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Evaluating Relationships Between Perception-Reaction Times, Emergency Deceleration Rates, and Crash Outcomes Using Naturalistic Driving Data

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Disclaimer

ABSTRACT

Perception-reaction times (PRT) and deceleration rates are critical components in the design of highways and streets. This research has several objectives, including 1) evaluate differences in PRT and deceleration rates between crash and near-crash events, 2) assess the correlation between PRT and deceleration rate, 3) determine if there is a causal relationship between PRT and deceleration rate (and what it is), and 4) develop predictive models for PRT and deceleration rate that can be used for roadway design and crash reconstruction. These objectives were met by applying multiple statistical analysis techniques to the SHRP2 naturalistic driving data.

The analysis results indicated that crash events were associated with longer PRT values and lower deceleration rates. The Pearson correlation between PRT and deceleration rate was low. However, PRT was a causal factor of deceleration rate in both crash and near-crash events. In crash events, longer PRT values were associated with lower deceleration rates. In near-crash events, longer PRT values were associated with higher deceleration rates.

Regression models for crash reconstruction were estimated using panel and quantile regression methods. Applications of these models for both purposes are illustrated and discussed. The results for design applications are compared with existing AASHTO design guidance.

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EXECUTIVE SUMMARY

Perception-Reaction Time (PRT) and deceleration rate are two key components in geometric design of highways and streets. Combined with a design speed, they determine the minimum required stopping sight distance (SSD). Current American Association of Highway Transportation Officials (AASHTO) SSD guidance related to PRT and deceleration rate are based on 90th percentile PRT and 10th percentile deceleration rate values from experiments that were completed in Texas in the mid-1990s *(3)*. These experiments lacked real-world distractions, were limited in the age range and abilities of drivers, did not test a wide variety of initial speeds and lighting conditions that may impact PRT and deceleration rates, and they did not account for potential correlations between the PRT and deceleration rates. Thus, the values from these experiments may not be applicable in real-world scenarios.

The objectives of this research were: 1) evaluating differences in perception-reaction times (PRT) and deceleration rates between crash and near-crash events, 2) assessing the correlation between PRT and deceleration rate, 3) determining if there is a causal relationship between PRT and deceleration rate (and what it is), and 4) developing predictive models for PRT and deceleration rate that can be used for roadway design and crash reconstruction. These objectives were met by applying multiple statistical analysis techniques to SHRP2 naturalistic driving data. These methods included: 1) genetic matching (with Rosenbaum's sensitivity analysis), 2) Pearson correlation coefficients, 3) directed acyclic graphs (DAGs), 4) random effects panel models (with observation weighting), and 5) quantile models (with observation weighting and clustered robust standard errors).

The analysis results indicated that there were differences in PRT and deceleration rates for crash and near-crash events. The specific estimates were that, on average, drivers involved in crash events took 0.487 seconds longer to react and decelerated at 0.018 g's (0.58 ft/s^2) slower than drivers in equivalent near-crashes. These results were statistically significant. The PRT results were more robust (i.e., less sensitive) to unobserved confounders than the deceleration rate estimates.

The evaluation of Pearson correlation indicated there was not a strong Pearson correlation between the PRT and deceleration rate, regardless of whether the events were crash/near-crash. However, the DAG analysis results indicated there was a causal relationship between PRTs and deceleration rates. In particular, crash events with longer PRTs were associated with lower deceleration rates (i.e., for a 1-second longer PRT, the deceleration rate decreases by 0.0223 g's). In near-crash events, longer PRT values were associated with higher deceleration rates (i.e., for a 1-second longer PRT, the deceleration rate increases by 0.0059 g's).

Prediction models were developed for use in roadway design. These models were used to develop tables comparing existing SSD design criteria with SSD criteria based on the results of the predictive models. These predicted values indicated that minimum design SSD values would increase by 1.6 feet to 129.2 feet dependent on: 1) the design speed, 2) the SSD model used, and 3) if near-crash or crash outcomes are used to determine the PRT and deceleration rate values that should be used for design.

Regression models for predictive use in crash reconstruction. Using these models, it was shown that the mean values for the PRT and deceleration rate can be predicted using the regression models. It was also shown that confidence intervals can be constructed using the mean values, root mean squared error, and a lognormal distribution. These confidence intervals may be useful for characterizing the uncertainty in the predictions and the reconstruction when better data are unavailable (e.g., skid marks and friction measurements).

1. INTRODUCTION

1.1 Problem Statement

Providing a safe and efficient surface transportation system for users is an important outcome of the geometric design process. To facilitate these objectives, design criteria have been adopted by state transportation agencies to ensure consistent application of these criteria. Stopping Sight Distance (SSD) is considered a fundamental highway and street design criterion that is necessary for safe roadway design. It is one of the Federal Highway Administration's (FHWA) controlling criteria *(1)*, underscoring its importance among geometric design elements.

The *American Association of State Highway and Transportation Officials'* (AASHTO) *Policy on Geometric Design of Highways and Streets* (herein referred to as the Green Book [*2*]) specifies minimum SSD design values as a function of the design speed *(2)*. The Green Book states that the sight distance available to drivers should be at least as great as the minimum SSD for the given design speed at all points along the roadway. The minimum SSD in the Green Book is defined as the distance it takes for a driver to apply the brakes once an object on the roadway is visible (perception-reaction distance) and then the braking distance to stop *(2)*. Minimum SSD values also often control the minimum values for other design criteria, such as horizontal sightline offsets (HSO) and vertical alignment design elements, such as the length of a vertical curve.

The current Green Book SSD model is shown in equation 1.1 *(2, 3)*.

$$SSD = Vt_r + \frac{V^2}{2g\left(\frac{a}{g} + G\right)} \tag{1.1}$$

Where

$SSD =$ minimum stopping sight distance (ft),

$t_r =$ perception-reaction time (2.5 s),

$V =$ velocity of the vehicle (i.e., the selected design speed in ft/s),

$g =$ acceleration due to gravity (32.2 ft/s^2),

$a =$ deceleration rate of the vehicle (11.2 ft/s^2), and

$G =$ grade of the roadway (in decimal form).

For most applications in the Green Book *(2)*, it is assumed that G = 0. Thus, the SSD equation simplifies to equation 1.2.

$$SSD = Vt_r + \frac{V^2}{2a} \tag{1.2}$$

Current AASHTO SSD guidance related to PRT and deceleration rate is provided in the Green Book *(2)*. These values are based on 90th percentile PRT and 10th percentile deceleration rate values from experiments that were completed in Texas in the mid-1990s *(3)*. However, these experiments lacked real-world distractions that drivers are subject to, were limited in the age range and abilities of drivers, did not test a wide variety of initial speeds and lighting conditions that may impact PRT and deceleration rates, and did not account for potential correlations between the PRT and deceleration rates. Thus, the values from these experiments may not be applicable in real-world scenarios.

Recent research has used driving simulators and naturalistic data from the 100-car naturalistic driving study to evaluate PRT *(4, 5)*. However, the sample sizes and conditions accounted for were limited. Also, the relationship between PRT and deceleration rate was not accounted for. Little research has been done that evaluates average emergency deceleration rates.

The *Strategic Highway Research Program 2* (SHRP2) recently implemented a multi-year naturalistic driving study (NDS) data collection effort that included over 3,400 drivers across the United States in an effort to address the role of driver performance and behavior in traffic safety. This effort developed a database that researchers can use to assess driver characteristics and behaviors. This is a potential source that could be used to assess and develop models of the relationships between PRT and emergency deceleration rates. Given that data are available for crashes and near-crashes, evaluation of the differences in PRT and deceleration rates for crash and near-crash events may also reveal interesting differences that can be used to prevent crashes in the future.

There are likely multiple factors that influence the relationship between PRT and deceleration rate. The deceleration rate a driver is likely to select (i.e., the intensity of brake application) in braking situations is likely to depend on what level of risk the driver perceives. Thus, there is potential that PRT has a direct impact on emergency deceleration rates. Large values of PRT may occur due to inattentiveness, yet the driver may brake harder due to an impending collision when compared with a shorter PRT for the same situation. Conversely, attentive drivers with long PRT may have low deceleration rates if they judge the conflict to be low risk (i.e., there is little urgency for either PRT or braking). Thus, high PRT may be associated with high deceleration rates when drivers are inattentive while attentive drivers are likely to have low PRT and high deceleration rates (for high risk situations) and high PRT and low deceleration rates for low risk situations.

Understanding the relationship between PRT and deceleration rate can improve transportation engineers' understanding of human factors related to SSD, leading to improved design guidance and safer roadways. It could also improve crash reconstruction and the ability to determine what happened at crashes. Therefore, a study is needed to evaluate 1) the differences in PRT and deceleration rates between crash and near-crash events and 2) the relationship between PRT and deceleration rates. The results of this research could be used by transportation agencies to improve design guidance. The results could also be used in crash reconstruction and for developing policies aimed at reducing the number and severity of crashes that occur on and near the roadway.

1.2 Objectives

The objectives of this research are to:

1) Evaluate the differences in PRT and emergency deceleration rates between crash and near-crash events using a causal inference approach
2) Determine the strength of correlations between PRT and emergency deceleration
3) Determine if there is a causal relationship between PRT and emergency deceleration rates and, if so, what the relationship is
4) Develop a method and equations for predicting the PRT and deceleration rate for drivers that can be used for design and for crash reconstruction

1.3 Scope

The research objectives were met by accomplishing nine research tasks. A comprehensive literature review for PRT and emergency deceleration rates was performed in Task 1. An evaluation of differences in PRT and emergency deceleration rates between crash and near-crash events using the SHRP2 NDS data was performed in Task 2. The potential applications of the findings from Task 2 for improving transportation safety were then discussed in Task 3. Correlations between PRT and emergency deceleration rates, accounting for personal and observation specific characteristics were evaluated in Task 4. Potential causal relationships between PRT and emergency deceleration rates were also evaluated in Task 5. Predictive models for PRT and emergency deceleration rate were developed for design and crash reconstruction applications in Task 6 and Task 7, respectively. The resulting predictive models for geometric design were then compared to the PRTs and deceleration rates currently used in design in Task 8. Finally, all results were compiled into a report, and practical implementation strategies for the evaluations were provided in Task 9.

1.4 Outline of Report

The report is organized into seven sections as follows.

- A general introduction was provided in Section 1. The need for this research is outlined in the form of a problem statement. Research objectives and the research scope were described.
- Background information and a literature review on perception-reactions times and deceleration rates was provided in Section 2.
- Research methods used in this research were presented in Section 3.
- Data collection efforts, including data sources, protocol, and quality control steps, were described in Section 4.
- Modeling results and interpretations related to perception-reaction times and deceleration rates were provided in Section 5.
- Key findings, research conclusions, challenges, and limitations of the research were summarized in Section 6.
- Recommendations for future work and implementation of the results were included in Section 7.

2. BACKGROUND

2.1 Overview

Previous research has evaluated deceleration rates in braking maneuvers, as well as perception-reaction times of drivers in emergency situations. Each of the studies that evaluated both perception-reaction times and deceleration rates did not evaluate relationships and potential correlations between the two parameters *(6)*. This section provides a review of the published literature related to emergency deceleration rates and emergency (unexpected) perception-reaction times.

2.2 Literature Review

2.2.1 Deceleration Rate

A limited amount of research on deceleration rates for passenger cars with ABS brake systems is available in the published literature *(3, 5, 7)*. However, it is well known that these systems improve braking performance. Also, deceleration rates may be higher when skidding is avoided due to static friction coefficients being higher than dynamic friction coefficients.

A summary of reviewed deceleration rate research is provided in Table 2.1. The findings in the first few rows of Table 2.1 indicated that, for all drivers, the mean declaration rate was higher on tangents than on curves (although the difference is not statistically significant). It also indicated that the mean deceleration rate is also higher on dry pavement than on wet pavement. However, the standard deviation of deceleration rates was higher on dry pavement than on wet pavement, and higher on tangents than on curves.

Findings from a study using only young (18-25 years old) or old (65+ years old) drivers found that values for the mean and standard deviation of deceleration rates were smaller than the Fambro et al. study *(3)* that is currently used in AASHTO design guidance *(2)*. However, the Fitch et al. study *(3)* only had 10 drivers out of 64 who braked for an unexpected object that appeared 2.5 seconds before reaching the object, leaving the results subject to potential bias. For instance, the deceleration rate results from this study may be subject to truncation of the observations due to the study design (object appearing where the car was projected to be in 2.5 seconds). This may not have allowed sufficient time for the drivers to determine that braking was warranted given the hazard and to perform emergency braking before reaching the object.

Another study by Paquette and Porter used professional drivers in specific vehicles, starting at an initial speed of 36 mph and testing deceleration rates for hard braking maneuvers *(7)*. For each vehicle tested, this was repeated five times with a two- to three-minute wait time between runs to allow the brake rotors to cool. For this study, there is an issue with transferability to general drivers due to differences in driver braking performance between professional and nonprofessional drivers.

Researchers in Europe recently completed research on deceleration rates using data from the Field Operational Tests of Aftermarket and Nomadic Devices in Vehicles (TeleFOT) project *(8)*. This was a field trial where participants drove along a specified route in Leictershire, England. The study included six male and ten female drivers, all between the ages of 23-59. A single vehicle was instrumented to collect data, including deceleration rates. The make, model, and age of the vehicle used were not specified. Deceleration rates at junctions, or any other location where emergency braking occurred, were used to determine deceleration rates.

Table 2.1 Deceleration Rate Summary from the Published Literature

Professional Drivers	Tangent/ Curve	Pavement Condition	Driver Ages	Vehicle Make/Model /Year	Mean Deceleration Rate (g's)	Deceleration Standard Deviation (g's)	Source
No	Curve	Dry	Mixed	Not specified	0.54	0.11	*(3)*
	Tangent				0.57	0.12	
	Curve	Wet			0.51	0.09	
	Tangent				0.55	0.08	
No	Tangent	Dry	18-25, 65+ Years	2006 Mercedes-Benz R350 or 2007 Volvo S80	0.48	0.03	*(5)*
Yes			Not Specified	2001 Nissan Maxima	0.77	-	*(7)*
Yes			Not Specified	2005 Volvo VC70	0.75	-	
Yes			Not Specified	2011 Mitsubishi RVR SE	0.81	-	
Yes			Not Specified	2008 Honda Civic	0.83	-	
No			23-59 Years	Single vehicle, not specified (data from TeleFOT)	0.27-0.67 (dependent on other variables)	-	*(8)*
Not Specified			Not Specified	Motorcycles	0.56	0.17	*(9)*

A Malaysian study by Ariffin et al. evaluated the deceleration rates of motorcycle braking maneuvers *(9)*. Six motorcycles (100-150cc) with different combinations of front and rear disk and drum brakes were used. The braking maneuvers were done from an initial speed of 30 mph to stopping. A total of 48 maneuvers were used for analysis (24 using rear brakes only and 24 using front and rear brakes). The mean deceleration rates and the deceleration standard deviations of the combined braking maneuvers are shown in Table 2.1.

A separate issue that the above deceleration rate studies did not consider, and which limits the applicability of the results to general emergency maneuvers, was that the objects drivers were reacting to were not a vehicle or other large object that would have provided drivers with a sense of urgency to stop or undertake some other evasive maneuver. It is possible that when there is a high level of urgency, the mean deceleration rate will increase/decrease. It is also possible that the dispersion (i.e., variance) of deceleration rates will change with higher urgency levels.

Finally, other research by Akçelik and Besley has shown that deceleration rates change as initial speed changes *(10)*. Their findings indicated that average deceleration rates were lower at higher initial speeds than at lower initial speeds. This is consistent with previous *American Association of State Highway Officials* (AASHO) and AASHTO guidance that used lower coefficients of friction at higher design speeds, and higher coefficients of friction at lower design speeds. The authors suggested that the mean deceleration rate can be found using equation 2.1, as implemented in the SIDRA network analysis software *(10)*:

$$decel = \frac{-f_d\left(p_1 + p_2\sqrt{v}\right)}{3.6} \tag{2.1}$$

Where
$decel =$ average deceleration rate,
$f_d =$ adjustment factor,
$p_1 =$ coefficient,
$p_2 =$ second coefficient, and
$v =$ the initial velocity.

The values of the coefficients, the adjustment factor, and the units for the variables were not provided. The model fit statistics for the model used to estimate the coefficients were also not provided. The model also fails to account for the variation in deceleration rates due to individual driver and vehicle differences. While the model has no practical use here, it demonstrates that deceleration rates are likely to change based on the initial speed of the vehicle.

2.2.2 Crash Reconstruction

Crash reconstruction often utilizes skid marks to estimate initial operating speeds for vehicles involved in crashes *(11, 12)*. Tire mark length can be used, with the dynamic coefficient of friction, to estimate the initial speed of the vehicle(s). However, the amount of friction being used during braking maneuvers varies and is not always available for crash reconstruction calculations (i.e., there were no skid marks, there were breaks in the skid marks due to ABS, the skid marks were not measured, or the pavement properties were not available). It has also been indicated that failing to account for braking prior to skidding leads to underestimated initial speeds *(13)*.

Several researchers *(12, 14, 15)* have attempted to estimate deceleration rates and/or braking distances for crash reconstruction purposes using experimental data. Each of these experiments used professional drivers in controlled driving environments. These experiments attempted to estimate the maximum possible deceleration rates possible for passenger cars. The results of these studies are summarized in Table 2.2.

Table 2.2 Deceleration Rate Parameters from Crash Reconstruction Literature (with ABS)

Deceleration Rate or Braking Distance	Professional Drivers	Vehicle Types	Initial Speed (mph)	Average Maximum Deceleration (g's)	Source
Deceleration Rate	Yes	Not Specified	24.9	0.82	*(14)*
			37.3	0.86	
			49.7	0.90	
Braking Distance/ Deceleration Rate			24.9, 37.3, and 49.7	0.76	*(15)*
		Renault Megane Coach 1.9 dCi	Various	0.71	*(12)*
		Fiat Bravo 1.6		0.75	
		Renault Clio II 1.2		0.78	
		Fiat Punto 55 SX		0.60	

While the maximum deceleration rates estimated from controlled experiments using professional drivers are useful for determining the shortest braking distance possible, it is not very useful for crashes where the driver performing emergency braking does not reach the maximum possible deceleration rate and does not leave skid marks. This situation is likely to be a frequent source of frustration for practitioners seeking to reconstruct vehicle crashes where it was known that braking occurred, but due to either a lack of driver braking urgency or very high available static friction values, skidding did not occur. In these situations it would be useful to have prediction models to determine deceleration rates.

2.2.3 Perception-reaction Time

Perception-reaction times for minimum SSD criteria in the Green Book are based on non-distracted drivers. However, there are many factors that could influence driver distraction levels. These factors should be accounted for, if possible, in the perception-reaction time, as long as distractions are a factor in driving.

Some factors that have been suggested as distractions include listening to music, cellular phone use (talking, texting, etc.), interacting with other people in the vehicle, eating/drinking, and adjusting vehicle controls *(16)*. Other possible factors that could slow response times include fatigue, alcohol use, and prescription, recreational, and illegal drug use *(17–21)*. The distractions indicated by these researchers are not comprehensive. While it is unrealistic to design for drivers who are under the influence of drugs or alcohol, distractions and fatigue are important considerations.

A review was conducted of studies that assessed perception-reaction time distributions for unexpected braking events. Distributions from driving on test tracks, from naturalistic driving data, and a simulator study are summarized in Table 2.3 *(3-5, 16, 24-26)*. The distribution types for the distributions of perception-reaction times were not provided in any of the studies in Table 2.3 (e.g., normal, lognormal, gamma distributions). Some researchers have suggested that perception-reaction times follow a lognormal distribution *(6, 22–24)*.

Table 2.3 Perception-Reaction Time Summary from the Published Literature

Sample Size	Ages	Mean	STDEV	Simulator/Test Driving/Naturalistic Data	Distracted/ Undistracted	Study
87	Mixed	1.140	0.320	Test Driving	Undistracted	*(24)*
839		1.300	0.600			*(25)*
1,644		1.210	0.630			*(26)*
70	Older	1.140	0.353			*(3)*
60	Younger	1.140	0.204			
162	Mixed	0.594	0.105	Simulator	Undistracted	*(16)*
		0.636	0.098		Distracted - Cell Phone Use	
10	18-25, 65+ Years	0.960	0.190	Test Driving	Undistracted	*(5)*
472	Mixed	1.550	1.080	Naturalistic Driving Data	Distracted	*(4)*
		1.300	1.030		Undistracted	
		1.450	1.070		Distracted and Undistracted	

As shown in Table 2.3, the means and standard deviations for perception-reaction times vary significantly depending on how each study was conducted (test drive, simulator, or naturalistic data). Since the goal of perception-reaction time in minimum SSD criteria is to allow enough time for a driver to see and react to an object in the road, the logical decision would be to use a distribution that includes both distracted and undistracted drivers and reflects actual driving circumstances. The only study found that meets these conditions is the naturalistic driving data distribution that includes both distracted and undistracted drivers. Also, participants of simulator studies and test driving experiments are more likely to change their driving behavior due to the knowledge that they are being observed as part of an experiment, making the results more likely to be biased.

3. RESEARCH METHODS

3.1 Overview

This section describes the statistical modeling methods used in this report. Statistical methods used to evaluate differences in perception-reaction times and deceleration rates between event outcome types (i.e., crash vs. near-crash) are described in section 3.2. Methods for evaluating correlation and causal relationships between perception-reaction times and deceleration rates are discussed in sections 3.3-3.5. Finally, methods used to develop predictive models for crash reconstruction and highway geometric design are described in sections 3.6-3.7.

3.2 Counterfactual Framework and Statistical Matching

One of the objectives of this study was to evaluate differences in perception-reactions times and emergency deceleration rates using causal inference. One of the most common methods for causal analysis is using the counterfactual framework. The counterfactual framework is based on randomization theory. Based on the theory and assumptions made in randomized experiments, assumptions that are required for all causal analyses in the counterfactual framework have been developed. The assumptions are as follows *(27–30)*:

1. Stable Unit Treatment Value Assumption (SUTVA). SUTVA is the assumption that when a treatment is applied to an entity, it does not affect the outcome for any other entity. In this study, the "treatment" for analysis is if the event were a crash (treatment status = 1) or a near-crash (treatment status = 0) with outcomes of perception-reaction time and emergency deceleration rate. Given that the events are all independent of each other, this assumption is reasonable for the current study.
2. Positivity. This is the assumption that the probability of receiving the treatment at any level is non-zero (i.e., all entities included in the analysis could potentially have received the treatment). This assumption is reasonable for this study as all events had the potential to result in a crash.
3. Unconfoundedness. The mechanism for treatment assignment is considered unconfounded if the treatment status (treated or untreated) is conditionally independent of the counterfactuals for a given set of covariates (i.e., ignorable treatment assignment or that there are no important variables omitted from the analysis). To justify this assumption, a method was applied for evaluating the sensitivity of the results to potential hidden bias.

Statistical matching methods include propensity score matching, Mahalanobis matching, optimal matching, genetic matching, and others *(27–41)* These methods estimate counterfactuals (i.e., unobserved outcomes for the "treated" entities) by finding entities without the treatment that are comparable to the treated entities (and vice versa). The outcomes for the "matched" entities serve as the observed and counterfactual outcomes in the process of estimating the treatment effects. When statistical matching is employed, either 1:1 (one treated to one untreated) matching or 1:n (1 treated to n untreated) matching is used. If the sample sizes of the treated and untreated groups are similar, or if the untreated group is smaller than the treated group, 1:1 matching is typically the preferred choice *(30)*. Otherwise, 1:n matching may result in improved matching results.

3.2.1 Matching Method

For this study, genetic matching was used. Genetic matching uses a sequential process to optimize covariate balance by finding the best matches for each treated entity *(30)*. Covariate balance is achieved when the distributions of observed variables are approximately the same for the treated and comparison groups *(27, 42, 43)*. The genetic matching process minimizes imbalance across the covariates (measured using standardized bias or K-S tests) *(33)*. This is accomplished by minimizing a general Mahalanobis distance (GMD) defined in equation 3.1 *(33)*.

$$GMD(\vec{x},\vec{y},W)=\sqrt{(\vec{x}-\vec{y})^{T}\left(S^{-1/2}\right)^{T}S^{-1/2}W(\vec{x}-\vec{y})} \tag{3.1}$$

Where

$S =$ the covariance matrix between x and y,

$(\vec{x}-\vec{y}) =$ the matrix of the differences in values between groups x and y for the variables included in the matching,

$S^{-1/2} =$ the Cholesky decomposition of S (i.e., $S = S^{-1/2}\left(S^{-1/2}\right)^{T}$), and

$W =$ a weighting matrix.

3.2.2 Covariate Balance

The variables used in the matching process are determined by the analyst. Based on the results of the matching algorithm, variables may be added to or taken out of the matching specification. Regardless of which variables are used for matching, all variables available should be checked for covariate balance after the matching is complete. If the results are not satisfactory, adjustments to the matching specification should be made.

To check for covariate balance, standardized bias is typically used. The equation for standardized bias (for continuous covariates) is specified in equation 3.2 *(28)*. The equation for standardized bias for binary variables is specified in equation 3.3 *(43)*.

$$SB=\frac{100(\bar{x}_T-\bar{x}_C)}{\sqrt{\frac{(S_T^2+S_C^2)}{2}}} \tag{3.2}$$

$$SB=\frac{100(\hat{P}_T-\hat{P}_C)}{\sqrt{\frac{\hat{P}_T(1-\hat{P}_T)+\hat{P}_C(1-\hat{P}_C)}{2}}} \tag{3.3}$$

Where

$\bar{x}_T =$ the sample mean of the treated group for variable x,

$\bar{x}_C =$ the sample mean of the comparison group for variable x,

$S_T^2 =$ the sample variance of the treated group for variable x,

$S_C^2 =$ the sample variance of the comparison group for variable x,

$\hat{P}_T =$ the proportion of the treated group with a value of “1” for variable x, and

$\hat{P}_C =$ the proportion of the comparison group with a value of “1” for variable x.

Comparisons of standardized bias for the propensity score and other covariates from before and after matching can provide an indication of the improvement in covariate balance due to matching on the propensity score. Some researchers have stated that a standardized bias with an absolute value of 20 or smaller indicates no statistical difference between the treated and comparison groups (i.e., they are equivalent) *(30)*. However, others have used a threshold of 10 *(42, 43)*.

3.2.3 Estimating the Treatment Effect

The average effect of a treatment on a continuous outcome, using statistical matching, can be estimated using the mean difference in the outcome of interest between the treated and comparison group after matching. This is shown in equation 3.4 *(27)*.

$$\tau = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{treated,i} - Y_{untreated,i}\right) \tag{3.4}$$

Where
τ = the average treatment effect,
N = the number of treated observations,
$Y_{treated,i}$ = the outcome for the treated condition for observation i, and
$Y_{untreated,i}$ = the outcome for the untreated condition for observation i (i.e., the mean value of the outcome for the untreated observations that are matched to treated observation i).

The variance of the treatment effect (based on equation 14) accounts for matched data being used *(27)*. Given that replacement is not allowed (i.e., untreated observations can each only be matched to one treated observation), the standard error of the treatment effect is estimated using equation 3.5 *(27, 44)*. The treatment effect is divided by the standard error to estimate a t-statistic, which is then used to estimate the associated p-value for the treatment effect.

$$SE(\tau) = \sqrt{\frac{1}{2N}\sum_{i=1}^{N}\left(Y_{treated,i} - Y_{untreated,i} - \tau\right)^2} \tag{3.5}$$

3.2.4 Hidden Bias Sensitivity Analysis

Methods have been developed that assess the sensitivity of results using matching methods to hidden bias *(40, 41, 45–47)*. The method used in this study was the Wilcoxon signed-rank test based method proposed by Rosenbaum *(40, 41)*. This method is based on the assumption that, in order for the treatment effect to be biased due to an unobserved variable (i.e., hidden bias), the unobserved variable would need to have a bias of at least a certain magnitude. Thus, the method tests how strong of an impact an unobserved variable must have on the odds of both matched entities receiving the treatment ($\frac{\pi_j(1-\pi_k)}{\pi_k(1-\pi_j)}$ for matched observations j and k) in order to cause a significant bias in the results *(27)*. The test uses the odds ratio for units with the same values for observed variables is, at most, some value of $\Gamma \geq 1$, specified in equation 3.6 *(27, 40, 41)*.

$$\frac{1}{\Gamma} \leq \frac{\pi_j(1-\pi_k)}{\pi_k\left(1-\pi_j\right)} \leq \Gamma \tag{3.6}$$

Using a Wilcoxon signed-rank test, p-values for various values of Γ can be estimated *(40, 41)*. When Γ is large enough that a p-value is greater than 0.05, this is the value of Γ that is considered to be the measure of sensitivity for hidden bias. The larger the value of Γ in the sensitivity analysis, the less likely it is that the results are biased due to unobserved confounders. For details regarding the computational procedures for this test, see Guo and Fraser; or Rosenbaum *(27, 40, 41)*.

3.3 Correlation

When two variables have trends that are not independent of each other, they are considered to be correlated. In statistics, correlation often refers to shared linear trends between variables *(48)*. These trends can be positive or negative. Correlation between variables does not imply that there is a causal link between the variables. The correlation can be due to many factors that are non-causal (e.g., selection bias, non-randomized data, and two variables that share a common latent causal factor, and others).

The most common statistical measure of correlation is the Pearson correlation coefficient. This coefficient is sensitive to linear relationships between two variables. It may indicate correlation even if there is a nonlinear relationship between the variables. The Pearson correlation coefficient (ρ) is defined in equation 3.7 *(49)*.

$$\rho(X_1, X_2) = \frac{\sum (X_1 - \mu_1)(X_2 - \mu_2)}{\sigma_{X_1}\sigma_{X_2}} \tag{3.7}$$

Where
X_1 = the first variable,
X_2 = the second variable,
μ_1 = the mean value of variable 1,
μ_2 = the mean value of the second variable,
σ_{X_1} = the standard deviation of the first variable, and
σ_{X_2} = the standard deviation of the second variable.

For the Pearson correlation coefficient, possible values range from -1 to 1 *(50)*. A value of 1 indicates perfect linear correlation between the variables. A value of -1 indicates a perfectly negative linear relationship between the two variables. Correlations can be calculated for the entire sample and for subgroups of the dataset. When subgroups are evaluated, it helps to control for variables that the subgroups have in common. For this report, correlations between perception-reaction time and deceleration rate were evaluated for the entire dataset, for the crash and near-crash subgroups, and other subgroups identified in the results section.

3.4 Graphical Causal Models

In order to evaluate potential causal relationships between perception-reaction times and deceleration rates, graphical causal models (i.e., directed acyclic graphs or DAGs) were used. Causal graphs (i.e., path diagrams, causal Bayesian networks or DAGs) are graphical models used to encode assumptions about the data-generating process. Causal graph models have received significant attention in the social, demographic and health sciences due to the motivation to establish cause-and-effect relationships (*1*). However, it has received little attention in transportation safety studies. For instance, Vishesh et al. (*2*) explored the causal effects of pavement marking retroreflectivity (PMR) on nighttime crashes by applying both propensity score-potential outcomes and causal diagram frameworks. Ali et al. (*3*) applied Bayesian Networks (BNs) as graphical probabilistic models to interpret traffic accident causality using a directed acyclic graphical structure.

In causal graphs, variables are represented by vertices or nodes. Variables in directed graphs are connected by arcs or edges. For example, as shown in Figure 3.1, a graph model has three variables: initial vehicle speed before drivers' reaction (Speed), road lighting condition (Lighting), and crash severity (Severity). In this graph, a directional fork indicates where both $Speed$ and $Severity$ have the same ancestor, $Lighting$. The causal effects $Lighting \rightarrow Speed$ implies $Lighting$ causes $Speed$, but it does not specify whether those variables have linear, interactive, or nonlinear relationships**.**

Figure 3.1 A Causal Graph Representing the Relationship of the Initial Speed, Lighting Condition and Crash Severity

Structural Equation Modeling (SEM) is a multivariate statistical analysis technique used to analyze structural relationships. The method performs a structural search over the SEM by maximizing model scores in terms of model fit and complexity. In a combination of a model with factor analysis, path analysis, and regression analysis, SEM provides a flexible tool to visualize causal inference by a graphical path diagram (i.e., DAG). However, estimation of a causal graph from data is computationally difficult due to the large size of the space of DAGs. Previously, there have been some successful causal discovery approaches or algorithms to construct the graphical causal model, e.g., PC-algorithm (*4*), greedy equivalent search (GES) (*5*), and PC-Max (*6*). PC-Max algorithm selects the conditioning set with the highest p-value. The advantage of PC-Max is that this algorithm avoids bi-directed edges so there are no ambiguities in DAGs (*6*). This study uses the PC-Max algorithm for causal discovery applications.

Given that variables X and Y are independent and conditional on some set of variables, S, including $\boldsymbol{S_1}$, $\boldsymbol{S_2}$, …, $\boldsymbol{S_n}$, an independence test for X and Y conditional on each of $\boldsymbol{S_i}$ subsets results in p-values $\boldsymbol{p_1}$, $\boldsymbol{p_2}$, …, $\boldsymbol{p_n}$. PC-Max picks the conditional set with the highest p-value to minimize the number of independences found. Given the hypothesis H_0 (independence) and H_1 (dependence), PC-Max minimizes the relevant dependence region under the distribution of H_1. That is, we should maximize the p-value that we calculate under H_0.

The general form of structural equations is shown in Equation 3.8.

$$X_i = f_i(S_i, \varepsilon_i), i = 1, \dots, n. \qquad (3.8)$$

Where
S_i = a set of variables considered to be direct causes of X_i, and
ε_i = the error term.

The causal model is represented by a DAG. Chi-square x^2, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Bayesian Information Criterion (BIC) are used to measure the data fit and model selection. RMSEA is defined in Equation 3.9. CFI is defined in Equation 3.10. BIC is defined in Equation 3.11.

$$RMSEA = \frac{\sqrt{\chi^2 - df}}{\sqrt{df(n-1)}} \quad (3.9)$$

$$CFI = \frac{d(Null\ Model) - d(Proposed\ Model)}{d(Null\ Model)} \quad (3.10)$$

$$BIC = 2L - k \cdot \ ln\ (n) \quad (3.11)$$

Where
X^2 = the chi-square statistic,
df = the degrees of freedom,
$d() = X^2 - df$,
L = the maximum likelihood,
k = the degrees of freedom, and
n = the sample size.

For this report, the conditional model with the lowest BIC was selected as the final model.

3.5 Panel Regression

Fixed effects or random effects panel regression models are appropriate if the data are composed of repeated measurements for the individuals (e.g., drivers) in the dataset. Fixed effects models eliminate the effects of omitted variable bias given that: 1) the omitted variables are time-invariant (i.e., do not change over the repeated measurements), 2) the time-invariant (observed and unobserved) variables do not produce heterogeneous growth (change in effects on the outcome over time), and 3) the current outcomes are not determined by prior outcomes *(48, 51–53)*. Among these three conditions, the first is the most likely to be true in most applications *(52)*. Options for investigating and correcting for the second and third issues are available and include interacting time-invariant covariates with time-dummy variables or other time-variant predictor variables, or using lagged dependent variable models *(51)*. For this study, it is assumed that the outcomes are not determined by prior outcomes; so the conditions required for fixed-effects panel models hold.

The form of the panel models used for this study is shown in Equation 3.12.

$$\mathrm{Y}_{\mathrm{ij}} = \rho_i + X_i \beta + \psi_i + \varepsilon_{ij} \quad (3.12)$$

Where
Y_{ij} = the dependent variable for individual i during observation j,
ρ_i = the intercept for each individual,
β = a vector of coefficients,
X_{ij} = a vector of predictor variables for individual i and observation j,
ψ_i = the error term that varies across individual mean values, and
ε_{ij} = the error term that varies within individuals (over the repeated observations).

This model structure is valid for both the fixed and random effects panel models. For fixed effects models, ψ_i has a value of zero since ρ_i is explicitly taken into account. For random effects models, ρ_i is a random parameter. The differences between the fixed effects and random effects models are that: 1) the fixed effects model controls for time-invariant unobservable variables, while the random effects model does not (fixed effects models essentially ignore between-individual variation), 2) the fixed effects model can only estimate the effects for parameters that vary over time, while the random parameters can estimate the effects of parameters that do not vary over time, and 3) standard errors for coefficients estimated using fixed effects regression are often larger than those estimated using random effects regression *(51, 53)*.

The random effects model assumes that the random intercept (ρ_i) is not correlated with either of the error terms and is independent of all of the predictor variables included in the model *(53)*. This implies there is no omitted variable bias *(51, 52)*. This assumption can be tested using a Hausman test *(54)*. If the test indicates no statistically significant differences between the random effects and fixed effects models, the random effects model is considered consistent and efficient (i.e., is preferred over the fixed effects model). The random effects model is more efficient (i.e., smaller standard errors for the coefficient estimates) and results in better model fit since it uses the between individual variation, while the fixed effects model essentially discards the between individual variation for model estimation *(51)*. Thus, random effects models are useful for predictive purposes (at the individual level), even if the Hausman test indicates that the results are different from the fixed effects model *(51)*. However, in this situation the random effects model parameters should not be interpreted as indicating causal effects *(51)*. Fixed effects models, instead, are useful for determining causal effects of treatments and for generalized predictions (based on the sample average for the intercept) *(51)*. Given that the use of panel models in this research are for predictive modeling and not causal inference, only random effects models are provided in this report.

For the random effects linear panel models estimated in the present study, there are three different r-squared values used to assess goodness-of-fit – within, between, and overall *(53)*. The within r-squared is the usual r-squared calculated for the variation within the individuals (does not include the variation between the individuals). The between r-squared is the squared correlation between the observed and predicted individual-specific mean of the dependent variable (variation of the means between individuals). The overall r-squared is the squared correlation between actual values of the dependent variable and the predicted values of the dependent variable (the total variation of within and variation between individuals).

A separate issue related to panel models is that the estimates may become biased when the number of observations per individual differs significantly (highly unbalanced), and the difference in the number of observations per individual are not due to random selection *(54–57)*. When the data are highly unbalanced and observations are not missing at random, the fixed effects model requires adjustments to account for the missing observations. One method to adjust fixed effects models to account for unbalanced panels (with non-random missing observations) is to use weighting *(54–56, 58)*. Weighting is accomplished by giving each observation a weight of $1/N_i$ where N_i is the number of observations for the individual.

It should be noted that random parameters linear models were considered for this research. However, chi-square tests indicated that they were no better at fitting the data than the simpler panel regression models described in this section. Thus, panel regression models were used to develop the final models reported in the results chapter.

3.6 Quantile Regression

Quantile regression can be used to estimate the values for a specified quantile (i.e., percentile) of a distribution (i.e., the quantile) *(55, 59–61)*. Quantile regression for linear models is estimated using a likelihood function *(59–61)*. The optimization function for a linear quantile model is defined in Equation 3.13 *(59)*.

$$\min\left(\sum_{\varepsilon\in\left(y_i\geq x_i^T\beta\right)}\alpha\left|y_i-x_i^T\beta\right|+\sum_{\varepsilon\in\left(y_i<x_i^T\beta\right)}(1-\alpha)\left|y_i-x_i^T\beta\right|\right) \tag{3.13}$$

Where

$\alpha =$ the quantile being estimated,

$\beta =$ a vector of coefficients,

$y_i =$ the dependent variable for individual i,

$x_i^T =$ a vector of predictor variables for individual i, and

$\varepsilon =$ the error term.

Quantile regression is also subject to unobserved heterogeneity and clustering issues. These can be accommodated using random parameters quantile regression. While these models were tested, they did not provide any benefit over simple linear quantile models (determined using chi-square tests). As with the panel models, weights were used to account for unbalanced panels and robust clustered standard errors were used in the quantile models *(54)*. Quantile regression model fit was assessed using the McFadden pseudo R^2 (ρ^2). This is a measure of the improvement of the likelihood compared with an intercept-only model (i.e., the percent improvement in the likelihood).

Quantile regression is useful for data analysis when values other than the mean or median values are of interest *(54, 59–61)*. For deceleration rates used in design, low percentile deceleration rates are usually of interest. Thus, quantile regression was used in this project to estimate the 10^{th} percentile deceleration rates as well as the 90^{th} percentile perception-reaction times using naturalistic driving data.

4. DATA COLLECTION AND PROCESSING

4.1 Overview

This section describes the data used in this report. Data definitions and comparisons are provided for 1) perception-reaction times and 2) deceleration rates by variable categories.

4.2 Data

The SHRP2 Naturalistic Driving Study (NDS) data are used to explore how the likelihood of crashes and near-crashes in PRT depends on emergency deceleration accounting for personal and observation specific characteristics such as gender, age, initial speed, weather conditions, conflict type, and other factors. The data used in this study were provided by the Virginia Tech Transportation Institute (VTTI).

Table 4.1 shows crash events by event level in all six states as of December 2016 extracted from the SHRP2 NDS data. In total, there are 4,236 vehicle crash events. Each event is represented by a time series data file, including a set of variables such as timestamp, GPS/vehicle speed, acceleration rate, gyro rotation rate, headway and turn signals. A Java application was developed to extract PRT and deceleration rate from the time series data. Events with unavailable/invalid PRT and deceleration data were removed from the dataset. For this study, 2,971 event data were extracted. Table 4.2 gives the definition of variables. Figure 4.1 shows the PRT percentile, indicating 90% overall events have PRT less than four seconds (including both crash and near-crash events). Figure 4.2 shows that the 10^{th} percentile deceleration rate is below 10 ft/s^2. This includes all observations (distracted and non-distracted). A distributional analysis of PRT and Avg_Decel is provided in the appendix.

Table 4.1 SHRP2 Naturalistic Data Event Severity by Location

Severity Level	Florida	Indiana	New York	North Carolina	Pennsylvania	Washington	Total
Crash	422	116	226	296	73	322	1455
Near-Crash	688	143	401	490	92	896	2710
Crash-Relevant	4	1	3	3	1	2	14
Non-Subject Conflict	20	1	7	14	-	15	57
Total	1134	261	637	803	166	1235	4236

Table 4.2 Definition of Variables (2971 of Total Samples) and Descriptive Statistics from the SHRP2 NDS Data

Variable	Definition
Male	Driver's gender 0 if female (52%) 1 if male (48%)
Age	Driver's age 1 if 16-19 (21%) 2 if 20-29 (38%) 3 if 30-39 (9%) 4 if 40-49 (7%) 5 if 50-59 (8%) 6 if 60-69 (7%) 7 if 70-79 (5%) 8 if above 80 (5%)
Alignment	0 if the road segment is straight alignment (87%) 1 if the road segment is curve alignment (13%)
Event	Event severity 0 if it is a near-crash event (85%) 1 if it is a crash event (15%)
Severity	Crash severity 0 if it is not a crash (85%) 1 if it is low-risk tire strike (2%) 2 if it is a minor crash (8%) 3 if it is a police-reportable crash (3%) 4 if it is a most severe crash (2%)
Lighting	Road lighting condition 0 if it is daylight (or lighted) (79%) 1 if it is dawn, dusk, or dark (unlighted) (21%)
Surface	Road surface condition 0 if it is dry (80%) 1 if it is wet (17%) 2 if it is icy (1%) 3 if it is snowy (2%)
Avg_Decel	Average deceleration rate(g) during the brake time [Min, Max]: [0.238, 1.09] STDDEV:0.209 Mean: 0.442
Speed	Vehicle speed before driver's reaction (km/h) [Min, Max]: [0.018,191.88] STDDEV:29.20 Mean:50.65
PRT	Perception-reaction time (s) [Min, Max]: [0.004, 6.889] STDDEV: 1.358 Mean:1.66

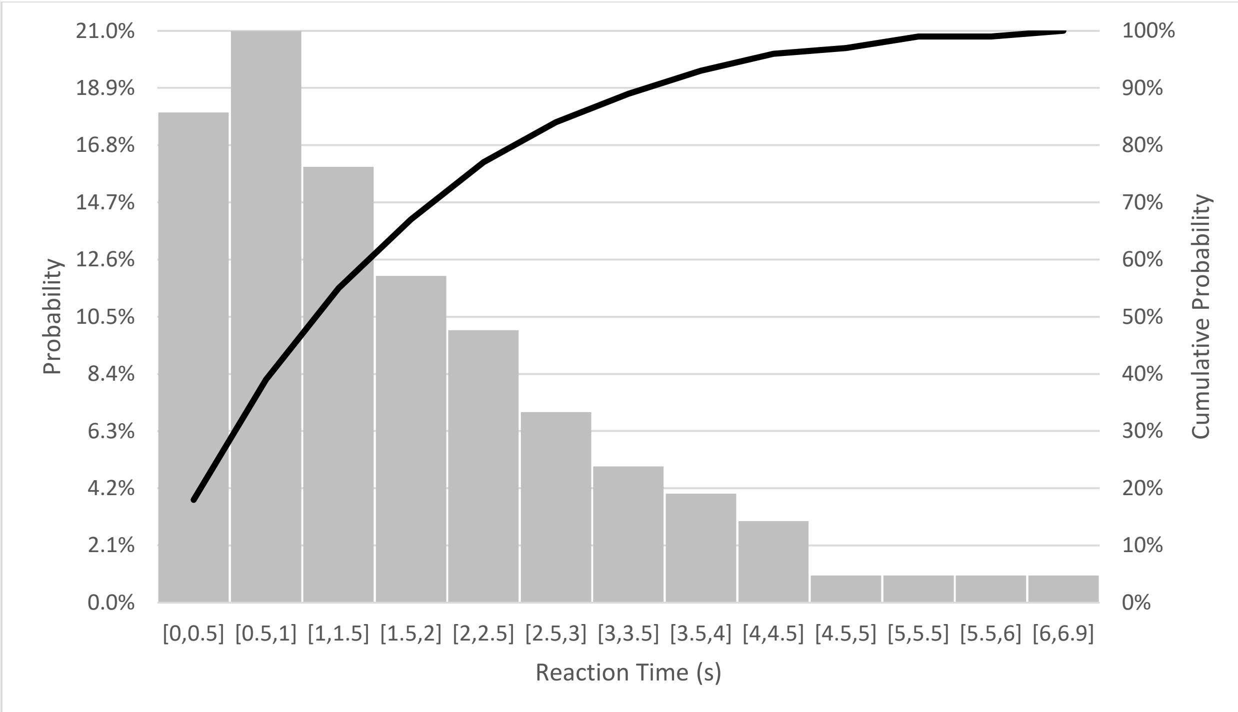

Figure 4.1 Histogram and Cumulative Density Function (Solid Line) of PRT Indicating the Skewed Distribution of Values

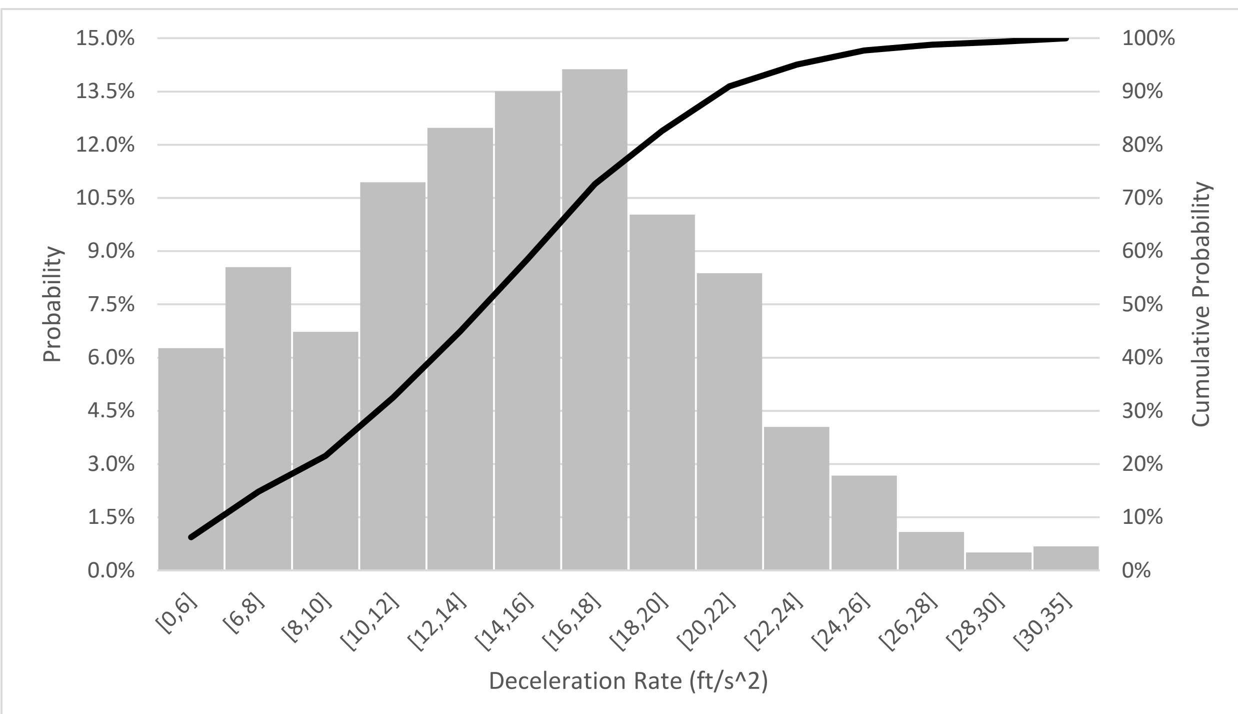

Figure 4.2 Histogram and Cumulative Density Function (Solid Line) of Average Deceleration Rate Indicating the Skewed Distribution of Values

4.3 Data Exploration

4.3.1 Event Severity

Table 4.3 shows that the mean and median deceleration rates for crash events are lower than those of near-crash events, while the mean and median of PRT for crash events have slower response times than those of near-crash events.

Table 4.3 The Effect of Decelerate Rate, PRT and Speed by Event Severity Using SHRP2 NDS Data

Event Level	Count	Deceleration rate (g)			PRT (s)			Speed (mph)		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Crash	455	0.41	0.34	0.34	2.03	1.78	1.52	44.38	42.71	29.94
Near-Crash	2556	0.45	0.46	0.23	1.60	1.23	1.50	51.62	49.96	28.89
Total	3011	0.44	0.45	0.26	1.66	1.29	1.51	50.53	48.91	29.16

4.3.2 Crash Severity

Table 4.4 shows four categories of crash severity. The most severe crashes have the smallest mean PRT and the highest mean speed among four crash levels. This indicates that the speed may contribute to the severity of the crashes, although its deceleration rate is larger than other lower-severity crash events.

Table 4.4 The Effect of Decelerate Rate, PRT and Speed by Crash Severity Using SHRP2 NDS Data

Crash Severity	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
I - Most Severe	68	0.68	0.52	1.58	1.13	52.15	30.94
II - Police-reportable Crash	98	0.52	0.33	1.98	1.48	42.69	33.61
III - Minor Crash	231	0.32	0.22	2.03	1.56	46.64	29.09
IV - Low-risk Tire Strike	58	0.25	0.18	2.64	1.65	29.16	18.50

4.3.3 Gender

The gender effect is shown in Table 4.5. Overall, the mean PRTs of female drivers for crashes/near-crashes were slower than those of male drivers. However, females also tend to decelerate at slightly higher rates than male drivers. These differences are negligible in magnitude (up to 0.05 g's (1.61 ft/s^2) difference in deceleration rate and up to 0.08 seconds difference in reaction time). Additionally, male drivers tend to drive at slightly higher speeds than female drivers when the events occurred. This does not indicate that male drivers drive faster than female drivers in general. It only indicates that there was a difference in speeds between males and females involved in crash/near-crash events within the dataset.

Table 4.5 Crash and Near-Crash Differences by Gender Using SHRP2 NDS Data

Gender	Severity	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
			Mean	STDEV	Mean	STDEV	Mean	STDEV
Female	Crash	241	0.43	0.36	2.07	1.53	42.72	29.51
	Near-Crash	1301	0.46	0.17	1.61	1.33	51.32	28.83
	Total	1542	0.45	0.21	1.68	1.37	49.97	29.10
Male	Crash	211	0.38	0.31	1.98	1.51	46.37	30.42
	Near-Crash	1241	0.44	0.18	1.58	1.31	52.07	28.98
	Total	1452	0.43	0.20	1.64	1.34	51.23	29.25

4.3.4 Age

Eight age categories were classified as shown in Tables 4.6 and 4.7. In crash events, drivers in the 16-19 and 20-29 age groups tend to have higher PRT than driver aged 30-39. The age group above 80 had the highest PRT values. There are no significant differences between age group, deceleration rate, and PRT in near-crashes.

Table 4.6 Age Effect on Decelerate Rate, PRT and Speed for Crash Events Using SHRP2 NDS Data

Age Group	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
16-19	126	0.43	0.37	1.93	1.41	49.08	30.51
20-29	178	0.40	0.30	1.99	1.53	44.01	29.32
30-39	19	0.39	0.35	1.62	1.25	45.72	32.61
40-49	17	0.38	0.19	2.19	1.91	53.73	30.58
50-59	17	0.40	0.22	2.05	1.64	36.65	36.62
60-69	28	0.36	0.28	2.42	1.58	34.09	28.78
70-79	27	0.39	0.27	2.19	1.46	39.79	29.43
above 80	38	0.46	0.54	2.28	1.73	39.57	26.19

Table 4.7 Age Effect on Decelerate Rate, PRT and Speed for Near-Crash Events Using SHRP2 NDS Data

Age Group	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
16-19	491	0.45	0.19	1.57	1.30	53.74	27.81
20-29	957	0.45	0.18	1.63	1.29	54.52	29.88
30-39	257	0.43	0.18	1.45	1.33	53.92	27.88
40-49	186	0.45	0.17	1.54	1.36	51.49	30.16
50-59	206	0.43	0.16	1.56	1.23	47.56	27.85
60-69	193	0.47	0.17	1.63	1.56	44.19	26.13
70-79	132	0.45	0.16	1.70	1.27	46.73	29.68
above 80	104	0.48	0.16	1.77	1.28	40.74	24.80

4.3.5 Road Alignment

As shown in Tables 4.8 and 4.9, the mean deceleration rate along curved alignments is lower than along tangential alignments. The mean speed at the curved road is higher than that of tangent roadways. Given that drivers tend to drive slower along horizontal curves than tangent roadway sections (*63*, *72*), the higher speeds along the horizontal curves may indicate that the vehicles at higher speeds along horizontal curves are more likely to be involved in crash/near-crash events.

Table 4.8 Road Alignment Effect on Decelerate Rate, PRT and Speed for Crash Events Using SHRP2 NDS Data

Alignment	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
Straight	369	0.44	0.35	2.09	1.59	43.00	30.30
Curve	86	0.27	0.21	1.78	1.19	50.29	27.74

Table 4.9 Road Alignment Effect on Decelerate Rate, PRT and Speed for Near-Crash Events Using SHRP2 NDS Data

Alignment	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
Straight	2236	0.45	0.17	1.62	1.32	50.72	29.18
Curve	320	0.41	0.18	1.49	1.29	58.00	25.90

4.3.6 Pavement Surface Condition

In crash or near-crash events, surface conditions impact the average decelerate rate significantly. When the pavement is not dry, the available friction is reduced. The mean deceleration rate is higher in magnitude on dry pavement than it is on wet, icy, and snowy pavement, as shown in Tables 4.10 and 4.11. In crash events, the speed is higher for events that occur on wet and icy pavements than on dry and snowy pavements. In near-crash events, the speed is highest for events that occur with icy conditions.

Table 4.10 Road Surface Condition Effect on Decelerate Rate, PRT and Speed for Crash Events Using SHRP2 NDS Data

Road Condition	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
Dry	314	0.45	0.37	2.11	1.58	41.93	31.37
Wet	100	0.38	0.25	1.88	1.44	52.23	27.74
Icy	10	0.14	0.09	1.63	1.31	54.80	23.91
Snowy	30	0.15	0.06	1.79	1.24	41.04	16.38

Table 4.11 Road Surface Condition Effect on Decelerate Rate, PRT and Speed for Near-Crash Events Using SHRP2 NDS Data

Road Condition	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
Dry	2108	0.46	0.17	1.58	1.30	52.34	29.21
Wet	401	0.42	0.16	1.69	1.38	48.01	26.76
Icy	14	0.31	0.18	1.61	0.95	59.12	31.36
Snowy	29	0.11	0.07	1.81	1.55	47.54	30.57

4.3.7 Lighting

Road lighting conditions impact the average deceleration rate, as shown in Tables 4.12 and 4.13. The mean deceleration rate is higher for events that occur during daylight conditions than events that occur during dark road conditions. The initial speed is higher for crash events that occur during dark conditions than crash events that occur during daylight conditions.

Table 4.12 Lighting Effect on Decelerate Rate, PRT and Speed for Crash Events Using SHRP2 NDS Data

Light Condition	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
Daylight	306	0.42	0.37	2.11	1.52	42.97	31.45
Darkness; lighted	93	0.38	0.27	2.03	1.55	44.24	24.59
Dawn	8	0.32	0.23	2.41	1.79	55.55	24.59
Dusk	20	0.43	0.28	1.91	1.39	38.15	29.43
Darkness; not lighted	28	0.34	0.21	1.14	1.29	61.53	26.07

Table 4.13 Lighting Effect on Decelerate Rate, PRT and Speed for Near-Crash Events Using SHRP2 NDS Data

Road Condition	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
Daylight	2021	0.45	0.18	1.60	1.30	50.99	29.04
Darkness; lighted	367	0.45	0.18	1.58	1.37	50.16	27.18
Dawn	24	0.50	0.12	1.92	1.45	45.00	26.47
Dusk	74	0.43	0.16	1.85	1.39	57.91	27.60
Darkness; not lighted	70	0.43	0.19	1.19	1.42	73.35	26.35

4.3.8 Speed

The deceleration rate and PRT in near-crash events change with speed, while speed is correlated with the PRT and crash severity in crash events. Overall, the mean PRT has a negative relationship with the mean initial speed, as shown in Tables 4.14 and 4.15.

Table 4.14 Speed Effect on Decelerate Rate and PRT for Crash Events Using SHRP2 NDS Data

Speed (km/h)	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
0-20	109	0.47	0.46	2.54	1.52	8.58	6.11
20-40	113	0.32	0.33	2.53	1.52	30.08	5.96
40-60	95	0.43	0.26	1.86	1.46	50.25	5.53
60-80	88	0.42	0.25	1.41	1.27	68.20	5.54
80-100	26	0.48	0.24	1.30	1.54	88.99	6.90
Above 100	24	0.31	0.22	1.09	0.86	115.44	11.84

Table 4.15 Speed Effect on Decelerate Rate and PRT for Near-Crash Events Using SHRP2 NDS Data

Speed (km/h)	Count	Deceleration rate (g)		PRT (s)		Speed (mph)	
		Mean	STDEV	Mean	STDEV	Mean	STDEV
0-20	365	0.45	0.17	2.03	1.34	9.33	6.06
20-40	548	0.46	0.16	1.66	1.30	30.71	5.75
40-60	733	0.46	0.18	1.53	1.26	49.79	5.60
60-80	499	0.46	0.18	1.53	1.36	69.37	5.66
80-100	237	0.43	0.19	1.42	1.28	88.75	6.00
Above 100	174	0.35	0.18	1.24	1.23	112.57	12.75

5. ANALYSIS AND RESULTS

5.1 Overview

This section provides the analysis results, along with related discussion. Section 5.2 analyzes the differences between crash and near-crash events in terms of PRT and deceleration rate. Section 5.3 analyzed the correlation and causal links between PRT and deceleration rates for crash, near-crash, and combined events. Section 5.4 develops predictive models for the mean value (PRT and deceleration rate) and 10th percentile (deceleration rate), 15th percentile (deceleration rate), 85th percentile (PRT), and 90th percentile (PRT). It should be noted that vehicle class was evaluated, but was not found to be a meaningful variable in any of the models in this research when other factors were controlled for.

5.2 Differences Between Crash and Near-crash Events

The genetic matching algorithm was used to match near-crash events to the crash events. The matching results were analyzed using standardized bias. The standardized bias value for before and after matching are shown in Figure 5.1. As shown, the genetic matching resulted in significantly improved standardized bias values (all below 10% for the matched data with many at or near values of 0%).

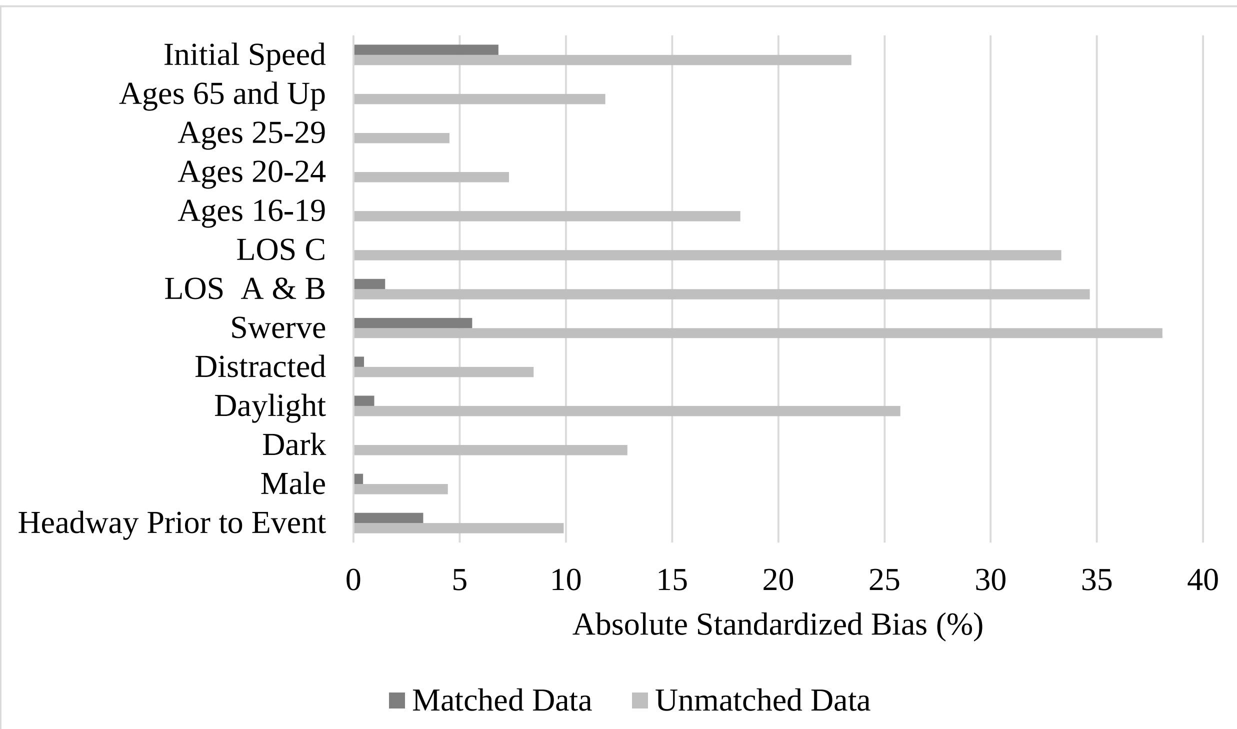

Figure 5.1 Standardized Bias Results for Before (Unmatched) and After (Matched) Genetic Matching

The treatment effect for both perception-reaction time and deceleration rate were estimated using the matched data. The results of the analysis, including Rosenbaum's sensitivity analysis, are provided in Table 5.1. The sensitivity is the required odds of being in the "treated" group (i.e., crash) due to unobserved factors in order to make the results not statistically significant at the 95% confidence level. An alternative interpretation is that the results are robust to unobserved factors provided they do not change the odds of being in the "treated" group by more than the specified sensitivity value *(27)*. As shown, the perception-reaction times for crash events are 0.487 seconds longer, on average, for crash events than for the equivalent near-crash events. This estimate is robust to unobserved confounders (i.e., has a sensitivity value of 1.6). The deceleration rates for crash events are 0.018 g's lower for crash events than for the equivalent near-crash events. This estimate is not robust to unobserved confounders (i.e., has a sensitivity value of 1.1). Given that deceleration rates for braking in crash events were truncated at the time of collision (along with the sensitivity of the estimate), the difference in deceleration rates between crash and near-crash events could be due to the truncation. These findings are explored in further detail in section 5.3.

Table 5.1 Estimated Treatment Effects and Sensitivities to Unobserved Confounders

Outcome	Effect	t-statistic	P-Value	Wilcoxon Sensitivity Value
Perception-Reaction Time (s)	0.487	4.547	<0.001	1.6
Deceleration Rate (g's)	-0.018	-1.982	0.049	1.1

5.3 Correlation and Causation Between Perception-reaction Times and Deceleration Rates

The software package Tetrad (*7*), developed by Carnegie Mellon University, was used to construct DAGs from NDS data. Tetrad provides several causal search algorithms (e.g., PC, CPC, and PC Stable) to evaluate the causal relationships of graphical representations. By using PC-Max algorithm, this study analyzed causal graphical models for crash events, near-crash events, and combined events at the 95% significance level, respectively.

5.3.1 DAG for Crash Events

Figure 5.2 shows the DAG pattern of crash events. Table 5.2 shows the result of the effect between PRT, emergency deceleration rates, and crash outcomes. Table 5.3 provides the correlation matrix. Vehicle speed directly affects PRT and crash severity. PRT has a cause-effect relationship in deceleration rate and crash severity. Alignment and road surface condition are causal factors for the mean deceleration rate. Emergency deceleration rates directly affect crash severity/outcomes. Each of these effects is statistically significant with p-values smaller than 0.05.

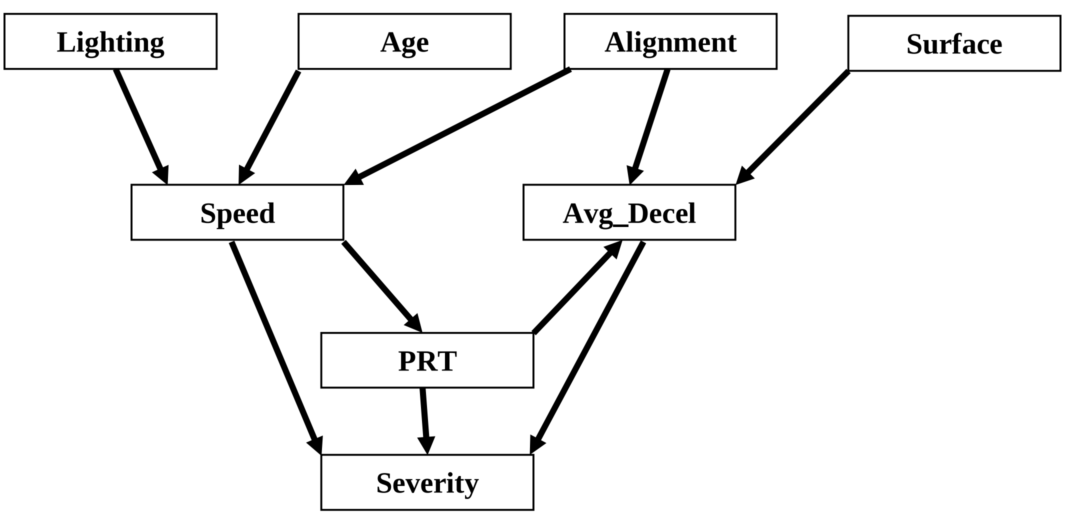

Figure 5.2 Causal Graph for Crash Event with Edge Coefficients (Degrees of Freedom = 17, Chi Square = 29.2384, P Value = 0.0324, BIC Score = -74.5810, CFI = 0.9667, RMSEA = 0.0401)

Table 5.2 Edge Statistics for Crash Causal Graph Model

From	To	Edge Coefficient	Standard Error	P-value
Lighting	Speed	2.1007	0.9807	0.0327
Alignment	Avg_Decel	-0.1462	0.0401	0.0003
Age	Speed	-1.4066	0.6085	0.0213
Surface	Avg_Decel	-0.0914	0.0186	<0.0001
Speed	Severity	0.0043	0.0013	0.0013
PRT	Avg_Decel	-0.0223	0.0101	0.0277
PRT	Severity	-0.0590	0.0260	0.0236
Alignment	Speed	7.4511	3.6247	0.0404
Speed	PRT	-0.0168	0.0023	<0.0001
Lighting	Severity	-0.0802	0.0261	0.0023
Avg_Decel	Severity	-1.0942	0.1101	<0.0001

Table 5.3 Correlation Matrix for Crash Causal Graph Model with Measured Variables

	Age	Alignment	Lighting	Severity	Surface	Avg_Decel	Speed	PRT
Age	1.0000							
Alignment	0.0000	1.0000						
Lighting	0.0000	0.0000	1.0000					
Severity	-0.0206	-0.0511	-0.1096	1.0000				
Surface	0.0000	0.0000	0.0000	-0.0936	1.0000			
Avg_Decel	-0.0036	-0.1644	0.0003	0.4261	-0.2259	1.0000		
Speed	-0.1079	0.0960	0.1000	0.1716	0.0000	0.0174	1.0000	
PRT	0.0359	-0.0319	-0.0333	-0.1837	0.0000	-0.0952	-0.3326	1.0000

The results of the model in Table 5.2 indicate that higher PRT times are associated with smaller deceleration rates (i.e., for a 1-second longer PRT, the deceleration rate decreases by 0.0223 g's). Given that longer PRT is associated with smaller deceleration rates in crash events, this indicates that drivers involved in crash events may have been able to avoid the crash had they responded faster and/or decelerated at a higher rate.

The correlation matrix in Table 5.3 also indicates some interesting relationships. The correlations assume a linear relationship. If the relationships are non-linear (or linear conditional on other variables), then the non-linear correlation would have larger absolute values than the linear relationships shown. Of particular interest are the correlations of each variable with the severity. The three variables with the strongest correlations to severity were the average deceleration rate, PRT, and speed. The average deceleration rate was the variable with the strongest correlation with severity for crash events. It should be noted that the average deceleration rate for crash events did not include any of the deceleration rates experienced after the start of the collision (i.e., it was the average deceleration rate prior to the start of the collision).

5.3.2 DAG for Near-crash Events

Figure 5.3 shows the DAG pattern of near-crash events. Lighting, driver age, and pavement surface condition have a cause-effect relationship with the vehicle initial speed. Vehicle speed has a direct effect on PRT and average deceleration rate. PRT has a direct effect on deceleration rate. Alignment and road surface condition have direct effects on deceleration rates. The model estimates are shown in Table 5.4, and the correlation matrix is provided as Table 5.5.

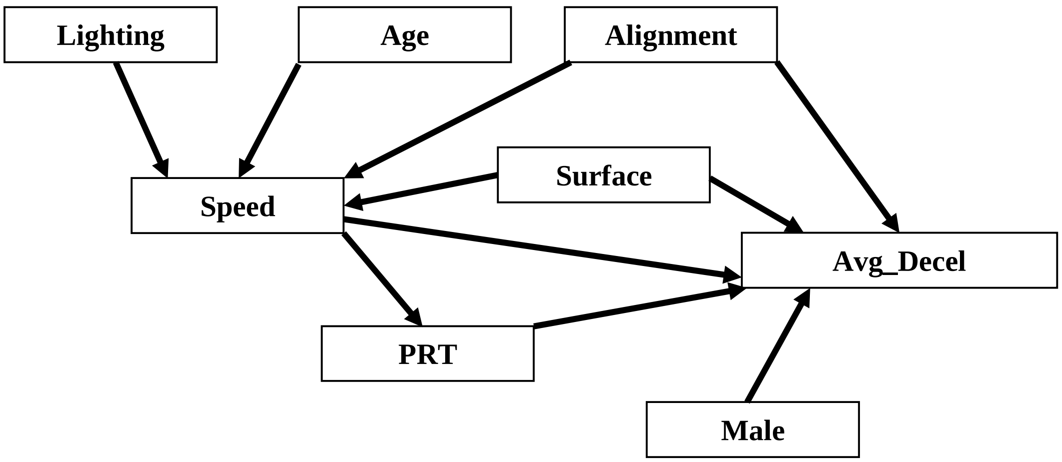

Figure 5.3 Causal Graph for Near-crash Event with Edge Coefficients (Degrees of Freedom = 18, Chi Square = 132.7409, P Value < 0.0001, BIC Score = -8.2568, CFI = 0.7180, RMSEA = 0.0503)

Table 5.4 Edge Statistics for Near-crash Causal Graph Model

From	To	Edge Coefficient	Standard Error	P-value
Surface	Speed	-3.8654	1.1680	0.0009
Age	Speed	-1.8100	0.2828	<0.0001
Speed	PRT	-0.0068	0.0009	<0.0001
Surface	Avg_Decel	-0.0674	0.0071	<0.0001
Male	Avg_Decel	-0.0177	0.0070	0.0109
Alignment	Speed	7.4135	1.7186	<0.0001
PRT	Avg_Decel	0.0059	0.0027	0.0263
Lighting	Speed	1.1515	0.4780	0.0161
Alignment	Avg_Decel	-0.0290	0.0106	0.0061
Speed	Avg_Decel	-0.0006	0.0001	<0.0001

Table 5.5 Correlation Matrix for Near-crash Causal Graph Model with Measured Variables

	Male	Age	Alignment	Lighting	Surface	Avg_Decel	Speed	PRT
Male	1.0000							
Age	0.0000	1.0000						
Alignment	0.0000	0.0000	1.0000					
Lighting	0.0000	0.0000	0.0000	1.0000				
Surface	0.0000	0.0000	0.0000	0.0000	1.0000			
Avg_Decel	-0.0495	0.0126	-0.0621	-0.0048	-0.1788	1.0000		
Speed	0.0000	-0.1266	0.0849	0.0479	-0.0658	-0.0918	1.0000	
PRT	0.0000	0.0189	-0.0127	-0.0072	0.0098	0.0564	-0.1493	1.0000

The results of the model in Table 5.4 indicate that higher PRT times are associated with larger deceleration rates (i.e., for a 1-second longer PRT, the deceleration rate increases by 0.0059 g's). Given that longer PRT is associated with larger deceleration rates (i.e., harder braking) in crash events, this indicates that drivers responding in this manner are more likely to avoid a crash, compared with the results in section 5.3.1. Driver gender was also found to impact deceleration rates for near-crash events, while it did not have a causal impact on deceleration rates for crash events.

The correlation matrix in Table 5.5 also indicates some interesting relationships compared with the correlations in Table 5.3. Overall, the magnitudes of the correlations are smaller. Additionally, the signs of the correlations are typically the same, with the exceptions of PRT and deceleration rate, age and deceleration rate, lighting and deceleration rate, and surface and speed.

5.3.3 DAG for Combined Events

Figure 5.4 shows the DAG pattern of combined events. Lighting, age, and alignment have direct effects on speed. Vehicle speed has a direct effect on PRT, event, and crash severity. PRT has a direct effect on event and severity. Alignment, driver gender (i.e., male), speed, and road surface condition have direct effects on deceleration rate. Deceleration rate has a direct impact on event. The model estimates are shown in Table 5.6, and the correlation matrix is provided as Table 5.7.

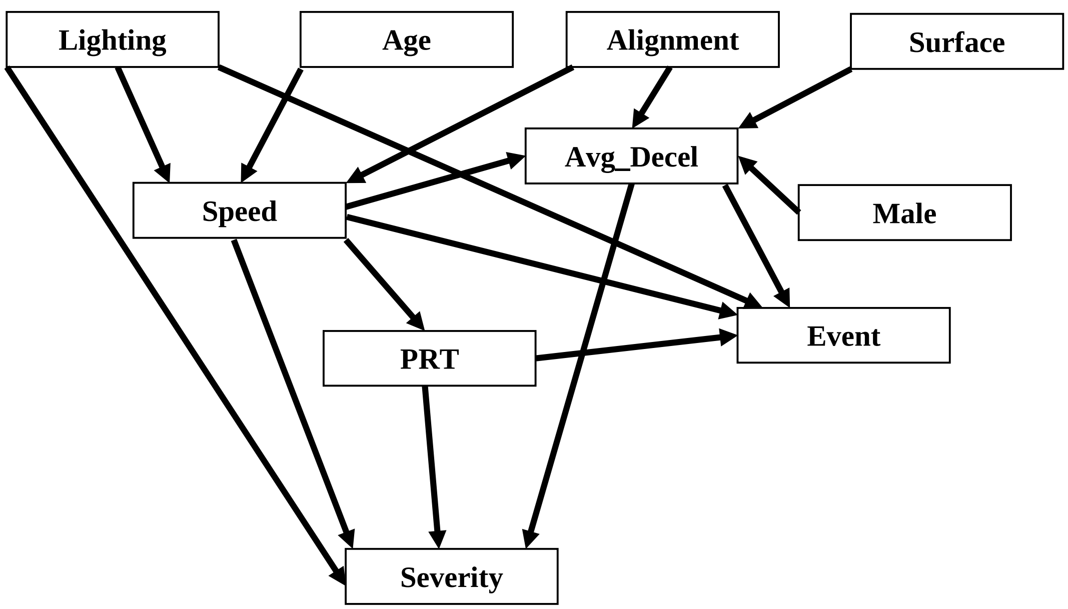

Figure 5.4 Causal Graph for Combined Event with Edge Coefficients (Degrees of Freedom = 29, Chi Square = 215.6681, P Value < 0.0001, BIC Score =-16.2349 CFI = 0.9994, RMSEA = 0.0466)

Table 5.6 Edge Statistics for Combined Causal Graph Model

From	To	Edge Coefficient	Standard Error	P-value
Speed	Event	-0.0004	0.0001	<0.0001
Alignment	Speed	6.5268	1.5545	<0.0001
PRT	Event	0.0093	0.0018	<0.0001
Lighting	Severity	0.0755	0.0196	0.0001
Avg_Decel	Event	0.1801	0.0112	<0.0001
Alignment	Avg_Decel	0.0559	0.0110	<0.0001
Lighting	Speed	1.5435	0.6177	0.0125
PRT	Severity	0.0465	0.0126	0.0002
Male	Avg_Decel	0.0217	0.0074	0.0036
Speed	PRT	-0.0088	0.0008	<0.0001
Speed	Avg_Decel	0.0006	0.0001	<0.0001
Speed	Severity	-0.0017	0.0006	0.0044
Age	Speed	-1.6814	0.2567	<0.0001
Lighting	Event	0.0104	0.0027	0.0001
Surface	Avg_Decel	0.0794	0.0074	<0.0001

Table 5.7 Correlation Matrix for Combined Causal Graph Model with Measured Variables

	Male	Age	Alignment	Event	Severity	Lighting	Surface	Avg_Decel	Speed	PRT
Male	1.0000									
Age	0.0000	1.0000								
Alignment	0.0000	-0.0000	1.0000							
Event	0.0054	0.0113	0.0016	1.0000						
Severity	0.0000	0.0079	-0.0050	0.9279	1.0000					
Lighting	0.0000	0.0000	0.0000	0.0852	0.0678	1.0000				
Surface	0.0000	0.0000	0.0000	0.0225	0.0000	0.0000	1.0000			
Avg_Decel	-0.0518	0.0093	-0.0907	-0.0963	0.0052	-0.0036	-0.2147	1.0000		
Speed	0.0000	-0.1192	0.0763	-0.0905	-0.0622	0.0455	0.0000	-0.0848	1.0000	
PRT	0.0000	0.0000	-0.0145	0.1117	0.0781	-0.0086	0.0000	-0.0161	-0.180	1.0000

The combined model was also run with the PRT as a cause of the deceleration rate. However, the coefficient between PRT and deceleration rate was 0.0008 with a p-value of 0.7855. This indicates that PRT does not have a statistically significant or practically significant impact on deceleration rate when the crash and near-crash events are combined. A possible reason for this is that the reaction times are higher for crash events than near-crash events. In addition, the drivers in crash events did not break as hard as the drivers in near-crash events. When the drivers in the near-crash events had longer reaction times, they tended to make up for the added travel distance by braking harder. While the drivers in crash events with longer reaction times had less intense braking maneuvers, this may be due to them not having adequate time to reach full braking. It may also be due to the drivers involved in crashes not having as much time at full braking prior to the crash occurring. Thus, the findings here (as well as those shown in the models in sections 5.3.1 and 5.3.2 (e.g., coefficients linking PRT to deceleration rate of -0.0223 if crash, 0.0059 if near-crash) may not be due to driver error.

5.4 Predictive Models

As discussed in section 3, regression models for predicting the mean values of PRT and deceleration rates were estimated using random effects panel models. Predictive models for the 85th percentile PRT and 15th percentile deceleration rates were estimated using quantile regression. For the quantile regression, no predictors were found to be significant for the combined data or the crash data. Thus, only quantile models using the near-crash data are provided in this section.

The predictive models for mean PRT and deceleration rates based on the combined crash and near-crash data are provided in Table 5.8. As shown, speed was the only variable that was significant in predicting PRT using the combined data. The presence of a horizontal curve (alignment) and speed were the only factors found to be significant in predicting the average deceleration rate using the combined data. Including an indicator variable for a crash vs. near-crash outcome did not improve the models. Due to the large differences between the characteristics of crash and near-crash events, as shown in the preceding sections, these combined models are not recommended for use in predicting PRT and deceleration rate.

Table 5.8 Predictive Models for Mean Values of PRT and Deceleration Rate Using Combined Data

Combined Data						
Outcome	**Natural Log of Reaction Time (s)**			**Avg_Decel (g)**		
Variable	Coef.	Std. Error	P-Value	Coef.	Std. Error	P-Value
Alignment	-	-	-	-0.0534	0.0107	<0.001
Speed	-0.0109	0.0011	<0.001	-0.0005	0.0002	0.008
Constant	0.3063	0.0426	<0.001	0.4556	0.0084	<0.001
Between Unit Variance	0.0917			0.0077		
Within Unit Variance	0.9787			0.0341		
Root Mean Squared Error	1.0346			0.2044		
Within R^2	0.0762			0.0262		
Between R^2	0.0824			0.0438		
Overall R^2	0.0849			0.0375		

Predictive models for PRT and deceleration rate developed using only crash events are provided in Table 5.9. As shown, daylight and speed are both significant predictors of the mean PRT in crash events. Reaction times and the presence of a horizontal curve are significant predictors of the average deceleration rate. It is interesting that speed is not a significant predictor of deceleration rate in the crash event model (the p-value was greater than 0.75 when it was included). The differences between these models, the models for the combined events, and the models for near-crash events indicate that predictive models for crash events are significantly different from near-crash events. This finding is consistent with the causal models in sections 5.2-5.3. The standard deviation of the residuals of these models (overall) are 1.0486 seconds for PRT and 0.1850 g's for deceleration rate.

Table 5.9 Predictive Models for Mean Values of PRT and Deceleration Rate Using Crash Data

Crash Events						
Outcome	**Natural Log of Reaction Time (s)**			**Natural Log of Avg_Decel (g)**		
Variable	**Coef.**	**Std. Error**	**P-Value**	**Coef.**	**Std. Error**	**P-Value**
Reaction Time	-	-	-	-0.0679	0.0279	0.015
Lighting	-0.2285	0.1074	0.033	-	-	-
Alignment	-	-	-	-0.5026	0.11	<0.001
Speed	-0.0205	0.0028	<0.001	-	-	-
Constant	1.8100	0.1277	<0.001	-0.4245	0.0757	<0.001
Between Unit Variance	0.1336			0.1697		
Within Unit Variance	0.9660			0.6312		
Root Mean Squared Error	1.0486			0.1850		
Within R^2	0.1571			0.1307		
Between R^2	0.1485			0.0428		
Overall R^2	0.1597			0.0541		

The point estimates for the models in Table 5.9 are of interest. The results indicate that daylight (or lighted nighttime) conditions are associated with longer PRT values than nighttime/unlighted conditions. In addition, drivers traveling at higher speeds have shorter reaction times than drivers traveling at lower speeds. It should be remembered that these findings are for predictive purposes and are not causal estimates. However, the signs of the estimates are consistent with the causal models in section 5.3.1.

The estimates for the deceleration rate predictive model in Table 5.9 is different from the causal graph in section 5.3.1. The model structures are different. The predictive model was optimized to provide the best predictions while the causal model was developed to provide the least biased estimates of the contributions of different factors on the PRT and deceleration rates. The results in Table 5.9 indicate that higher reaction times are associate with smaller deceleration rates (consistent with the causal analysis results). The alignment (i.e., presence of a horizontal curve) was also associated with smaller deceleration rates. This is also consistent with the causal model. The difference between the two models is that the surface conditions was not found to be a meaningful predictor of deceleration rates for crash events in the predictive model.

The predictive models for PRT and deceleration rate estimated using near-crash events are shown in Table 5.10. The results indicate that the condition of the surface (i.e., wet, icy, etc.) impacts the predicted deceleration rate, but not the PRT. This is not surprising considering deceleration rate is dependent on available friction, which is reduced when the pavement is wet, icy, or snowy. The negative coefficients for these variables are consistent with the reduction in available friction between the pavement and tires. The alignment is also a strong predictor of deceleration rate. This is also consistent with engineering theory. When side friction is used (in horizontal curves), the available lateral friction is reduced. Thus, the deceleration rate would be expected to be smaller on horizontal curves.

Table 5.10 Predictive Models for Mean Values of PRT and Deceleration Rate Using Near-Crash Data

Near-Crash Events						
Outcome	**Natural Log of Reaction Time (s)**			**Natural Log of Avg_Decel (g)**		
Variable	Coef.	Std. Error	P-Value	Coef.	Std. Error	P-Value
Surface = Wet	-	-	-	-0.0618	0.0324	0.057
Surface = Icy	-	-	-	-0.7835	0.3401	0.021
Surface = Snowy	-	-	-	-0.4494	0.1579	0.004
Alignment	-	-	-	-0.0868	0.0358	0.015
Speed	-0.0088	0.0011	<0.001	-0.0029	0.0007	<0.001
Constant	0.2082	0.0462	<0.001	-0.5919	0.0172	<0.001
Between Unit Variance	0.0768			<0.0001		
Within Unit Variance	0.9683			0.3412		
Root Mean Squared Error	0.7511			.1502		
Within R^2	0.0635			0.0782		
Between R^2	0.0747			0.1208		
Overall R^2	0.0755			0.1016		

The only factor that was significant in predicting both PRT and Avg_Decel was Speed. In both cases, the estimated coefficient was negative. This indicates that drivers are likely more alert and react faster at higher speeds. It is also known that available friction is lower at higher speeds than at lower speeds, which is consistent with the negative coefficient for Speed in the deceleration rate model. Interestingly, PRT was not a significant factor in the predictive model for Avg_Decel (the p-value was 0.621 when included in the model). This highlights the fact that these models should be used for predictions only (i.e., not interpreted as causal effects) given the difference between the regression analysis and the analysis in section 5.3.2.

The quantile models for PRT (90th percentile) and Avg_Decel (10th percentile) are provided in Table 5.11. For the quantile models, only Speed was found to be a significant predictor. In both PRT and Avg_Decel quantile models, the coefficients for Speed were negative, consistent with the models in Table 5.10. While other predictors were not significant (and not included), these models indicate that different PRT and deceleration rate values may be useful for design purposes. This is discussed in section 5.5.

Table 5.11 Predictive Models for 90th Percentile PRT and 10th Percentile Deceleration Rate Using Near-Crash Data

Quantile Models for Near-Crash Events						
Outcome	**Natural Log of Reaction Time (s)**			**Natural Log of Avg_Decel (g)**		
Variable	**Coef.**	**Std. Error**	**P-Value**	**Coef.**	**Std. Error**	**P-Value**
Speed	-0.0024	0.0005	<0.001	-0.0017	0.0001	<0.001
Constant	1.1450	0.0529	<0.001	-0.9066	0.0472	<0.001
Pseudo R^2	0.0137			0.0305		
Percentile	90th			10th		

5.5 Design Recommendations

Using the quantile models, 90th percentile PRT and 10th percentile deceleration rates were calculated for design speeds ranging between 10-80 mph. These are shown in Table 5.12. Given that Speed was in kilometers per hour (kph) for the regression models, the equivalent kph values are provided alongside the mph values. Current AASHTO standards use a PRT value of 2.5 seconds and deceleration rate of 11.2 ft/s^2 (*2*). These represent the 90th and 10th percentile values from previous research (*3*), which was completed using experiments at 55 mph in the mid-1990s. As seen in Table 5.12, the 10th percentile value for PRT reaches 2.5 seconds between 55 and 60 mph while the deceleration rate reaches 11.2 ft/s^2 between 50 and 55 mph. This indicates that the findings of this research are consistent with this previous study at the same speeds. However, this research indicates that PRT (90th percentile) and Avg_Decel (10th percentile) values change as the speed changes.

Table 5.12 Predicted PRT and Deceleration Rate Values Using Quantile Models Based on Near-Crash Events

Speed (kph)	Speed (mph)	PRT (s)	Deceleration Rate (g)	Deceleration Rate (ft/s^2)
16	10	3.02	0.393	12.65
24	15	2.97	0.388	12.48
32	20	2.91	0.382	12.31
40	25	2.85	0.377	12.15
48	30	2.80	0.372	11.98
56	35	2.75	0.367	11.82
64	40	2.69	0.362	11.66
72	45	2.64	0.357	11.50
80	50	2.59	0.352	11.34
89	55	2.54	0.347	11.19
97	60	2.49	0.343	11.04
105	65	2.44	0.338	10.89
113	70	2.40	0.334	10.74
121	75	2.35	0.329	10.59
129	80	2.31	0.324	10.45

Using the AASHTO SSD model *(2)*, the predicted PRT and deceleration rate values from this report can be used to calculate new SSD values. These values, the current AASHTO design SSD values, and the difference between these models (i.e., the increase in SSD, labeled as “Change in SSD (ft)”) are shown in Table 5.13. The increase in SSD ranges from 1.6 feet (at 40 mph) to 23.1 feet (at 80 mph).

Table 5.13 Stopping Sight Distance (SSD) Using Predicted PRT and Deceleration Rates from Quantile Models vs. Traditional AASHTO Model *(2)*

Speed (mph)	New SSD (AASHTO Model) (ft)	AASHTO Design SSD (ft)	Difference in SSD (ft)
10	53.0	50	3.0
15	84.9	80	4.9
20	120.6	115	5.6
25	160.5	155	5.5
30	204.6	200	4.6
35	253.2	250	3.2
40	306.6	305	1.6
45	365.0	360	5.0
50	428.5	425	3.5
55	497.6	495	2.6
60	572.3	570	2.3
65	652.9	645	7.9
70	739.8	730	9.8
75	833.1	820	13.1
80	933.1	910	23.1

A new SSD model was suggested by Wood and Donnell (*6*). In this model, the distance from the front of the vehicle to the driver's eye is accounted for. The authors suggested using a value of 8.5 feet for this measurement, based on the 90th percentile value for this variable. Using this model, including the PRT and Avg_Decel values from Table 5.12, the new SSD value, the AASHTO design SSD, and the change in SSD are provided in Table 5.14. As shown, the increase in SSD ranges from 10.1 feet (at 40 mph) to 31.6 feet (at 80 mph).

Table 5.14 Stopping Sight Distance (SSD) Using Predicted PRT and Deceleration Rates from Quantile Models (Estimated Using Wood & Donnell (*6*) Model) vs. Traditional AASHTO Model *(2)*

Speed (mph)	New SSD (Wood & Donnell Lighted/Daytime Model (*6*)) (ft)	AASHTO Design SSD (ft) *(2)*	Difference in SSD (ft)
10	61.5	50	11.5
15	93.4	80	13.4
20	129.1	115	14.1
25	169	155	14.0
30	213.1	200	13.1
35	261.7	250	11.7
40	315.1	305	10.1
45	373.5	360	13.5
50	437	425	12.0
55	506.1	495	11.1
60	580.8	570	10.8
65	661.4	645	16.4
70	748.3	730	18.3
75	841.6	820	21.6
80	941.6	910	31.6

Based on this analysis, the SSD values in Table 5.14 are recommended for use in future roadway design guidance. While these values are larger than the current design values, it should be remembered that the SSD model assumes the following:

1. The object in the roadway is present as soon as it becomes visible to the driver.
2. The driver only brakes (i.e., does not perform any other braking maneuver).

The values of SSD for design also use the following:

1. PRT values where the majority of drivers will react at least that fast
2. Deceleration rates where the majority of drivers can maintain control of the vehicle (*2*)
3. Deceleration rates where the majority of drivers will have at least as great deceleration

Given these constraints, the current SSD model is very conservative. Thus, the finding that SSD values should be increased (as shown in Tables 5.13-5.14) does not indicate issues with current SSD guidelines. However, it should be remembered that these results are based on near-crash events (i.e., drivers with proper responses). The results of the analysis in section 5.2 indicated that PRT values for crash events were 0.487 seconds longer (on average) and deceleration rate was 0.018 g's less (on average) than for near-crash events. Providing SSD, based on crash events (which are rare), would result in higher design values, as shown in Table 5.15. Given that quantile models based on crash events were not found to be significant, the design values for PRT and deceleration rate in Table 5.15 are the values from Table 5.12 (based on the quantile models for near-crash events) plus the average differences from Table 5.1. As shown, using the Wood and Donnell model, results in SSD increases ranging from 19 feet (at 10 mph) to 129 feet (at 80 mph). While it may be possible in to use these values in design rather than the values in Tables 5.13-5.14, the additional cost of providing the additional SSD may be prohibitive. This should be considered, along with the conservative nature of the SSD model, when determining updated roadway design policy.

Table 5.15 Stopping Sight Distance (SSD) Using PRT and Deceleration for Crash Events

Speed (mph)	PRT (s)	Deceleration Rate (ft/s^2)	New SSD (AASHTO Model) (ft)	New SSD (Wood & Donnell (*6*)) (ft)	AASHTO Design SSD (ft)	Change in SSD (AASHTO) (ft)	Change in SSD (Wood & Donnell) (ft)
10	3.51	12.08	60.5	69.0	50	10.5	19.0
15	3.46	11.91	96.6	105.1	80	16.6	25.1
20	3.40	11.72	136.7	145.2	115	21.7	30.2
25	3.34	11.56	181.1	189.6	155	26.1	34.6
30	3.29	11.40	230.3	238.8	200	30.3	38.8
35	3.24	11.24	284.3	292.8	250	34.3	42.8
40	3.18	11.08	342.9	351.4	305	37.9	46.4
45	3.13	10.92	407.3	415.8	360	47.3	55.8
50	3.08	10.75	477.3	485.8	425	52.3	60.8
55	3.03	10.59	553.2	561.7	495	58.2	66.7
60	2.98	10.47	634.3	642.8	570	64.3	72.8
65	2.93	10.30	722.7	731.2	645	77.7	86.2
70	2.89	10.18	817.4	825.9	730	87.4	95.9
75	2.84	10.01	919.7	928.2	820	99.7	108.2
80	2.80	9.85	1030.7	1039.2	910	120.7	129.2

5.6 Crash Reconstruction

One of the objectives of this research was to develop models that can be used in crash reconstruction. This was accomplished by estimating regression models using crash data (as shown in Table 5.9). The prediction using the models in Table 5.9 can also be compared with predictions made using the near-crash models (in Tables 5.10-5.11). Using the predictions for the mean values and the associated root mean square errors for PRT and Avg_Decel, confidence intervals can be constructed for reaction times and deceleration rates. While this is useful when skid marks or other information that can be used to estimate these values are not available, these estimates do not provide specific values for individual crashes (as the exact reaction time and deceleration rates for each specific crash are typically not measurable). Thus, it is important to provide estimated confidence intervals to convey the uncertainly of the estimates.

An example of predicting the mean PRT and Avg_Decel for a crash (including confidence intervals) is shown below. In this example, the crash occurred during the day (i.e., Lighting=1), on a horizontal curve (Alignment=1), with an initial speed of 35 mph (56.3 kph). Using the crash models from Table 5.9 (based on crash outcomes), the predicted PRT and Avg_Decel are as follows.

$$PRT = \exp(-0.2285(0) - 0.0205(56.3) + 1.8100) = 1.927s$$

$$Avg\_Decel = \exp(-0.0679(0.462) - 0.5026(1) - 0.4245) = 0.347g = 11.18\,ft/s^2$$

Since the prediction models are for the natural log transformed PRT and Avg_Decel, the 95% confidence intervals for these predictions are estimated using a lognormal distribution (the standard deviation of the lognormal distribution is $sd = \sqrt{\ln\left(1+\left(\frac{RMSE}{\mu}\right)^2\right)}$ where *RMSE* is the Root Mean Squared Error and μ is the predicted mean value). Using this to predict the 95% confidence intervals results in:

$$sd_{PRT} = \sqrt{\ln\left(1+\left(\frac{1.0486}{1.927}\right)^2\right)} = 0.509$$

$$sd_{Avg\_Decel} = \sqrt{\ln\left(1+\left(\frac{0.1850}{0.347}\right)^2\right)} = 0.500$$

$$95\%CI_{PRT} = \exp(\ln(1.927) \pm 1.96(0.509)) = [0.711s, 5.226s]$$

$$95\%CI_{Avg\_Decel} = \exp(\ln(0.347) \pm 1.96(0.500)) = [0.130g, 0.925g] = [4.19\ ft/s^2, 29.77\ ft/s^2]$$

6. CONCLUSIONS

6.1 Summary

This report investigated differences in driver reaction times and deceleration rates between crash and near-crash events using naturalistic driving data. The values for these variables were extracted from time-series data using a Java program developed by the research team. Perception-reaction time and deceleration rates are key variables in the design criteria (e.g., stopping sight distance) and crash reconstruction. Providing improved understanding of the relationship between PRT and deceleration rate is anticipated to improve transportation engineers' understanding of human factors related to SSD, leading to improved design guidance and safer roadways. It could also improve crash reconstruction and the ability to determine what happened during crashes. Therefore, this study evaluated 1) the differences in PRT and deceleration rates between crash and near-crash events and 2) the relationship between PRT and deceleration rates.

The specific objectives of this research were as follows:

1) Evaluate the differences in PRT and emergency deceleration rates between crash and near-crash events using a causal inference approach.
2) Determine the strength of correlations between PRT and emergency deceleration.
3) Determine if there was a causal relationship between PRT and emergency deceleration rates and, if so, the relationship.
4) Develop a method and equations for predicting the PRT and deceleration rate for drivers for use in roadway design and crash reconstruction.

These objectives were met through the application of multiple analysis methods, including the following:

1) Genetic matching (with Rosenbaum's sensitivity analysis)
2) Pearson correlation coefficients
3) Directed Acyclic Graphs (DAGs)
4) Random effects panel models (with observation weighting)
5) Quantile models (with observation weighting and clustered robust standard errors)

The analysis results were then discussed, including applications to geometric design and crash reconstruction. A review of the findings is provided below.

6.2 Findings

The genetic matching results indicated there were differences in PRT and Avg_Decel for crash and near-crash events. Results indicated that drivers involved in crash events took 0.487 seconds longer to react and decelerated at 0.018 g's (0.58 ft/s^2) slower than drivers in equivalent near-crashes, on average. These results were statistically significant. The PRT results were more robust in terms of sensitivity to unobserved confounders than the deceleration rate estimates.

These differences indicate that drivers involved in crash events are more likely to react slower than drivers involved in near-crashes. However, the differences in deceleration rates may be due to the braking maneuvers in crash events being truncated at the time of collision. The finding for longer reaction times in crash events is consistent with previous research that found human error to be the largest contributing factor to crashes occurrence (*68-71*).

Further evaluation indicated that Pearson correlation was not strong between PRT and Avg_Decel, regardless of whether the events were crash or near-crash. However, the DAG analysis results indicated there was a causal relationship between PRT and Avg_Decel. The findings indicated that, in crash events, longer PRT was associated with lower deceleration rates (i.e., for a 1-second longer PRT, the deceleration rate decreases by 0.0223 g's). In near-crash events, longer PRT values were associated with higher deceleration rates (i.e., for a 1-second longer PRT, the deceleration rate increases by 0.0059 g's). This is also consistent with the genetic matching results, indicating that human error is a large contributing factor to crashes occurring (also indicated by the DAG results that link to crash occurrence).

Finally, prediction models were developed for use in roadway design and crash reconstruction. These models were used to develop tables comparing existing SSD design criteria with SSD criteria based on the results of the predictive models. These predicted values indicated that design SSD would increase by 1.6 feet to 129.2 feet, dependent on 1) the design speed, 2) the SSD model used, and 3) if near-crash or crash outcomes are used to determine the PRT and Avg_Decel values that should be used for design.

When using the regression models for crash reconstruction, it was shown that the mean values for PRT and Avg_Decel can be predicted using the regression models. It was also shown that confidence intervals can be constructed using the mean values, root mean squared error, and a lognormal distribution. These confidence intervals may be useful for characterizing the uncertainty in the predictions and the reconstruction when better data are unavailable (e.g., skid marks and friction measurements).

6.3 Limitations

The analysis provided in this report has the potential to improve roadway design and safety. However, as with any analysis, there are limitations. Some limitations in this research include the following:

1. There was not a large sample of crashes.
2. The data were several years old (at the time of analysis).
3. The data were not collected using random sampling.

These limitations are noted to provide context for the findings. Analysis methods that account for the non-random sampling were used, and there was an adequate sample size of crash events to produce statistically significant results. It is not anticipated that driver behavior has changed considerably in the last several years; thus, the results can be used to guide the development of design criteria. The results can be used in crash reconstruction.

7. RECOMMENDATIONS

7.1 Recommendations and Implementation

This report presented a unique study on perception-reaction times and deceleration rates. Previous research on these topics has been limited to experiments where the drivers knew they were being tested, simulator studies, and small-sample naturalistic studies. The present study used data from a large naturalistic driving study to evaluate PRT and Avg_Decel that are representative of real-world outcomes. The results of this study will likely have the benefits discussed in Sections 5-6. As with any observational study, there are limitations. Some of these limitations were discussed in Section 6.3. Specific recommendations follow.

7.1.1 Design

The analysis result provided values of PRT and deceleration rates that can be used in roadway design. These values were compared with current AASHTO design guidance. As discussed in Section 5.5, the SSD model assumes the following:

1. The object in the roadway is present as soon as it becomes visible to the driver.
2. The driver only brakes (i.e., does not perform any other braking maneuver, such as swerving).

The values of variables for determining SSD design guidance also use the following:

1. PRT values where the majority of drivers will react at least that fast (approximately 90%)
2. Deceleration rates where the majority of drivers can maintain control of the vehicle, even on wet pavements
3. Deceleration rates where approximately 90% of drivers will brake at least that hard

Analysis of results indicated that drivers involved in crashes typically did not respond in a proper manner (e.g., higher PRT times and lower deceleration rates than would be expected). Design values using crash outcomes were provided. Design values based on near-crash outcomes were also provided. The design values based on crash events resulted in longer SSD values than design values based on near-crash events. While it may be possible to use crash event values in design rather than based on near-crash events, the additional cost of providing the larger SSD values may be prohibitive. This should be considered, along with the conservative nature of the SSD model, when determining updated roadway design policy.

7.1.2 Crash Reconstruction

Regression models using crash data were developed for predicting PRT and deceleration rate values for crash reconstruction using crash events. Section 5.6 illustrated how these models can be used to predict PRT and Avg_Decel values for crashes, including confidence intervals. It was shown that including the confidence intervals was necessary for indicating the level of uncertainty when using these models for prediction.

While these predictive models may be useful for crash reconstruction when skid marks, friction measurements, or other data used in crash reconstruction are not available, they should not be used as a replacement for these data sources when they are available. The traditional data sources used for crash reconstruction, when available, are typically more accurate and case specific. Thus, using these values rather than the predictive models developed in this research leads to lower levels of uncertainty in the crash reconstruction.

7.1.3 Auto Industry

The evaluations in this report may be useful for the auto industry when developing driver assistance technologies (e.g., Automatic Emergency Braking [AEB] systems). The results may also be useful in designing autonomous vehicle systems, accounting for driver behavior to make the autonomous systems comfortable for the passengers.

7.2 Future Work

Future work should use different datasets, in the United States and abroad, to validate the findings detailed in this report. Current naturalistic driving studies in Europe and China could be used. Differences should also be evaluated using the datasets because these are often collected for different populations and different cultures.

Future work should also consider the impacts of new technologies on driver PRT and deceleration rates. Current technologies, such as collision warning, AEB, and lane keep, may be associated with changes in driver behaviors that impact PRT and deceleration rates. Thus, such examples should be considered in future research.

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APPENDIX: DISTRIBUTION ANALYSIS OF REACTION TIMES AND DECELERATION RATES

The distributions of PRT and Avg_Decel were analyzed using K-S tests on raw data. The published literature often assumes distributions for these variables (e.g., normal, lognormal), but the authors of this report are unaware of any analysis that has evaluated the statistical fit of various distributions to determine the best distribution for approximating these variables.

The Kolmogorov-Smirnov (K-S) test is a nonparametric test for comparing distributions *(63)*. The K-S test compares differences in the cumulative distribution of the data with a theoretical distribution. Based on this comparison, the statistical fit is estimated (*63*). This test uses the maximum difference (D_n) between the cumulative distributions to estimate the statistical fit. The distance was calculated equation A.1 (*63*).

$$D_n = \max\left|F_n(x_i) - S_n(x_i)\right| \tag{A.1}$$

Where $D_n =$ the maximum difference, $F_n(x_i) =$ the cumulative stepwise distribution of a variable at value i, and $S_n(x_i) =$ the estimated cumulative distribution at value i.

The p-value for the K-S test is estimated using bootstrapping. This was implemented for this study using the R package *fitdistrplus*.

The normal and the lognormal distributions are both commonly assumed for PRT and deceleration rate in the published literature (*6*, *22-24*, *64-67*). However, other distributions, including gamma and Weibull distributions, may provide good approximations of the distributions for these variables. Thus, for PRT and Avg_Decel, the truncated normal (only allowing values of 0 or larger), lognormal, gamma, and Weibull distributions were evaluated for statistical fit in approximating the distributions for each variable. Due to the relatively small sample of crash events (which displayed poor fit in all cases), and the results of the analysis in this report, the following analysis uses only near-crash events. Maximum likelihood was used to fit the distributions. Table A.1 provides the results of the distributional analysis for PRT. Table A.2 provides the results of the distributional analysis for Avg_Decel.

Table A.1 Distribution Fit Statistics for PRT (Standard Errors in Parenthesis) Based on K-S Tests

Statistic	Distribution Type			
	Truncated Normal	Lognormal	Gamma	Weibull
P-Value	0.226	0.058	0.033	0.029
Mean	1.23 (0.025)	-0.445 (0.022)	-	-
Standard Deviation	1.50 (0.018)	1.316 (0.015)	-	-
Shape	-	-	0.897 (0.018)	0.912 (0.011)
Rate/Scale	-	-	0.829 (0.020)	1.173 (0.022)

Table A.2 Distribution Fit Statistics for Avg_Decel (Standard Errors in Parenthesis) Based on K-S Tests

Statistic	Distribution Type			
	Truncated Normal	**Lognormal**	**Gamma**	**Weibull**
P-Value	0.055	0.140	0.106	0.069
Mean	0.460 (0.004)	-0.961 (0.011)	-	-
Standard Deviation	0.232 (0.003)	0.686 (0.008)	-	-
Shape	-	-	2.869 (0.064)	2.056 (0.028)
Rate/Scale	-	-	6.236 (0.151)	0.518 (0.004)

The findings of the distributional analysis are intriguing. The results indicate that a normal distribution (truncated at a value of 0, forcing the values to always be positive) provides the best approximation of the PRT distribution while all other distributions provide much poorer approximations. The lognormal distribution provides the best approximation of the deceleration rate distribution, followed by the gamma distribution. This indicates that analyses attempting to use distributions for PRT and Avg_Decel should use truncated normal and lognormal distributions for these variables, respectively.