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

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Abstract

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 is based on 90th percentile PRT and 10th percentile deceleration rate values from experiments completed in the mid-1990s. These experiments lacked real-world distractions, and so forth. Thus, the values from these experiments may not be applicable in real-world scenarios. This research evaluated (1) differences in PRTs and deceleration rates between crash and near-crash events and (2) developed predictive models for PRT and deceleration rate that could be used for roadway design. This was accomplished using (1) genetic matching (with Rosenbaum's sensitivity analysis) and (2) quantile regression. These methods were applied to the Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) data.

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 s longer to react and decelerated at 0.018 g's (0.58 ft/s^2) slower than drivers in equivalent near-crashes. 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 10.5–129.2 ft, dependent on the design speed and SSD model used.

Providing a safe and efficient surface transportation system for users is the core objective of the geometric design process. To facilitate this, design criteria have been developed and adopted by transportation agencies. Stopping sight distance (SSD) is considered a fundamental street design criterion that is necessary for safe roadway design (*1–3*). It is one of the Federal Highway Administration's (FHWA) controlling criteria, underscoring its importance among geometric design elements (*4*, *5*).

The American Association of State Highway and Transportation Officials' (AASHTO) Policy on Geometric Design of Highways and Streets (here referred to as the Green Book) specifies minimum SSD design values as a function of the design speed (*6*). 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 (*6*). 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 (*6*, *7*).

$$SSD = Vt_r + \frac{V^2}{2g(\frac{a}{g} + G)} \quad (1)$$

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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 because of 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).

Current AASHTO SSD guidance related to perception-reaction time (PRT) and deceleration rate is provided in the Green Book (*6*). 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 (*7*). However, these experiments lacked real-world distractions that drivers are subject to, were limited in the age range and abilities of drivers, and did not test a wide variety of initial speeds and lighting conditions that may affect PRT and deceleration rates. Thus, the values from these experiments may not be applicable in real-world scenarios.

There are likely many factors that influence 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 dependent on the level of risk perceived by the driver. Thus, there is potential that PRT has a direct impact on emergency deceleration rates. Large values of PRT may occur because of inattentiveness, yet the driver may brake harder because of an impending collision when compared with a shorter PRT for the same initial conditions. 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).

Objectives

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. Therefore, this research (1) evaluated the differences in PRT and deceleration rates between crash and near-crash events and (2) developed prediction models for the 90th percentile PRT and 10th percentile deceleration rates. The results of this research could be used by transportation agencies in developing future design guidance.

Literature Review

Deceleration Rate

A limited amount of research on deceleration rates for passenger cars with anti-lock braking systems (ABS) is available in the published literature (*7–9*). However, it is well known that these systems improve braking performance. Also, deceleration rates may be higher when skidding is avoided because of static friction coefficients being higher than dynamic friction coefficients.

Current AASHTO design guidance is based on findings from experiments conducted in Texas in the mid-1990's (*7*). The experiments included wet and dry pavements on horizontal and tangent road sections. The results had mean deceleration rates of 0.51–0.57 g's with standard deviations of 0.08–0.12 g's. The 10th percentile deceleration rate values from this study are used for the current AASHTO SSD requirements.

A separate 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 values currently used in AASHTO design guidance (*3*). These results indicated that the mean deceleration rate was 0.48 g's with a standard deviation of 0.03 g's. However, only 10 drivers out of 64 drivers included in the study braked for an unexpected object that appeared 2.5 s before reaching the object, leaving the results subject to potential bias.

Other studies used: professional drivers to perform hard braking maneuvers from 36 mph; a field trial involving six male and 10 female drivers, all between the ages of 23 and 59; motorcycles; or unspecified testing sample and methodology (*9–12*). Each of these studies is not generalizable to the general driving population. Thus, the detailed results of these studies are not discussed here.

Perception-Reaction Time (PRT)

PRTs 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 PRT, as long as distractions are a factor in driving.

Some factors that have been suggested as driving distractions include listening to music, cellular phone use, interacting with other people in the vehicle, eating/drinking, and adjusting vehicle controls (*13*). Other possible factors that could slow response times include fatigue, alcohol use, and prescription, recreational, and illegal drug use (*14–18*). 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 PRT distributions for unexpected braking events. The mean values from published research range from 0.594 to 1.550 s with standard deviations in the range 0.098–1.080 s, depending on the type of study and whether distracted driving was considered (*7, 8, 13, 19–22*). Since the goal of PRT 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 the authors found that meets these conditions was a naturalistic driving data distribution that includes both distracted and undistracted drivers (based on the 100-car Naturalistic Driving Study [NDS] dataset) (*19*). In this case, the mean PRT was 1.450 s with a standard deviation of 1.070 s.

Research Methods

Counterfactual Framework and Statistical Matching

One of the objectives of this study was to evaluate differences in PRT and deceleration rates between crash and near-crash events. To do this, a statistical matching approach was used. Assumptions that are required for the matching to produce valid and accurate results include (*23–27*):

1. Stable unit treatment value assumption (SUTVA): 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 PRT and emergency deceleration rate. Given that the events are all independent of each other, this assumption is reasonable.
2. Positivity: 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 of resulting in a crash.
3. Unconfoundedness: the treatment status (treated or untreated) is conditionally independent of the counterfactuals for a given set of covariates (i.e., there are no important variables omitted from the analysis or the results are not sensitive to potentially important omitted variables). To justify this assumption, Rosenbaum's sensitivity analysis was applied to assess the sensitivity of the results to potential hidden bias (*23*, *28*, *29*).

Statistical matching methods include propensity score matching, Mahalanobis matching, optimal matching, genetic matching, and others (*23–26, 28–38*). These methods estimate counterfactuals (i.e., unobserved outcomes for the "treated" entities) by finding entities without the treatment that are comparable with 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 (*26*). The matching employed in this study was 1:1 matching.

Matching Method

For this investigation, genetic matching was used to compare PRTs and deceleration rates between crash and near-crash events. Genetic matching uses a sequential process to optimize covariate balance by finding the best matches for each treated entity (*26*). Covariate balance is achieved when the distributions of observed variables are approximately the same for the treated and comparison groups (*23*, *39*, *40*). The genetic matching process minimizes imbalance across the covariates (measured using standardized bias or K-S tests) (*32*). This is accomplished by minimizing the general Mahalanobis distance (GMD), defined in Equation 2 (*32*).

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

where
$S =$ covariance matrix between x and y,
$(\vec{x}-\vec{y})$ matrix of the differences in values between groups x and y for the variables included in the matching,
$S^{-1/2}$ Cholesky decomposition of S, and
$W =$ weighting matrix.

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 (i.e., which variables are including in the matching algorithm, the functional forms of the variables, the matching algorithm used, etc.).

To check for covariate balance, standardized bias is commonly used. The equation for standardized bias (for continuous covariates) is specified in Equation 3 (*24*). The equation for standardized bias for binary variables is specified in Equation 4 (*40*).

$$SB = \frac{100(\bar{X}_T - \bar{X}_C)}{\sqrt{\frac{S^2{}_T + S^2{}_C}{2}}} \quad (3)$$

$$SB = \frac{100(\widehat{P_T} - \widehat{P_C})}{\sqrt{\frac{\widehat{P_T}(1-\widehat{P_T}) + \widehat{P_C}(1-\widehat{P_C})}{2}}} \quad (4)$$

where
X_T = sample mean of the treated group for variable x,
$\bar{X}_C$ = sample mean of the comparison group for variable x,
$S^2{}_T$ = sample variance of the treated group for variable x,
$S^2{}_C$ = sample variance of the comparison group for variable x,
$\widehat{P_T}$ = proportion of the treated group with a value of "1" for variable x, and
$\widehat{P_C}$ = 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 because of matching on the propensity score. Standardized bias results with an absolute value of 10 or smaller are commonly interpreted as indicating no statistical difference between the treated and comparison groups (i.e., they are equivalent) (*26*, *39*, *40*). As a rule, the smaller the value of standardized bias, the less biased the results are likely to be because of the observed covariates (*23*, *28*, *39*, *40*).

Estimating the Treatment Effect

The average effect of a treatment on a continuous outcome (e.g., difference in PRT or deceleration rates), using statistical matching, can be estimated using Equation 5 (*23*).

$$\tau = \frac{1}{N}\sum_{i=1}^{N}(Y_{\text{treated},i} - Y_{\text{untreated},i}) \quad (5)$$

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

The variance of the treatment effect (estimated using Equation 6) accounts for matched data being used (*23*, *41*). 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.

$$SE(\tau) = \sqrt{\frac{1}{2N}\sum_{i=1}^{N}(Y_{\text{treated},i} - Y_{\text{untreated},i} - \tau)^2} \quad (6)$$

Hidden Bias Sensitivity Analysis

Methods have been developed that assess the sensitivity of statistical matching results to hidden bias (*28, 29, 42–44*). The method used in this study was the Wilcoxon signed-rank test method proposed by Rosenbaum (*28*, *29*). This method is based on the assumption that, in order for the treatment effect to be biased because of 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 an impact an unobserved variable must have on the odds of both matched entities receiving the treatment $\left(\frac{\pi_j(1-\pi_k)}{\pi_k(1-\pi_j)}\right)$ (for matched observations j and k) to cause a significant bias in the results (*23*). The test uses odds ratio values with gamma values greater than or equal to 1 (i.e., $\Gamma \geqslant 1$) in Equation 7 (*23*, *28*, *29*).

$$\frac{1}{\Gamma} \leqslant \frac{\pi_j(1-\pi_k)}{\pi_k(1-\pi_j)} \leqslant \Gamma \quad (7)$$

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, the value of Γ 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 because of unobserved confounders. For details in relation to the computational procedures for this test, see Guo and Fraser, or Rosenbaum (*23*, *28*, *29*).

Quantile Regression

Quantile regression can be used to estimate the values for a specified percentile of a distribution, which was used for developing PRT and deceleration rate predictive models in this study (*45–48*). The optimization function for a linear quantile model is defined in Equation 8 (*46*).

$$\min\left(\sum_{\varepsilon\in(y_i \geqslant x_i^T\beta)} \alpha\left|y_i - x_i^T\beta\right| + \sum_{\varepsilon\in(y_i < x_i^T\beta)} (1-\alpha)\left|y_i - x_i^T\beta\right|\right) \quad (8)$$

where
α = quantile being estimated,
β = vector of coefficients,
y_i = dependent variable for individual i,
x_i^T = vector of predictor variables for individual i, and
ε = 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 the simpler linear quantile models (determined using chi-square tests).

A separate issue related to regression models is that the estimates may become biased when the number of observations per individual differs significantly (highly unbalanced panels), and the difference in the number of observations per individual is not because of random selection (*45, 49–51*). When the data are highly unbalanced and observations are not missing at random, the model requires adjustments to account for the missing observations. One method to adjust for unbalanced panels (with non-random missing observations) is to use weighting (*45*, *49*, *50*, *52*). Weighting was accomplished by giving each observation a weight of $1/N_i$ where N_i is the total number of observations for the individual. Robust clustered standard errors were used in the quantile models to improve estimation of the standard errors (and associated p-values) (*49*).

Quantile regression is useful for data analysis when values other than the mean or median values are of interest (*46–49*). For deceleration rates used in design, low percentile deceleration rates are usually of interest. Thus, quantile regression was used to estimate the 10th percentile deceleration rates as well as the 90th percentile PRTs using naturalistic driving data, consistent with previous design guidance (*7*).

Table 1. Variable Definitions (2,971 of Total Samples) and Descriptive Statistics

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 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%)
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) SD: 0.209 Mean: 0.442
Speed	Vehicle speed before driver's reaction (mph) (Min., Max.): (1.05, 119.26) SD: 18.15 Mean: 31.48
PRT	Perception-reaction time (s) (Min., Max.): (0.004, 6.889) SD: 1.358 Mean: 1.66

Note: Min. = minimum; Max. = maximum; SD = standard deviation.

Data

The Strategic Highway Research Program 2 (SHRP2) 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. The SHRP2 data collection effort developed a database that researchers use to assess driver characteristics and behaviors.

The SHRP2 NDS data were used to explore whether differences in PRT depend on emergency deceleration between crash and near-crash events, accounting for personal and observation-specific characteristics such as gender, age, initial speed, weather conditions, conflict type, and other factors (*53*).

In total, there were 4,236 crash/near-crash events available for processing. Each event was 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. In total, 2,971 events were extracted with PRT and average deceleration rate values for use in the analysis. Table 1 provides variable definitions and descriptive statistics for the variables used in the statistical matching (because of the large number of variables available in the dataset, checked for covariate balance, Table 1 only includes the variables used for genetic matching and the outcome variables).

The average deceleration rate was derived using the accelerometer data and brake pedal position. The deceleration rate was only considered during braking (i.e., no deceleration due only to other resistance factors such as aerodynamic and rolling resistance was included in the calculations). This was done to ensure that the results

Table 2. 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

were for deceleration experienced during braking maneuvers. Also, only deceleration from breaking before the time of collision was included for crash events, to avoid bias from deceleration because of the impact.

The PRT values were computed as the time from the start of event until the time the driver began braking. This is not the same value as the time from when the driver first notices the potential conflict until the start of braking (which is sometimes considered the "true" driver PRT); rather, the measure used in this research captures the time from the start of event until the driver reacts, which is the reaction time used in roadway design. Maneuvers where the driver swerved were initially considered, but did not provide significant insights into the behavior of drivers during braking maneuvers (or braking and swerving).

Analysis and Results

Differences Between Crash and Near-Crash Events

The genetic matching algorithm was used to match near-crash events to the crash events (1:1 matching). The matching results were analyzed using standardized bias. The results of 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%). The standardized bias for the unmatched data had values in excess of 35% for the majority of covariates. Readers interested in details of the standardized bias results are referred to Wood and Zhang (*54*).

The treatment effect for both PRT and deceleration rate were estimated using the matched data. The results of the analysis, including Rosenbaum's sensitivity analysis, are provided in Table 2. This indicates that the results are robust to unobserved factors, provided the unobserved factors do not change the odds of being in the "treated" group by more than the specified sensitivity value (*23*). As shown, the PRTs for crash events are 0.487 s longer, on average, for crash events than for the equivalent near-crash events. This estimate is moderately 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). Since 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 because of the truncation.

Predictive Models

Predictive models for the 90th percentile PRT and 10th percentile deceleration rates were estimated using quantile regression. For the quantile regression, no predictors were found to be significant for the combined data (near-crash and crash events) or the crash events only. Thus, only results for quantile models using the near-crash data are provided.

For the quantile models, only Speed was found to be a significant predictor (p-values < 0.001). In both PRT and Avg_Decel quantile models, the coefficients for Speed were negative, indicating shorter PRT and slower deceleration rates at higher initial speeds. This finding for deceleration rates is consistent with previous research (*12*). 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. The equation for estimating the 90th percentile PRT is provided as Equation 9. The equation for estimating the 10th percentile deceleration rate is provided as Equation 10 (including $32.2\,\mathrm{ft/s^2}$ to set the deceleration rate estimates in imperial units). The speed in both equations is in mph. For details of the regression models, see Wood and Zhang (*54*).

$$PRT_{90th} = \exp(1.145 - 0.0039\text{speed}) \tag{9}$$

$$\text{Avg\_Decel}_{10th} = \exp(-0.9066 - 0.0027) + 32.2 \tag{10}$$

It should be remembered that the results in Equations 9–10 are based on near-crash events. The results of the genetic matching analysis indicated that PRT values for crash events were 0.487 s 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 for SSD. Given that quantile models based on crash events were not found to be significant, conservative design values for PRT and deceleration rate based on the quantile models for near-crash events plus the average differences from the genetic matching results could be used. These

Table 3. Stopping Sight Distance (SSD) using Perception-Reaction Time (PRT) and Deceleration for Crash Events

Speed (mph)	PRT (s)	Deceleration rate (ft/s^2)	New SSD (AASHTO model) (ft)	New SSD (Wood and Donnell model) (ft)	AASHTO design SSD (ft)	Change in SSD (AASHTO) (ft)	Change in SSD (Wood and 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	1,030.7	1,039.2	910	120.7	129.2

Note: AASHTO = American Association of Highway Transportation Officials.

values can be estimates using Equation 11 (for PRT) and Equation 12 (for deceleration rate).

$$PRT_{90th} = \exp(1.145 - 0.0039speed) + 0.487 \quad (11)$$

$$Avg\_Decel_{10th} = (\exp(-0.9066 - 0.0027speed) - 0.018^{*}32.2 \quad (12)$$

Discussion

Using the quantile models, 90th percentile PRT and 10th percentile deceleration rates were calculated for design speeds ranging between 10 and 80 mph (based on crash outcomes using Equations 11–12). These are shown in Table 3. Current AASHTO standards use a PRT value of 2.5 s and deceleration rate of 11.2 ft/s^2 (*2*). However, the results of the PRT and deceleration rate analyses in this paper indicate that PRT (90th percentile) and Avg_Decel (10th percentile) values are functions of the initial speed.

Using the AASHTO SSD model, the predicted PRT and deceleration rate values from this paper can be used to calculate new SSD values (*6*). 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 3. The increase in SSD ranges from 10.5 ft (at 10 mph) to 120.7 ft (at 80 mph).

A new SSD model was suggested by Wood and Donnell (*55*). In this model, the distance from the front of the vehicle to the driver's eye is accounted for, leading to the vehicle stopping before the front of the vehicle reaches an object in the road. This model is shown in Equation 13.

$$SSD = Vt_r + \frac{V^2}{2a} + L \quad (13)$$

where
L = distance from the driver's eye to the front of the vehicle (ft), and other variables are as previously defined.

The authors suggested using a value of 8.5 ft for L, based on the 90th percentile value for this variable. Using this model and the current AASHTO design SSD values, the updated SSD values and change in SSD are shown in Table 3. As shown, the increase in SSD ranges from 19.0 ft (at 10 mph) to 129.2 ft (at 80 mph).

Based on this analysis, the SSD values in Table 3 could be used 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 (6)
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 findings in Table 3 do not indicate issues with current SSD guidelines. Additionally, providing SSD based on crash events (which are rare) results in longer SSD design values compared with when using near-crash events. If Equations 9–10 were used in place of Equations 11–12, the resulting SSD values would be shorter.

As shown, using the Wood and Donnell model, results in SSD increases were 8.5 longer than the AASHTO SSD model. While it may be possible in to use these values in design rather than the values based on the AASHTO model, 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 developing updated roadway design policy.

Conclusion

Summary

This paper 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. PRT and deceleration rates are key variables in the design criteria (e.g., SSD). It is anticipated that providing improved understanding of the PRT and deceleration rate could improve transportation engineers' understanding of human factors related to SSD, leading to improved design guidance and safer roadways. Therefore, this study evaluated the differences in PRT and deceleration rates between crash and near-crash events, and developed predictive models that could be used for improved geometric design criteria. These were accomplished through the application of genetic matching (with Rosenbaum's sensitivity analysis) and quantile regression models.

Findings

The genetic matching results indicated there were differences in PRT and average deceleration for crash and near-crash events. Results indicated that drivers involved in crash events took 0.487 s 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 relation to sensitivity to unobserved confounders than the deceleration rate estimates.

Predictive models for PRT and deceleration rate were developed for potential use in roadway design. These models were used to compare existing SSD design guidance with SSD values based on the predictive models. This comparison indicated that design SSD would increase by 10.5–129.2 ft, dependent on the design speed and SSD model used.

Recommendations and Implementation

The analysis result provided values of PRT and deceleration rates that could be used in roadway design. These values were compared with current AASHTO design guidance. As discussed, 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.

Design values using crash outcomes were provided based on quantile regression models and the difference in PRT and deceleration rates between crash and bear-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.

Limitations and Future Work

As with any analysis, there are limitations to this work. 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 could be used to guide the development of design criteria.

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 forward collision warning, automatic emergency brakes (AEB), and lane keep assist, may be associated with changes in driver behaviors that affect PRT and deceleration rates. Thus, such technologies should be considered in future research.

Finally, future work should consider the mechanistic and probabilistic relationships between SSD, available sight distance, likelihood of an object being in the road, and SSD-related collisions in a causal inference framework. The results of this analysis could provide insights into new mitigation strategies and potential for performance-based design guidelines related to SSD.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: J. Wood, S. Zhang; data collection: J. Wood, S. Zhang; analysis and interpretation of results: J. Wood, S. Zhang; draft manuscript preparation: J. Wood. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

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