

It should be clarified that crashes and near-crashes are two different types of events defined by severity. The intention of this analysis is not to prove that crashes and near-crashes are identical but rather to assess the relationship between them. The use of surrogate measures is based on the premise that surrogate events happen more frequently than crashes and that better risk assessment can be achieved with an increased number of observations. The definition of surrogate measure varies according to the purpose of the research and its context. For naturalistic driving studies, a surrogate measure should have the following properties:

- The causal mechanism for surrogates (near-crashes) and crashes are the same or similar.
- There is a strong association between the frequency of surrogate measures and crashes under different settings.

The rationale for these two properties will be discussed in detail in the analysis section, and the two principles were used to guide the subsequent analyses.

The remainder of the report is organized as follows. Chapter 2 briefly introduces the 100-Car Naturalistic Driving Study. This includes an explanation of the data acquisition system (DAS), data collection procedure, event identification and reduction, and baseline identification and reduction method. Chapter 3 discusses the principle of surrogate measures. Chapter 4 presents an empirical analysis and results using the 100-Car Study data. Finally, Chapter 5 contains the conclusions and discussion.

CHAPTER 2. METHODS

An abbreviated methods section for the 100-Car Naturalistic Driving Study will be presented here; however, interested readers are directed to the more detailed method as published by Dingus et al. (2006). It is important to note that the following methods, including data collection and data reduction, were performed under a different contract. The abbreviated Methods section here is presented only to provide context for the analyses presented in the subsequent sections.

INSTRUMENTATION

The 100-Car instrumentation package was engineered by the Virginia Tech Transportation Institute (VTTI) to be rugged, durable, expandable, and unobtrusive. It constituted the seventh generation of hardware and software (developed during a 15-year period) that has been deployed for a variety of purposes. The system consisted of a Pentium-based computer that received and stored data from a network of sensors distributed around the vehicle. Data storage was achieved via the system's hard drive, which was large enough to store data for several weeks of driving before requiring data downloading.

Each of the sensing subsystems in the car was independent, so any failures that occurred were constrained to a single sensor type. Sensors included a vehicle network box that interacted with the vehicle network, an accelerometer box that obtained longitudinal and lateral kinematic information, a headway detection system to provide information about leading or following vehicles, side obstacle detection to detect lateral conflicts (available on approximately 20 percent of the vehicles), an incident box to allow drivers to flag incidents for the research team, a GPS sensor to record the vehicle location, a video-based lane tracking system to measure lane keeping behavior, and video to validate any sensor-based findings. The video subsystem was particularly important as it provided a continuous window into the happenings in and around the vehicle. This subsystem included five camera views monitoring the driver's face and driver side of the vehicle, the forward view, the rear view, the passenger side of the vehicle, and an over-the-shoulder view of the driver's hands and surrounding areas. An important feature of the video system was that it was digital with software-controllable video compression capability. This allowed synchronization, simultaneous display, and efficient archiving and retrieval of 100-Car data. A frame of compressed 100-Car video data is shown in Figure 4. The driver's face (upper left quadrant) is distorted to protect the driver's identity. The lower right quadrant is split into the left-side (top) and the rear (bottom) views.

Figure 4. A Compressed Video Image from the 100-Car Data

The system included several major components and subsystems that were installed on each vehicle. These included the main DAS unit mounted under the package shelf for the sedans (Figure 5) and behind the rear seat in the sport utility vehicles (SUVs).

Figure 5. The Main DAS Unit Mounted Under the Package Shelf of the Trunk

Doppler radar antennas were mounted behind special plastic license plates on the front and rear of the vehicle (Figure 6). The location behind the plates allowed the vehicle instrumentation to remain inconspicuous to other drivers.

Figure 6. Doppler Radar Antenna Mounted on the Front of a Vehicle, Covered by One of the Plastic License Plates Used for This Study

The final major components in the 100-Car hardware installation were mounted above and in front of the center rearview mirror (Figure 7). These components included an incident pushbutton box, which housed a momentary pushbutton that the subject could press whenever an unusual event happened in the driving environment. This flagged the event in the data stream and opened an audio channel for the driver to describe the incident. Also contained in the housing was an unobtrusive miniature camera that provided the driver face and left-side views. The camera was invisible to the driver because it was mounted behind a smoked Plexiglas cover (right-hand portion in Figure 7). Mounted behind the center mirror were the forward-view camera and the glare sensor. This location was selected to be as unobtrusive as possible and did not occlude any of the driver's normal field of view.

Figure 7. The Incident Push Button Box and Driver Face/Left Vehicle Side Camera Mounted Above the Rearview Mirror

PARTICIPANTS

One hundred drivers who commuted into or out of the Northern Virginia/Washington, D.C., metropolitan area were initially recruited as primary drivers to have their vehicles instrumented or to receive a leased vehicle for this study. Drivers were recruited by placing flyers on vehicles as well as by placing newspaper announcements in the classified section. Drivers who had their private vehicles instrumented (N=78) received $125.00 per month and a bonus at the end of the study for completing necessary paperwork. Drivers who received a leased vehicle (N=22) received free use of the vehicle, including standard maintenance, and the same bonus at the end of the study for completing necessary paperwork. Drivers of leased vehicles were insured under the Commonwealth of Virginia policy.

As some drivers had to be replaced for various reasons (for example, a move from the study area or repeated crashes in leased vehicles), 109 primary drivers were included in the study. Since other family members and friends would occasionally drive the instrumented vehicles, 132 additional drivers were identified and also included in the analysis.

VEHICLES

Since 100 vehicles had to be instrumented with a number of sensors and data collection hardware, and since the complexity of the hardware required a number of custom mounting brackets to be manufactured, the number of vehicle types had to be limited for this study. Six different vehicle models were selected based upon their prevalence in the Northern Virginia area. These included five sedan models (Chevrolet Malibu and Cavalier, Toyota Camry and Corolla, and Ford Taurus) and one SUV model (Ford Explorer). The model years were limited to those with common body types and accessible vehicle networks (generally 1995 to 2003). The distribution of these vehicle types was as follows:

- Toyota Camry: 17 percent
- Toyota Corolla: 18 percent

- Chevy Cavalier: 17 percent
- Chevy Malibu: 21 percent
- Ford Taurus: 12 percent
- Ford Explorer: 15 percent

PROCEDURE FOR DATA REDUCTION: 100-CAR STUDY EVENT DATABASE

Given the continuous nature of the data collection, project resources would not permit the manual review of more than six terabytes of video to identify potential crashes and near-crashes. Thus, the kinematic vehicle data were used to detect safety-relevant events. A sensitivity-specificity analysis was employed to identify potential sensor thresholds that would efficiently identify potential safety conflicts (e.g., crashes, near-crashes, and incidents) without a high number of false alarms. When this process was complete, the final trigger criteria were set, as shown in Table 8.

Table 8. Dependent Variables Used as Event Triggers

Trigger Type	Description
1. Lateral Acceleration	Lateral motion equal to or greater than 0.7 *g*.
2. Longitudinal Acceleration	Acceleration or deceleration equal to or greater than 0.6 *g*. Acceleration or deceleration equal to or greater than 0.5 *g* coupled with a forward TTC of 4 s or less. All longitudinal decelerations between 0.4 *g* and 0.5 *g* coupled with a forward TTC value of $\leq$4 s, and with a corresponding forward range value at the minimum TTC not greater than 100 ft.
3. Event Button	Activated by the driver by pressing a button located by the rearview mirror when an event occurred that the driver deemed critical.
4. Forward TTC	Acceleration or deceleration $\geq$0.5 *g* coupled with a forward TTC of 4 s or less. All longitudinal decelerations between 0.4 *g* and 0.5 *g* coupled with a forward TTC value of $\leq$4 s, and with a corresponding forward range value at the minimum TTC not greater than 100 ft.
5. Rear TTC	Any rear TTC trigger value of 2 s or less that also has a corresponding rear range distance of $\leq$50 ft AND any rear TTC trigger value in which the absolute acceleration of the following vehicle is greater than 0.3 *g*.
6. Yaw Rate	Any value greater than or equal to a plus AND minus 4-degree change in heading (i.e., vehicle must return to the same general direction of travel) within a 3-s window of time.

Given the variability in light-vehicle driving performance, the sensitivity analysis proved to be challenging. VTTI researchers determined that the best option was to accept a very low miss rate while accepting a fairly high false alarm rate to ensure that few valid events were missed. This resulted in viewing more than 110,000 triggers in order to validate 10,548 events. The distribution of the total number of reduced events by severity is shown in Table 9. Note that incidents were not used in the current analyses, rather only crashes and near-crashes.

Table 9. The Total Number of Events Reduced for Each Severity Level

Event Severity	Total Number
Crash	69 (plus 13 without complete data)
Near-crash	761
Incidents (Crash-Relevant Conflicts and Proximity Conflicts)	8,295

After the trigger criteria were set, data reductionists watched 90-second epochs for each event (60 s prior to and 30 s after) and reduced and recorded information regarding the nature of the event, driving behavior prior to the event, the state of the driver, the surrounding environment, etc. The specific variables recorded in the data reduction process are described in detail in the data reduction software framework section of this chapter.

Recruiting and Training Data Reductionists

A data reduction manager interviewed, hired, and trained 14 data reductionists on how to access the data from the server and operate the data reduction software and provided training on all relevant operational and administrative procedures (approximately 4 hours of training). The manager gave each data reductionist a data reduction manual to guide him or her in learning the software and reduction procedures. All analyst trainees practiced data reduction procedures with another trained analyst prior to reducing data independently. After each trainee felt comfortable with the process, the trainee worked alone under the supervision of the data reduction manager. Once the trainee and manager felt confident of the analyst's abilities, the analyst began working independently, with spot-check monitoring from the project leader and other reductionists.

The data reductionists performed two general tasks while creating the event database. After the trigger criteria were set using the results from the sensitivity analysis, the data reductionists then validated the data, determined severity, and performed a full data reduction for the incidents. Only the data reduction manager and a senior researcher performed the reduction for the crashes and near-crashes. The data reductionists also recorded all of the required variables (as discussed below) to create an additional baseline database, hereafter referred to as the case-control baseline database.

Event Database Reduction Software Framework

The data reduction framework for the event database was developed to identify various driving behavior and environmental characteristics for safety-relevant conflicts. The operational definitions for the pertinent severity levels for the current analysis are presented in Table 10. Operational Definitions for the Event Severity Levels Critical to the Present Analysis

. The variables recorded for each of these safety-relevant events were selected based upon past instrumented-vehicle studies (Hanowski et al., 2000; Dingus et al., 2001), national crash databases (GES and Fatality Analysis Reporting System [FARS]), and questions on Virginia State Police Accident Reports.

Table 10. Operational Definitions for the Event Severity Levels Critical to the Present Analysis

Severity Level	Operational Definition
Crash	Any contact with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. Includes other vehicles, roadside barriers, objects on or off of the roadway, pedestrians, cyclists, or animals.
Near-crash	Any circumstance that requires a rapid, evasive maneuver by the participant 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.

The general method for data reduction was to have the data reduction manager and project manager perform all data reduction on the near-crashes and crashes. A total of four areas of data reduction were recorded for each event. These four areas included: vehicle variables, event variables, environmental variables, and driver state variables. Table 11 defines each area of data reduction, provides examples, and describes additional features of the data reduction.

Table 11. Areas of Data Reduction, Definition of the Area, and Examples

Area of Data Reduction	Definition	Example
Vehicle Variables	All of the descriptive variables including the vehicle identification (ID) number, vehicle type, ownership, and those variables collected specifically for that vehicle, such as vehicle miles traveled (VMT).	Vehicle ID, vehicle type, driver type (leased or private), and VMT.
Event Variables	Description of the sequence of actions involved in each event, list of contributing factors, and safety or legality of these actions.	Nature of event/crash type, pre-event maneuver, precipitating factors, corrective action/evasive maneuver, contributing factors, types of inattention, driver impairment, etc.
Environmental Variables	General description of the immediate environment, roadway, and any other vehicle at the moment of the incident, near-crash, or crash. Any of these variables may or may not have contributed to the event, near-crash, or crash.	Weather, ambient lighting, road type, traffic density, relation to junction, surface condition, traffic flow, etc.
Driver's State	Description of the instrumented-vehicle driver's physical state.	Hands on wheel, seat belt usage, fault assignment, eye glance etc.
Driver/Vehicle 2	Description of the vehicle(s) in the general vicinity of the instrumented vehicle and the vehicle's action.	Vehicle 2 body style, maneuver, corrective action attempted, etc.
Narrative	Written description of the entire event.	
Dynamic Reconstruction	Creation of an animated depiction of the event.	

A crash was operationally defined as, "Any contact with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated." A benefit of the naturalistic approach is that it is possible to record all of these events; however, the severity of the crashes must be delineated to better understand the data. Table 12 presents the types of events that were collected and the frequency of crash and near-crash occurrence.

Table 12. Number of Crashes and Near-Crashes for Each Conflict Type

Conflict Type	Crash	Near-Crash
Single vehicle	24	48
Lead vehicle	15	380
Following vehicle	12	70
Object/obstacle	9	6
Parked vehicle	4	5
Animal	2	10
Vehicle turning across participant vehicle path in opposite direction	2	27
Adjacent vehicle	1	115
Oncoming traffic	0	27
Vehicle turning across participant vehicle path in same direction	0	3
Vehicle turning into participant vehicle path in same direction	0	28
Vehicle moving across participant vehicle path through intersection	0	27
Merging vehicle	0	6
Pedestrian	0	6
Other/unknown	0	3

The 69 crashes were parsed into the following four crash categories. Some of these crashes, including low-speed collisions, were not police-reported. Note that 75 percent of the single-vehicle crashes were low *g*-force physical contact or tire strikes; in other words, most of the crashes involved very minor physical contact. The numbers of crashes by severity level and crash type are shown in Table 13.

- Level I: Police-reported air bag deployment and/or injury
- Level II: Police-reported property damage only
- Level III: Non-police-reported property damage only
- Level IV: Non-police-reported low *g* physical contact or tire strike (greater than 10 mph)

Table 13. Crash Type by Crash Severity Level

Conflict Type	Total	Level I	Level II	Level III	Level IV
Single vehicle	24	1	0	5	18
Lead vehicle	15	1	3	5	6
Following vehicle	12	2	2	5	3
Object/obstacle	9	0	1	3	5
Parked vehicle	4	0	0	2	2
Animal	2	0	0	0	2
Oncoming vehicle turning across participant vehicle path	2	1	1	0	0
Adjacent vehicle	1	0	0	1	0
Total	69	5	7	21	36

Since it was possible to detect all crashes regardless of severity, it is interesting to note the large number of drivers who experienced one or more collisions during the 12- to 13-month data collection period. Of all drivers, 7.5 percent of drivers never experienced an event of any severity. In contrast, 7.4 percent of the drivers experienced many near-crashes and three or four crashes. Thus, a handful of participants were either very risky drivers or very safe, with the majority of drivers demonstrating a relatively normal distribution of events across the data collection period.

CASE-CONTROL BASELINE DATABASE

The analysis of the naturalistic study follows a case-based approach in which the exposure variables (i.e., potential contributing factors) for the crashes were compared with the exposure variables for the normal driving conditions to evaluate the impact of each factor. Greenberg, Daniels, Flanders, Eley, and Boring (2001) argued that case-control designs allow for efficient means to study rare events, such as automobile crashes. These designs provide efficient means to evaluate the causal relationships that exist by using relatively smaller sample sizes than are used in typical crash database analyses.

The case-control baseline database comprised approximately 17,000 6-second segments in which the vehicle maintained a velocity greater than 5 mph (referred to as an epoch). Kinematic triggers on driving performance data were not used to select these baseline epochs. Rather, these epochs were selected at random throughout the 12- to 13-month data collection period per vehicle. A 6-second segment of time was used because this was the time frame used by data reductionists to ascertain whether a particular secondary task was a contributing factor for each crash, near-crash, and incident. For example, a driver would have to have taken a bite of a sandwich within 5 s prior to the onset of the conflict or some time during the event for the activity to be considered a contributing factor to the crash, near-crash, or incident. Each case-control baseline epoch was randomly selected from the 12 months of data collected on each vehicle. The selection of the baseline is totally random, and thus the baseline epochs are representative of normal driving conditions. Note that this baseline differs from the one originally used on the 100-Car analyses which was a stratified-random sample (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006). The original sample was weighted such that vehicles that were likely to be involved in crashes had more baseline samples. In the baseline data set used for the current analyses, the number of baseline samples for each vehicle was proportional to the total driving hours of the particular vehicle and not related to its crash/near-crash involvement.

The primary metric in evaluating the impact of a factor on traffic safety is the odds ratio. The odds represent the likelihood of event occurrence. The odds compare the frequency of event occurrence (i.e., presence of drowsiness) to the frequency of event non-occurrence (i.e., absence of drowsiness). That is, the odds of event occurrence are defined as the probability of event occurrence divided by the probability of non-occurrence. A contributing factor is considered to have a significant impact on safety if the odds of presence for events are much higher than the odds of presence in baseline events. Therefore the ratio of the odds for safety events to the odds for baseline is a measure of the safety impact of the contributing factor. The odds ratio is defined as:

$$OR = \frac{odds_{event}}{odds_{baseline}} = \frac{p_{event}/(1-p_{event})}{p_{baseline}/(1-p_{baseline})},$$

where p_{event} and $p_{baseline}$ are the probability of the presence of a contributing factor for incidents and baseline.

An odds ratio with a value of 1.0 indicates a factor that has no elevated risk in the event situation above normal, baseline driving. An odds ratio of less than 1.0 indicates that this activity is safer than normal, baseline driving, or that it creates a protective effect. An odds ratio of greater than 1.0 indicates that this activity increases one’s relative risk of a crash or near-crash by the value of the odds ratio. For example, if the odds ratio for drowsiness is 3.0, then this indicates that a driver is three times more likely to be involved in a crash or near-crash while traveling in a state of drowsiness than if he or she was driving in an alert condition.

CHAPTER 3. PRINCIPLES OF SURROGATE MEASURE ANALYSIS

As discussed previously, the primary criteria for using near-crashes as surrogate measures for crashes are the following:

- The causal mechanism for surrogates (near-crashes) and crashes are the same or similar.
- There is a strong association between the frequency of surrogate measures and crashes under different settings.

In this section the motivation for these two criteria are discussed, and the corresponding analyses are conducted to evaluate them empirically.

CAUSAL MECHANISM

One key requirement for using near-crashes as a surrogate measure is that they possess the same causal mechanism as crashes (the only difference between a crash and an appropriate near-crash surrogate is the severity of the safety outputs). For example, suppose there are two potential calamities in a working environment: 1) a hand injury caused by operating a machine, and 2) a fatality caused by objects falling from the roof. In this example, although the frequency of hand injuries is higher than that of falling-object fatalities, the former is not an ideal surrogate measure of the latter because the two calamities are based on different causal mechanisms. In other words, there is no causal connection to indicate that making safety improvements to reduce the number of hand injuries will also reduce the risk of fatalities, as described above. From a modeling perspective, the contributing factors identified for hand injuries provide biased or wrong information for the contributing factors for falling-object fatalities. In the context of naturalistic studies, the contributing factors for near-crashes and crashes should be similar or identical (e.g., distractions can lead to both near-crashes and crashes), and their differences should be merely of severity. Only then can near-crashes be used to evaluate factors that affect traffic safety, instead of analyzing crash data directly.

In the literature, the definition of surrogate measures varies within different contexts. The majority of these definitions are based on a single measurement. The traffic conflict, which might lead to a crash and happens immediately before the crash, is a commonly used surrogate that is objectively measured using TTC, deceleration rates, encroachment time, etc. In naturalistic studies, a near-crash is identified through the combination of several factors, including vehicle kinematic measures and visual evaluation for the severity of events. A near-crash contains more information and is potentially a better surrogate measure than those based on a single metric. Furthermore, many factors associated with near-crashes share similar characteristics with crashes (for example, the same kinematic triggers were used to detect both crashes and near-crashes). Thus it is expected that the causal mechanism for near-crashes would be similar for crashes.

As discussed previously, the validity of using near-crashes as surrogates for crashes demands that the underlying mechanisms be identical and that any differences between crashes and near-crashes exist solely in the severity of the event. However, quantitatively verifying the similarity of the causal factors for near-crashes and crashes is challenging. First, the causal mechanisms among crashes are often different and thus probably different for near-crashes as well. Most existing traffic safety studies are based on crash frequency, and only the association between crash and contributing factors can be established. The causal mechanism cannot be directly evaluated from frequency data. Secondly, the causal mechanisms for crashes are complicated. It is rarely the case that a single factor would cause a crash, but the combination of several factors will. Therefore it is not appropriate to state that one particular factor causes an accident. In epidemiology, the sufficient risk set (which is defined as the set of all necessary conditions for an accident to happen) is used. A similar concept, the cut set, can be found in the Fault Tree Analysis. The sufficient risk set/cut set in most cases is unique for each individual event. It is challenging to find all elements of the sufficient risk set for a particular crash using frequency data. Using appropriate accident reconstruction techniques and causal analysis methods (e.g., Fault Tree Analysis), it is possible to potentially reveal the critical contributing factors; however, that is not the focus of this report.

The complexity and high variability of the causal mechanisms for crashes and near-crashes make the evaluation of the identical causal mechanism assumption very difficult, if not impossible, using existing frequency data. Instead of directly addressing the causal issue, the comparison used in this report focused on the quantitative evaluation of the presence of contributing factors in crashes and near-crashes. The similarity between the frequencies of factors for crashes and near-crashes were used as an indirect measure for the causal mechanism.

The random nature of the crash and near-crash implies that the presence of a high risk factor will not necessarily lead to a crash or near-crash. Instead, the probability of a crash/near-crash will increase. For example, the presence of drowsiness will not definitively lead to a crash, but a crash/near-crash is more likely to happen under drowsiness. The same causal mechanism can also be understood as the factor that will lead to the elevated probability of a crash will also lead to a high probability of a near-crash. As the probability can be measured by relative frequency, the frequency of factors for crash and near-crash events can indeed imply causal mechanism.

In this report, a thorough examination of the contributing factors for crash and near-crashes will be presented. Please note that each contributing factor will be examined in isolation in this report (no combinations of contributing factors will be examined). Specifically, the analysis will focus on the following questions:

- Are there individual contributing factors present in crashes but not in near-crashes?
- Are there levels of a contributing factor whose presence varies significantly for crashes and near-crashes?
- Does the number of contributing factors for crashes and near-crashes differ significantly? For example, a driver with night-blindness symptoms combined with driving at night in a vehicle with a damaged headlight will almost surely result in a crash. However, the presence of each individual factor may have little consequence.

FREQUENCY RELATIONSHIP

From a practical point of view, the frequency of a surrogate measure should be strongly associated with the frequency of crashes. That is, if a certain number of surrogates are observed, a accurate estimate of the number of crashes to occur will be obtainable. This is directly corresponding to the motivation for using surrogate measures: instead of modeling or evaluating the relatively small number of crashes observed, the relatively larger number of surrogates can be used to attain an improved assessment of traffic safety. A strong association will guarantee that an analysis using surrogate measures will not depart significantly from the results of an analysis using crashes only. The association between crashes and near-crashes can be measured by the ratio between them. A stable crash-to-near-crash ratio for all general analyses or categories of interest (e.g., level of traffic density or drivers in a certain age group) indicates a strong association.

An empirical study of the frequency relationship between crashes and non-crashes was conducted using the 100-Car database. In order to obtain a reasonable number of observations, the data were aggregated based on the categories for which the crash-to-near-crash ratios might be different:

- Driver
- Level of service (LOS)
- Age
- Gender
- Weather conditions

The analyses will focus on the following research questions:

- Is there a trend of high frequencies of near-crashes being associated with high frequencies of crashes?
- Does the crash-to-near-crash ratio vary significantly across strata? What is the pattern of variation (e.g., how does the ratio vary according to frequencies of near-crashes)?

The consistency of the crash-to-near-crash ratio is the key for assessing whether using near-crashes as surrogates is appropriate in practice. Near-crashes are less severe than crashes, and their frequency of occurrence is expected to be higher than crashes, which the 100-Car Study data verified. It can also be shown that if there is a perfect relationship (constant crash-to-near-crash ratio), the odds ratios (or risk ratios) for using crashes alone and combining crashes and near-crashes will be identical. However, the combined analysis will provide a more accurate estimation (tighter confidence intervals). A hypothetical example is discussed below to illustrate this point.

Suppose there is a sample of 15 crashes and 150 baselines. Distractions are observed for 10 of these 15 crashes and 50 of the 150 baselines. If there is a perfect relationship between crashes and near-crashes with a ratio of 1:3, then for a given sample of 45 near-crashes, distraction should be observed for 30 near-crashes. The resulting contingency table is shown in Table 14.

Table 14. Constant Crash-to-Near-Crash Ratio Contingency Table (Hypothetical)

	Crash-to-Near-Crash Ratio	Crash	Near-Crash	Crash and Near-Crash	Baseline
Distraction	1:3	10	30	40	50
No Distraction	1:3	5	15	20	100

On the other hand, suppose the ratios vary with factors. For example, the crash-to-near-crash ratios for distraction and no distraction are 1:1.5 and 1:6, respectively. Suppose there are still 45 near-crashes. The resulting table is as follows (Table 15). The total number of near-crashes is identical for Table 14 and Table 15.

Table 15. Non-Constant Crash-to-Near-Crash Ratio Contingency Table (Hypothetical)

	Crash-to-Near-Crash Ratio	Crash	Near-Crash	Crash & Near-Crash	Baseline
Distraction	1:1.5	10	15	25	50
No Distraction	1:6	5	30	35	100

Table 16 provides the odds ratios, corresponding confidence intervals, and *p*-values for the three scenarios: crash only, combined analysis for constant ratio, and combined analysis for non-constant ratio. As can be seen, the point estimates for crash only and combined constant ratios are exactly the same: 4. However, the analysis using combined data provides a much narrower confidence interval (2.13, 7.52), thus a more precise estimation.

Table 16. Comparison of Odds Ratio for Constant and Non-Constant Crash-Near-Crash Ratio (Hypothetical)

	Ratio	Odds Ratio	Confidence Interval	*p*-value
Crash Only	NA	4	(1.35, 11.79)	0.021*
Crash and Near-Crash Combined	Constant ratio	4	(2.13, 7.52)	<0.001*
	Non-constant ratio	1.43	(0.77,2.63)	0.268

For the case of non-constant crash-to-near-crash ratio, the odds ratio estimation is 1.43, which is significantly smaller than that based on crash-only data. More importantly, the *p*-value is 0.268, and thus it can be concluded that distraction is not a risk factor. This result is contrary to the analysis based on crash-only data.

The above hypothetical example illustrates the critical role of a constant crash-to-near-crash ratio. It can be shown mathematically that the results are always true. The proof is shown as follows.

Denote a contingency table of safety outcomes versus where the driver is exposed to a potential hazardous condition as shown in Table 17.

Table 17. Contingency Table Demonstrating Odds Ratio Calculation

	Exposure	Non-Exposure
Crash	A	B
Baseline	C	D

The calculation of odds ratio is given by:

$$OR = \frac{A * D}{B * C}$$

The variance of the estimation is given by:

$$Var(\log(OR)) = \frac{1}{A} + \frac{1}{B} + \frac{1}{C} + \frac{1}{D}.$$

The 95 percent confidence interval is:

$$(OR \cdot exp(-z\sqrt{v}),\ OR \cdot exp(z\sqrt{v})),$$

where z is the $100(1 - \frac{\alpha}{2})$ percentile of the standard normal distribution. For the 95 percent confidence interval, $z = 1.96$.

The length of the confidence interval is:

$$\text{OR}\ (exp(z\sqrt{v}) - exp(-z\sqrt{v}))$$

Assume a surrogate measure was used and the constant near-crash to crash ratio is λ. That is,

$$\frac{A_{surrogate}}{A} = \frac{B_{surrogate}}{B} = \lambda.$$

The total observations for crash and near-crash combined are:

$A + A_{surrogate} = (1 + \lambda)A$ for exposure

and $B + B_{surrogate} = (1 + \lambda)B$ for non-exposure.

The contingency table with surrogate observation is shown in Table 18.

Table 18. Contingency Table with Surrogate Observation

	Exposure	Non-Exposure
Crash+Near-Crash	$(1 + \lambda)A$	$(1 + \lambda)B$
Baseline	C	D

The odds ratio of combined data using both crash and surrogates is equal to that of using crash alone, as shown in the following simple derivation:

$$OR' = \frac{A(1+\lambda)*D}{B(1+\lambda)*C} = \frac{A*D}{B*C} = OR$$

The variance of the estimation using crashes and surrogates combined is smaller than that of using crash alone, as shown below.

$$v' = Var(\log(OR)) = \frac{1}{A(1+\lambda)} + \frac{1}{B(1+\lambda)} + \frac{1}{C} + \frac{1}{D} < \frac{1}{A} + \frac{1}{B} + \frac{1}{C} + \frac{1}{D} = v \text{ for all } \lambda > 0$$

Thus the corresponding length of the confidence interval is smaller:

$$OR \cdot \{exp(z\sqrt{v'}) - exp(-z\sqrt{v'})\} < OR \cdot \{exp(z\sqrt{v}) - exp(-z\sqrt{v})\}$$

The resulting three equations above indicate that a constant ratio will lead to identical point estimations for the odds ratios but shorter confidence intervals (i.e., a more precise estimation) given a positive ratio $\lambda > 0$. Furthermore, the reduction in length of confidence interval depends on factor λ; a larger λ will lead to a more precise estimation.

A more general case is when there is a strong linear relationship but not a constant ratio. A perfect linear relationship implies:

$$A_{surrogate} = \beta_0 + \lambda A$$

$$B_{\mathrm{surrogate}} = \beta_0 + \lambda B$$

Note that a constant crash-to-near-crash ratio is a special case of the above general form when $\beta_0 = 0$. The corresponding contingency table is shown in Table 19.

Table 19. Contingency Table Demonstrating Odds Ratio Calculation

	Safety Events	Exposure	Non-Exposure
Crash Only	Crash	A	B
	Baseline	C	D
Crash & Near-Crash Combined	Crash and Near-Crash	$A+\beta_0+\lambda A$	$B+\beta_0+\lambda B$
	Baseline	C	D

The risk estimation using near-crashes and crashes combined will be:

$$OR' = \frac{(A+\beta_0+\lambda A)*D}{(B+\beta_0+\lambda B)*C} = \frac{(A+\beta_0+\lambda A)*B}{(B+\beta_0+\lambda B)*A} * \frac{A*D}{B*C} = \frac{(A+\beta_0+\lambda A)*B}{(B+\beta_0+\lambda B)*A} * OR = \frac{1+\lambda+\beta_0/A}{1+\lambda+\beta_0/B} * OR$$

The OR' differs from OR by a factor of $\frac{1+\lambda+\beta_0/A}{1+\lambda+\beta_0/B}$.

In summary, the relationship between the frequency of crash and near-crash is critical for evaluating surrogate measures. A constant crash-to-near-crash ratio is an ideal situation where risk estimation using either crash alone or in combination with near-crash will lead to identical results. Even when the constant ratio is not satisfied, a strong linear relationship between crash and near-crash will also provide valuable information about crash risk.

CHAPTER 4. EMPIRICAL ANALYSIS USING 100-CAR DATA

The principles discussed in the previous section guided the analysis in this section. Due to the random nature of crashes and the relatively small number of observed events, it is unlikely that the analysis of a single factor will lead to a definitive conclusion. Instead, the present study is looking for coherence in the evidence provided by each individual analysis. The conclusions will be based on the synthesis of results from three analyses conducted in this task. The first analysis investigated the sequence of factors that occur before a crash or near-crash. This analysis helps by illuminating the differences between crashes and near-crashes and thus sheds light on the underlying causal mechanisms involved in each. The second analysis investigated the relationship of individual contributing factors occurring for crashes and near-crashes. The third analysis was a sensitivity analysis to investigate the impacts of combining crashes and near-crashes in risk evaluation.

Unless otherwise specified, the statistical analysis is based on contingency tables similar to Table 17. The statistical hypothesis is that the ratios of crashes to near-crashes are identical across different exposure levels; i.e., A/C=B/D by the notations in Table 17. The chi-square test for homogeneity was used to test this hypothesis. A p-value was provided when sample size was sufficiently large. It should be noted that the power of statistical tests is in detecting difference rather than proving similarity. Thus, while we cannot statistically prove the similarity of crashes and near-crashes, demonstrating that no statistical differences exist may be taken as evidence that crashes and near-crashes may be quite similar. The reader is reminded that a statistically non-significant result can be caused by a small sample size. Caution should be used when interpreting the non-significant results.

SEQUENTIAL FACTOR ANALYSIS

For each crash and near-crash, a sequence of factors was recorded to capture not only the vehicle trajectory but also the relevant driver behavior and driver response to the situation. This sequence of behaviors/factors can best be characterized as shown in Figure 8. The pre-incident maneuver captures the driver's action just prior to the beginning of the event. The precipitating factor is the action by the 100-Car Study driver or another driver in the near vicinity that begins the sequence of factors. The evasive maneuver is the action, typically by the 100-Car Study driver, that is performed either successfully (resulting in a near-crash) or unsuccessfully (resulting in a crash). Contributing factors can occur at any point in time or be present for the duration of the event. Contributing factors include particular driver factors (e.g., driver drowsiness), environmental states (e.g., icy road conditions), or mechanical problems with the vehicle (e.g., flat tire).

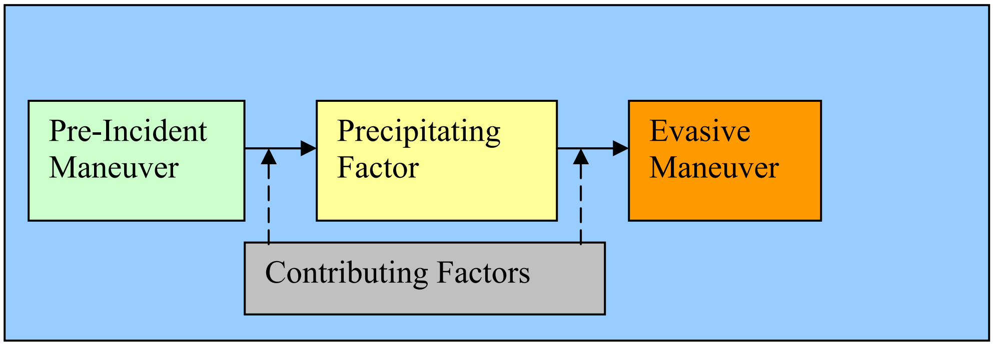

Figure 8. Sequential Factors of a Crash or Near-Crash

Evasive Maneuver

The evasive maneuver is defined as the participant driver's reaction or evasive maneuver in response to the precipitating factor. This is independent of maneuvers associated with the resulting crash or near-crash.

Table 20 provides the reaction of drivers prior to each crash and near-crash. The results show that 23/(23+45)=34 percent of drivers have no-reaction before a crash. In contrast, in near-crashes, only approximately 37/(37+723)=5 percent of drivers have no-reaction. The statistical chi-square test for equal percentage is highly significant, supporting the observed unequal percentages.

Table 20. Driver Reaction to Crash and Near-Crash

	Crash	Near-Crash
Reaction	45	723
No-Reaction	23	37
Percentage Reaction	66%	95%

p-value≤0.0001

The significant difference in driver reaction for crashes and near-crashes implies that driver response is critical in distinguishing between these two types of events. However, this difference shall not be considered as evidence against the identical causal mechanism. The causal mechanism in this study is considered as the risk factors that trigger the safety events, not the driver's last response to avoid a crash. A crash and a near-crash can have exactly the same causal mechanism but a different safety outcome because of the evasive maneuver.

The details of the evasive maneuvers are shown in Table 21. As can be seen, for crash events, the most frequent response is non-reaction. Brake only (both lockup and non-lockup) is the second most frequent response. A steering response is also common for crashes, and it is interesting that steering left is far more frequent than steering right (10 versus 2). Note that these steering maneuvers all took place in single-vehicle crashes and were likely due to attempting to steer back on to the road during a lane departure.

Table 21. Evasive Maneuvers for Crash and Near-Crash

Evasive Maneuver	Crash		Near-Crash	
	Frequency	Percentage	Frequency	Percentage
Accelerated	0	0%	3	0%
Accelerated and steered left	0	0%	4	1%
Accelerated and steered right	0	0%	3	0%
Braked and steered left	6	9%	124	16%
Braked and steered right	5	7%	142	19%
Braking (lockup)	1	1%	7	1%
Braking (lockup unknown)	1	1%	41	5%
Braking (no lockup)	16	24%	332	44%
Steered to left	10	15%	27	4%
Steered to right	2	3%	32	4%
No-reaction	23	34%	37	5%
Unknown if action was attempted	2	3%	1	0%
Other reaction	2	3%	3	0%

A stratified analysis was conducted for single-vehicle, lead-vehicle, and following-vehicle conflicts. The types of conflict were defined based on the relationship between the 100-Car vehicle and the vehicles in close vicinity. The definitions are listed below.

- *Conflict with a lead vehicle*: Interaction with a vehicle in front of the subject vehicle (traveling in the same direction as the subject vehicle or stopped).
- *Conflict with a following vehicle*: Interaction with a vehicle behind the subject vehicle (traveling in the same direction as the subject vehicle).
- *Single vehicle conflict*: Any non-motor vehicle conflict occurring on or off the roadway not described in other categories.

The results are presented in Table 22 through Table 27. The lead-vehicle conflict (Table 22 and Table 23) contains the most obvious patterns. There were 377 near-crashes and five crashes where the driver reacted. In contrast, there are nine crashes in which the drivers failed to react. The message is clear: in the conflict with a leading vehicle, failure to react will dramatically increase the risk of crash (in this case, all nine events with no-reaction led to crashes).

Table 22. Driver Reaction for Lead-Vehicle Conflict

Evasive Maneuver	Crash	Near-Crash
Reaction	5	377
No-reaction	9	0
Percentage Reaction	36%	100%

p-value<0.0001

Table 23. Itemized Evasive Maneuver for Lead-Vehicle Conflict

Evasive Maneuver	Crash		Near-Crash	
	Frequency	Percentage	Frequency	Percentage
Accelerated and steered left	0	0%	2	1%
Accelerated and steered right	0	0%	1	0%
Braked and steered left	0	0%	37	10%
Braked and steered right	1	7%	71	19%
Braking (lockup)	1	7%	4	1%
Braking (lockup unknown)	0	0%	32	8%
Braking (no lockup)	3	20%	224	59%
Steered to left	0	0%	4	1%
Steered to right	0	0%	2	1%
No-reaction	9	60%	0	0%
Unknown	1	7%	0	0%

The results from following-vehicle (Table 24 and Table 25) and single-vehicle (Table 26 and Table 27) conflicts are not conclusive. The statistical chi-square test for equal probability does not significant difference.

Table 24. Driver Reaction for Following-Vehicle Conflict

Driver Reaction	Crash	Near-Crash
Reaction	5	49
No-reaction	7	21
Percentage reaction	42%	70%

p-value=0.0558

Table 25. Itemized Evasive Maneuver for Following-Vehicle Conflict

Driver Reaction	Crash		Near-Crash	
	Frequency	Percentage	Frequency	Percentage
Accelerated	0	0%	3	4%
Accelerated and steered right	0	0%	1	1%
Braked and steered left	1	8%	5	7%
Braked and steered right	0	0%	4	6%
Braking (lockup unknown)	0	0%	2	3%
Braking (no lockup)	4	33%	32	46%
No-reaction	7	58%	21	30%
Steered to right	0	0%	2	3%

Table 26. Driver Reaction for Single-Vehicle Conflict

Driver Reaction	Crash	Near-Crash
Reaction	20	47
No-reaction	2	1
Reaction Percentage	91%	98%

p-value=0.1789

Table 27. Itemized Evasive Maneuver for Single-Vehicle Conflict

Evasive Maneuver	Crash		Near-Crash	
	Frequency	Percentage	Frequency	Percentage
Braked and steered left	4	17%	7	16%
Braked and steered right	3	13%	1	2%
Braking (lockup unknown)	0	0%	1	2%
Braking (no lockup)	1	4%	0	0%
Steered to left	10	42%	19	44%
Steered to right	2	8%	11	26%
No-reaction	3	13%	1	2%
Unknown if action was attempted	1	4%	0	0%
Other reaction	0	0%	3	7%

Number of Contributing Factors

The analysis for the number of contributing factors is motivated by the hypothesis that crashes can be caused by the combination of several factors. Thus, the number of contributing factors represents the level of driving burden. If crashes are associated with a higher driving burden than near-crashes, the number of factors for crashes should be higher than that for near-crashes. Table 28 and Table 29 display the frequencies with which the six factors listed below occurred for the three main conflict types and the aggregate of all conflict types:

- Distraction
- Surface conditions
- Traffic density
- Lighting
- Weather
- Visual obstruction

The statistical hypothesis being tested is that the mean number of contributing factors is equivalent for crashes and near-crashes. A standard t-test was used to test the difference. The mean number of contributing factors for each level is listed at the end of each table. As can be seen, the only statistically significant result is for conflict-with-lead-vehicle for which the mean number of contributing factors for crashes (2.93) is higher than that for near-crashes (2.27). This implies that, for this particular type of conflict, the presence of more contributing factors will more likely result in crashes. In general, for most conflict types, the number of crash and near-crash is not significantly different.

Table 28. Number of Contributing Factors for All Conflict Types

# of Factors	Crash	Near-Crash
0*	3	25
1	21	183
2	25	311
3	11	161
4	6	62
5	1	14
6	1	4
Mean	**2.04**	**2.14**

p-value=0.46
*A crash can have 0 contributing factors when the crash was caused by another driver. For example, the subject driver was sitting at a stop light and the vehicle behind collided with our driver.

Table 29. Number of Contributing Factors by Conflict Type

	Lead-Vehicle Conflict		Single Vehicle Conflict		Following-Vehicle Conflict	
# of Factors	**Crash**	**Near-Crash**	**Crash**	**Near-Crash**	**Crash**	**Near-Crash**
0	0	5	1	3	0	3
1	1	76	13	18	2	15
2	6	163	6	22	7	29
3	4	88	3	2	2	15
4	2	36	1	4	1	7
5	1	6			0	1
6	1	2				
Mean	**2.93**	**2.27**	**1.58**	**1.71**	**2.17**	**2.16**
P-Value for Equal Means	**0.01**		**0.58**		**0.98**	

Precipitating Factors

The precipitating factors for crash and near-crash were compared. This comparison will help understanding of the potential difference between crash and near-crash. There are 78 categories defined that provide very detailed information for precipitating factors. The table relationship between crashes and near-crashes is presented in Appendix A. Figure 9 is a plot of this table relationship. As shown in Figure 9, there are five outliers with very large or small crash-to-near-crash ratios. As can be seen, “Other vehicle ahead - but at a slower constant speed” has 155 near-crashes but 0 crashes. One possible explanation is that the following vehicles tend to get closer while the leading vehicles are traveling at a constant slow speed. This scenario will produce a small TTC (thus a near-crash) but will rarely lead to a crash. It is interesting that when the lead vehicle stops, the number of crashes observed increases as seen for the two precipitating factors, “Other vehicle ahead - slowed and stopped less than 2 seconds” and “Other vehicle ahead - stopped on roadway more than 2 seconds." The crash-to-near-crash ratio was much larger for the latter category compared to the former category.

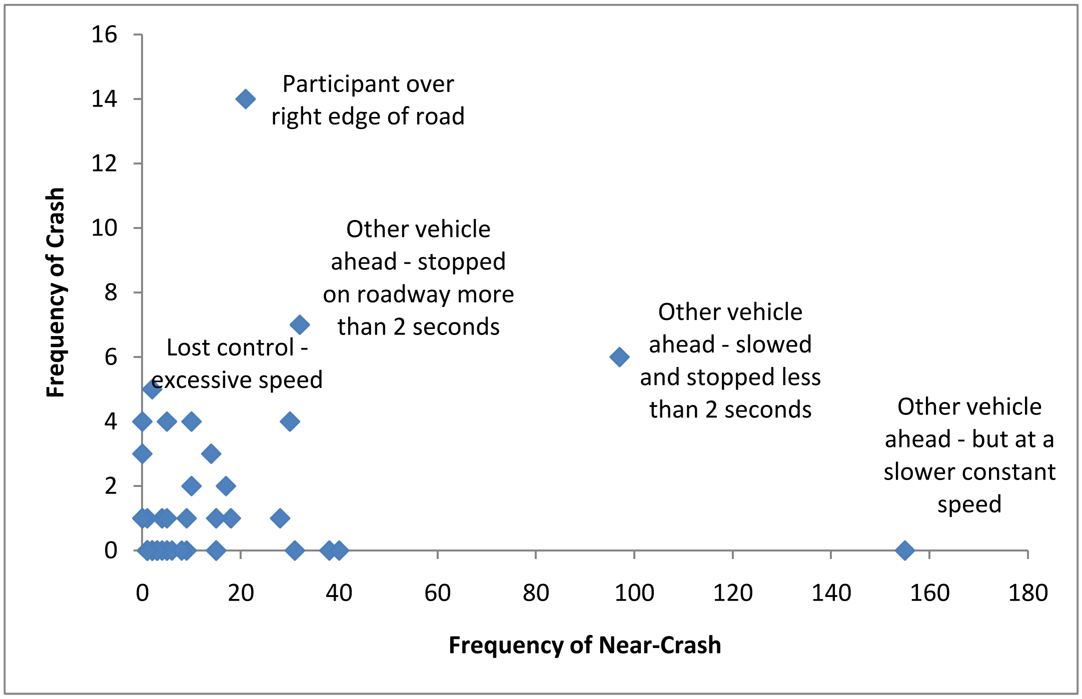

Figure 9. Crash and Near-Crash by Precipitating Factors

The "Participant over right edge of road" category has the highest crash-to-near-crash ratio. On the other side, the category "Lost control - excessive speed" contains five crashes and only two near-crashes. This result indicates that at higher speed, avoiding crashes is more difficult. Another interesting category is the "Participant vehicle backing" (not labeled in the plot), where three crashes occurred but no near-crashes. Due to the low speed involved in backing crashes, near-crashes are difficult to identify.

A stratified analysis was also conducted, and the tables are presented in Appendix A (Table 48. Precipitating Factors for All Conflict Types, Table 49. Precipitating Factors for Single-Vehicle Conflict, Table 50. Precipitating Factors for Lead-Vehicle Conflict, and Table 51. Precipitating Factors for Following-Vehicle Conflict). As can be seen, all of the 14 crashes with the precipitating factor "Participant over right edge of road" are single-vehicle conflicts. No other obvious patterns can be seen from the stratified analysis.

Summary for Sequential Factor Analysis

The sequential factor analysis presented above indicates that the evasive maneuvers for crashes and near-crashes show different patterns. The most significant pattern occurs for driver reaction. The percentage of no-reactions for crashes is substantially higher than that for the near-crash data. This indicates that the no-reaction response is the key factor to determine whether an event will result in a crash or near-crash (for a large proportion of events). However, the difference in evasive maneuvers does not indicate a distinct causal mechanism. The argument is that the evasive maneuver is almost the last action taken by the driver before a crash/near-crash. Of more interest to this study are the risk factors that lead to the safety event (e.g., driver inattention, drowsiness, weather conditions, etc.). From this perspective, this is not a violation of the causal mechanism principle.

The analysis for the number of contributing factor indicates that except for the “conflict with lead vehicle”, there is not an obvious difference between crashes and near-crashes. There is not strong evidence that the drivers in a crash event experience a more complex situation than near-crash.

The precipitating factors analysis shows that two categories containing “other vehicle stopped” have a large number of crashes and near-crashes. For high-speed situations, there are only a couple of near-crashes but a relatively large number of crashes. This is most likely due to the speed differential of a stopped vehicle versus a slowing vehicle. The slowing vehicle situation is more forgiving and thus will result in a higher proportion of near-crashes. A stopped vehicle is not as forgiving and will thus result in a higher proportion of crashes.

In summary, the sequential factor analysis shows that the evasive maneuver have a great impact on whether the outcome of a safety conflict is a crash or a near-crash. There is minor difference in the number of contributing factors for crash and near-crash.

FREQUENCY RELATIONSHIP BETWEEN CRASHES AND NEAR-CRASHES

Regression Analysis by Driver

The relationship of drivers’ involvement in crashes versus near-crashes was analyzed for each individual driver, with 234 drivers used in the analysis. A strong relationship would indicate that the number of crashes a driver would be involved in is predictable based on the driver’s frequency of involvement in near-crashes. A Poisson regression model was then fitted using the number of near-crashes as covariates. The model setup is as follows:

$$y_i \sim Poisson(\lambda_i)$$

$$\log(\lambda_i) = \beta_0 + \beta_1 x_i,$$

where y_i is the number of crashes, λ_i is the expected number of crashes, and x_i is the number of near-crashes for driver i. β_0 and β_1 are the regression parameters. The model fitting is shown in Table 30.

Table 30. Poisson Regression Results

	Coefficient	Standard Error	*p*-value
Intercept	-2.31	0.25	<.0001
Near-Crash	0.21	0.04	<.0001

The coefficient for near-crashes is highly significant. This coefficient also implies that for every additional near-crash in which a driver is involved, the frequency of crash involvement will increase by a factor of exp(0.21)=1.23. This result indicates that there is a positive relationship between the frequency of crash and near-crash involvement. The intercept represents the offset in near-crash rate. This parameter is not directly related to the relationship between crash and near-crash.

Gender Effect

The gender effect is shown in Table 31. There is no statistical evidence that the two ratios differ.

Table 31. Crash and Near-Crash by Gender

Gender	Crash	Near-Crash	Ratio
Female	26	340	0.08
Male	43	420	0.10

p-value=0.26

Age Effect

There were 109 primary drivers and approximately 250 actual drivers identified through video reduction. Although the exact ages of the primary drivers are available, the ages of the other drivers had to be gleaned through video reduction. Four age categories were classified as shown in Table 32 and Figure 10. The age group 21-40 shows the highest crash-to-near-crash ratio. However, the statistical test for constant crash to near-crash ratio did not show a significant result.

Table 32. Crash and Near-Crash by Age Group

Age	Crash	Near-crash	Ratio
<20	14	184	0.08
21-40	39	327	0.12
41-60	15	214	0.07
>60	1	35	0.03

Testing for constant crash-to-near-crash ratio: p-value=0.14
Measure of association: R-Squared=0.91, Adjusted R^2=0.87

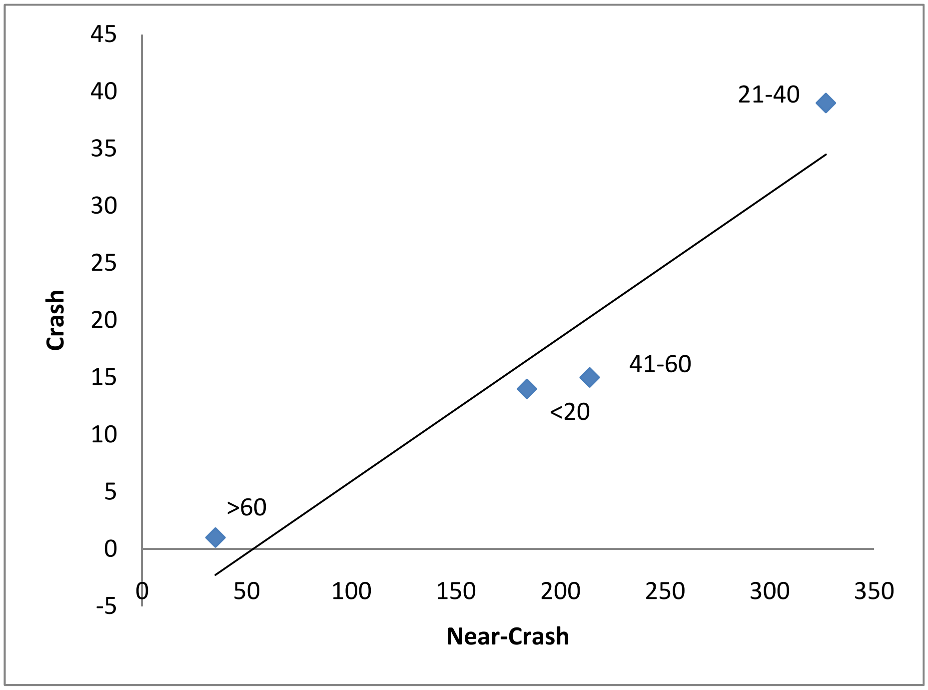

Figure 10. Relationship between Crash and Near-Crash by Age Group

Traffic Density/LOS

The traffic density is evaluated by the LOS, which includes six levels. The definitions of the six LOS levels are as follows:

- LOS A: Free flow
- LOS B: Flow with some restrictions
- LOS C: Stable flow, maneuverability and speed are more restricted
- LOS D: Unstable flow, temporary restrictions substantially slow driver
- LOS E: Flow is unstable, vehicles are unable to pass, temporary stoppages, etc.
- LOS F: Forced traffic flow condition, with low speeds and traffic volumes below capacity

The relationship between crash and near-crash by the LOS is shown in Table 33 and Figure 11. As can be seen from the table and plot, there is a curve-shaped pattern. The ratio decreases with increasing traffic density but increases again when traffic flow becomes unstable. The crash-to-near-crash ratio for free flow (LOS A) is highest, and the ratio for stable flow (LOS C) is the lowest. The statistical test for event ratio shows a highly significant result (*p*-value<0.001).

Table 33. Crash and Near-Crash by LOS

LOS	Crash	Near-Crash	Ratio
A	41	244	0.17
B	14	233	0.06
C	7	191	0.04
D	4	64	0.06
E & F	3	29	0.10

Testing for constant crash-to-near-crash ratio: p-value<0.01
Testing for level of association: R-Squared=0.50, Adjusted R^2=0.33
(second order regression R^2=0.72 adjusted R^2=0.45)

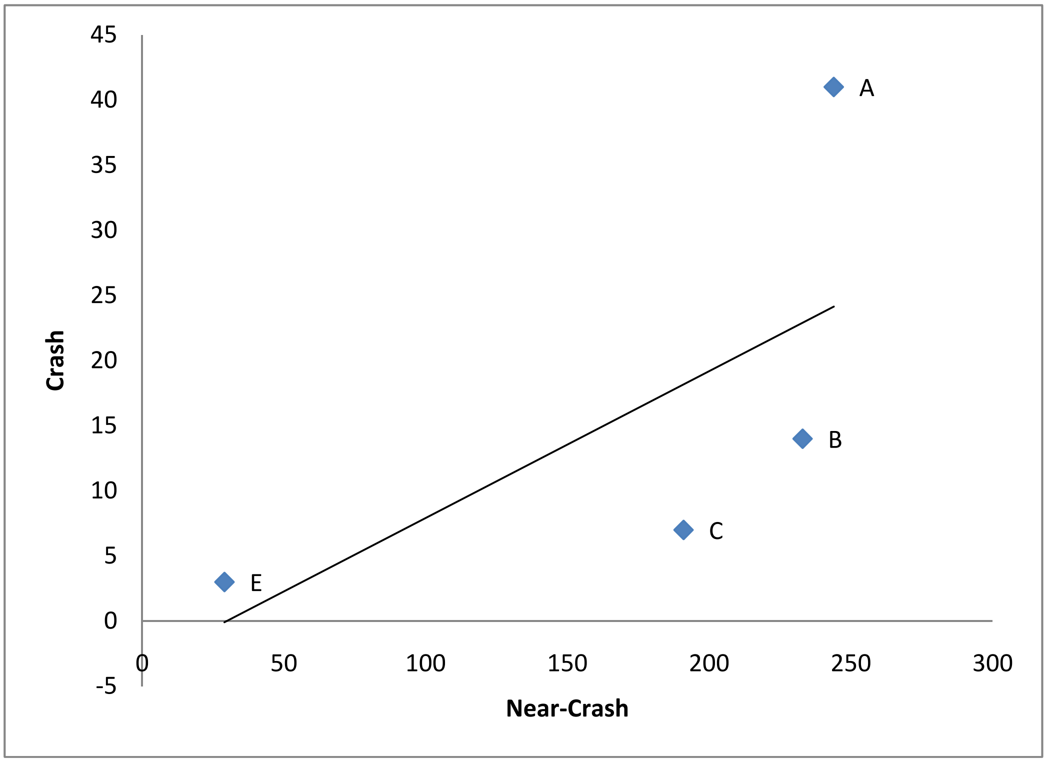

Figure 11. Plot of Crash and Near-Crash by LOS

The majority of safety events are affected by the interaction between vehicles, which is related to traffic density. When the traffic density is low (e.g., LOS A), there are relatively few interactions between vehicles, and thus relatively fewer near-crashes and a high crash-to-near-crash ratio. When traffic density increases, there are more interactions, and thus an increased number of near-crashes but relatively fewer crashes. This could be due to increased vigilance of drivers because of the high traffic density. When traffic flow is unstable (LOS D-F), the chance of crashes increases again, thus a higher crash-to-near-crash ratio is observed.

Lighting

Table 34 shows the contingency table for the lighting type for all crash types. The test for unequal frequency gives a relatively large *p*-value of 0.4143, which indicates that there is no evidence that unequal frequency will bias the results. Figure 12 shows the plot of the data points in Table 34. As can be seen, the data points are scattered around a straight line, which indicates a strong, linear relationship between crashes and near-crashes.

Table 34. Lighting Conditions for All Crash Types

Lighting Type	Crash	Near-Crash	Ratio
Darkness lighted	17	126	0.14
Darkness not lighted	5	54	0.09
Dawn	1	14	0.07
Daylight	43	502	0.09
Dusk	3	65	0.05

p=0.414
R-squared=0.97, adjusted R-squared: 0.95

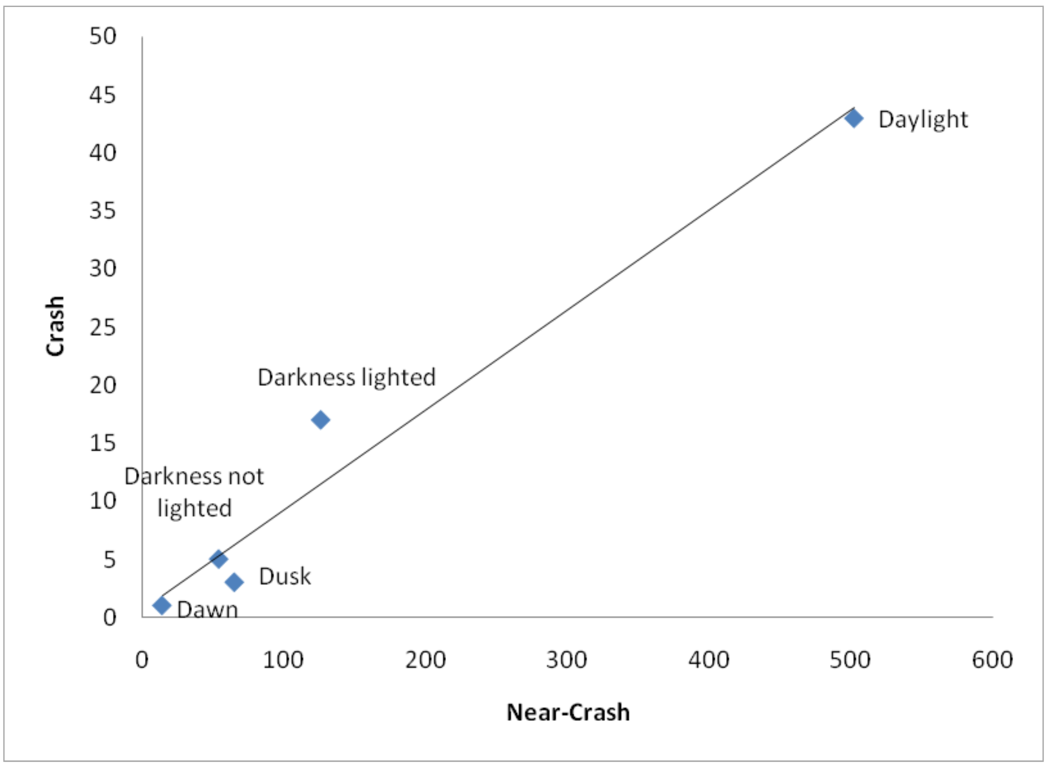

Figure 12. Plot of Crash and Near-Crash by Lighting Type

Road Alignment

The crash-to-near-crash ratio for each road alignment type is shown in Table 35 and Figure 13. The ratio for the curved grade is the highest, and the ratio for straight level alignment is relatively small (the number of crashes for straight grade is too small for a meaningful comparison). This result indicates that driving errors are most likely to result in crashes on a curve grade than on straight-level road sections.

Table 35. Crash and Near-Crash by Road Alignment

Alignment	Crash	Near-Crash	Ratio
Curve Grade	3	7	0.43
Curve Level	13	99	0.13
Straight Grade	1	15	0.07
Straight Level	52	638	0.08

p-value=0.02
R-squared=0.99; adjusted R-squared: 0.99

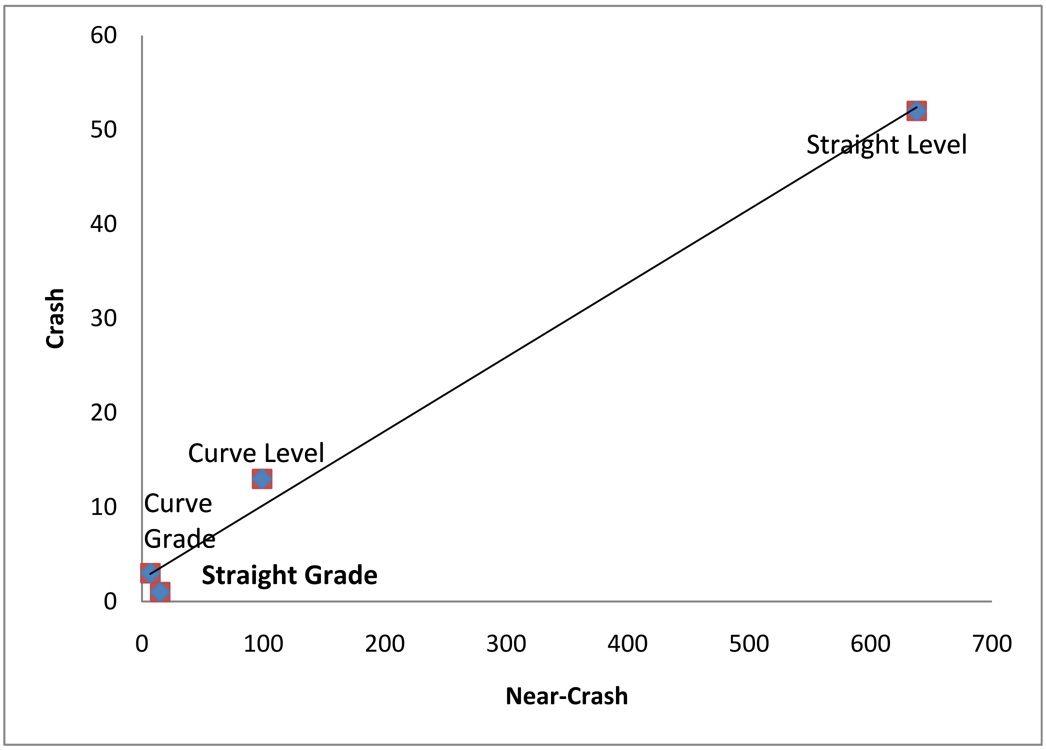

Figure 13. Crash versus Near-Crash by Road Alignment

Surface Condition

The crash-to-near-crash ratios for surface conditions are presented in Table 36 and Figure 14. As can be seen, the ratio for the dry condition is lower than for other categories. Icy and snowy conditions have the highest ratio, although the number of observations is very small. The wet road surface also shows an elevated crash-to-near-crash ratio compared to dry road. This implies that, in poor road surface conditions, there tends to be a high percentage of crashes compared to the number of near-crashes.

Table 36. Crash versus Near-Crash by Surface Conditions

Surface Condition	Crash	Near-Crash	Ratio
Dry	51	654	0.08
Icy	1	4	0.25
Snowy	4	4	1
Wet	13	98	0.13

p-value=0.02
R-squared=0.99; adjusted R-squared=0.99.

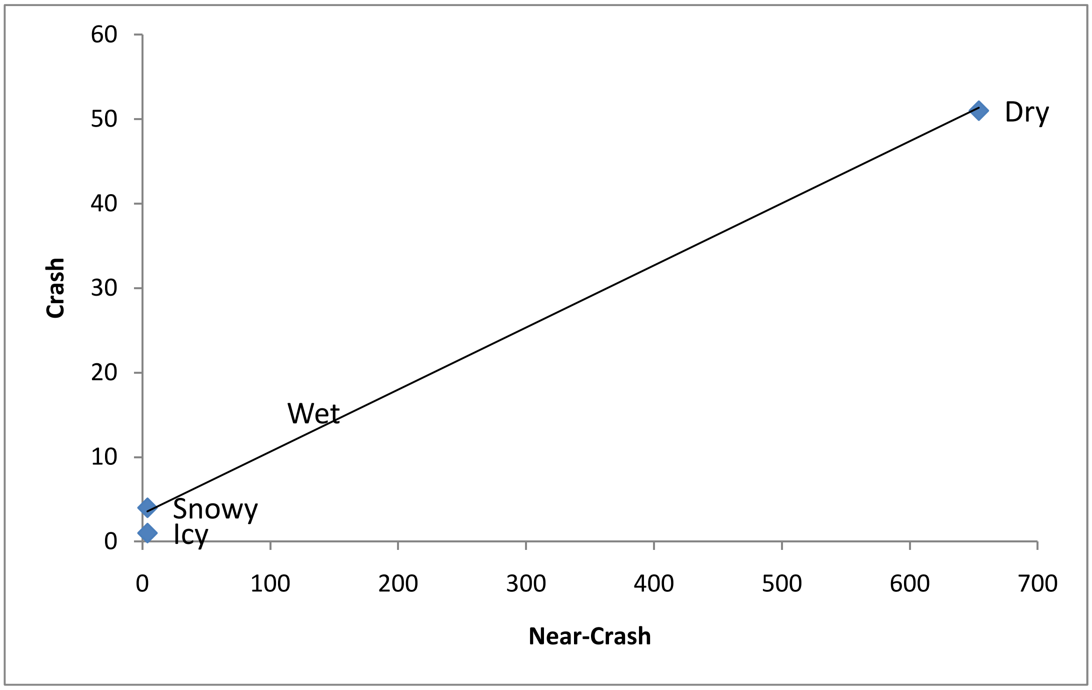

Figure 14. Crash versus Near-Crash by Surface Conditions

Weather

Seven weather conditions were defined as shown in Table 37 and Figure 15. As can be seen, snow, mist, and fog include few observations (even for near-crashes), and therefore no meaningful comparisons can be conducted. The crash-to-near-crash ratio for rainy days (0.14) is higher than that for clear (0.06) and cloudy days (0.09). However, a chi-square test for equal ratios did not show significant results (p=0.32).

Table 37. Crash and Near-Crash by Weather Conditions

Weather	Crash	Near-Crash	Ratio
Clear	54	599	0.09
Cloudy	6	99	0.06
Fog	0	1	0
Mist	0	1	0
Rainy	8	57	0.14
Snowy	1	3	0.33

p-value=0.32
R-squared: 0.99, adjusted R-squared: 0.99

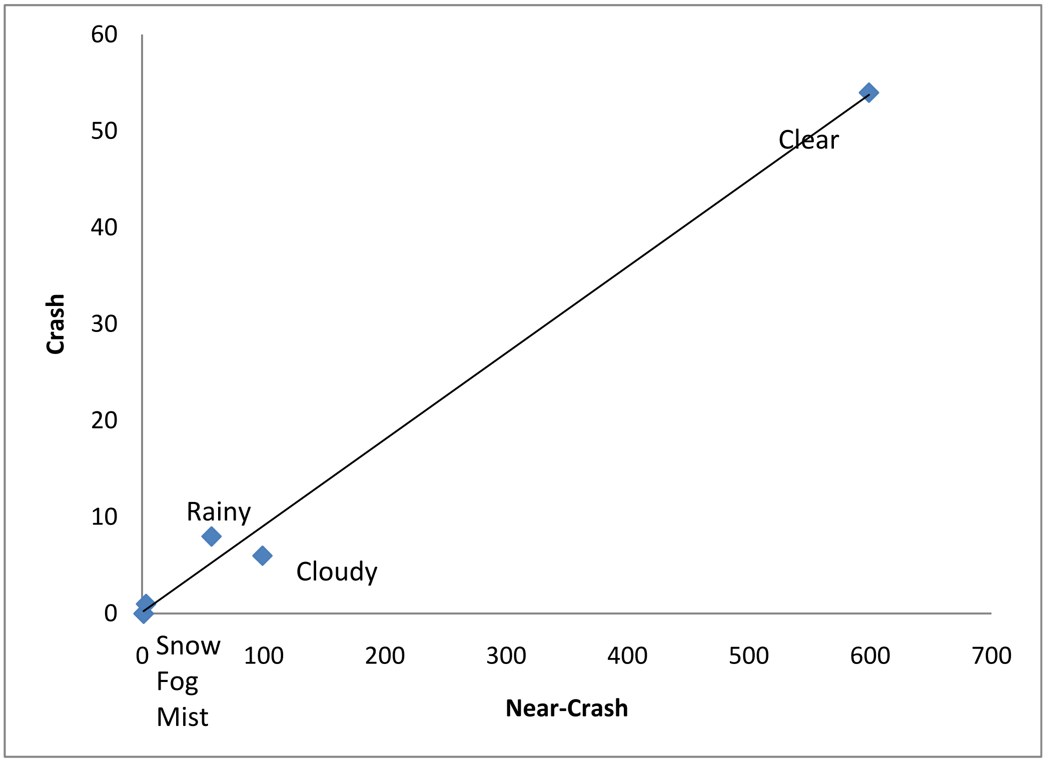

Figure 15. Crash versus Near-Crash by Weather Conditions

Summary of Relationship between Crash and Near-Crash Analysis

The present analyses generally indicate a positive correlation between the number of crashes and near-crashes. That is, the categories with more near-crashes tend to also have more crashes. However, analyses also indicate that the ratio depends upon the scenario. For example, the apparent curve patterns in the LOS (relates to traffic density) indicate that crash-to-near-crash ratios change as a function of traffic density.

Overall there is a trend that the crash-to-near-crash ratio for poor driving conditions is higher than the ratio for normal driving conditions. The possible reason is that under poor driving conditions, the tolerance for driver mistakes or other risks is relatively low, which will lead to crashes that can be avoided under normal driving conditions.

While the changes in these ratios are easily explained from an engineering point of view, they do suggest that the crash-to-near-crash ratios are not stable. Therefore, although a large portion of statistical tests conducted are inconclusive as summarized in Table 38, the assumption of a constant crash-to-near-crash ratio should not be considered as constant across all comparisons. A direct consequence of this result is that the unbiased property as discussed in the Principles of Surrogate Measure Analysis does not hold.

However, the R-squared values indicate that there is a strong linear relationship between the frequency of crashes and near-crashes. This implies that a near-crash is a quality predictor for the frequency of crashes.

Table 38. Summary of the Testing Results for Constant Crash to Near-Crash Ratio

	Test for Constant Crash to Near-Crash Ratio		Measure for Association	
Factors	**p-value**	**Significant**	**R-squared**	**Adjusted R-Squared**
Gender	0.26	NO	NA	NA
Age Group	0.23	NO	0.91	0.87
LOS	<0.001	YES	0.5 (0.72*)	0.33 (0.45*)
Lighting Conditions	0.414	NO	0.97	0.95
Road Alignment	0.02	YES	0.99	0.99
Road Surface Condition	0.02	YES	0.99	0.99
Weather	0.32	NO	0.99	0.99

**the R-squared value using polynomial regressions*

STRATIFIED ANALYSIS

The analyses above are based on aggregated data including all conflict types. As part of the frequency analysis, a stratified analysis was also conducted by type of conflict. For the stratified analysis, the events were classified by the nature of the conflict. The purpose of this stratified analysis is to evaluate the relationship between crashes and near-crashes for different types of conflicts as each conflict type contains similarities in the sequence of events and potential contributing factors whereas these similarities get lost when assessing across all types of conflicts.

Table 39 shows the different types of conflicts and the number of crashes and near-crashes for each type. As can be seen, the most frequent type of crash is a single-vehicle conflict, and the most frequent type of near-crash is a conflict with a lead vehicle. Aside from these two, only the following-vehicle conflict type has a reasonable number of observations for both crashes and near-crashes. Therefore, the stratified analysis will include only lead-vehicle conflicts, single-vehicle conflicts, and following-vehicle conflicts.

Table 39. Conflict Types by Severity

Conflict Type	Near-Crash	Crash	Sum
Conflict with a lead vehicle	380	15	395
Conflict with a following vehicle	70	12	82
Conflict with vehicle in adjacent lane	115	1	116
Conflict with obstacle/object in roadway	6	9	15
Single-vehicle conflict	48	24	72
Conflict with oncoming traffic	27	0	27
Conflict with vehicle moving across participant vehicle path (through intersection)	27	0	27
Conflict with vehicle turning into participant vehicle path (same direction)	28	0	28
Conflict with pedestrian	6	0	6
Conflict with vehicle turning across participant vehicle path (opposite direction)	27	2	29
Conflict with parked vehicle	5	4	9
Conflict with animal	10	2	12
Conflict with merging vehicle	6	0	6
Conflict with vehicle turning across participant vehicle path (same direction)	3	0	3

Lighting

The stratified tables for lighting are presented in Table 40, and the corresponding plots are shown in Figure 16, Figure 17, and Figure 18. The large *p*-value for lead-vehicle conflicts indicates there is not sufficient evidence to infer unstable frequencies across lighting conditions. The sample sizes in the following-vehicle conflicts and single-vehicle conflicts are too small to draw a meaningful conclusion. The plots from all three strata do show the overall pattern of increasing numbers of crashes with increasing numbers of near-crashes, suggesting a stable relationship in the frequency of occurrence for both crashes and near-crashes for these three conflict types across lighting conditions.

Table 40. Lighting Condition by Conflict Type

	Lighting Condition	Crash	Near-Crash	Crash to Near-Crash Ratio	P-value	R-squared
Lead-Vehicle Conflict	Darkness lighted	2	74	0.03	0.730	0.97 (0.96)
	Darkness not lighted	1	24	0.04		
	Dawn	1	7	0.14		
	Daylight	10	242	0.04		
	Dusk	1	33	0.03		
Single Vehicle Conflict	Darkness lighted	6	5	1.20	0.11	0.81 (0.74)
	Darkness not lighted	2	11	0.18		
	Dawn	0	1	0.00		
	Daylight	16	26	0.62		
	Dusk	0	5	0.00		
Following-Vehicle Conflict	Darkness lighted	2	6	0.33	0.547	0.96 (0.96)
	Darkness not lighted	0	3	0.00		
	Dawn	0	2	0.00		
	Daylight	10	51	0.20		
	Dusk	0	8	0.00		

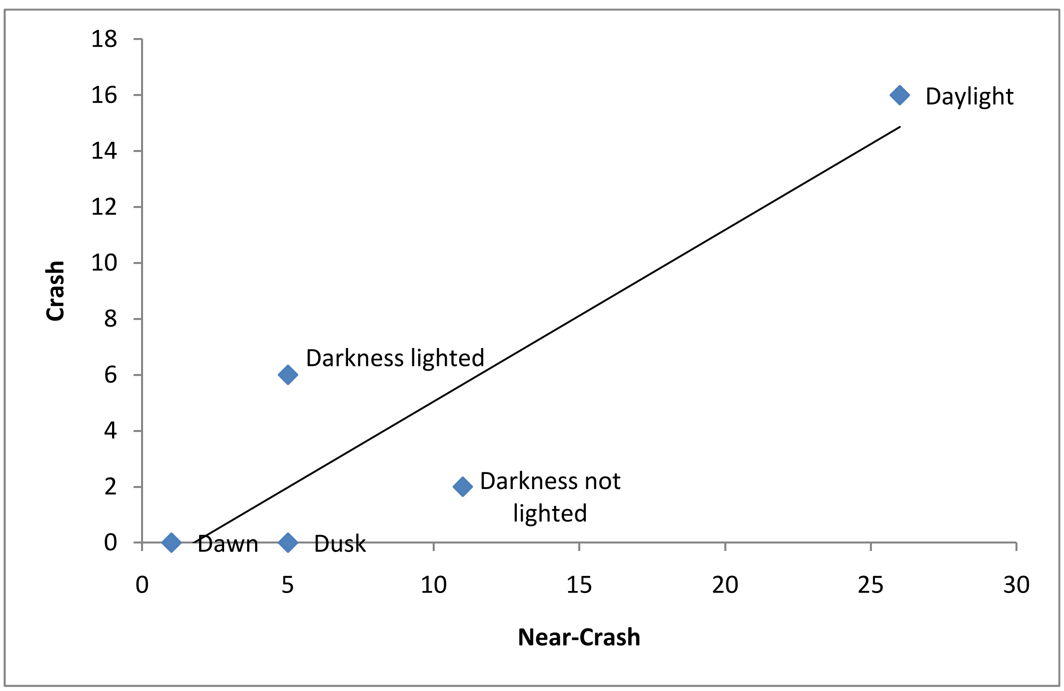

Figure 16. Single-Vehicle Conflict by Lighting Conditions

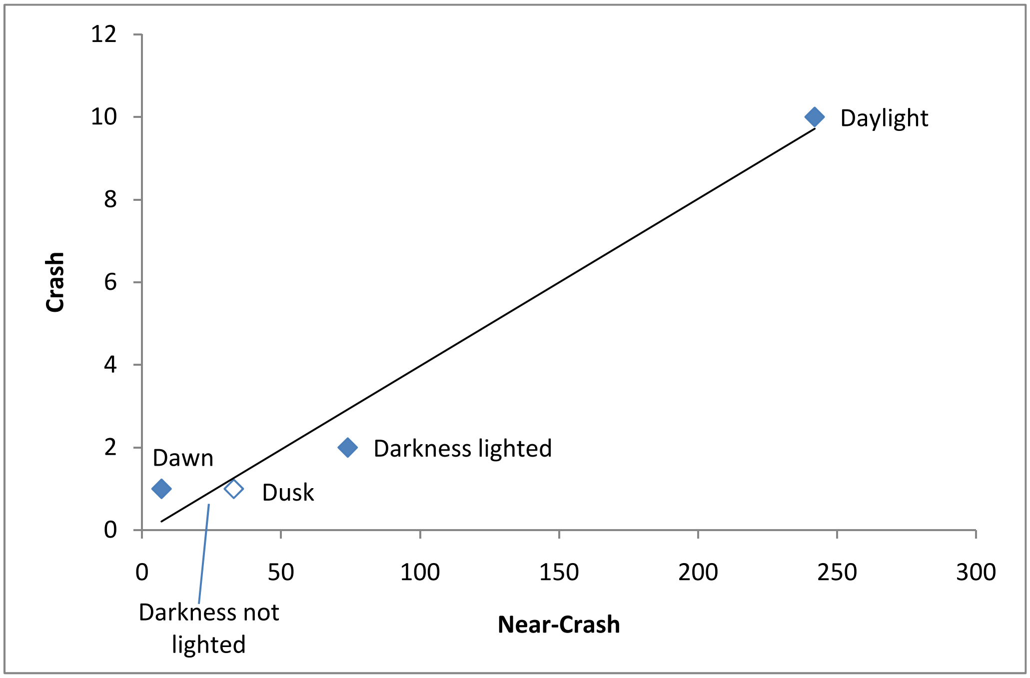

Figure 17. Lead-Vehicle Conflict by Lighting Conditions

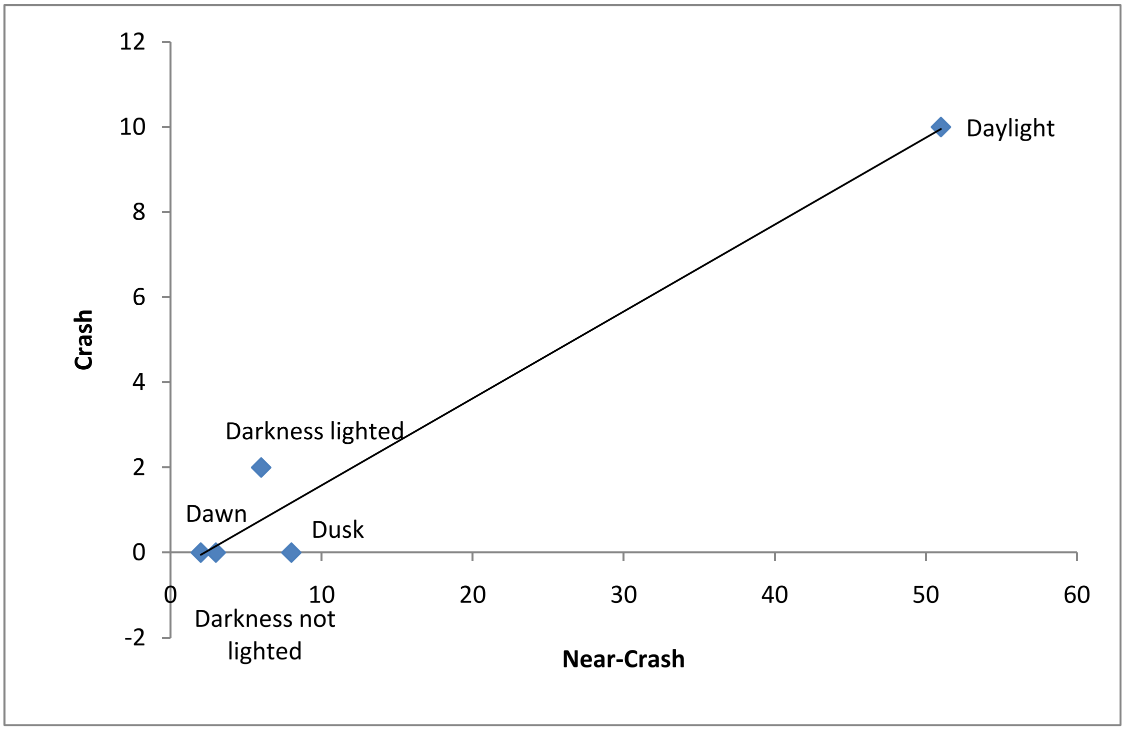

Figure 18. Following-Vehicle Conflict by Lighting Conditions

Road Alignment

Road alignment was classified as either straight or some other orientation (e.g., curve, straight grade, or curve grade). Single-vehicle conflicts and lead-vehicle conflicts both produced *p*-values greater than 0.05, signifying that the distributions of crashes and near-crashes are not statistically different from one another (Table 41). Following-vehicle conflicts, as well as the compilation of all conflicts (Table 35), show a significantly different trend between crashes and near-crashes.

Table 41. Road Alignment by Conflict Type

	Road Alignment	Crash	Near-Crash	Crash to Near-Crash Ratio	P-value
Lead-Vehicle Conflict	Curve	2	42	**0.05**	**0.783**
	Straight level	13	338	**0.04**	
Single-Vehicle Conflict	Curve	7	22	**0.32**	**0.174**
	Straight level	17	26	**0.65**	
Following-Vehicle Conflict	Curve	5	8	**0.63**	**0.008**
	Straight level	7	62	**0.11**	

Traffic Density

The six traffic density categories were combined into the following three categories: "Free flow and flow with some restrictions," "Stable flow and flow is unstable," and "Unstable flow and forced traffic." No significant conclusion can be drawn for single-vehicle conflicts and following-vehicle conflicts partly due to the small sample size (Table 42. Traffic Density by Conflict Type). The crash to near-crash ratio does vary for lead-vehicle conflict, and the patterns are similar for the analysis based on all conflict types (Table 33) in which the high density and low density scenarios tend to have higher crash ratios.

Table 42. Traffic Density by Conflict Type

	Traffic Density	Crash	Near-Crash	Crash-to-Near-Crash Ratio	P-value
Lead-Vehicle Conflict	Free flow + flow w/some restrictions	9	206	**0.04**	**0.014**
	Stable flow + flow is unstable	3	157	**0.02**	
	Unstable flow + forced traffic	3	17	**0.18**	
Single-Vehicle Conflict	Free flow + flow w/some restrictions	23	45	**0.51**	**0.716**
	Stable flow + flow is unstable	1	3	**0.33**	
	Unstable flow + forced traffic	0	0	**NA**	
Following-Vehicle Conflict	Free flow + flow w/some restrictions	8	36	**0.22**	**0.4519**
	Stable flow + flow is unstable	4	28	**0.14**	
	Unstable flow + forced traffic	0	6	**0.00**	

Surface Condition

The condition of the road, classified as either dry or not, is found to give similar distribution results for crashes and near-crashes for single-vehicle conflicts and conflicts with following vehicles, as can be seen in Table 43. Road Surface Conditions Stratified by Conflict Type. Lead-vehicle conflicts have a significantly different distribution between crash and near-crash occurrence.

Table 43. Road Surface Conditions Stratified by Conflict Type

	Surface Condition	Crash	Near-Crash	Crash-to-Near-Crash Ratio	P-value
Lead-Vehicle Conflict	Dry	8	334	0.02	<0.001
	Other	7	46	0.15	
Single-Vehicle Conflict	Dry	17	39	0.44	0.316
	Other	7	9	0.78	
Following-Vehicle Conflict	Dry	10	60	0.17	0.829
	Other	2	10	0.20	

Weather

The weather conditions were classified as clear and non-clear. Lead-vehicle conflict situations show that crashes and near-crashes are significantly different (Table 44. Weather Conditions Stratified by Conflict Type). The ratio of crash to near-crash for the non-clear condition (0.09) is much higher than that for the clear condition (8/303=0.026). Thus, Lead-Vehicle conflicts tend to have a high percentage of crashes in non-clear conditions. With respect to weather, single-vehicle conflicts and following-vehicle conflicts are not found to be significantly different.

Table 44. Weather Conditions Stratified by Conflict Type

	Weather	Crash	Near-Crash	Crash to Near-Crash Ratio	P-value
Lead-Vehicle Conflict	Clear	8	303	0.03	0.014
	Non-clear	7	77	0.09	
Single-Vehicle Conflict	Clear	21	35	0.60	0.161
	Non-clear	3	13	0.23	
Following-Vehicle Conflict	Clear	8	53	0.15	0.507
	Non-clear	4	17	0.24	

Summary of Stratified Analysis

The results from the stratified analysis are very similar to the analysis of the aggregated data. Again, there is a strong relationship between the frequency of the crash and near-crash. However, the crash-to-near-crash ratio is scenario dependent.

SENSITIVITY ANALYSIS

The bias and precision are the most critical criteria in quantitatively evaluating a risk factor. The precision is directly related to the sample size; thus, improved precision can be obtained by combining surrogates with crashes into risk assessment (with respect to both crash and surrogates). The bias, the difference between the risk estimated using crash alone and the risk estimated combining the surrogate measure with crashes, is thus the key to assess a proper crash surrogate and is directly related to the validity of these analyses.

As the crash is often the primary measure of traffic safety, it is reasonable to assume that risk estimation based on crashes alone will lead to the correct/unbiased estimation. If a near-crash is a proper surrogate, the risk estimation (odds ratios in current analysis framework) achieved by combining crashes and near-crashes shall be either comparable or shall show a consistent pattern to the risk assessment using crash alone. The primary question is whether the benefits of combined analysis outweigh whatever bias may exist. The analyses presented here are thus focusing on evaluating the magnitude and direction of the potential bias, and this is conducted through a sensitivity analysis.

As shown in the frequency analysis, a constant crash-to-near-crash ratio will lead to an unbiased estimation. However, it is almost certain that this ratio will not be exactly constant for real data due to the random nature of the crash data or potential systematic mechanism. Thus some levels of bias could be introduced when using near-crashes as surrogates. As discussed in the Frequency Relationship between Crash and Near-Crash Analysis, two approaches can be used to evaluate the crash-to-near-crash ratio: a statistically significant difference and the magnitude of the difference. The chi-square statistical test can confirm if the difference in the ratio is random or whether there are systematic differences. The magnitude of the difference (also known as engineering meaningful difference) is equally important. For example, two ratios, 0.1 and 0.11, can be significantly different from each other statistically, but the difference may be trivial from an engineering point of view. The engineering meaningful difference requires some level of subjective expert judgment, or it can be evaluated more objectively through a sensitivity analysis.

The sensitivity analysis is commonly used to evaluate the impact of invalid model assumptions on model output. In the context of this study, near-crash and crash data should be merged when the two principles of surrogate measure analysis are satisfied: 1) the causal mechanism for surrogates and crashes are the same or similar and 2) there is constant crash-to-near-crash ratio between the frequency of surrogate measures and crashes under different settings. However, as implied in the previous analyses, from a practical perspective it is unlikely that both principles can be fully satisfied. For example, for the first principle, 90 percent of crashes and near-crashes could share the same causal mechanism while the remaining 10 percent of crashes may differ. It is also quite possible that there is not enough information to further separate those cases. For the second principle, there could be marginally unstable crash-to-near-crash ratios across contributing factors (either statistically insignificant or trivial from an engineering point of view). Under these conditions, some level of bias will be introduced when assessing risk using combined data. The sensitivity analysis provides an opportunity to quantitatively assess both the magnitude and direction of the bias.

The sensitivity analysis consists of two parts. First, the analysis is conducted using crashes alone. By comparing only crashes with baseline data, the parameter of interest is inferentially assessed using odds ratios and/or population-attributable risks. In the second part of the analysis, the risk parameters are estimated using crashes and near-crashes combined. The motivation for the combined analysis is to maximize the sample size for increases in statistical power. Conducting separate analyses for crash and near-crash respectively will lead to smaller sample sizes compared to combined analysis. As shown in the Principle of Surrogate Measure Analysis section, when the ratio is perfectly stable (ratio difference is zero), the odds ratios estimated using crashes alone or crashes and near-crashes combined will be identical. In other words, there is no bias introduced by using near-crash data, and the estimation is more accurate due to the increased number of observations (i.e., tighter confidence intervals). The comparison between the crashes alone and crashes and near-crashes combined will indicate the impact (i.e., bias introduced) of using near-crashes as a surrogate measure.

The data used in this analysis were the 69 crashes, the 761 near-crashes, and 17,344 randomly sampled baseline data. Five potential risk factors were analyzed including drowsiness, distraction, lighting condition, road surface condition, and weather condition. The contingency table for the sensitivity analysis is shown in Table 46. Sensitivity Analysis: Contingency Table. The results of the sensitivity analysis (i.e., the risk assessment using crash alone and using crash and near-crash combined) are provided in Table 47. Sensitivity Analysis: Risk Assessment and also illustrated in Figure 19.

Drowsiness

The driver's drowsiness status was extracted from video archives. The driver is either considered as drowsy or non-drowsy. For both drowsy levels, the number of near-crashes is about 10 times the number of crashes as can be seen from Table 46. Sensitivity Analysis: Contingency Table. However, the ratio of crash-to-near-crash is not exactly equal, and drowsiness appears more frequently in crashes than in near-crashes. Thus, bias will be introduced when using near-crashes as crash surrogates. The magnitude of the bias can be accessed from the difference in the point estimation of the odds ratios. The odds ratio using crash alone is 65 percent higher than the combined analysis (7.12 versus 4.32). This implies that using a near-crash as a surrogate to evaluate the effects of drowsiness will underestimate the actual crash risk. On the positive side, the combined analysis provides a much narrower confidence interval as can be clearly seen from Figure 19. This result illustrates the benefit of using surrogate measures. Both analyses show statistically significant results.

Distraction

Distraction is commonly present during driving. The level of distraction is associated with the complexity of non-driving related tasks. Three levels of manual/visual complexity were defined as shown in Table 45. Three Levels of Manual/Visual Complexity. The three levels of secondary tasks are complex secondary tasks, moderate secondary tasks, and simple secondary tasks. The complexity levels are based on whether the task requires either multi-step, multiple eye glances away from the forward roadway, and/or multiple button presses (Dingus, Antin, Hulse, and Wierwille, 1989). Moderate tasks are those that require at most two glances away from the roadway and/or at most two button presses, while simple tasks are those that require none or one button press and/or one glance away from the forward roadway. Based on the previous study, the complex secondary tasks have significant impacts on safety and were considered as distractions in the sensitivity analysis.

Table 45. Three Levels of Manual/Visual Complexity

Simple Secondary Tasks	Moderate Secondary Tasks	Complex Secondary Tasks
1. Adjusting radio	1. Talking/listening to hand-held device	1. Dialing a hand-held device
2. Adjusting other devices integral to the vehicle	2. Hand-held device-other	2. Locating/reaching/ answering hand-held device
3. Talking to passenger in adjacent seat	3. Inserting/retrieving CD	3. Operating a PDA
4. Talking/singing: no passenger present	4. Inserting/retrieving cassette	4. Viewing a PDA
5. Drinking	5. Reaching for object (not hand-held device)	5. Reading
6. Smoking	6. Combing or fixing hair	6. Animal/object in vehicle
7. Lost in thought	7. Other personal hygiene	7. Reaching for a moving object
8. Other	8. Eating	8. Insect in vehicle
	9. Looking at external object	9. Applying makeup

Similar to the analysis of drowsiness, the point estimation of the odds ratio for crashes and near-crashes combined is smaller than that of crashes alone. The combined analysis provides a much narrower confidence interval.

Lighting Conditions

The lighting conditions were classified as daylight and other lighting conditions, including dusk, dawn, darkness lighted, and darkness not lighted. In general, the daylight condition is expected to be safer than the others. Similar to the analysis of drowsiness, the point estimation of the odds ratio for crashes only (1.40) is greater than that of the combined data (1.21). The length of the confidence interval also decreases with the combined data. More importantly, the confidence interval for combined data does not include 1.0, which indicates a statistically significant increase in risk. Compare this to the confidence interval using crash data alone, which was large enough to include 1.0, and thus indicates no increase in risk level for lighting conditions.

Surface Condition

The surface conditions were classified into two categories: dry surface and other conditions (including icy, muddy, snowy, and wet). It is expected that driving on a non-dry surface is more dangerous as confirmed by the results from odds ratio calculation. The comparison of the odds ratios for combined data and crashes only shows some drastic changes. The odds ratio drops from 3.11 when using crashes to only 1.56 when using combined data. The decrease in the length of confidence interval is also substantial: from 5.33-1.81=3.52 to 1.9-1.28=0.62. However, the test based on the 0.05 significance level remains the same (both confidence intervals exclude 1.0).

Weather Conditions

The weather conditions were classified into two categories: inclement weather condition (including rain, fog, snow, and sleet conditions) and normal (including clear and cloudy conditions). Consistent with other factors, the odds ratio estimation for combined data is smaller than that for crashes alone, and combined data produce a shorter confidence interval. The test result remains the same: both confidence intervals include 1.0 and thus are not significant at the 0.05 level.

Table 46. Sensitivity Analysis: Contingency Table

	Crash	Crash and Near-Crash	Baseline
Distracted	5	47	241
Not Distracted	64	783	17207
Other Lighting	26	285	5,259
Daylight	43	545	12,189
Drowsy	14	111	599
Not Drowsy	55	719	16,745
Inferior Weather	9	71	1,343
Normal Weather	60	758	16,094
Inferior Surface	18	125	1,780
Dry Surface	51	705	15,668

Table 47. Sensitivity Analysis: Risk Assessment

		Odds Ratio	p-value	95% Confidence Limits	
Distraction	Crash only	5.58	<0.001	2.23	13.98
	Crash & near-crash	4.29	<0.001	3.11	5.91
Lighting Condition	Crash only	1.40	0.173	0.86	2.28
	Crash & near-crash	1.21	0.01	1.04	1.4
Surface Condition	Crash only	3.11	<0.001	1.81	5.33
	Crash & near-crash	1.56	<0.001	1.28	1.9
Weather Condition	Crash only	1.79	0.097	0.89	3.63
	Crash & near-crash	1.12	0.364	0.87	1.44
Drowsiness	Crash only	7.12	<0.001	3.94	12.87
	Crash & near-crash	4.32	<0.001	3.48	5.36

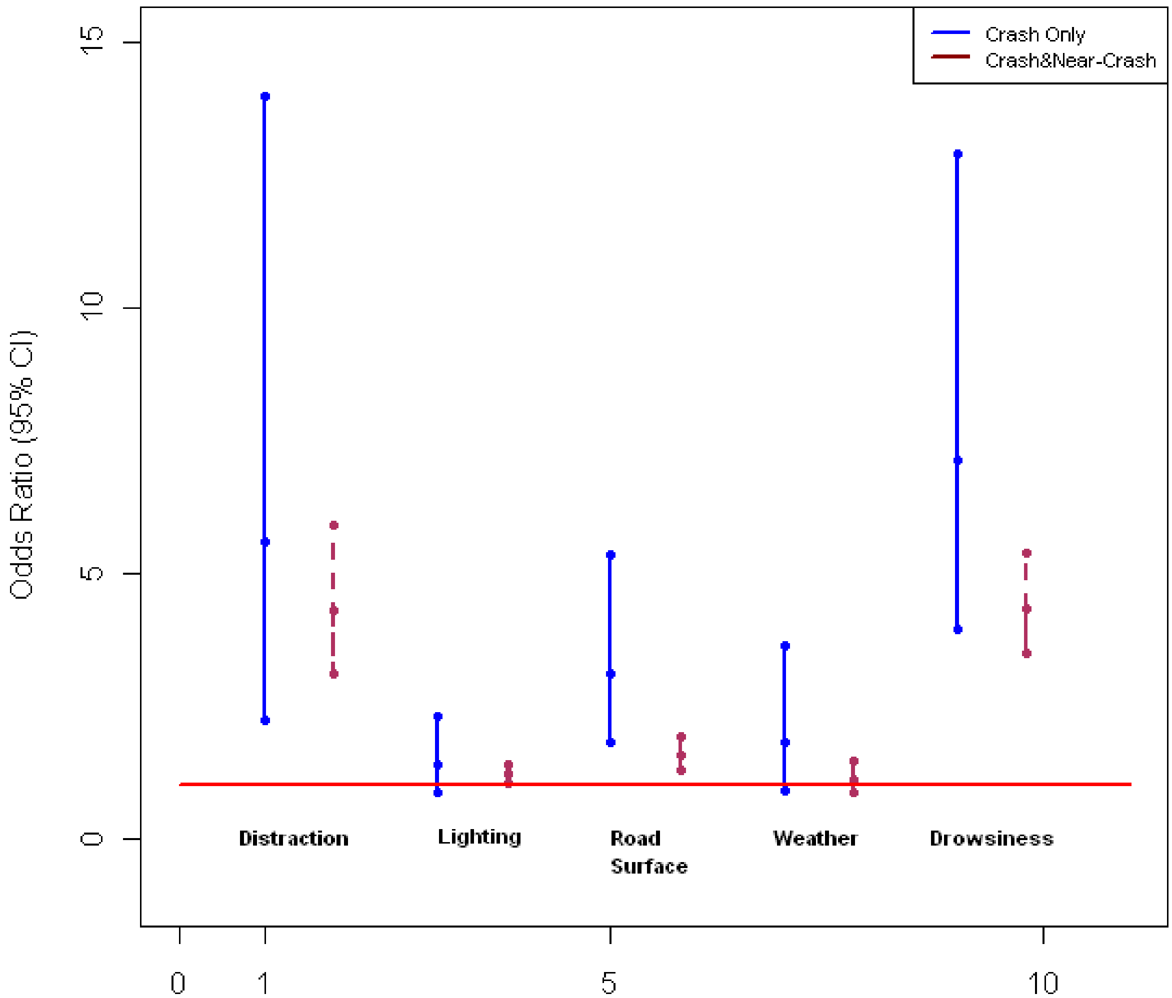

Figure 19. Sensitivity Analysis: Odds Ratio and 95 Percent Confidence Interval

Summary of Sensitivity Analysis

The sensitivity analysis produced consistent results: the point estimation for odds ratios using combined data was always smaller than for using crash data alone. The precision of the estimator, as measured by the length of the confidence intervals, is always better than that of using crashes alone. The consistency of the results has a significant implication: using surrogate measures tends to provide conservative risk estimates, yet with statistically significant test results. Therefore, a significant risk factor identified using near-crash surrogates will be at least as dangerous as the analysis indicated with crashes alone. The estimated odds ratio can be considered as a lower bound of the mean of "true" odds ratios by using crashes alone (if there are sufficient data). This suggests that assessing the risk of various contributing factors using near-crashes as surrogates will provide conservative results as compared to calculating risk using crashes alone.

CHAPTER 5. SUMMARY AND CONCLUSIONS

Naturalistic driving studies can significantly improve our understanding of traffic safety from several perspectives that otherwise cannot be sufficiently evaluated. Although the naturalistic data crash sample size is small, from a crash database perspective, there is detailed information about the driver, vehicle, traffic, and environment. In addition, there is precise information regarding the timing of factors (e.g., distraction). While this detailed information has the potential to provide great insight into improving driver safety, it demands that novel approaches to data analysis and modeling be developed.

Given the small crash sample size, analyses have been conducted that combine crashes with the safety surrogate near-crashes. The definition of near-crash combines various kinematic and environmental factors; thus, near-crashes provide more information than the single kinematic-measure-based surrogates (i.e., time-to-collision). Using near-crashes as surrogate metrics for crashes can both increase the sample size and increase the amount of information collected from the data.

The 100-Car Naturalistic Driving Study is the largest NDS collected to-date with a relatively large number of crashes and near-crashes observed. There are relatively smaller studies, such as the Naturalistic Teenage Driver Study (40 participants) and Older Driver Naturalistic Driving Study (20 participants), in which the number of crashes is too small for risk analysis purposes. The results of this study will provide useful information for these smaller scale studies that must incorporate near-crashes for analyses.

There is no debate that crashes and near-crashes are two different types of events. This is not only true by operational definition but several results in this report demonstrate that the two cannot be completely identical. However, this does not eliminate using near-crashes as crash surrogates for a specific purpose. This analysis focused on the validity of the surrogate approach for risk assessment.

Two principles, namely the identical causal mechanism and the strong frequency relationship between crashes and near-crashes, were proposed and thoroughly discussed. An ideal condition, a constant crash-to-near-crash ratio, was also proposed. It was shown that under this condition, the risk estimation will be unbiased and the precision of estimation will be improved when compared to using crashes alone.

Three analyses were conducted to assess these two principles:

- Sequential factor analysis
- Frequency relationship of the presence of behaviors between crashes and near-crashes
- Sensitivity analysis

The following are the primary results from each of these analyses:

- The driver's reaction and evasive maneuver is the primary difference distinguishing crash and near-crash.

- There were no significant differences found in the number of contributing factors present for both crashes and near-crashes, which suggests that for both types of events, the driver is clearly in a similar complex situation.
- The contributing factors and risk factors, which are considered to be related to the causal mechanism, are not significantly different for crashes and near-crashes.
- There is a strong relationship between the frequency of crashes and near-crashes. However, as a much stronger condition, the crash-to-near-crash ratio is scenario-dependent and not constant in general. This result implies that using near-crashes as a surrogate will provide useful information about crash risk. However, the risk estimation will likely be different than using crashes alone.
- The sensitivity analysis indicated that when combined crash and near-crash data are used, the precision of the estimation will increase as measured by the shorter length of the confidence interval surrounding the point estimate. This is expected due to the increased sample size. An interesting result relates to the pattern of the bias of odds ratio: the odds ratios from combined analysis are consistently smaller (thus more conservative) than when using crashes alone. This result has significant implications in the analysis of naturalistic data: the combined analysis will provide a conservative odds ratio point estimate but may also indicate a statistically significant effect. For example, a combined analysis may indicate that inattention increases the risk of crashes and near-crashes by three times and demonstrates increased risk; however, the analysis using crashes alone will produce a point estimate of at least three times more risk but may not be significantly different from the neutral value 1.0. Therefore, the risk factors identified through combined crash and near-crash data appear to provide a more conservative estimate but provide enough data to identify significant effects. The other analyses provide support that these data can be combined to provide better estimates of the true effect (though it is likely conservative).

Note that due to the limitation of the data, the analyses were conducted at an aggregated level (i.e., all types of crashes and near-crashes, not just rear-end striking). With the upcoming large-scale SHRP 2 Naturalistic Driving Study, it will be possible to conduct a more detailed study. Some key criteria, such as constant crash-to-near-crash ratios, might be satisfied under a finer stratification.

While it is not possible to conclusively prove either the causal mechanism or the frequency relationship principles discussed, the analyses presented in this report show strong support that the near-crashes a) have similar contributing factors to crashes and b) there is a strong relationship between the frequency of crashes and near-crashes. Given that there was support and no obvious contradictions, i.e., contributing factors only found in crashes and not near-crashes, we conclude that near-crashes can be used as a crash surrogate for risk assessment. Furthermore, the sensitivity analysis was conducted to provide a method for researchers to determine the ramifications of conducting analyses using both crashes and near-crashes as opposed to crashes alone.

This study was based on the frequency of factors in safety outcomes and baselines. The interactions between the driver, vehicle, and driving environment were not accounted for and cannot be retrieved from this frequency data alone. Future research that considers a complete reconstruction of the safety events and identification of the critical risk path would provide a better understanding of the underlying mechanisms of crashes and near-crashes, thus getting one step closer to the causal mechanisms of crashes. More interestingly, near-crashes also contain important information about how the driver avoids a potential crash, which will be critical for developing and evaluating safety countermeasures.

In summary, the relationship between crashes and near-crashes is complex and context dependent. There are no simple or absolute criteria to prove near-crashes can be used as crash surrogates for a general purpose. The empirical study using 100-Car data indicates the following main conclusions: 1) there is no evidence suggesting that the causal mechanism for crashes and near-crashes are different; 2) there is a strong frequency relationship between crashes and near-crashes; 3) using near-crashes will have biased results; however, the direction of the bias is consistent based on this empirical study; and 4) using near-crashes as surrogates can significantly improve the precision of the estimation. This result is analogous to the trade-off between bias and precision in many statistical estimation problems. For small-scale studies with limited numbers of crashes, using near-crashes as surrogate measures is informative for risk assessment and will help identify those factors that have a significant impact on traffic factors.

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APPENDIX A. PRECIPITATING FACTORS

Table 48. Precipitating Factors for All Conflict Types

Precipitating Event	Crash	Near-Crash
Animal approaching roadway	0	1
Animal in roadway	2	9
End departure	2	0
Lost control - excessive speed	4	2
Lost control - other cause	0	1
Lost control - poor road conditions	4	9
Lost control - unknown cause	0	1
No analyzed data	0	1
Object in roadway	5	5
Object in unknown location	0	2
Other vehicle - backing	0	3
Other vehicle - traveling in opposite direction	0	1
Other vehicle ahead - and accelerating	0	1
Other vehicle ahead - but at a slower constant speed	0	7
Other vehicle ahead - but decelerating	0	175
Other vehicle ahead - slowed and stopped less than 2 seconds	7	85
Other vehicle ahead - stopped on roadway more than 2 seconds	8	46
Other vehicle entering intersection - intended path unknown	0	1
Other vehicle entering intersection - left turn across path	1	30
Other vehicle entering intersection - straight across path	0	13
Other vehicle entering intersection - turning into opposite direction	0	8
Other vehicle entering intersection - turning same direction	0	32
Other vehicle from driveway - straight across path	0	1
Other vehicle from driveway - turning into opposite direction	0	1
Other vehicle from driveway - turning into same direction	0	4
Other vehicle from driveway - intended path unknown	1	0
Other vehicle from parallel/diagonal parking lane	0	2
Other vehicle lane change - left other	1	0
Other vehicle lane change - left in front of subject	0	38
Other vehicle lane change - left_ sideswipe threat	0	16
Other vehicle lane change - right in front of subject	0	42
Other vehicle lane change - right other	0	1
Other vehicle lane change - right_ sideswipe threat	0	32
Other vehicle oncoming - over left line	0	8
Pedestrian approaching roadway	0	3
Pedestrian in roadway	0	5
Subject ahead - but decelerating	4	22
Subject ahead - slowed and stopped less than 2 seconds	3	16
Subject ahead - stopped on roadway more than 2 seconds	4	0
Subject in intersection - passing through	0	1

Subject in intersection - turning left	1	8
Subject in intersection - turning right	0	2
Subject lane change - left behind vehicle	0	2
Subject lane change - left in front of vehicle	0	12
Subject lane change - left other	0	2
Subject lane change - left_ sideswipe threat	1	22
Subject lane change - right behind vehicle	0	4
Subject lane change - right in front of vehicle	0	7
Subject lane change - right other	0	2
Subject lane change - right_ sideswipe threat	1	16
Subject over left edge of road	5	14
Subject over left lane line	0	16
Subject over right edge of road	14	21
Subject over right lane line	1	8

Table 49. Precipitating Factors for Single-Vehicle Conflict

Precipitating Factor	Crash	Near-Crash
Lost control - excessive speed	2	0
Lost control - other cause	0	1
Lost control - poor road conditions	4	7
Participant lane change - left other	0	1
Participant over left edge of road	4	13
Participant over left lane line	0	3
Participant over right edge of road	14	21
Participant over right lane line	0	2

Table 50. Precipitating Factors for Lead-Vehicle Conflict

Precipitating Factor	Crash	Near-Crash
Other vehicle ahead - but at a slower constant speed	0	6
Other vehicle ahead - but decelerating	0	160
Other vehicle ahead - slowed and stopped less than 2 seconds	7	83
Other vehicle ahead - stopped on roadway more than 2 seconds	7	44
Other vehicle entering intersection - left turn across path	0	2
Other vehicle entering intersection - turning same direction	0	5
Other vehicle from driveway - turning into same direction	0	2
Other vehicle from parallel/diagonal parking lane	0	1
Other vehicle lane change - left in front of participant	0	34
Other vehicle lane change - right in front of participant	0	34
Other vehicle lane change - right other	0	1
Other vehicle lane change - left other	1	0
Participant ahead - but decelerating	0	2
Participant lane change - left behind vehicle	0	2
Participant lane change - right behind vehicle	0	3
Participant over left lane line	0	1

Table 51. Precipitating Factors for Following-Vehicle Conflict

Precipitating Factor	Crash	Near-Crash
Other vehicle ahead - and accelerating	0	1
Other vehicle ahead - but decelerating	0	12
Other vehicle ahead - slowed and stopped less than 2 seconds	0	2
Other vehicle ahead - stopped on roadway more than 2 seconds	1	0
Pedestrian approaching roadway	0	1
Participant ahead - but decelerating	4	20
Participant ahead - slowed and stopped less than 2 seconds	3	16
Participant ahead - stopped on roadway more than 2 seconds	4	0
Participant in intersection - turning right	0	1
Participant lane change - left in front of vehicle	0	10
Participant lane change - right in front of vehicle	0	7

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