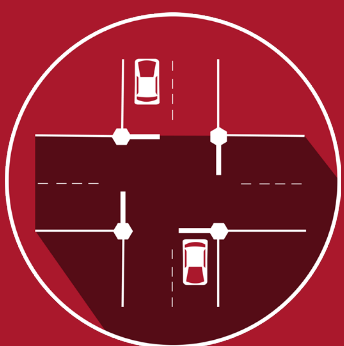
Evaluating the Relationship Between the Driver and the Roadway to Address Rural Intersection Safety by Using SHRP2 Naturalistic Driving Study Data and the Roadway Information Database

PUBLICATION NO. FHWA-HRT-24-140

JULY 2024



U.S. Department of Transportation

Federal Highway Administration

Research, Development, and Technology
Turner-Fairbank Highway Research Center
6300 Georgetown Pike
McLean, VA 22101-2296

FOREWORD

The Federal Highway Administration posted a Broad Agency Announcement that it would conduct research on potential safety improvements in two phases by using the Naturalistic Driving Study (NDS) database and the Roadway Information Database (RID) SHRP 2 – Roadway Information Database Center for Transportation Research and Education, both of whose contents had been collected as part of the second Strategic Highway Research Program (SHRP2) (VTTI 2019, RID 2024, FHWA, n.d.). Phase 1 of the research served as a proof of concept to determine whether researchers could develop meaningful conclusions or countermeasures by using the NDS database and RID. Phase 2 enabled the researchers to conduct more in-depth analyses, leading to specific highway safety improvements.

In this study, the researchers successfully used the SHRP2 NDS database and the RID to observe driver behavior at high-speed rural intersections. The researchers analyzed driver behavior at three different types of rural intersections: two-way stop-controlled intersections, T-intersections, and all-way stop-controlled intersections. The analyses covered the points at which drivers reacted to intersections, drivers' stopping behaviors at intersections, and driver behavior surrounding safety-critical events. The analyses found that several factors influenced driver behavior at intersections, and those factors are discussed in the report. This research will be of interest to roadway designers, safety professionals, and others with an interest in rural intersection safety.

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Recommended citation: Federal Highway Administration, *Evaluating the Relationship Between the Driver and the Roadway to Address Rural Intersection Safety by Using SHRP2 Naturalistic Driving Study Data and the Roadway Information Database* (Washington, DC: 2024) https://doi.org/10.21949/1521585.

TECHNICAL REPORT DOCUMENTATION PAGE

<table>
<tr><td>1. Report No.
FHWA-HRT-24-140</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient's Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Evaluating the Relationship Between the Driver and the Roadway to Address Rural Intersection Safety by Using SHRP2 Naturalistic Driving Study Data and the Roadway Information Database</td><td colspan="2">5. Report Date
July 2024</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="2">7. Author(s)
Nicole Oneyear (ORCID: 0000-0002-1328-9099), Shauna Hallmark (ORCID: 0000-0001-5187-8022), Amrita Goswamy (ORCID: 0000-0003-0113-3094), Raju Thapa (ORCID: 0000-0002-1930-0535), and Guillermo Basulto-Elias (ORCID: 0000-0002-5205-2190)</td><td colspan="2">8. Performing Organization Report No.</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
Center for Transportation Research and Education
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Ames, IA 50010-8664</td><td colspan="2">10. Work Unit No. (TRAIS)</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
DTFH61-16-H-00002</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Organization Name and Address
Federal Highway Administration
Office of Safety Research and Development
Turner-Fairbank Highway Research Center
6300 Georgetown Pike
McLean, VA 22101-2296</td><td colspan="2">13. Type of Report and Period Covered
Final Report;
January 2016–November 2019</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code
HRSO-20</td></tr>
<tr><td colspan="4">15. Supplementary Notes
The Contracting Officer's Representative/Government Task Manager was Charles Fay (HRSO-20; ORCID: 0000-0002-2498-9795).</td></tr>
<tr><td colspan="4">16. Abstract
Rural intersections account for 30 percent of all crashes in rural areas and 6 percent of fatal crashes, representing a significant but poorly understood safety problem (Zwerling et al. 2005). The objective of this study was to use second Strategic Highway Research Program Naturalistic Driving Study data and Roadway Information Database data to observe driver behavior at high-speed rural intersections. The overarching goal was to better understand how drivers react at rural intersections. The study's researchers observed driver behavior firsthand by using video, vehicle and driver kinematic, and roadway data to determine how roadway, driver, environmental, and vehicle factors interact to affect driver safety at rural intersections. The research team conducted various analyses to examine driver behavior at different intersection types: two-way stop-controlled intersections, T-intersections, and all-way stop-controlled intersections. The analyses included the points at which drivers reacted to intersections, stopping behavior at intersections, and driver behavior surrounding safety-critical events. The models showed that several factors influence driver behavior at an intersection, including type of movement through the intersection, presence of a vehicle or vehicles on an opposing or major approach, presence of certain countermeasures, and vehicle speeds upstream of the intersection. The results can ultimately lead to better intersection design, more informed selection of traffic control devices, effective countermeasures, and targeted information to inform policy decisions.</td></tr>
<tr><td colspan="2">17. Key Words
Driver behavior, high-speed rural intersections, intersection safety, naturalistic driving, safety-critical events, stopping behavior</td><td colspan="2">18. Distribution Statement
No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161.
https://www.ntis.gov</td></tr>
<tr><td>19. Security Classif. (of this report)
Unclassified.</td><td>20. Security Classif. (of this page)
Unclassified.</td><td>21. No. of Pages
120</td><td>22. Price
N/A</td></tr>
</table>

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
AIC	Akaike information criterion
ANOVA	analysis of variance
CI	confidence interval
CSV	comma-separated value
DOT	department of transportation
EMS	emergency medical service
FHWA	Federal Highway Administration
GIS	geographic information system
GLME	generalized linear mixed effects
GPS	Global Positioning System
ID	identification
LME	linear mixed effects
MUTCD	*Manual on Uniform Traffic Control Devices*
NDS	naturalistic driving study
RID	Roadway Information Database
SHRP2	Second Strategic Highway Research Program
TAC	technical advisory committee

CHAPTER 1. INTRODUCTION

BACKGROUND

Rural intersections account for 30 percent of all crashes in rural areas and 6 percent of fatal crashes, representing a significant but poorly understood safety problem. Crashes at rural intersections are particularly problematic when high speeds on intersection approaches occur. Additionally, motor vehicle crash injury rates are higher in rural versus urban areas due in part to increased emergency medical service (EMS) times, reliance on volunteer EMS personnel, and increased transport time to definitive care (Zwerling et al. 2005). EMS response times in rural areas are 1.6 to 2 times longer than in urban areas (Gonzalez et al. 2009, NHTSA 2006), and fatal injury crash rates are two times higher in rural than in urban areas (FHWA 2019, Zwerling et al. 2005).

Inappropriate gap selection has been found to be a major contributing cause of crashes at rural intersections. In a study conducted in 2003 (Preston et al. 2004; Harder, Bloomfield, and Chihak 2003), inappropriate gap selection accounted for 56 percent of all right-angle crashes at rural Minnesota minor stop-controlled intersections. Right-angle collisions—which are the results of drivers' selections of gaps that are too small or drivers' failures to observe traffic control—account for 36 to 50 percent of crashes at intersections on high-speed divided highways, while such collisions account for only 28 percent of crashes at intersections on other types of roads (Alexander et al. 2007).

Researchers found that drivers who fail to stop on minor approaches have accounted for 25 percent of right-angle crashes (Harder, Bloomfield, and Chihak 2003). Retting, Weinstein, and Solomon (2003) found that crashes in which drivers failed to stop at stop signs were more likely to result in injuries than were crashes in which drivers stopped. Characteristics correlated to failure to yield right of way include age (McGwin and Brown 1999; Keay et al. 2009), speeding, vision obstruction, and inattention or distraction (Campbell, Smith, and Najm 2004).

Roadway characteristics also play a significant role in intersection crashes. Intersections located on or near horizontal and vertical curves tend to have higher crash rates than intersections on tangent segments (Savolainen and Tarko 2005; Burchett and Maze 2005; Khattak 2006; Van Maren 1977). Barua, Azad, and Tay (2010) evaluated crashes at rural, undivided intersections in Alberta, Canada, and found that crash risk is higher during fall than during winter—possibly due to harvesting—at nighttime, at offset intersections, at T-intersections, and on horizontal or sag curves. Leckrone, Tarko, and Anastasopoulos (2011) evaluated minor-approach, stop-controlled intersections in Indiana and found that the presence of acceleration lanes for both left and right turns, median width, and a nearly perpendicular intersection angle resulted in lower likelihood of a severe crash. Additionally, they found that crash risk was lower at T-intersections than at intersections with four approaches.

OBJECTIVE

Crash data provide little information about driver behavior leading up to rural intersection crashes. Police officers rely either on information observed after an event or on witness testimony, which may not provide a comprehensive picture of the actual events that led to a crash. Several studies have attempted to gain additional insights into driver behavior by using field-collected data (Woldeamanuel and Hankes 2011), simulators (Montella et al. 2011), closed-course studies (Muttart et al. 2011), and controlled instrumented vehicles with test drivers (Bao and Boyle 2008).

The drawbacks to the aforementioned types of studies are that they are limited by the number of drivers who can be included, and they have difficulty in reproducing and testing real-world conditions. One method to evaluate driver stopping behavior is to collect and reduce video data at actual intersections, which requires the collection of data for significant distances upstream of an intersection by using multiple video data collection arrays; however, driver characteristics cannot be obtained using that method. Additionally, field studies do not provide context regarding what drivers are doing as they approach an intersection. The presence of field data collectors or data collection equipment may also influence driver behavior. The manual collection of data also limits the number of sites where data can be collected and the number of samples that can be collected.

The second Strategic Highway Research Program (SHRP2) conducted a large-scale naturalistic driving study (NDS) by using instrumented vehicles (VTTI 2019). The SHRP2 study produced a significant amount of on-road driving data for a range of drivers. The present study used data from the SHRP2 NDS as well as the SHRP2 Roadway Information Database (RID) to observe driver behavior at rural intersections firsthand by using video, kinematic vehicle and driver, and roadway data to determine how roadway, driver, environmental, and vehicle factors interact to affect driver safety at rural intersections (RID 2024, FHWA, n.d.). The overarching objective of this study was to better understand how drivers react at rural intersections.

TECHNICAL ADVISORY COMMITTEE

A technical advisory committee (TAC) consisting of several safety experts from the Iowa Department of Transportation (DOT) assembled early in the project to seek input. The TAC provided instruction in several ways. First, the committee provided input as to which countermeasures and intersection features were of the most interest. Using that information, the research team attempted to select intersections with the identified features and countermeasures. For instance, the TAC was particularly interested in the impact of skew on driver behavior at intersections. As a result, the team ensured the inclusion of intersections with different skew angles in the study. The TAC also provided feedback as models got developed.

SUMMARY OF DATA USED

The research team identified a set of rural intersections within the six States covered by the SHRP2 NDS—Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington—by using the RID and other sources such as Google® Earth™ (VTTI 2019, RID 2024, FHWA, n.d.). The team selected the intersections to represent a cross section of geometric features (e.g., skew angle) and intersection countermeasures (e.g., overhead beacons or on-pavement signing) for all-way stop-controlled intersections, two-way stop-controlled intersections, and T-intersections. Ultimately, 199 intersections were used in the study. The team requested and received time series traces, forward roadway video, and static driver characteristics (e.g., age and gender) from the subcontractor that archives SHRP2 NDS data. The team reduced the data, and 7,470 time series traces reflecting a range of driver ages and genders were viable and used in the analyses. Time series traces provide kinematic vehicle data—such as speed, acceleration, and Global Positioning System (GPS) location—at 0.1-s intervals and represent one driver trip through one intersection.

The team extracted roadway characteristics such as skew angle, number of approaches, and type of countermeasure from the RID or Google Street View™ and confirmed them for each time series trace by using the forward roadway video (FHWA, n.d.). The team also reduced environmental characteristics such as time of day and ambient conditions and the presence of opposing vehicles from the forward roadway video.

The team identified and mapped roadway features such as location of a stop sign or an advance warning sign to vehicle position within each of the time series traces. As a result, the team could determine the distance of a vehicle from a particular characteristic such as an upstream advance warning sign. The team reduced the data along the corresponding approach from the location of the stop sign to 600 m (1,969 ft) upstream and approximately 5 m (16 ft) downstream. Then the team identified the maximum speed within that distance, along with whether the driver was 2.24 or 4.47 m/s (5 or 10 mph) over the posted speed limit at any point within the 600 m (1,969 ft).

Type of stop was coded using the following criteria:

- Full stop: Speed was reduced to approximately 0 m/s (0 mph).
- Rolling stop: Clear braking was observed, and vehicle speed was greater than 0 m/s (0 mph) but less than approximately 2.24 m/s (5 mph).
- Nonstop: Vehicle speed was greater than approximately 2.24 m/s (5 mph).

Initially, the team reduced kinematic driver characteristics, but the subcontractor that archives the SHRP2 NDS data later completed the reduction, since that was more cost effective. The team coded both glance locations and distractions, coding distractions if they occurred when drivers took their eyes off the forward roadway. The team allocated both glance locations and distractions to the positions near the intersections at which they occurred (e.g., 0–100 m (0–328 ft) upstream of an intersection, 100–200 m (328–656 ft) upstream, and so on). The team further categorized glance location as follows:

- Forward: Forward glances.
- Scanning: Left and right glances not associated with a distraction.
- Situational awareness: Left, right, steering wheel, and rearview-mirror glances not associated with distractions.
- Non-roadway: Up, down, center console, over the shoulder, other, missing, and any glance associated with a distraction.

Due to the cost of reducing kinematic vehicle characteristics, the team reduce those characteristics only for a subset of the viable time series traces data (922).

SUMMARY OF ANALYSES

The team developed several different models to assess driver behavior at rural intersections, as described in the following subsections. Kinematic driver variables were available for approximately 12 percent of the total viable time series traces that the team reduced with roadway and environmental characteristics. As a result, each analysis resulted in a model that included all available traces as well as a model that included only the subset of data for which kinematic driver variables were available.

Analysis of Driver Reaction Point

The objective of this analysis was to assess where drivers began reacting to an upcoming intersection. The research team used the assessment as a surrogate for driver awareness of the intersection. The team assumed that drivers who reacted sooner to an upcoming intersection were more prepared to stop. The analysis included time series traces from all intersections (7,044), since driver behavior upstream of the intersection was not expected to be related to type of traffic control.

The team used changes in speed and acceleration to assess the reaction point, which the team calculated using a structural linear change model for each time series trace. On average, drivers reacted 204 m (669 ft) upstream of the location of the corresponding stop sign. The team used linear mixed-effects (LME) models for these analyses. An LME model is similar to regular linear regression, but it allows for a certain amount of dependency between observations.

Reaction point varied by State. The team used Florida as the baseline, and drivers in Indiana reacted 38 m (125 ft) before drivers in Florida did. The team also noted differences between drivers in other States; those differences ranged from 23 to 51 m (75 to 167 ft). The finding suggests that some differences exist between drivers in each State. Additionally, the finding may imply that intersections within individual States are more similar to one another than they are to intersections in other States—a situation that the model could not detect.

When no skew was present, drivers reacted 17 m (55 ft) sooner than when the intersection was skewed left from the perspective of the driver. Similarly, when the intersection was skewed right, drivers reacted 36 m (118 ft) later than when the intersection was skewed left. That finding was unexpected because in most cases, drivers reacted well before arriving at the intersection, and therefore skew had not been expected to affect driving behavior upstream.

When on-pavement signing existed, drivers reacted sooner than when no on-pavement signing existed. On-pavement stop signs resulted in reactions 64 m (210 ft) sooner, and on-pavement stop-ahead signs resulted in reactions 38 m (125 ft) sooner. Interestingly, approaches that displayed both messages—stop ahead followed by stop—resulted in reactions that were 19 m (62 ft) later than when no on-pavement signing existed.

Time of day, too, had an impact on reaction point. During the day, drivers reacted 75 m (246 ft) later than at dawn or dusk, and at night, drivers reacted 55 m (180 ft) later.

Turning movement also affected reaction point. Drivers turning right reacted 55 m (180 ft) later than those turning left, and drivers going through the intersection reacted 76 m (249 ft) sooner than right-turning drivers.

Next, the team considered a second-order polynomial to determine the effect of maximum speed in meters per second within 600 m (1,969 ft) upstream of the intersection on reaction point. Due to the complex relationships among the variables, the reader is referred to Figure 23.

The team developed a separate model by using just the time series traces when kinematic driver variables were available. The model did not yield significantly different results, and consequently, the team used only the model with all traces.

Analysis of Stopping Behavior at Two-Way Stop-Controlled Intersections

Analysis of stopping behavior at two-way stop-controlled intersections involved examination of the relationship between type of stop and driver, roadway, and environmental characteristics. The team assumed that a rolling stop and no stop were less safe than a full stop. Two-way stop-controlled intersections included those with major through approaches and minor stop-controlled approaches. In all cases, the minor stop-controlled leg consisted of two lanes.

A total of 1,073 viable time series traces were available for two-way stop-controlled intersections. The total consisted of 128 unique drivers at 58 unique intersections. Kinematic driver variables were available for 288 time series traces, which represented 100 unique drivers at 54 unique intersections. The team developed two models to capitalize on all available samples. The first model included data from all viable time series traces, and the second included only traces where kinematic driver variables had been reduced. The response variable was type of stop, and one observation was coded for each time series trace. Independent variables included approach characteristics (e.g., presence of a stop bar or intersection lighting), time of day (dawn, dusk, day, or night), and static driver characteristics (e.g., age and gender). Kinematic driver characteristics (i.e., glance location and distraction) were available for a subset of the traces.

Initially, the team used an ordered logit model to assess differences between the three different stopping behaviors (full stop, rolling stop, no stop). However, the team noted no differences between the rolling-stop and the full-stop data and combined the two kinds for further analyses. The team then used a logistic mixed-effects regression to model the probability (odds ratio) of a driver's not stopping (coded as "no stop") on the corresponding rural intersection approach.

The first analysis used data for all available time series traces. The model showed that the presence of another vehicle on a major approach made drivers 2.22 times more likely to engage in a rolling/full stop at the intersection, while the presence of another vehicle on the opposite approach made drivers 1.64 times more likely to engage in a rolling/full stop.

In contrast, a driver traveling 2.24 m/s (5 mph) or more over the speed limit within 600 m (1,969 ft) of the intersection was 2.10 times more likely not to stop at the intersection. Driving during the night made drivers 2.65 times more likely not to stop compared with driving during dawn or dusk, while driving during the day made drivers 1.25 times more likely not to stop compared with driving during dawn or dusk.

The team found two notable interactions: one between intersection skew and turning movement and another between presence of a stop bar and turning movement. The results of such interactions are easiest to explain graphically using credible sets, as shown in chapter 5, but summaries are given in the following subsections. The probability of not stopping is the metric of interest in this case.

For the interaction between intersection skew and turning movement, the results indicated that the probability of not stopping was greater for all movements when an intersection was skewed left (skew is from the perspective of the driver). The probability of not stopping was lowest for right-turning drivers at intersections with no skew. For left-turning drivers, the probability of not stopping was very low and was similar for intersections with no skew and those with right skew, although more variability resulted for intersections with no skew. Additionally, in all cases, the team found a highlight in that a right turn resulted in a higher probability of a driver's not stopping.

The results for interaction between presence of a stop bar and turning movement indicated that left-turning and through drivers had low probabilities of not stopping when no stop bar was present (approximately 5 percent and 8 percent, respectively) but much higher probabilities of not stopping when a stop bar was present (approximately 18 percent and 55 percent for left-turning drivers and through drivers, respectively). However, a significant amount of variance was evident when a stop bar was present. The probability of not stopping was also higher for right-turning drivers when a stop bar was present. However, the team found a significant amount of overlap in the credible sets for right-turning drivers in the presence or absence of a stop bar, which suggests that right-turning drivers on two-way stop-controlled approaches were less likely to come to a rolling stop or full stop when a stop bar was present.

The second model used data from time series traces where kinematic driver variables had been reduced. As a result, the second model used a subset of the data used for the previous model. The model showed that both right-skewed intersections and non-skewed intersections were 3.09 times more likely to result in rolling stops or full stops compared with left-skewed intersections. Moreover, when a vehicle was on a major approach, drivers were 2.45 times more likely to engage in a rolling/full stop. However, drivers making a right turn were 4.68 times more likely not to stop compared with those making a left turn or going through. Drivers at intersection approaches with stop bars were 2.86 times more likely not to stop at the intersections.

Analysis of Stopping Behavior at T-Intersections

The team modeled stopping behavior at T-intersection approaches similarly to the analysis the team conducted for two-way stop-controlled intersections. Based on the results of that analysis, the team combined the data for rolling stop and full stop for this analysis. The T-intersections in this study typically involved single two-lane stop-controlled approaches intersecting two-lane major approaches.

The team modeled the likelihood of drivers' making no stop versus making a rolling or full stop on T-intersection approaches. To model the probability (odds ratio) of drivers' making no stop, the team used logistic mixed-effects regression by developing two separate models. One model included all traces, and the other included the subset of traces where kinematic driver behaviors had been reduced. Overall, the two models provided similar results.

The first model, which included data for all available time series traces for T-intersections, indicated that when a vehicle was present on a major approach, the driver was 55.53 times more likely to engage in a rolling/full stop. When lighting was present at the intersection, drivers were 2.32 times more likely to engage in a rolling/full stop. Time of day was also significant. Drivers were 2.47 times more likely during the daytime and 1.60 times more likely at night to engage in a rolling/full stop than at dawn or dusk. Drivers traveling over the posted speed limit were 2.23 times more likely not to stop than were drivers traveling at or below the speed limit.

Interactions were present between intersection skew and turning movement and between turning movement and presence of an advance intersection warning sign. Chapter 6 presents the results of both interactions graphically by using credible sets. The probability of not stopping was the metric of interest.

For interaction between intersection skew and turning movement, left-turning drivers had a low probability of not stopping for all skew scenarios: left skew, right skew, and no skew (skew direction is from the perspective of the driver). However, those drivers were more likely not to stop when left skew was present. Right-turning drivers were more likely not to stop when either no skew (62 percent) or right skew (70 percent) was present. Right-turning drivers were less likely not to stop (approximately 28 percent) when left skew was present. However, the credible sets are rather large.

For interaction between presence of an advance intersection warning sign and turning movement, right-turning vehicles at T-intersections had a high probability of not stopping regardless of the presence of advance signing. Left-turning drivers had a low probability of not stopping when no advance signing was present but a 25-percent probability of not stopping when advance signing was present. This result was unexpected, since the purpose of the signing is to warn drivers of an upcoming intersection. However, advance signing and other countermeasures are placed at locations where problems with safety or driver behavior already exist. As a result, the presence of a countermeasure may be a surrogate for a problem location. In such cases, a before-and-after analysis may yield more representative results.

The second model for T-intersections included data from time series traces where kinematic driver variables (i.e., distraction and glance location) had been reduced. As a result, the data used in this model consisted of a subset of the data used in the previous model. The results indicated that when a vehicle was present on the major approach, the driver was 127.29 times more likely to engage in a rolling/full stop. When intersection lighting was present, a driver was 180.57 times more likely to engage in a rolling/full stop. Drivers traveling over the posted speed limit upstream of the intersection were 55.02 times more likely not to stop. Those odds ratios are higher than expected and are likely due to sample size.

The model also showed that a driver who had engaged in a non-roadway glance within 100 m (328 ft) before arrival at the stop bar was 5.17 times more likely to engage in a rolling/full stop. That result was unexpected, since glances away from the roadway are often associated with distractions. However, a driver who is glancing at multiple locations—even locations not related to the roadway—may be more likely to be alert.

Interactions were present between intersection skew and turning movement and between presence of an advance intersection warning sign and turning movement. The results are presented graphically in chapter 6 by means of credible sets.

For interaction between intersection skew and turning movement, the results showed that when no skew or right skew was present, right-turning drivers had a high probability of not stopping (> 75 percent). However, when an intersection was skewed left from the perspective of the driver, right-turning drivers had a much lower probability of not stopping (approximately 13 percent), which may have been due to the fact that when neither no skew nor right skew is present, drivers have much better sight distance and feel more comfortable proceeding. Left skew may limit sight distance, causing drivers to stop in order to scan the intersection. Left-turning drivers were much more likely not to stop in the presence of left skew (18 percent) or right skew (37 percent) than no skew (3 percent).

The team also found interaction between presence of an advance intersection warning sign and turning movement. Left-turning drivers were much more likely to stop when no sign was present versus when a sign was present (3 percent versus 62 percent, respectively). Right-turning drivers had similar probabilities of not stopping regardless of the presence of an advance sign.

Analysis of Stopping Behavior at All-Way Stop-Controlled Intersections

The team modeled stopping behavior on all-way stop-controlled intersection approaches similarly to the analysis conducted for two-way stop-controlled intersections. Based on the results of that analysis, the team combined the data for rolling stop and full stop for this analysis. The all-way stop-controlled intersections in this study typically involved four approaches, and all locations were rural.

The team used logistic mixed-effects regression to model the probability (odds) of a driver's making no stop on an all-way stop-controlled approach. The team developed two separate models. One included data for all traces, and one included the subset of traces where kinematic driver behaviors had been reduced.

The first model, which included data from all viable time series traces on all-way stop approaches, showed that when one or more vehicles were present on an opposing approach, drivers were 7.60 times more likely to stop at the intersection. The team also found a correlation between speeding and the likelihood of a stop. Drivers traveling 4.47 m/s (10 mph) or more over the speed limit upstream of the intersection were 1.85 times more likely not to stop than were drivers who were not speeding.

Interactions were present between turning movement and presence of a stop bar and between turning movement and presence of a beacon. Due to the complexity of the interactions, chapter 7 presents the results graphically by using credible sets, with the probability of not stopping as the metric of interest.

For the interaction between turning movement and presence of a stop bar, the probabilities of a left-turning driver not stopping when a stop bar was present versus not present were similar (25 percent and 30 percent, respectively). Similarly, through vehicles had similar probabilities of not stopping in the presence or absence of a stop bar (25 percent and 28 percent, respectively). Right-turning vehicles were much more likely not to stop when no stop bar was present (> 75 percent) compared with when a stop bar was present (approximately 50 percent). Overall, in the model for all-way stop-controlled intersections, the stop bar did not have much impact on left or through movements but did improve the stopping behavior of right-turning vehicles. This result is the opposite of what was found for stopping behavior of the T-intersection model.

For the interaction between turning movement and presence of a beacon, the probability that a right-turning vehicle did not stop was greater than 75 percent when a beacon was either present or absent, with drivers slightly more likely not to stop when a beacon was present. However, the credible sets had significant overlap. Through drivers were slightly more likely not to stop when no beacon was present (25 percent) than when a beacon was present (18 percent), although significant overlap was present in the credible sets. Finally, left-turning drivers were much more likely not to stop when no beacon was present (26 percent) compared with when a beacon was present (11 percent). Overall, the presence of a beacon appears to have a positive impact for left-turning and through drivers.

The second model only included data from the time series traces where kinematic driver variables (i.e., distraction and glance location) were coded. As a result, this model used a subset of the data included in the previous model. The results indicated that the presence of a vehicle on the opposite approach resulted in higher odds of the subject vehicle's engaging in a rolling stop or full stop than when another vehicle was not present. Drivers traveling 4.47 m/s (10 mph) or more over the posted speed limit upstream of the intersection were 6.44 times more likely not to stop.

Interactions were present between several sets of variables and are shown graphically in chapter 7 by means of credible sets.

An interaction between presence of a stop bar and turning movement indicated that drivers making through movements were more likely not to stop when a stop bar was present (61 percent) than when a stop bar was not present (37 percent). However, the credible sets had significant overlap. Left-turning vehicles had a small probability of not stopping when no stop bar was present but a 32 percent chance of not stopping when one was present. Most right-turning drivers did not stop when no stop bar was present, but only 50 percent did not stop when a stop bar was present.

Interaction between presence of a beacon and turning movement indicated that drivers making through movements had a 32 percent probability of not stopping when no beacon was present but a 19 percent chance of not stopping when a beacon was present. However, there was significant overlap in the credible sets. Right-turning drivers had a high probability of not stopping in either the presence or absence of a beacon. However, the team observed less variance in the probability of drivers' not stopping when a beacon was present, thereby suggesting that drivers were slightly more likely not to stop when a beacon was present. Left-turning vehicles had a low probability of not stopping in either the presence or absence of a beacon. Much less variance was observed when a beacon was present, suggesting that drivers were less likely not to stop when a beacon was present.

Finally, an interaction was found between whether a driver was engaged in a distraction within 100 m (328 ft) upstream of an intersection and whether the driver glanced away from the roadway in the interval within 100–250 m (328–820 ft) upstream of the intersection. In general, the relationship suggests that drivers who engage in multiple distracting activities are less likely to stop.

Analysis of Safety-Critical Events

The most promising outcome of the SHRP2 NDS data (FHWA, n.d.) has been the ability to assess crash and near-crash events firsthand so as to be able to identify such factors as driver distraction, which theretofore could not be observed (VTTI 2019). However, once crashes are disaggregated by roadway type and other factors, the available sample size is smaller than might be expected. As a result, the team further used stopping behavior and the point at which drivers react to the upcoming intersection, as described in the previous sections—Analysis of Driver Reaction Point and Analysis of Stopping Behavior at All-Way Stop-Controlled Intersections—to more fully assess rural intersection safety.

The team identified rural-intersection-related, safety-critical events (crash, near crash, and crash relevant) on the *InSight Data Access Website: SHRP2 Naturalistic Driving Study* (VTTI 2019), which is hosted by the subcontractor that archives the SHRP2 NDS data. The team removed events attributable to adverse weather or in which intersection configuration could not be determined. Further, the team retained only events in which the subject driver was at fault. That resulted in 38 safety-critical events.

Baseline events for the intersections where safety-critical events occurred were provided, and the subcontractor that archives the SHRP2 NDS data reduced and coded glance location and secondary tasks for the baseline events 5 s before a vehicle arrived at the stop sign location or began a turning movement.

Data were insufficient for developing a statistical model. As a result, the team performed a simple statistical analysis to evaluate the data. The data were disaggregated by events that had occurred on a stop-controlled approach where drivers would have been expected to stop (19 safety-critical events and 111 baseline events) and by events that had occurred on a major street approach with no traffic control (19 safety-critical events and 103 baseline events). Further disaggregation by type of intersection (e.g., two-way versus T-intersection) or by type of driver was not practical due to sample size.

Approximately 21 percent of safety-critical events involved a full stop versus 25 percent of baseline events. Similarly, 37 percent of safety-critical events involved a rolling stop compared with 44 percent of baseline events. Finally, drivers in 42 percent of safety-critical events did not stop compared with drivers in 32 percent of baseline events.

The team calculated simple odds ratios for several characteristics. For events on a major approach, the odds of experiencing any type of distraction in the 5 s before a crash event or near-crash event were 1.52 times those of a baseline event, with a 95-percent confidence interval (CI) of 0.57–4.11. For a crash or near crash on a stop-controlled approach, the odds of engagement in a distraction were 3.56 higher (CI = 0.85–7.68). The odds of a driver's not stopping in a crash event or near-crash event were 1.65 higher (CI = 0.61–4.47) than in a baseline event.

The analyses suggest that drivers involved in crashes at rural intersections were more likely to have become distracted or to have engaged in unsafe stopping behaviors. However, none of the results are statistically significant because the CI includes one. The wide CI is likely due to the small sample size of crash events and near-crash events.

DISCUSSION OF FINDINGS

Table 1 summarizes results from the various models. As noted earlier in Analysis of Driver Reaction Point and Analysis of Stopping Behavior at All-Way Stop-Controlled Intersections, two models each were developed for two-way stop-controlled intersections, T-intersections, and all-way stop-controlled intersections. For each intersection type, the notation "(all)" indicates that the model included data for all available traces. The notation "(with kinematic)" indicates that the model included only traces whose kinematic driver variables (i.e., glance location and distraction) were coded. In all cases, the model denoted "(with kinematic)" used a subset of data from the model that included all traces. In most cases, as noted, the results for the two models were reasonably similar.

Table 1. Summary of findings for various analyses.

Driver Behavior or Intersection Characteristic	Reaction Point	Two-Way Stop (All)	Two-Way Stop (With Kinematic)	T-Intersection (All)	T-Intersection (With Kinematic)	All-Way Stop (All)	All-Way Stop (With Kinematic)	Safety Critical Versus Baseline
On-pavement signing	Reacts 38–64 m (125–210 ft) sooner	—	—	—	—	—	—	—
Stop bar	—	All movements more likely not to stop	2.9× more likely not to stop	—	—	Right turn more likely to stop	Left turn or through less likely to stop, right turn more likely to stop	—
Beacon	—	—	—	—	—	Through or left skew more likely to stop	Through or left skew more likely to stop	—
Skew	Right skew 36 m (118 ft) later than left	All movements less likely to stop with left skew	No skew or right skew 3.1× more likely to stop than left skew	Left turn more likely not to stop with left skew, right turn more likely not to stop with right skew or no skew	Left turn more likely not to stop with any skew, right turn more likely not to stop with right skew or no skew	—	—	—
Lighting	—	—	—	2.3× more likely to stop	180.6× more likely to stop	—	—	—
Advance intersection warning sign	—	—	—	Left turn more likely not to stop	Left turn more likely not to stop	—	—	—

Driver Behavior or Intersection Characteristic	Reaction Point	Two-Way Stop (All)	Two-Way Stop (With Kinematic)	T-Intersection (All)	T-Intersection (With Kinematic)	All-Way Stop (All)	All-Way Stop (With Kinematic)	Safety Critical Versus Baseline
Vehicle on opposing approach	—	1.6× more likely to stop	—	—	—	7.6× more likely to stop	26.0× more likely to stop	—
Vehicle on main approach	—	2.2× more likely to stop	2.5× more likely to stop	55.5× more likely to stop	127.3× more likely to stop	—	—	—
Time of day	Reacts 20 m (66 ft) later for day	2.7× more likely to stop in day, 1.3× more likely at night than at dawn or dusk	—	2.5× more likely to stop in day, 1.6× more likely at night than at dawn or dusk	—	—	—	—
Maximum speed > posted speed	Impact depends on speed	—	—	2.2× more likely not to stop	55.0× more likely not to stop	—	—	—
2.24 m/s (5 mph) over speed limit within 600 m	—	1.6× more likely not to stop	—	—	—	—	—	—
4.47 m/s (10 mph) over speed limit within 600 m	—	—	—	—	—	1.9× more likely not to stop	6.4× more likely not to stop	—
Non-roadway glances	—	—	—	—	5.2× more likely to stop when glancing away within 100 m	—	Less likely to stop when engaged in a distraction and take a subsequent glance away from roadway	—

Driver Behavior or Intersection Characteristic	Reaction Point	Two-Way Stop (All)	Two-Way Stop (With Kinematic)	T-Intersection (All)	T-Intersection (With Kinematic)	All-Way Stop (All)	All-Way Stop (With Kinematic)	Safety Critical Versus Baseline
Distraction (crash or near crash versus baseline)	—	—	—	—	—	—	Less likely to stop when engaged in a distraction and take a subsequent glance away from roadway	1.5× more likely on major approach, 3.6× more likely on minor approach
No stop (crash or near crash versus baseline)	—	—	—	—	—	—	—	1.65× more likely
Right turn	Reacts 55 m (180 ft) later than left	Less likely to stop for all skew conditions	4.7× more likely not to stop than left skew or through	More likely not to stop than left turn	More likely not to stop than left turn	More likely not to stop than left turn	More likely not to stop than left turn	—

—Insufficient data or not applicable.

The different models illustrated the impacts of certain intersection characteristics. Stopping point was used as a surrogate for driver awareness of an intersection, and the team assumed that if drivers reacted sooner, they were aware of the upcoming intersection and therefore more likely to react appropriately.

Several models indicated positive driver responses to certain intersection characteristics. The reaction point model indicated that when on-pavement signing was present, drivers reacted sooner than when it was not present. On-pavement signing uses such wording as “Stop Ahead” or “Intersection Ahead” placed on the pavement to alert drivers to an upcoming intersection in a more dramatic way than does vertical signing, which can get lost in the clutter of a streetscape.

Presence of a stop sign beacon or overhead beacon resulted in improved stopping behavior in the all-way stop-controlled-intersection model for left-turning and through vehicles. The countermeasure did not have an effect on the two-way stop-controlled-intersection and T-intersection models, but the countermeasure is likely not applied as frequently at those locations.

Presence of intersection lighting resulted in drivers’ being more likely in general to stop in the T-intersection model. The team found no interaction between time of day and intersection lighting but assumed that the impact most likely applies to nighttime driving.

Several models also showed that certain intersection characteristics were associated with negative driver responses. Presence of a stop bar affected stopping behavior in several models but with mixed results. In many cases, presence of a stop bar resulted in higher likelihood of not stopping. However, some evidence showed that the presence of a stop bar improved the stopping behavior of right-turning vehicles. The team could not account for the negative relationship, which may have been due to bias regarding the sites where that countermeasure was present. Instruction often suggests using stop bars on intersections’ minor approaches that some approaching motorists are not currently recognizing. Therefore, this countermeasure may be present especially at intersections already with propensities for drivers not to stop.

Additionally, the presence of an advance intersection warning sign resulted in left-turning drivers’ being more likely not to stop. Advance intersection warning signs include those showing an image of a stop sign or a yield sign. As with stop bars, the negative impact of this countermeasure for left-turning drivers was counterintuitive. The negative impact may be due to the fact that, like stop bars, advance warning signs are also placed at locations that have had problems with stopping behavior.

The team found that intersection skew affected stopping behavior in several of the models. The direction of skew was relevant and usually associated with turning movement. The models for two-way stop-controlled intersections showed that drivers were less likely to stop when left skew was present, and the model for T-intersections showed that left-turning vehicles were less likely to stop when left skew was present. The direction of skew in some cases appeared to assist drivers. For instance, T-intersections with left skew were associated with a lower probability of not stopping (or a higher probability of stopping) compared with intersections with no skew or right skew, which may be due to the fact that at certain angles, drivers are better able to see oncoming traffic. The team assessed intersection skew from the perspective of the driver. As a result, left skew for one approach would be right skew for another approach, leading to a conclusion that skew in general has a negative impact on stopping behavior.

The team found that various other factors were also relevant to stopping behavior, finding that the presence of a vehicle on the opposing approach was associated with the likelihood of a driver's engaging in a rolling stop or a full stop. The team found that the presence of a vehicle on the main approach improved stopping behavior. The team found that time of day, too, affected stopping behavior in the models.

The team found that several driver behaviors were relevant to stopping behavior. For instance, the team found that speed affected stopping behavior in all models except the safety-critical analysis. The team measured speeding as a driver's highest speed within 600 m (1,969 ft) upstream of an intersection. The team found that any speed over the posted speed limit was relevant in the T-intersection models, while a speed of 2.24 or 4.47 m/s (5 or 10 mph) over the posted speed limit was relevant in the two-way and all-way stop-controlled-intersection models. The reaction point model showed that speed had a major impact on reaction point. As a result of those findings, the team concluded that drivers who speed are also less likely to stop. Among speeding vehicles, right-turning vehicles were consistently less likely to stop than were through or left-turning vehicles.

The team found that glance behavior affected stopping behavior in two of the models, but with opposite effects. A glance away from the roadway within 100 m (328 ft) of an intersection was associated with improved likelihood of stopping. However, as shown by the all-way stop-controlled-intersection model, when drivers engaged in a distraction and a non-roadway-related glance upstream, they were less likely to stop. Drivers who were engaged in distractions were 1.5—3.6 times more likely to be involved in safety-critical events.

All the models agree that drivers engaging in right turns were more likely not to stop than were drivers engaging in left turns or through movements. All the models also agree that the presence of a vehicle on a conflicting approach resulted in drivers' being more likely to stop.

The team found that several intersection countermeasures correlated to reaction point and stopping behavior. The reaction model showed that the presence of on-pavement signing (Stop or Stop Ahead) resulted in drivers' reacting 38–64 m (125–210 ft) sooner than when such signing was not present. The presence of a flashing beacon in the form of a stop sign either mounted or overhead at an all-way stop also resulted in higher likelihood of a full stop or a rolling stop for through and left-turning vehicles than when that countermeasure was not present. The presence of a stop bar at an all-way stop resulted in higher likelihood of stopping, while drivers were less likely to stop at two-way stop-controlled intersections that had that countermeasure. That finding may be due to the fact that two-way stop-controlled approaches are less likely to have stop bars; moreover, stop bars may more likely be placed at locations that have issues with driver stopping or yielding behavior.

All the models agree that drivers engaged in speeding (in terms of unit increases in speed or a maximum speed of 2.24 or 4.47 m/s (5 or 10 mph) over the speed limit) within 600 m (1,969 ft) of the intersection were more likely not to stop. That behavior may suggest a correlation between risk-taking behavior in general and the likelihood of not stopping.

When drivers engaged in relatively high amounts of scanning behavior 200 m (656 ft) upstream of an intersection, they were more likely to stop (as evidenced by the all-way-stop model). Scanning significantly upstream of the intersection suggests that drivers are well aware of the intersection. Conversely, drivers who engaged in a relatively high amount of scanning behavior within 100 m (328 ft) of the intersection were less likely to stop. The team speculates that drivers who scan just prior to an intersection are assessing potential conflicts, and when they note no conflicts, they feel emboldened to proceed without stopping.

The simple analysis of crash events, near-crash events, and baseline events showed that drivers involved in safety-critical events were more likely to have been engaged in distractions within 5 s of the impacts. The more complicated models did not yield as much insight into driver behavior as hoped, which was likely due to sample size. Only 12 percent of the 7,470 available time series traces had kinematic driver characteristics coded due to resource constraints. Even within that set of traces, distraction was a rare occurrence, with distractions present in approximately 3 percent of the time series traces where kinematic driver characteristics had been reduced.

The team hoped the project could more fully assess the effects of roadway features on driving behavior at rural intersections. However, the approach taken may have been too broad. While 199 unique intersections were included with the 7,470 time series traces, too many combinations of characteristics and countermeasures may have prevented detection of the effect of any single countermeasure. The team suggests in the future a narrower scope, potentially choosing one or two countermeasures of interest and finding intersections similar to one another except for the presence of the countermeasures. The project results did allow for the isolation of a few intersection characteristics, such as skew, transverse rumble strips, stop bars, and on-pavement signing, which is useful for agencies considering such countermeasures. The lack of findings showing relationships between driving behavior and other countermeasures such as the presence of beacons does not intend that drivers construe a suggestion that such countermeasures are ineffective. Their impact may be better revealed by taking a more targeted approach.

Nevertheless, the approach the team used did provide valuable insight into how driver behavior in general (e.g., speeding and scanning) plays a role in the ways drivers negotiate rural intersections.

CHAPTER 2. BACKGROUND OF COUNTERMEASURES USED AT RURAL INTERSECTIONS

Countermeasures have been put in place extensively at rural intersections to help improve safety. Previous research has helped determine the effectiveness of countermeasures in improving safety. Following are descriptions of countermeasures typically used at rural intersections and a summary of studies on their effectiveness.

DOUBLE STOP SIGNS

This countermeasure involves installing a second stop sign either in the median, if present, as shown in figure 1, or on the left side of an approach in order to increase the conspicuity of the stop and to draw drivers' attention to the signs (Atkinson et al. 2014).

Figure 1. Photo. Example of double stop signs.

A study by Polanis (1999) found that the installation of double stop signs decreased angle crashes by 55 percent.

TRANSVERSE RUMBLE STRIPS

Transverse rumble strips, or advance stop line rumble strips, are grooved strips milled or rolled into the pavement upstream of a stop-controlled intersection on the stop-controlled approach. They provide drivers with an auditory and tactile warning to alert them to the intersection ahead (figure 2).

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Figure 2. Photo. Example of transverse rumble strips.

A previous study found that the use of transverse rumble strips in Iowa and Minnesota reduced fatal crashes at T-intersections by 59 percent and at four-approach intersections by 35 percent. Total crashes at those sites were found to slightly increase, however (increases of 22 percent and 7 percent, respectively) (Srinivasan, Baek, and Council 2012).

FLASHING BEACONS

Beacons are flashing lights intended to draw a driver's attention to the associated traffic control. Flashing beacons supplement stop signs and are intended to reinforce awareness of existing stop signs. Two different types of intersection beacon are typically used: standard overhead beacons mounted over the intersection, as in figure 3, and sign-mounted beacons mounted on the stop sign or stop ahead and intersection ahead signs, as in figure 4.

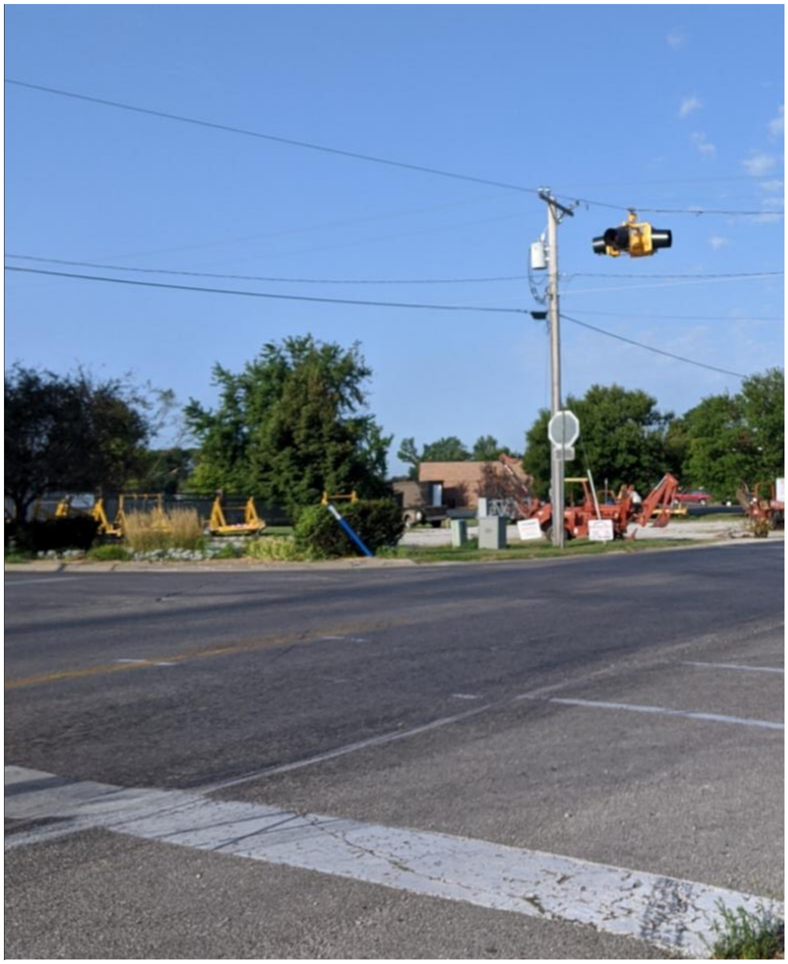


Figure 3. Photo. Example of overhead flashing beacon.

Figure 4. Photo. Example of sign-mounted beacon.

Previous studies have found overhead flashing beacons reduce crashes by 12 percent to 19 percent for angle crashes (Srinivasan et al. 2008; Pant et al. 1992) and by 12 percent to 40 percent for total crashes (Murphy and Hummer 2007; Stackhouse and Cassidy 1996).

When mounted to stop signs, flashing beacons were found to decrease angle crashes by 58 percent (Srinivasan et al. 2008). When placed on stop ahead and Intersection Ahead signs, total crashes were reduced by 40 percent (Stackhouse and Cassidy 1996).

ON-PAVEMENT SIGNING

On-pavement signing uses either wording such as stop ahead or intersection ahead or a diagram of an intersection placed on pavement to alert drivers to an upcoming intersection in a more dramatic way than vertical signing does, because vertical signing can get lost in the clutter of a streetscape.

A Federal Highway Administration (FHWA) study found through an empirical Bayes analysis that the use of stop head pavement markings can result in a 15 percent reduction in total crashes (FHWA 2008).

LIGHTING

Roadway lighting at intersections provides greater visibility of the intersection, signs, and markings (Atkinson et al. 2014; Neuman et al. 2003). Lighting helps address intersection crashes that occur during nighttime hours due to drivers' inability to see conflicting traffic or drivers' lack of awareness of an intersection until too late to avoid a collision. A study in Iowa found that the mean number of nighttime crashes at intersections with no lighting was two times higher than at locations with lighting (Isebrands et al. 2010). Figure 5 shows an example of intersection lighting.

Figure 5. Photo. Example of rural intersection lighting.

Two studies conducted in Iowa found either no change or up to a 49 percent reduction in nighttime crashes at rural intersections with lighting (Carstens and Berns 1984; Walker and Roberts 1975). More recent studies, in Minnesota, found reductions of 25 percent up to 40 percent (Isebrands et al. 2006; Preston and Schoenecker 1999).

ADVANCE WARNING SIGNS

Advance warning signs are placed upstream of rural intersections. Such signs can be W2 series signs from the *Manual on Uniform Traffic Control Devices* (MUTCD) (FHWA 2009a) as well as the stop sign ahead signage shown in figure 6. One or two signs can be installed.

Figure 6. Photo. Example of stop sign ahead signage.

Researchers found that improving the visibility of intersections through the installation of enhanced signing and delineation such as advance warning signs reduced crashes by 40 percent (FHWA 2009b).

INTERSECTION CONFLICT WARNING SYSTEMS

Intersection conflict warning systems use sensors placed on the major approach to alert drivers on the minor approach through either a static sign with flashing beacons or a dynamic sign—as shown in figure 7—that vehicles are approaching on the major approach.

Figure 7. Photo. Example of intersection conflict warning system (Hallmark et al. 2017).

A simple before-and-after crash analysis conducted for the Missouri DOT showed that intersection conflict warning systems reduced crashes on average by 51 percent and severe angle crashes by 77 percent (Sorenson 2011).

CHAPTER 3. DESCRIPTION OF DATA

This chapter describes how the research team collected and reduced in general the data used in this study. In some cases, the team conducted additional data reduction for a particular analysis. In such cases, the additional reduction is described in the section of the chapter corresponding to that analysis.

DATA SOURCES

Data for this project came from two main sources: the SHRP2 NDS and RID (VTTI 2019, RID 2024). The research team reduced additional data on the study intersections from such sources as Google Earth. Following are descriptions of the data sets and the data variables reduced.

NDS Data

SHRP2 conducted the largest and most comprehensive NDS undertaken to date. The study collected data during a 3-yr period from more than 3,000 male and female volunteer passenger vehicle drivers aged 16–98 yr, with most drivers participating for 1–2 yr. The research team collected data from sites located in six States: Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington.

The team collected in-vehicle data via a data acquisition system comprising a number of vehicle variables, including speed, acceleration, braking, vehicle controls when available, offset from lane center, forward radar, and several video views (figure 8): forward, rear, driver's face and hands, and over driver's shoulder toward center console.

Figure 8. Screenshot. Example of video views.

The NDS data file contains about 50 million vehicle-mi (about 80 million km), 5 million trips, more than 3,900 vehicle-yr, and more than 1 million h of video, for a total of about 2 PB of data.

RID

The RID contains detailed roadway data gathered using mobile data collection methods for approximately 12,500 centerline mi (20,117 km) in the SHRP2 NDS study States. Roadway attributes include such items as curve radius and length, presence of rumble strips, lane width, grade, number of lanes, and speed limit. The RID also includes relevant data from several other sources, including State DOTs, FHWA's Highway Performance Monitoring System, and other supplemental data sources covering most of the roadways in the study States (FHWA 2023). Time series traces extracted from the NDS data can be linked to the RID by using GPS location.

Time Series Data

The research team extracted variables such as speed and lateral acceleration at 10-Hz (0.1-s intervals). The team extracted other variables such as GPS location at a lower resolution. The NDS data files report attributes at 0.1-s intervals. The team extracted GPS location so it could import the data into a geographic information system (GIS) program and overlay that GPS location data with the RID data and aerial imagery. The extracted data are referred to as "time series data." The team linked video and time series data by using time stamps. Raw data collected through the data acquisition system were compiled into comma-separated-value (CSV) files by the subcontractor that archives the SHRP2 NDS data; the raw data could be converted to an Excel® worksheet or other database format.

Trip Density Maps

The subcontractor that archives the SHRP2 NDS data created trip density maps to show numbers of trips and numbers of drivers by roadway link. The subcontractor provided a geographic file that the research team could use to identify roadways with certain numbers of trips. The maps identified potential numbers of trips through an intersection of interest.

Google Earth

Some roadway variables used in the study were not available in the RID. In cases in which variables of interest such as the presence of overhead flashing beacons were not included, the variables were collected manually using Google Earth during the initial selection of intersections. The roadway variables were also noted or confirmed using the forward video.

IDENTIFICATION OF INTERSECTIONS

The team selected 65,404 rural intersections by using a query in the RID. Rural two-lane/two-lane and two-lane/four-lane intersections that were 800 m (2,625 ft) or more outside corporate boundaries were flagged and then overlain with trip density shapefiles created by the subcontractor that archives the SHRP2 NDS data. Trip density files provided number of individual trips and number of unique drivers on a particular roadway section. Locations were further filtered to those where at least 10 trips occurred at the intersection.

This process resulted in approximately 2,000 intersections in the six study States. The researchers viewed the set of locations by using either RID Videolog (InTrans, 2024) or Google Maps™. When possible, the team identified information about roadway geometry (i.e., number of lanes as well as the presence of countermeasures of interest) for each intersection. The team noted intersections with skewed approaches because skewed approaches represented an area of interest to the TAC. Next, the team reduced the list of intersections to try to obtain a balance of countermeasure types. The final set of intersections consisted of 195 T-intersections, 108 two-way stop-controlled intersections, and 46 all-way stop-controlled intersections.

The researchers gave the list of intersections to the subcontractor that archives the SHRP2 NDS data, and the subcontractor returned a summary of the total number of trips at each intersection that met certain criteria. The criteria were as follows:

- Presence of minor street movements, since drivers on minor streets are typically the ones who need to stop or yield at intersections.
- Availability of gas-pedal, brake-pedal, GPS, speed, and acceleration information for at least 90 percent of the time series trace.
- Balance of daytime versus nighttime trips.
- Maximum number of unique drivers.
- Balance of driver ages and genders.

The data request was for up to 10,000 traces and used the criteria specified next for each type of intersection.

The two-way stop and T-intersection request stipulated the following criteria:

- No traces for which the "Ages" variable was "null."
- If available, 10 traces from each driver, with a mixture of day and night trips.
- A mixture of traces, with the driver traveling from the minor approach to the minor or major approach by using the following movements:
    - Left turns.
    - Right turns.
    - Through movements.

The all-way stop-controlled intersection request stipulated the following criteria:

- No traces for which the "Ages" variable was "null."
- At intersections with fewer traces requested than available, the following criteria were used:

- Approximately two trips per driver (one day and one night if available).
- If fewer trips than drivers were requested, a mixture of trips from drivers in each age-group and gender was requested.

- A mixture of movements (left, right, and through) and approaches; if possible, one-third of traces for each intersection for each movement.

The subcontractor that archives the SHRP2 NDS data provided time series traces that included at least 600 m (1,969 ft) upstream and downstream of the intersection, forward video, and rearview video for each unique intersection trip. The time series data included vehicle dynamics such as speed and acceleration as well as other kinematic data, which were reported at 0.1-s intervals. GPS data were also provided once per second. Data were provided in a CSV file.

The research team received a total of 9,710 traces for 219 intersections. Table 2 summarizes the number of traces per intersection type and the number of intersections per type.

Table 2. Summary of data received.

Data Type	Two-Way Stop	Controlled T	All-Way Stop	Grand Total
Traces	2,068	1,716	5,926	9,710
Intersections	71	101	47	219

The research team requested traces only for intersection approaches that had stop signs. For instance, only time series traces for the two stop-controlled approaches at rural two-way stop-controlled intersections, time series traces for the single stop-controlled approach at T-intersections, and time series traces for all approaches at all-way stop-controlled intersections were reduced.

The selected intersections included a variety of countermeasures such as overhead flashing beacons, double stop signs, on-pavement signing, advance warning signage for intersection ahead and stop sign ahead, and various enhancements to those warning signs. Only a few intersections could be identified that had transverse rumble strips or intersection conflict warning systems.

DATA REDUCTION

The team reduced a set of events by using the time series data. One event or time series trace included one trip through one intersection.

Intersection Characteristics

Each intersection was given a unique identification (ID), and the team extracted intersection characteristics from several sources for each minor approach. Some information, such as number of lanes, was available in the RID for a subset of intersections. The team also consulted Google Earth to determine intersection characteristics. Finally, the forward roadway view confirmed the presence of intersection characteristics at the time of data collection.

The research team collected data for the intersection as a whole. The data consisted of number of approaches, stop control, skew angle (see figure 14 for an example), and presence of any intersection-wide countermeasures such as lighting or overhead flashing beacons.

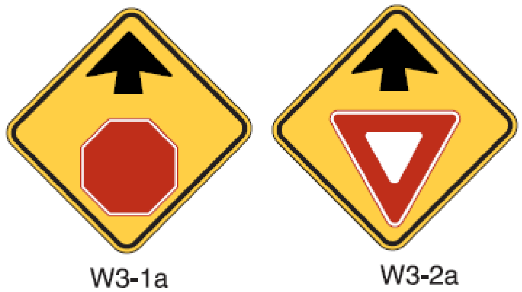
The team also extracted data for each individual approach. These data consisted of information on number of lanes, lane width, channelization, speed limit, presence of medians, and type of shoulder. Advisory speed limit was also collected; however, none of the advisory speeds were related to the intersections; the speeds were instead posted due to the presence of curves. The team coded the following types of countermeasures:

- Stop sign beacons.
- Double stop signs.
- On-pavement signing.
- Advance intersection warning signs.
- Intersection warning signs.
- Double advance intersection warning signs (typically one in the regular position to the driver's right and one placed in the center of the approach).
- Stop bars.
- Transverse rumble strips.
- Intersection conflict warning systems.
- Stop and advance warning sign enhancements (such as stop sign flags and reflective post treatments).

Examples of several of these countermeasures are shown in figure 9 through figure 15.

Figure 9. Photo. Post-mounted stop sign beacon.

Figure 10. Photo. Transverse rumble strips.



Source: FHWA.

Figure 11. Illustration. Examples of advance intersection warning signs (FHWA 2009a).

Figure 12. Photo. Stop sign reflective post treatment.

Figure 13. Photo. Overhead flashing beacon.

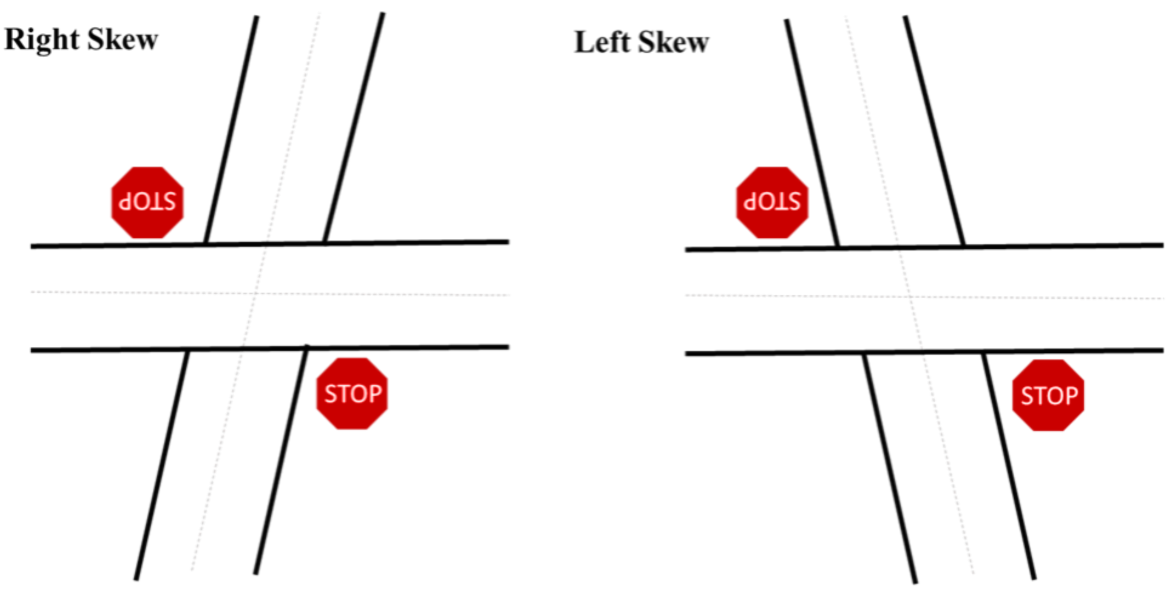
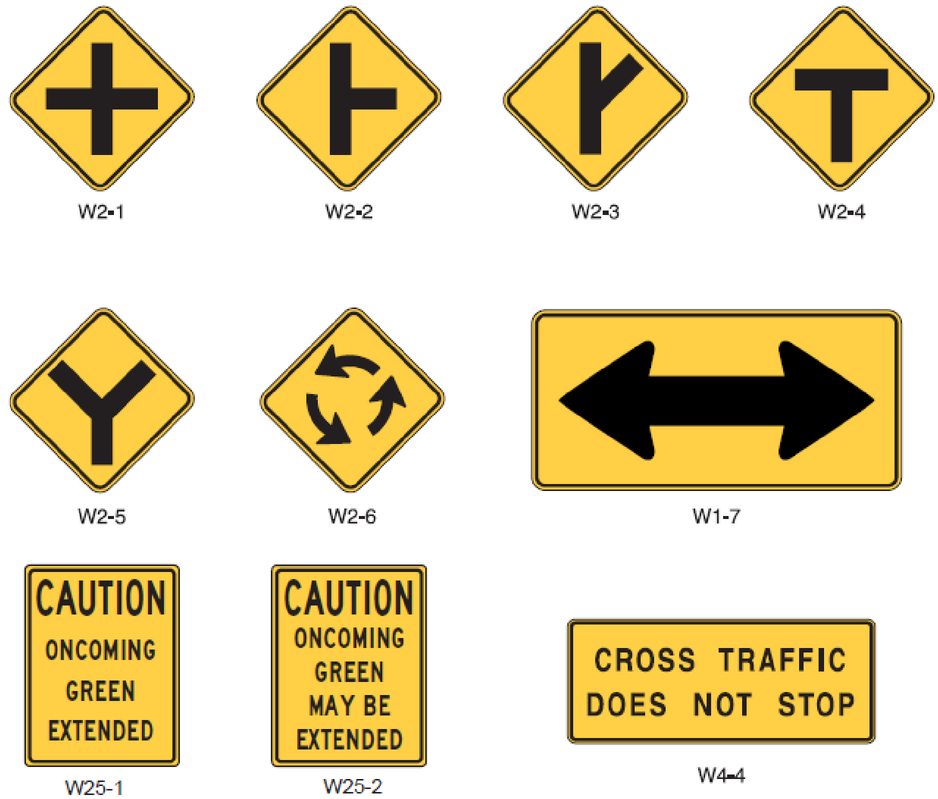


Figure 14. Diagram. Examples of intersection skew.



Source: FHWA.

Figure 15. Illustration. Examples of intersection warning signs (FHWA 2009a).

Locating Intersection Features Within Time Series Data

The team manually coded for each time series trace both the location of the stop sign and the location of the stop bar at each intersection. The team decided to code both features to provide a standard location (distance from stop sign) for use in the reaction point model and to ensure that a driver's stopping behavior was captured, given that drivers may stop at either the stop sign location or the stop bar. The time stamp associated with the driver's arrival at the stop sign was first extracted. Additionally, the location of the stop bar (if present) was coded. If a stop bar was not present, the approximate position where one would have been placed was determined, and the time stamp for that location was extracted.

Once the team found the time stamps for the two locations, the team defined the intersection location within the time series data. Next, the team used speed and time to calculate the driver's distance from the intersection at any point within the trace. To standardize the data for analysis, the team reduced each time series trace to include only 600 m (1,969 ft) upstream of the intersection and 5 m (16 ft) downstream. For instance, if a vehicle approached the intersection on the west approach and turned onto the north approach, the 600 m (1,969 ft) just prior to the intersection on the north approach and a 5-m (16 ft) section just downstream of the intersection on the north approach were coded. The team noted the location of the stop bar (or approximate location if not present) and the location of the stop sign within the time series traces. As a result, a particular analysis could use the distance upstream of the stop bar or stop sign as needed.

Identifying Stopping and Speed Characteristics

Once the team had updated these time series traces with the driver's distance from the intersection, the minimum speed within 5 m (16 ft) of the stop bar or stop sign was noted for each time series trace to determine stopping behavior. The team coded type of stop by using the following definitions:

- Full stop: Speed was reduced to approximately 0 m/s (0 mph).
- Rolling stop: Clear braking was noted, and vehicle speed was greater than 0 m/s (0 mph) but less than approximately 2.24 m/s (5 mph).
- Nonstop: Vehicle speed was greater than approximately 2.24 m/s (5 mph).

Additionally, the team found the maximum upstream speed for each time series trace for each event, which was the maximum speed within the 600 m (1,969 ft) upstream of the approach stop sign or stop bar. The information determined whether a driver was speeding upstream of the intersection.

Environmental Characteristics

The team collected data on various environmental characteristics for each trace by using the forward video. The data included time of day (i.e., day, dawn or dusk, or night) and weather conditions. The team determined time of day to be dawn or dusk when it was not fully dark but streetlights or vehicles' headlights were on. Weather conditions were coded as "clear," "raining," or "snowing." Any traces of active snowing or snow on the roadway were removed from the analyses.

The team also extracted from the forward video additional variables related to the driving environment that may have affected or elucidated driver behavior: confirmation of a driver's movement at the intersection (left/right/through), whether a driver was following another vehicle, presence of a queue at an intersection, and presence of drivers on a major approach or other stop-controlled approach(es).

The team categorized drivers' following behaviors into three groups: closely following, following, and not following. The coding criteria the team used were:

- Closely following: A vehicle ahead of the subject driver that was close enough to affect the behavior of the subject driver (headway of approximately 3 s or less).
- Following: A vehicle ahead of the subject driver that did not affect the subject driver's behavior (headway greater than 3 s).
- Not following: No vehicle present ahead of the subject driver.

The team removed from the reaction point analysis any traces where a subject driver was closely following another vehicle, since such behavior would have affected driver behavior. The team coded following behavior was coded only upstream of the intersection because the team assumed that following behavior would affect mainly reaction behavior. Therefore, if the subject driver caught up to another vehicle and was following closely within 50 m (164 ft) of the intersection, the scene was not coded as closely following and was still included in the reaction analysis.

The team coded presence of a queue at an intersection so that traces where a queue was present could be removed from the stopping analysis so as to capture the behavior of drivers who were able to act freely without being affected by the behavior of a car or cars ahead. The queue variable was a binary yes or no. A queue was considered to be present if the subject driver arrived at the intersection and had to significantly slow down upstream of the stop sign or stop bar due to the presence of another vehicle ahead. Therefore, even if the vehicle ahead of the subject driver pulled away before the subject driver reached the stop sign, if the vehicle was close enough that the subject driver slowed down significantly, then a queue was coded as being present.

Finally, the team also coded the presence of vehicles on the conflicting stop-controlled approach or approaches or the presence of vehicles on the mainline. Both of those situations were coded using a single binary yes or no variable. The variable was coded yes if at least one vehicle passed on the mainline or if a vehicle was present at any time on any of the other stop-controlled approaches from the time the subject driver was three seconds upstream of the intersection until the driver entered the intersection. If no cars were present during this time frame on either the mainline or other approaches, then that variable was coded no.

Driver Characteristics

A number of static driver variables were available in the data provided by the subcontractor that archives the SHRP2 NDS data. The variables were a unique ID for each driver and such characteristics as age, gender, number of years driving, and age at which the driver received a driver's license. In some cases, the driver's age was not given, but the number of years driving and age at which the driver received a driver's license were listed. In those cases, the latter characteristics approximated the age of the driver when the trip occurred. Additionally, for most drivers, the number of moving-violation citations they had received and the number of crashes they had experienced were also provided.

Initially, the team reduced kinematic driver data (i.e., glance locations and distractions) for a subset of the data manually. Because the reduction had to be done manually at a secure enclave in Blacksburg, VA, that was operated by the subcontractor that archives the SHRP2 NDS data, the exercise became resource intensive. The team worked with the subcontractor, whose team reduced further data by using the coding criteria the research team had developed. Glance and distraction data were reduced for a distance of 600 m (1,969 ft) upstream of a stop sign and approximately 5 m (16 ft) downstream of a stop sign. Those distances were chosen because they included data from outside the suspected reaction distance as well as data through the intersection.

The team reduced kinematic data by using a tool by the subcontractor that archives the SHRP2 NDS data had developed. The tool enabled an analyst to code glance location and distractions while observing the various camera views simultaneously. The team determined driver attention by way of the location on which the driver had focused during each sampling interval. Because eye tracking is not possible with NDS data, the team used glance location as a proxy.

Figure 16 shows the practical areas of glance locations for manual eye glance data reduction.

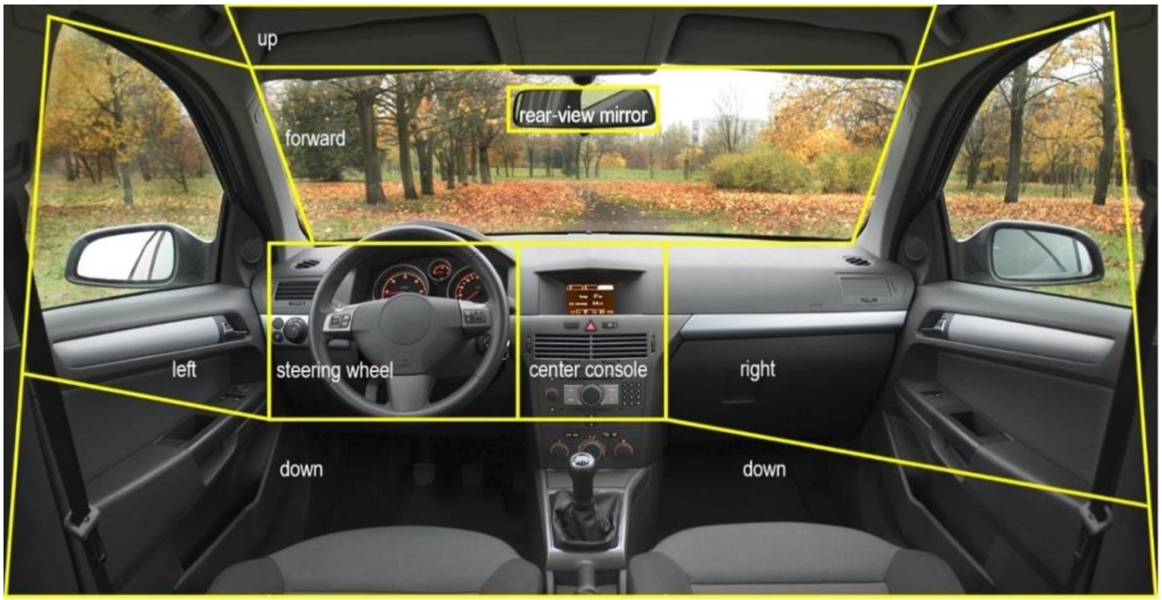


Figure 16. Photo. Glance locations.

Figure 16 does not show "over-the-shoulder," "missing," or "other" eye glance locations. "Missing" was used when a driver's face was obscured due to glare or when a glance location could not be determined. The team established glance locations based on previous work the team had conducted and coded using the camera view of the driver's face, with a focus on eye movements but taking into consideration head tilt when necessary.

The research team discussed with the subcontractor that archives the SHRP2 NDS data how to categorize forward glances into forward, left, and right categories and how to further classify left and right glances as far left or far right. However, due to accuracy issues with that type of coding, the team decided to continue using the previously established definitions of left and right. The definitions of scanning glances are as follows:

- Left glance: Any gazes to the left of the A-pillar were coded as "left," whether the driver was looking at the left mirror or out the driver-side window.
- Right glance: Any gazes that involved both eye movement and head movement to the right were coded as "right," whether the driver was looking at the right mirror, the glove box, the front-seated passenger, or out the passenger-side window.

The team determined potential distractions by examining both the view of the driver's face and the view over the driver's right shoulder, which showed whether the driver's hands were on or off the steering wheel. The team identified distractions when a driver looked away from the forward roadway. Potential distractions included the following:

- Route planning (locating, viewing, or operating).
- Moving object or dropped object in vehicle.
- Cell phone (locating, viewing, operating).
- Portable media player (locating, viewing, operating).
- Personal hygiene.
- Passenger.
- Animal or insect in vehicle.
- In-vehicle controls.
- Drinking or eating.
- Smoking.

The team coded glance location and distractions for each trace. The data reductionist indicated each time the glance location changed, and the data reduction tool recorded the time stamp. The start and end times for distractions were also recorded.

Ultimately, the team reduced glance and distraction data for 922 traces, which was a subset of the time series traces initially reduced. The limitation was due to resource constraints. At least three traces per intersection were requested when available. When possible, the traces for each intersection included at least one full stop, one rolling stop, and one no stop. The team also requested a wide sample of drivers. At some intersections that had large numbers of traces, additional traces were included in the glance and distraction data reduction. In those cases, the team included traces with wide differences in reaction points to try to determine whether glance location or distractions played roles.

The data, once received, were summarized for use in the braking and stopping models. The team grouped glance locations into the following categories:

- Forward: Forward glances.

- Scanning: Left and right glances not associated with a distraction.

- Situational awareness: Left, right, steering wheel, and rearview-mirror glances not associated with a distraction.

- Non-roadway: Up, down, center console, over-the-shoulder, other, and missing glances, as well as any glance associated with a distraction.

The team then summarized the data into 50-m segments upstream of the intersection. For each segment, the team calculated the percentage of time a driver spent on each of the four glance categories, along with the percentage of time the driver engaged in any distraction. The team made an initial attempt to treat cell phone distraction separately. However, the observed number of cell phone–related tasks was small. Additionally, only 34 of the 922 time series traces involved a distraction, and within the 300 m (984 ft) upstream of the intersection, the number reduced to only 23 traces. For each segment, the team also recorded total time spent on each of the glance and distraction categories so that the data could be aggregated together more easily.

In addition to reducing the kinematic driver factors for the 922 time series traces, the subcontractor that archives the SHRP2 NDS data also coded 214 baseline traces for crash and near-crash events. A similar protocol was followed, but data were reduced for only five seconds upstream and one second downstream of the intersection. Data reduction for the crash and near-crash baseline traces also included information about number of hands on the steering wheel and whether the driver's seatbelt was worn properly.

SUMMARY OF DATA AVAILABLE FOR ANALYSIS

Once the data reduction was completed and each trace manually reviewed, the team reduced the number of traces available for analysis to 7,470. The team removed traces for a variety of reasons:

- The trace did not go through the intersection.
- The video was black.
- Snow was on the roadway surface or it was actively snowing.
- A work zone or maintenance work was present.
- A traffic signal became installed at the intersection during the study.
- The driver was coded as closely following, or a queue was present at the intersection.

Table 3 summarizes the number of traces ultimately available by intersection type and movement. The number in parentheses for each set of traces is the number of traces available with kinematic driver data.

Table 3. Intersection trace summary.

Data Type	Two-Way Stop	Controlled T	All-Way Stop	Grand Total
Left	268 (78)	490 (86)	1,483 (58)	2,241(222)
Right	46 (125)	854 (147)	591 (244)	1,906 (316)
Through	45 (124)	0 (0)	2,866 (260)	3,323 (384)
Total	1,186 (327)	1,344 (233)	4,940 (362)	7,470 (922)
Number of intersections	62 (61)	90 (74)	47 (43)	199 (178)

Any further data removal that was necessary for each analysis is described in the corresponding chapter for that analysis.

CHAPTER 4. ANALYSIS OF DRIVER REACTION POINT

The objective of this analysis was to assess where drivers began reacting to an upcoming intersection. The assessment was used as a surrogate for driver awareness of the intersection. The research team assumed that drivers who reacted sooner to an upcoming intersection were more prepared to stop. The team used change in speed and acceleration to assess reaction point, as described in the following sections.

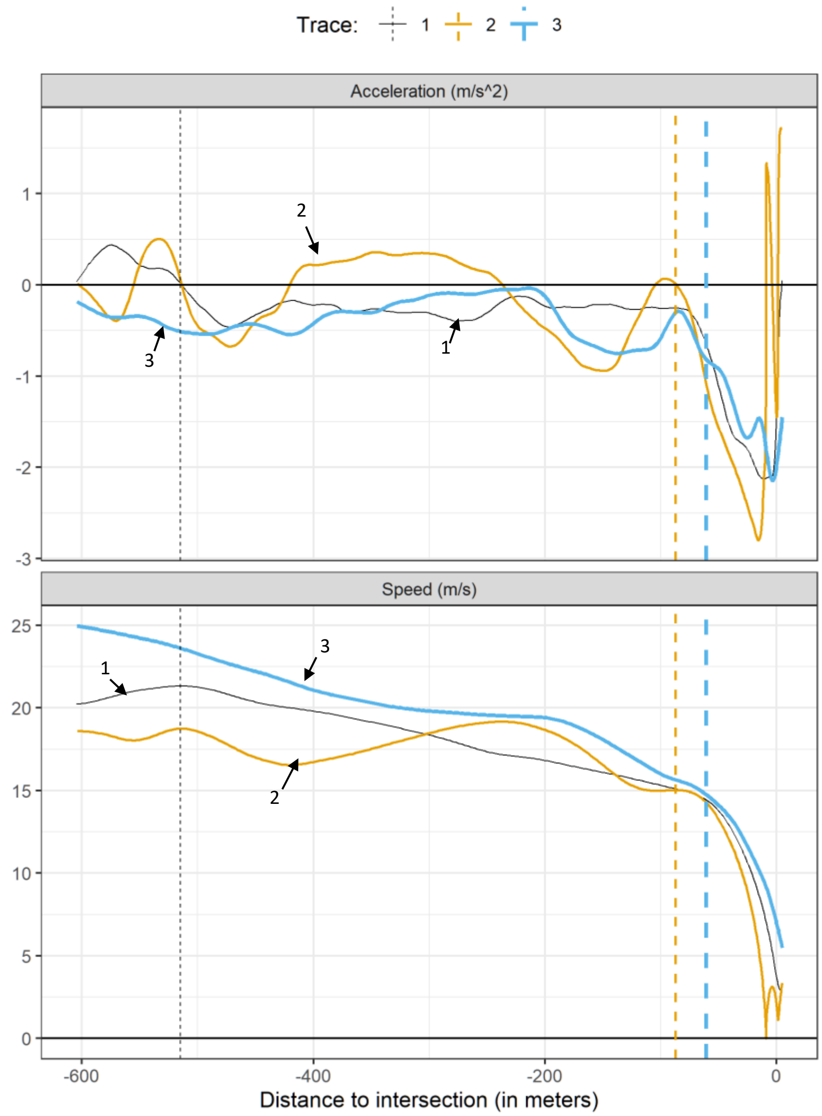
DATA USED

Some of the time series traces the team reduced as described in chapter 3 could not be included in the reaction point analysis. The team removed intersections where unusual features would have been likely to affect reaction point. Unusual features included significant downhill grades and railroad crossings. Additionally, the team removed time series traces in which the subject vehicle was coded as closely following another vehicle (i.e., a lead vehicle present with a headway of less than 3 s). The team effected such a removal because of feeling that the lead vehicle may have influenced the subject vehicle, making it difficult to isolate other factors affecting reaction point.

The team developed models to identify reaction point. Since kinematic driver characteristics (i.e., glance location or distraction) were not available for all traces, the team created two different models. One model included all available time series traces (7,044) and one included only traces with kinematic driver characteristics (896). Data were from all types of intersections (i.e., T-intersections, two-way stops, and all-way stops), since the type of traffic control downstream would not have been relevant to driver behavior upstream.

IDENTIFICATION OF REACTION POINT

Reaction point was defined as marked deceleration or application of brakes upstream of the intersection. Some amount of noise is present in the data, resulting in variations in speed and acceleration. Additionally, drivers may slow upstream of the intersection in response to other stimuli. Figure 17 gives an example of speed and acceleration patterns along an intersection approach.



Note: Dashed vertical lines indicate the corresponding reaction points.

Figure 17. Graph. Sample traces at an intersection approach showing speed and acceleration patterns.

To determine a response point to the intersection, the team considered various methodologies. First, the team considered brake application. However, in most cases, drivers have no reason to brake significantly in advance of an intersection. Several researchers have used changes in speed, acceleration, or deceleration. As a result, the team selected change in speed as the surrogate variable for reaction to intersection. Next, the team sought a threshold for the amount of speed decrease needed to distinguish a reaction from normal fluctuations in the data. Several researchers have used a speed reduction of 3.2–11.2 kph (2–7 mph) as a threshold to detect a response to work zone signs (Meyer 2003; Sorrell et al. 2007; Finley 2008; Benekohal et al.

2010; Edara, Sun, and Hou, 2013; Finley, Jenkins, and McAvoy 2014). However, no information was available on a threshold for detecting a response to an intersection.

After reviewing the data, the team decided to define the reaction point as the last positive acceleration closest to the intersection followed by a deceleration. An additional condition required the speed at the identified point to be greater than or equal to 6.71 m/s (15 mph) to avoid the inclusion of vehicles that were stopping and starting due to a queue at the approach stop bar. It is possible that drivers might slow upstream in response to an advance intersection sign or other intersection-related characteristics and then resume or even increase their speed until they reach the actual intersection. Because it is not otherwise possible to separate those reactions from normal speed fluctuations, the aforementioned criteria were used.

Figure 17 illustrates three speed and acceleration traces at an intersection approach as well as some fluctuations that occur along the upstream approach (150–600 m (492–1,969 ft)); but a noticeable change occurs just before the intersection (approximately 100–150 m (328–492 ft)). Further, the green trace illustrates the need for the speed threshold. This driver decelerated within 10 m (33 ft) of the intersection, but the fact that the reaction point occurred before the deceleration is clear.

In about 1 in 7 traces (1,180 out of 7,295), the driver did not accelerate or the driver decelerated for most of the trace (at least 90 percent of the time captured by the trace). In such cases, the acceleration or speed approach to find the reaction point does not apply because the last positive acceleration before the intersection cannot be found or does not represent the reaction point. Under such scenarios, the speed is practically monotonic, and therefore the team used a structural linear change model to determine reaction point. The “segmented()” function in *R* (Wikipedia, 2024) was used for this model (Muggeo 2003). Trace 3 in figure 17 represents a case in which the driver decelerated for most of the trace. That driver would not have been observed to react under the first set of reaction point criteria (i.e., the last positive acceleration closest to the intersection followed by a deceleration), since the speed constantly decreases. Several *R* packages from the package bundle “tidyverse” (version 1.2.1) were used extensively to manipulate the data and generate plots.

The team estimated reaction point for each time series trace and included the estimate in the analysis. Figure 18 shows a density plot of the estimated reaction points.

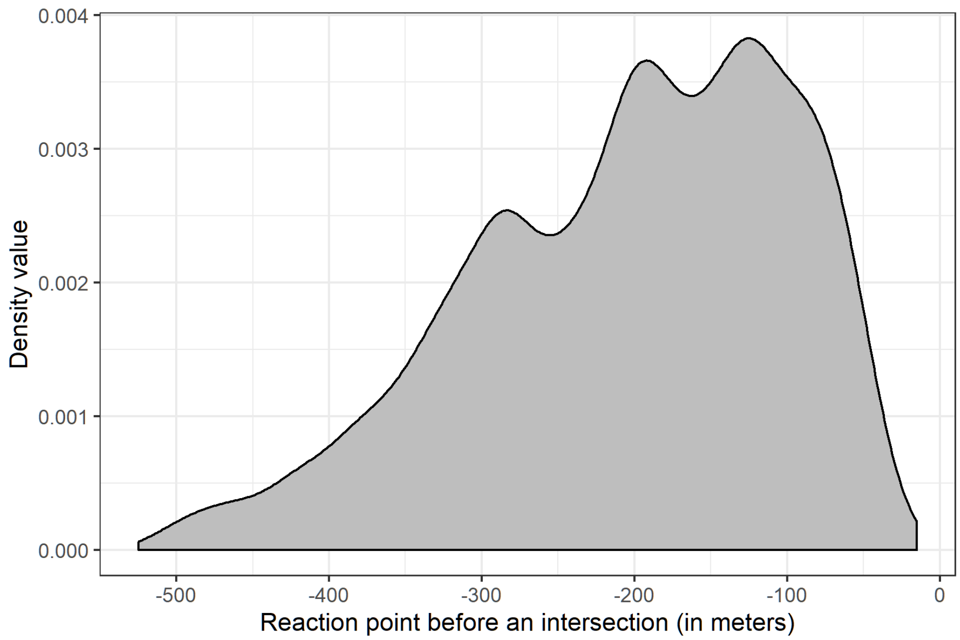


Figure 18. Graph. Density plot of estimated reaction points.

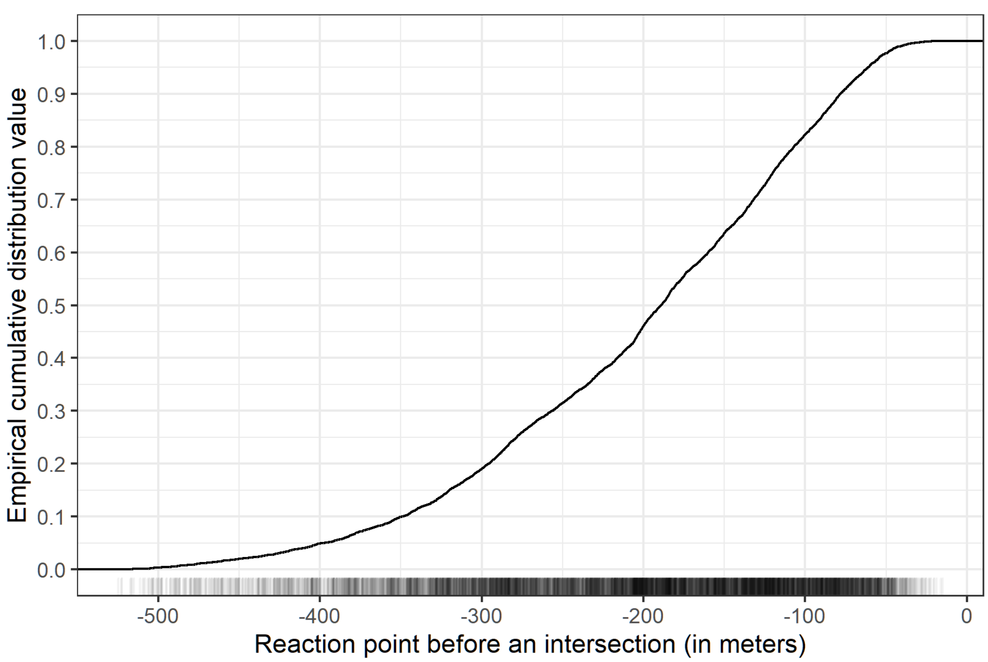


Figure 19. Graph. Cumulative distribution of reaction points.

The research team used a typical kernel density estimator to determine reaction points at the study intersections. Several intersections have many traces, which can produce a multimodal density. As figure 18 shows, the average reaction point was 62 m (203 ft) from the location of the corresponding stop sign.

Figure 19 shows the cumulative distribution of the reaction points. Figure 19 can help determine the reaction point of various percentiles.

Figure 20 through figure 22 illustrate deceleration characteristics of drivers between their reaction points and the locations of the stop signs. Figure 20 includes the cumulative distribution plots of the maximum deceleration value, the 85th-percentile deceleration value, and 50th-percentile deceleration value for each trace. The $x = 3.414$ m/s^2 (7.637 mph/s) line corresponds to the deceleration value that the American Association of State Highway and Transportation Officials (AASHTO) uses. The 90th percentile seen for maximum deceleration of traces was slightly greater than 5 m/s^2 (16.4 ft/s^2), which was a greater amount than AASHTO recommends (AASHTO 2011); however, both the 85th- and 50th-percentile decelerations were less than that.

Figure 21 shows that the majority of the maximum decelerations seen were near the intersection—especially maximum decelerations that were greater than the 3.414 m/s^2. Figure 22 illustrates the average deceleration of a driver between the reaction point and the stop sign corresponding to the point at which the driver reacted. All but two of the traces' average deceleration were below the 3.414 m/s^2 (7.637 mph/s) that AASHTO uses in stopping-sight-distance-deceleration equations. Overall, as expected, the closer to the intersection a driver reacts, the greater the driver's average deceleration was.

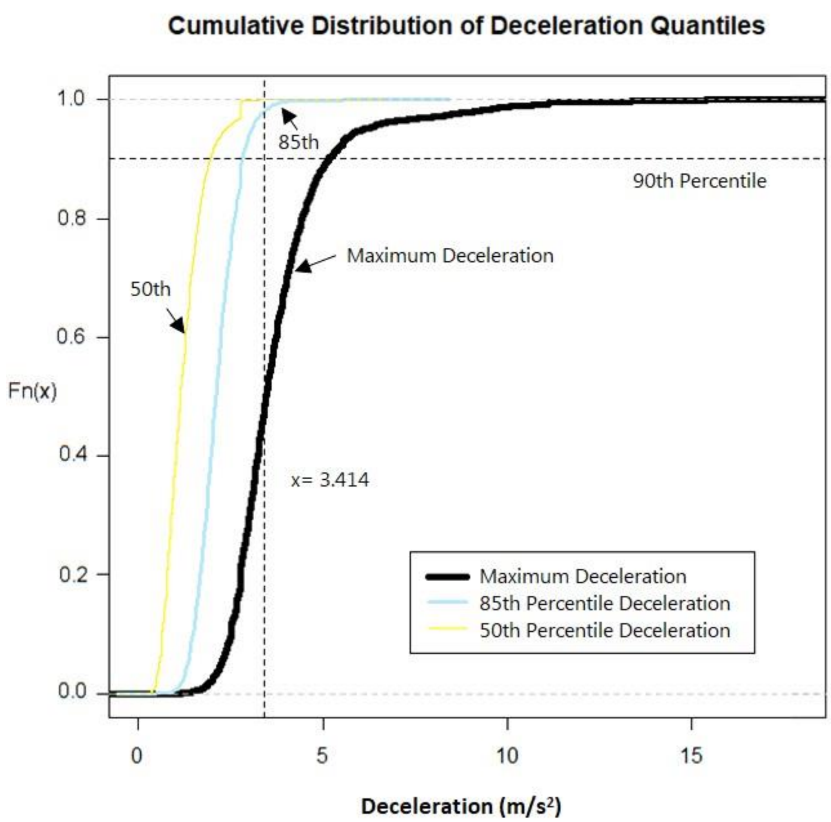


Figure 20. Graph. Cumulative distribution of decelerations.

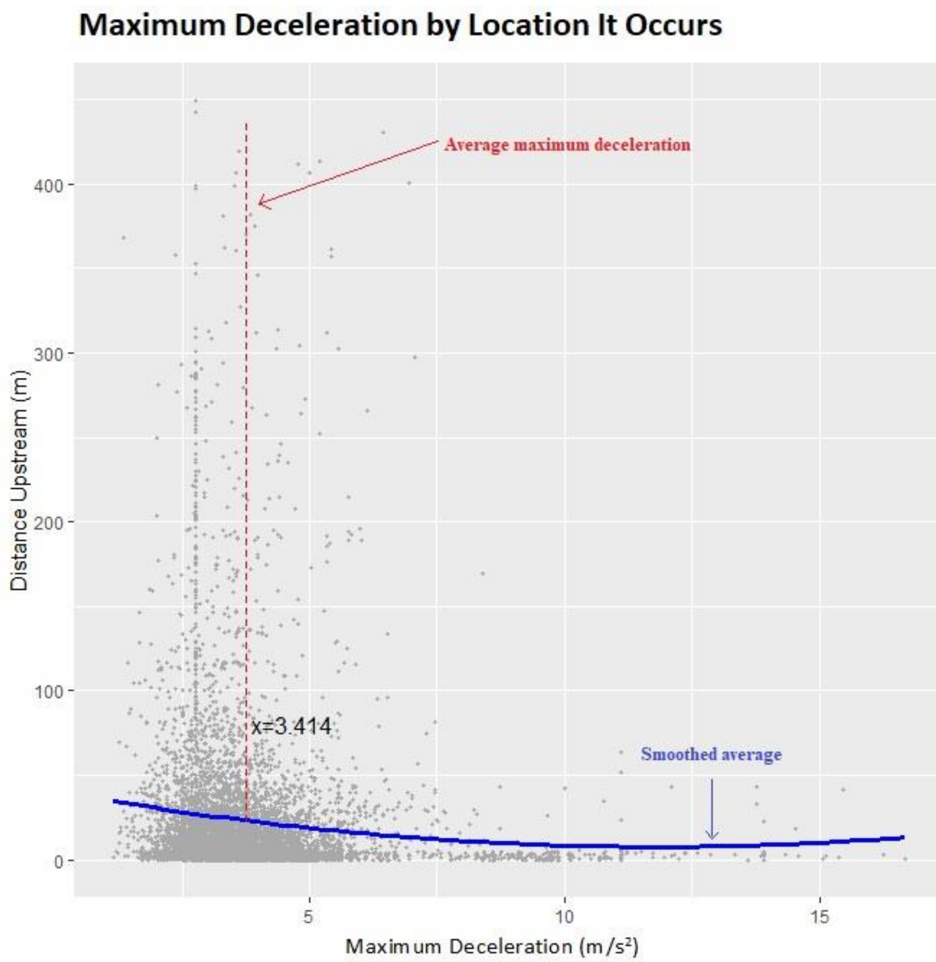


Figure 21. Graph. Plot of maximum deceleration per trace and the location where it occurs.

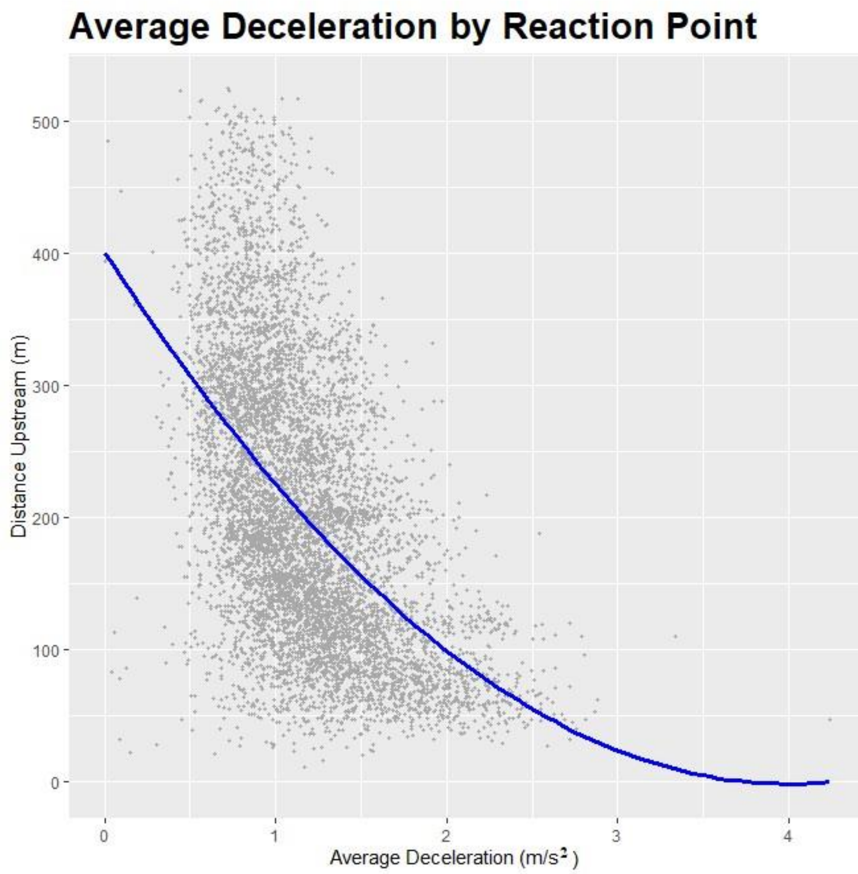


Figure 22. Graph. Plot of average deceleration per trace and the estimated reaction point.

MODEL DESCRIPTION FOR INTERSECTION REACTION POINT

The reaction point is expressed as the distance in kilometers to an intersection. Therefore, all reaction point values used in the model are positive. The team used an LME model for analyzing reaction point. An LME model is similar to a regular linear regression, but it allows certain dependencies among observations. Such dependencies are introduced in the form of additive terms, which are called "random effects." The rest of the terms are known as "fixed effects" or "main effects," and they are interpreted the same as in ordinary linear regression. For this analysis, the team considered three random effects: intersection, intersection approach, and driver, since, for example, the team could expect that the reaction point found in traces from the same driver would be correlated.

An alternative to the LME model is a generalized LME (GLME) model with gamma response, which is intended for strictly positive values, as is the case with reaction point. The research team estimated GLME models for reaction point and compared them with the LME models, which yielded similar results. The team preferred LME models to favor simplicity in interpretation and computation.

The team conducted data processing in *R* and produced plots by using *R* package ggplot2. The LME and GLME models were fitted with *R* package lme4. The team assessed the models by using residual plots and residual analyses and tested the significance of the random effects by using a full-versus-reduced *F*-test.

The data set of all traces without glance location and distraction coded consisted of 50 potential covariates. Even more variables were added for the subset of traces with glance location and distraction coded.

The team conducted preselection of the variables by using an importance ranking produced with a random forest. A random forest is a machine-learning regression technique based on classification trees used in both classification and regression problems. Though the random forest method focuses on prediction rather than on explanation of the underlying mechanism, the method produces rankings of the most important variables. The team fitted a random forest to the traces by using *R* package randomForest.

Once the ranking was produced, the top 25 variables were used as starting variables for the LME model. Then, a final selection was achieved using backward regression—that is, by eliminating variables one by one via a full-versus-reduced *F*-test and/or looking at the Akaike information criterion (AIC). The AIC is an index of a model's complexity that enables the comparison of two nested models.

RESULTS FOR INTERSECTION REACTION POINT

The research team developed an initial model that used only time series traces in which kinematic driver characteristics were present. However, none of the kinematic variables were found to be significant. Additionally, estimates for other variables were similar to those obtained using all-time series traces. As a result, the team developed a final model that did not include those variables and as a result included all viable 7,044 time series traces.

Table 4 presents the analysis of variance (ANOVA) results of the main effects of the model. The State in which the intersection was located is mildly significant. The team used a second-order polynomial for maximum upstream speed, represented as "poly(MaxSpeed, 2, raw = TRUE)"; and speed limit was scaled (the variable's mean was subtracted from each value and the result was divided by the variable's standard deviation).

Table 4. ANOVA results of fixed effects of the LME model for intersection reaction point.

Variable	Chi-Square Value	Degrees of Freedom	*Pr* (>Chi-Square)
Poly(MaxSpeed, 2, raw = true)	32.963	2	6.953e-08
Scale(SpeedLimit)	8.465	1	3.621e-03
State	10.429	5	6.396e-02
Skewed	6.924	2	3.136e-02
OnPavement	10.484	3	1.487e-02
Time of day	6.112	2	4.706e-02
Approaches	4.210	1	4.019e-02
Movement	7.122	2	2.842e-02

Table 5 presents the main effects of the model. For all the continuous variables except maximum upstream speed, the interpretation of estimates of the effects follows the typical process for models of this type: the expected change in the reaction point is noted when the variable in question increases by one unit.

Table 5. Fixed effects of the LME model for intersection reaction point.

Variable	Estimate	Standard Error	*t*-Value	Base Level
(Intercept)	−45.782	56.100	−0.816	N/A
Poly(MaxSpeed, 2, raw = true)1	17.878	3.589	4.982	N/A
Poly(MaxSpeed, 2, raw = true)2	−0.372	0.081	−4.573	N/A
Scale(SpeedLimit)	11.152	3.833	2.909	N/A
StateIN	−38.276	15.799	−2.423	Florida
StateNC	−23.865	17.217	−1.386	Florida
StateNY	−30.687	17.138	−1.791	Florida
StatePA	−51.738	19.840	−2.608	Florida
StateWA	−19.473	19.126	−1.018	Florida
Skewed (No skew)	−17.081	9.057	−1.886	Left
Skewed (Right)	3.600	9.178	0.392	Left
OnPavement (Type: Stop)	−64.036	24.988	−2.563	No
OnPavement (Type: Stop Ahead)	−38.408	22.031	−1.743	No
OnPavement (Type: Stop Ahead and Stop)	18.698	25.969	0.720	No
Time of day (Day)	7.481	4.925	1.519	Dawn/dusk
Time of day (Night)	0.547	5.517	0.099	Dawn/dusk
Approaches (Number of intersection approaches)	18.656	9.093	2.052	N/A
Movement (Right turn)	5.469	5.684	0.962	Left
Movement (Through)	−7.580	5.115	−1.482	Left

N/A = not applicable.

In the case of the categorical variables, a base level is specified in the last column. In those cases, the estimate represents the expected difference in reaction point between that level and the base level. For example, according to this model, drivers in Indiana reacted 0.038 km (38 m (125 ft)) sooner than drivers in Florida (the base level) did under the same conditions. Similarly, drivers in North Carolina reacted on average 23 m (75 ft) sooner, drivers in New York reacted 31 m (102 ft) sooner, drivers in Pennsylvania reacted 51 m (167 ft) sooner, and drivers in Washington reacted 19 m (62 ft) sooner. That finding suggests some differences between drivers in each State. Additionally, the finding may imply that intersections within individual States are more similar to one another than they are to intersections in other States—a situation that the model could not detect.

When no skew was present compared with when an intersection was skewed left from the perspective of the driver, the resulting reaction was 17 m (56 ft) sooner. Similarly, when an intersection was skewed right, drivers reacted 36 m (118 ft) later than when the intersection was skewed left. That finding was unexpected because in most cases, drivers reacted well before arriving at the intersection.

When on-pavement signing was present, drivers reacted sooner than when no on-pavement signing was present. On-pavement stop signs resulted in reactions 64 m (210 ft) sooner, and on pavement stop ahead signs resulted in reactions 38 m (125 ft) sooner.

Time of day, too, had an impact on reaction point. During the day, drivers reacted 75 m (246 ft) later than at dawn or dusk, and at night, drivers reacted 55 m (180 ft) later. A driver who turned right reacted 55 m (180 ft) later than a driver turning left, and a driver who went through the intersection reacted 76 m (256 ft) sooner than did a driver turning right.

Next, the team considered a second-order polynomial for maximum upstream speed (in m/s). Figure 23 shows the expected reaction point in meters depending on maximum speed within 600 m (1,969 ft) of intersection stop sign location.

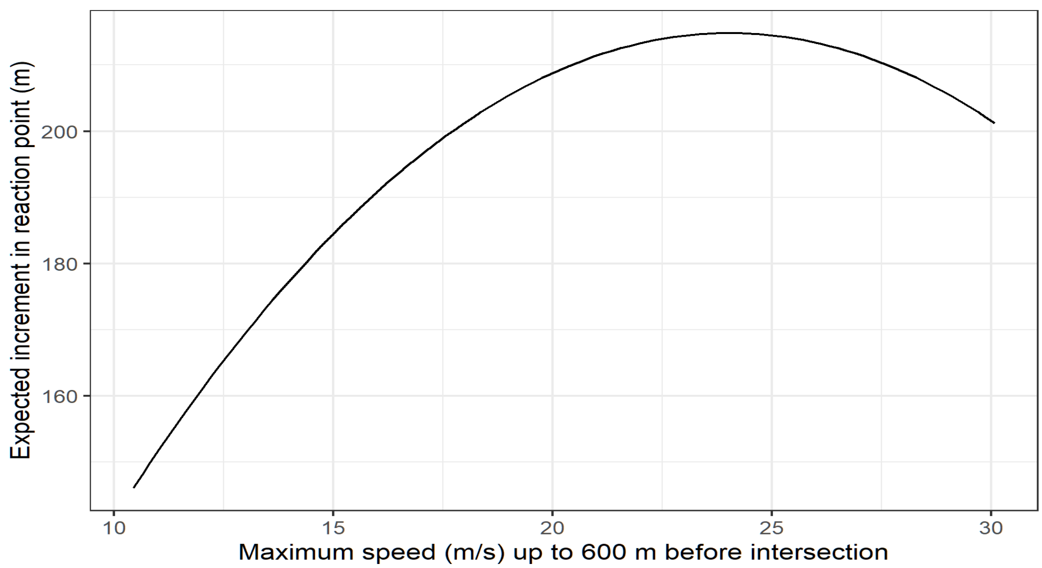


Figure 23. Graph. Effect of maximum upstream speed on reaction point.

The random effects are presented in table 6. As can be observed in the table, most of the random variability comes from the residual variation. However, full-versus-reduced tests were conducted to justify the presence of the other three random effects.

Table 6. Random effects of the LME model for intersection reaction point.

Random Effect	Standard Deviation Estimate
Driver ID	0.026
Approach ID	0.037
Intersection ID	0.019
Residual	0.087

DISCUSSION

The objective of this analysis was to assess where drivers began reacting to an upcoming intersection. The research team used the assessment as a surrogate for driver awareness of the intersection and assumed that drivers who reacted sooner to an upcoming intersection were more prepared to stop. The team used changes in speed and acceleration to assess reaction point, as described in this section.

After reviewing the data, the team decided to define reaction point as the last positive acceleration closest to the intersection followed by a deceleration. An additional condition required the speed at the identified point to be greater than or equal to 6.7 m/s (15 mph) to avoid the inclusion of vehicles that were stopping and starting due to a queue at the approach stop bar.

The team conducted a random forest analysis to determine the most relevant variables and then used an LME model to assess where drivers began reacting to the intersection. The team developed two separate LME models. One model included all traces, and one included the subset of traces in which kinematic driver behaviors were reduced.

The most important variable in all cases, according to the random forest analysis, was maximum upstream speed, which was consistent with both the model for reaction point that includes all traces and the model that includes the subset of the traces with kinematic driver characteristics. The claim makes sense because a driver's speed has a direct impact on stopping distance.

Additionally, the model was able to determine the effect of the posted speed limit on the reaction point. An agency could potentially use this model to determine average reaction distance for posted speed limit and use that value to determine placements of countermeasures to alert drivers of an upcoming intersection. In this way, countermeasures could be placed so as to alert drivers who are reacting late.

The model did find a slight variation in reaction point across the six NDS States, which may have been due to differences in driving behavior between the States or, as stated earlier, due to the possibility that intersections within individual States are more similar to one another than they are to intersections in other States—a situation that the model could not detect.

The model found that the presence of on-pavement signing appeared to result in drivers' braking sooner than when such signing was not present—except for when both stop ahead and stop signs were used at the same intersection. Only two intersections, with the majority of traces coming from one of the intersections, had a combination of stop ahead and stop signing, so the model may be identifying a latent factor related to that one intersection. The use of on-pavement signing, however, does show promise in drawing drivers' attention to an upcoming intersection, resulting in drivers' reacting to the intersection sooner.

Unfortunately, the team could not develop a satisfactory model that would incorporate kinematic driver factors. The team considered several models that included kinematic driver characteristics. The distraction (yes/no) and distraction by cell phone (yes/no) variables were considered stand-alone variables. Another variable—glance location (forward/scanning/non-roadway/situational awareness), was defined in terms of glance location and distraction in an effort to reduce the number of categories. Ultimately, however, the team did not identify those characteristics as significant in any of the models that were developed and run. A challenge in the modeling of glance location and distraction is that kinematic driver characteristics were available for only a relatively small subset of the traces (896), and for those traces for which data were available, drivers were looking forward more than 87.5 percent of the time.

CHAPTER 5. ANALYSIS OF STOPPING MODEL AT TWO-WAY STOP-CONTROLLED INTERSECTIONS

This chapter describes the analysis of stopping behavior at two-way stop-controlled intersections, which includes intersections with a major through approach and two minor stop-controlled approaches. In all cases, the minor stop-controlled approach had two lanes.

DATA USED

The research team reduced data as noted in chapter 3. The reduction included the coding of stopping behavior as either full stop, rolling stop, or no stop. The team modeled the likelihood of no stop versus a full or rolling stop at approaches for two-way stop-controlled intersections.

A total of 1,073 viable time series traces were available for two-way stop-controlled intersections. The traces comprised 128 unique drivers at 58 intersections. Kinematic driver variables were available for 288 of the time series traces, which represented 100 unique drivers at 54 unique intersections. The researchers developed two models to capitalize on all the available samples. The first model included all viable time series traces, and the second included only those for which kinematic driver variables had been reduced.

DESCRIPTION OF MODEL FOR ANALYSIS OF TWO-WAY STOP-CONTROLLED INTERSECTIONS

Ordered logit models, also known as "proportional odds models," were initially developed to assess the effect of driver, environmental, and roadway factors on the three types of stopping behavior. Listed in order from safest to least safe, the types were full stop, rolling stop, and no stop. The types were assumed to be of a discrete, ordinal nature classified on a three-point scale ranging from full stop to no stop. Consequently, the data are well suited for analysis using a proportional odds or ordered logit model. This model can be derived by defining a latent variable z, which can be specified as a linear function for each observation such that

$$z = \beta X + \varepsilon \tag{1}$$

Where:

X = the vector of variables determining the discrete ordering.
β = the vector of estimable parameters.
ε = a random disturbance term.

With the use of this equation, the observed safety level outcome y for each driver is defined as:

$y = 1$ if $z \leq \mu\_0$.
$y = 2$ if $\mu\_0 < z \leq \mu\_1$.
$y = 3$ if $\mu\_1 < z \leq \mu\_2$.
$y = \ldots$
$y = 1$ if $z \geq \mu\_(I{-}1)$

Where the estimable threshold parameters μ define y, which corresponds to integer ordering, and I is the highest integer-ordered response. The variable μ represents parameters that are jointly estimated using the model parameters β. If the error term is assumed to be distributed as standard normal across observations, an ordered probit model results. Setting the lower threshold $\mu\_0 = 0$ results in the outcome probabilities:

$$P(y = i) = \Phi(\mu\_i - \beta X) - \Phi(\mu\_(i + 1) - \beta X) \tag{2}$$

Where:

μ_i and $\mu\_(i + 1)$

represent the upper and lower thresholds, respectively, for response category i and where Φ(.) is the standard normal cumulative function. Estimation was done using standard maximum likelihood methods. Each variable was first examined individually and then simultaneously with other variables until the models providing the best balance of model fit and explanatory power were identified. AIC was used to assess model fit, and the "anova()" function in *R* was used to assess the significance of additional variables.

The "clmm()" function in the "ordinal" package of *R* was used to fit the models. The dependent variable was type of stop, with full stop < rolling stop < no stop. The variables for relevant interactions (e.g., overhead flashing beacons at night) were tested to determine whether they needed to be included in the model. Once the best fit models were found, the model assumptions were tested. The team found that the proportional odds ratio assumption was violated in both models, and therefore an ordinal model was not appropriate.

The data were then visualized through Andrews curves using the "andrews()" function in the "andrews" package of *R* to determine whether one type of stop differed greatly from the others. The researchers found that the no-stop data differed from the data for the two other stop types. Therefore, the team determined that the data could be modeled with the dependent variable collapsed to two levels—full/rolling stop or no stop—which greatly simplified the analysis.

Logistic regression is used to model binary responses—in this case, no stop versus full/rolling stop. Mixed-effects models have two components: fixed and random. Fixed effects are included to explain the relationship between the dependent variable—in this case, stopping behavior—and a set of independent variables. Random effects are included to control for the dependency among a group of observations within the same group or cluster. In this intersection analysis, approach ID and driver ID are the random effects.

The full-stop and rolling-stop classes could have been separated, resulting in three possible stopping-behavior classes: no stop, rolling stop, and full stop. Two popular models for problems with multiple classes—unlike logistic regression models, which are used for problems with two classes—are multinomial regression and ordered logit regression. Both models were fit. While the former yielded results similar to those of the logistic regression model, logistic regression was chosen because it is more parsimonious. Meanwhile, order logistic regression relies heavily on an assumption of proportional odds, which was not met.

Logistic mixed-effects regression was then used to model the probability (odds) of a driver making no stop at a rural intersection, indexed by i in random variables α_i and y_i, which follows a Bernoulli distribution for the probability of no stop, p_i.

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + B_1\, x_1 + \cdots + \beta_n\, x_n + \alpha_i + \gamma_i$$

$$\alpha_i \sim Normal(0, \sigma_d^2)$$

$$\gamma_i \sim Normal(0, \sigma_c^2)$$

(3)

One of the benefits of the logistic regression model is that the model's output consists of easily interpreted odds ratios. An odds ratio is the probability that an event happens in relation to the probability that the event does not happen.

The odds ratios were obtained by exponentiation of the ordered logit coefficients. An ordered logit model estimates a single equation (regression coefficients) over the values of the dependent variable. A direct relationship exists between the coefficients produced by a logit model and the odds ratios produced by a logistic model.

A logit function is defined as the log base e (log) of the odds:

$$logit(p) = \log(odds) = \log(p/q)$$

(4)

The range is negative infinity to positive infinity. In regression, it is easiest to model unbounded outcomes. Logistic regression is, in reality, an ordinary regression that uses the logit function as the response variable. The logit transformation allows for a linear relationship between the response variable and the coefficients, as follows:

$$logit(p) = a + bX$$

(5)

or

$$log\left(\frac{p}{q}\right) = a + bX$$

(6)

Equation 6 can be expressed as an odds ratio by eliminating the log, which is done by taking e to the power for both sides of the equation by using $e^{(\log(p/q))} = e^{(a+bX)}$ or $p/q = e^{(a+bX)}$.

The logistic regression model with mixed effects was adjusted in *R*. The analysis was conducted via a Bayesian implementation using the package "brms" for fitting, plotting, and summarizing the models. The priors for the parameters were noninformative; the convergence of the chains was assessed using trace plots and *R* values; and the model fit was assessed using posterior predictive checks.

VARIABLES USED FOR TWO-WAY STOP-CONTROLLED INTERSECTION MODELS

Table 7 through table 10 summarize data used in developing a model of stopping behavior at two-way stop-controlled intersection approaches by using all viable time series traces. As the tables show, the model comprised 1,073 traces from all six study States, including 128 unique drivers on 81 unique approaches at 58 intersections.

Table 7. Dependent variable for stopping model at two-way stop-controlled intersections with all traces.

Variable	Counts
Type of stop (0 = full or rolling stop, 1 = no stop)	0 = 830, 1 = 243 (total number of traces = 1,073)

Table 8. Random factors for stopping model at two-way stop-controlled intersections with all traces.

Factor	Count
Intersection ID	Unique ID = 58
Intersection approach ID	Unique ID = 81
Driver ID	Unique ID = 128
State ID	Unique ID = 6

Table 9. Continuous independent variables for stopping model at two-way stop-controlled intersections with all traces.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
MinSpeed	Minimum speed within 5 m (16 ft) of the intersection (m/s)	0.00	8.31	1.32	1.38
MajorLane	Number of major approach lanes	2.00	7.00	2.45	0.82
LaneWidth	Average lane width (m)	2.44	3.66	3.24	0.31
SpeedLimit	Speed limit (m/s) of the upstream approach	11.18	24.59	18.37	2.89
MaxSpeed	Maximum speed (in m/s) within the 600 m (1,969 ft) upstream of the intersection	10.61	27.73	20.39	3.33
YrsDriving	Number of years the driver has been driving	16.00	90.00	57.54	19.97

Table 10. Categorical independent variables for stopping model at two-way stop-controlled intersections with all traces.

Variable	Description	Counts
Movement	Vehicle movement	Left = 245, right = 418, through = 410
Following	Subjective measure of whether the subject vehicle was following	Closely following = 11, following = 27, not following = 1,035
Time of day	Time of day at which the trip occurred	Dawn/dusk = 56, day = 889, night = 128
Weather	Pavement condition	Clear = 971, raining = 102
Overhead	Presence of an overhead flashing beacon	Yes = 51, no = 1,022
Lighting	Presence of lighting at the intersection	Yes = 702, no = 371
Skewed	Presence of skew and direction from perspective of the approach vehicle	Left = 337, no = 496, right = 240
RightLane	Presence of right turn lanes on minor approach	Yes = 1,073, no = 0
LeftLane	Presence of left turn lanes on minor approach	Yes = 0, no = 1,073
Sight	Estimate of sight distance as driver approaches the intersection	good = 17, limited = 210, somewhat limited = 846
AdvisorySpeed	Presence of advisory speed limit upstream	Yes = 6, no = 1,067
AdvanceWarning	Presence of advance warning sign	Yes = 11, no = 1,062
AdvanceType	Type of advance warning sign	No = 348, “W3-1”* = 719, “W3-1a”* = 6
DoubleWarning	Presence of double advance warning signs	Yes = 725, no = 348
Enhancements	Presence of intersection-warning signs	Yes = 22, no = 848
DoubleStop	Presence of double stop signs at approach	Yes = 14, no = 1059
TransverseRumble	Presence of transverse rumble strips	Yes = 319, no = 754
Beacon	Presence of flashing overhead or stop sign beacon	Yes = 1, no = 1,072
Stop Bar	Presence of a stop bar	Yes = 60, no = 1,013
ICWS	Presence of intersection conflict warning system	Yes = 1, no = 1,072
Channelization	Presence of channelization on the approach	Yes = 320, no = 753
Median	Divided median on the major approach	Yes = 27, no = 1,046

Variable	Description	Counts
MedianType	Type of median (none, painted, raised, grass)	No = 1,046, grass = 27
Grade	Qualitative assessment of approach grade	Downhill = 229, flat = 703, uphill = 141
Splitter	Presence of a splitter island	Yes = 36, no = 1,037
Speeding	Maximum speed > speed limit	Yes = 873, no = 200
SpeedingAbove5	Maximum speed > 2.24 m/s (5 mph) over the speed limit	Yes = 440, no = 663
SpeedingAbove10	Max speed > 4.47 m/s (10 mph) over the speed limit	Yes = 189, no = 884
Gender	Driver gender	Male = 649, female = 424
Movement	Vehicle movement (left, right, or through)	Left = 245, right = 418, through = 410
MajorApproachVeh	Presence of vehicle on perpendicular major approach within 3 s of the subject vehicle's entrance into the intersection	Yes = 534, no = 539
Opposite	Presence of vehicle on opposite minor approach within 3 s of the subject vehicle's entrance into the intersection	Yes = 197, no = 876
AgeCategorical	Age when trip was collected treated as a categorical variable	Age <25 yr = 32, 25 ≤ age <65 = 636, age ≥65 yr = 405

*MUTCD sign designation.

Table 11 through table 15 summarize the data used in developing a model of stopping behavior at two-way stop-controlled intersection approaches, including kinematic driver data such as glance location and distraction. As the tables show, the model contains 288 traces from all six study States, including 100 unique drivers on 75 unique approaches at 54 intersections.

Table 11. Dependent variable for stopping model at two-way stop-controlled intersections with kinematic driver variables.

Variable	Counts
Type of stop (0 = full or rolling stop, 1 = no stop)	0 = 201, 1 = 87 (total number of traces = 288)

Table 12. Random factors for stopping model at two-way stop-controlled intersections with kinematic driver variables.

Factor	Count
Intersection ID	Unique ID = 54
Approach ID	Unique ID = 75
Driver ID	Unique ID = 100
State ID	Unique ID = 6

Table 13. Continuous independent variables for stopping model at two-way stop-controlled intersections with kinematic driver variables.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
MinSpeed	Minimum speed within 5 m (16 ft) of the intersection (m/s)	0.00	8.31	1.57	1.65
MajorLane	Number of major approach lanes	2.00	7.00	2.44	0.82
LaneWidth	Average lane width (m)	2.44	3.66	3.19	0.29
SpeedLimit	Speed limit (m/s) of the upstream approach	11.18	24.59	18.72	3.11
MaxSpeed	Maximum speed (in m/s) within the 600 m (1,969 ft) upstream of the intersection	13.33	29.96	20.95	3.29
YrsDriving	Number of years the driver has been driving	0.00	71.00	34.93	19.98
Age	Age of the driver when the trip occurred	16.00	90.00	53.18	19.86

Table 14. Categorical independent variables for stopping model at two-way stop-controlled intersections with kinematic driver variables.

Variable	Description	Counts
Movement	Vehicle movement (left, right, or through)	Left = 73, right = 120, through = 95
Following	Subjective measure of whether the subject vehicle was following another vehicle on the approach	Closely following = 2, following = 3, not following = 283
Time of day	Time of day in which the trip occurred	Dawn/dusk = 6, day = 237, night = 45
Weather	Pavement condition	Clear = 255, raining = 33
Lighting	Presence of lighting at the intersection	Yes = 23, no = 265
Skewed	Presence of skew and direction from perspective of the approach vehicle	Yes = 176, no = 112
RightLane	Presence of right turn lanes on minor approach	Left = 88, no = 110, right = 90
LeftLane	Presence of left turn lanes on minor approach	Yes = 288, no = 0
Movement	Vehicle movement (left, right, or through)	Yes = 0, no = 288
Following	Subjective measure of whether the subject vehicle was following another vehicle on the approach	Yes = 0, no = 288
Sight	Estimate of sight distance as driver approaches the intersection	Good = 12, limited = 62, somewhat limited = 214

Variable	Description	Counts
AdvisorySpeed	Presence of advisory speed limit upstream	Yes = 6, no = 282
AdvanceWarning	Presence of advance warning sign	Yes = 190, no = 98
AdvanceType	Type of advance warning sign	No = 98, “W3-1”* = 190
DoubleWarning	Presence of double advance warning signs	Yes = 54, no = 234
Enhancements	Presence of intersection warning signs	Yes = 3, no = 285
DoubleStop	Presence of double stop signs at approach	Yes = 84, no = 204
TransverseRumble	Presence of transverse rumble strips	Yes = 1, no = 287
Beacon	Presence of flashing overhead or stop sign beacon	Yes = 25, no = 263
Stop Bar	Presence of a stop bar	Yes = 119, no = 169
ICWS	Presence of Intersection Conflict Warning System	Yes = 1, no = 287
Channelization	Presence of channelization at the intersection	Yes = 0, no = 288
Median	Divided median on the major approach	Yes = 9, no = 279
MedianType	Type of median (no, painted, raised, grass)	No = 279, grass = 9
Grade	Qualitative assessment of approach grade	Downhill = 24, slightly downhill = 25, flat = 207, slightly uphill = 32, uphill = 0
Splitter	Presence of a splitter island	Yes = 19, no = 269
Speeding	Max speed > speed limit	Yes = 227, no = 61
SpeedingAbove5	Max speed > 2.24 m/s (5 mph) over the speed limit	Yes = 136, no = 152
SpeedingAbove10	Max speed > 4.47 m/s (10 mph) over the speed limit	Yes = 63, no = 225
Gender	Driver gender	Male = 174, female = 114
Opposite	Presence of vehicle on opposite minor approach within 3 s of the subject vehicle’s entrance into the intersection	Yes = 58, no = 230
MajorApproachVeh	Presence of vehicle on perpendicular major approach within 3 s of the subject vehicle’s entrance into the intersection	Yes = 144, no = 144
AgeCategorical	Age when trip was collected treated as a categorical variable	Age <25 yr = 24 25 ≤ age <65 = 180 Age ≥65 yr = 84

Table 15. Kinematic driver variables for stopping model at two-way stop-controlled intersections with kinematic driver variables.

Variable	Description	Counts
ScanDist	Distance upstream (in 50-m (164-ft) increments) at which the driver began scanning	Mean = 44.52, standard deviation = 54.55
Non_forward_100_to_250	Whether a driver engaged in glances away from roadway-related glance locations within 100–250 m (328–820 ft) upstream of the intersection	Yes = 68, no = 223
Non_forward_100	Whether a driver engaged in glances away from roadway-related glance locations within 100 m (328 ft) upstream of the intersection	Yes = 58, no = 233
Distract100_to_250	Whether a driver was engaged in a distraction within 100–250 m (328–820 ft) upstream of the intersection	Yes = 7, no = 284
Distract100	Whether a driver was engaged in a distraction within 100 m (328 ft) upstream of the intersection	Yes = 4, no = 287

This data set contains all the variables used in the model shown in table 7 through table 11 in addition to the kinematic driver variables. The latter include variables related to the percentage of time drivers spent scanning upstream of the intersection at various intervals, the percentage of time they were engaged in non-roadway-related glances at the intersection, and the percentage of time they were involved in any distractions.

ANALYSIS AND RESULTS OF STOPPING BEHAVIOR AT TWO-WAY STOP-CONTROLLED INTERSECTIONS

Model With All Viable Traces

A binomial mixed-effects logistic regression model was developed, with the dependent variable having possible values of full/rolling stop or no stop by using the “brm()” function of the “brms” package in *R*. Relevant interactions (e.g., overhead flashing beacons at night) were tested to determine whether they needed to be included in the model.

The team developed the final model by using the top 15 most important variables as determined by a random forest analysis. A random forest analysis is a machine-learning regression technique that considers complex relationships between dependent and independent variables. The technique does not provide insights about the mechanism of the model, and for that reason, a random forest was not used as the final model. Random forests can, however, provide a ranking of the most important variables. The random forests were fitted using the package “randomForest” in *R* (Liaw and Wiener 2002).

The best fit model is shown in table 16 through table 18. Since the model’s implementation is Bayesian, the table does not present *p*-values but, rather, 90-percent-credible intervals, which indicates that the corresponding parameter lies within that interval, with a probability of 90 percent. The inclusion of 0 within the credible interval means that 0 is a likely value for the parameter (i.e., that variable might not be significant).

Table 16. Dependent variable for final model for stopping behavior at two-way stop-controlled intersections with all traces.

Variable	Possible Values
Type of stop	0 = full or rolling stop, 1 = no stop

Table 17. Independent variables for final model for stopping behavior at two-way stop-controlled intersections with all traces.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^	Odds Ratio
Intercept	−2.963	0.909	−4.507	−1.524	0.052
SpeedingAbove5	0.740	0.236	0.356	1.124	2.096
Opposite	−0.493	0.287	−0.971	−0.026	0.611
Major approach vehicle	−0.799	0.206	−1.138	−0.468	0.450
Time of day = Day (baseline = dawn/dusk)	0.222	0.504	−0.592	1.0657	1.248
Time of day = Night (baseline = dawn/dusk)	0.973	0.551	0.0786	1.896	2.646
*Skewed = No (baseline = left skew)	−0.458	0.824	−1.778	0.910	0.632
*Skewed = Right (baseline = left skew)	−3.203	1.731	−6.302	−0.669	0.041
*Movement = Right (baseline = left)	2.119	0.841	0.772	3.539	8.320
*Movement = Through (baseline = left)	0.3619	0.695	−0.744	1.556	1.436
*Stop bar	1.331	0.817	0.0298	2.709	3.784
*Skewed—Movement = No—Right (baseline = left—left)	−0.334	0.973	−1.913	1.210	0.716
*Skewed—Movement = Right—Right (baseline = left—left)	3.121	1.870	0.374	6.405	22.660
*Skewed—Movement = No—Through (baseline = left—left)	−2.131	0.878	−3.559	−0.700	0.119
*Skewed—Movement = Right—Through (baseline = left—left)	1.409	1.831	−1.328	4.652	4.092
*Movement—Stop bar = Right—Yes (baseline = left—no)	−1.046	0.920	−2.575	0.447	0.351
*Movement—Stop bar = Through—Yes (baseline = left—no)	1.445	0.833	0.085	2.825	4.240

*Interaction term.
CI^ = confidence interval.

Table 18. Groups for final model for stopping behavior at two-way stop-controlled intersections with all traces.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^
Approach ID	0.714	0.336	0.223	1.310
Driver ID	2.007	0.393	1.406	2.685

Multiple categorical variables included time of day, intersection skew, and movement. Therefore, estimates were developed for the categories compared to the baseline. For example, with the intersection skew, the categories were right and no skew compared to the baseline of left skew.

Negative values for the estimates indicate an increased probability of a rolling/full stop, while positive values indicate an increased probability of no stop. Random effects for Driver ID and Approach ID were found to be significant, while State ID and Intersection ID were found to have no significant effect.

This model shows that the presence of vehicle on the major approach made drivers 1/0.4497 = 2.22 times more likely to engage in a rolling/full stop at the intersection, while the presence of a vehicle on the opposite approach made drivers 1/0.6107 = 1.6374 times more likely to engage in a rolling/full stop.

In contrast, a driver traveling ≥2.24 m/s (5 mph) over the speed limit within 600 m (1,969 ft) of the intersection was 2.10 times more likely not to stop at the intersection. Driving at night made drivers 2.65 times more likely not to stop compared to driving at dawn/dusk, while driving during the day made drivers 1.25 times more likely not to stop compared to driving at dawn/dusk.

Two notable interactions occurred: one between intersection skew and turning movement and another between presence of a stop bar and turning movement. The results of these interactions are easiest to explain using figure 24 and figure 25, respectively, where the *y*-axis represents the probability of not stopping at an intersection and the *x*-axis represents intersection skew. For instance, figure 24 shows that when no skew is present, an approximately 18 percent probability arises that a right-turning vehicle at the intersection will not stop.

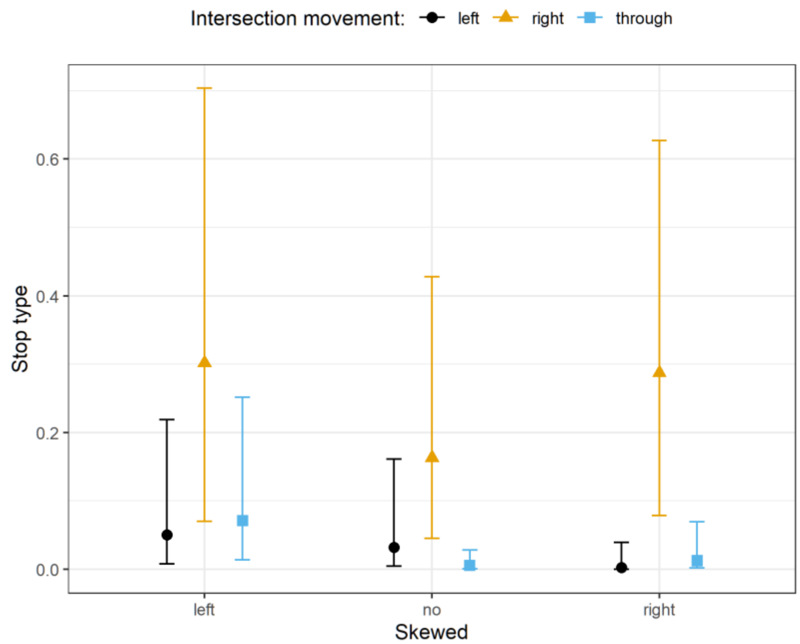


Figure 24. Graph. Interaction between turning movement and intersection skew for two-way stop-controlled intersections (all traces).

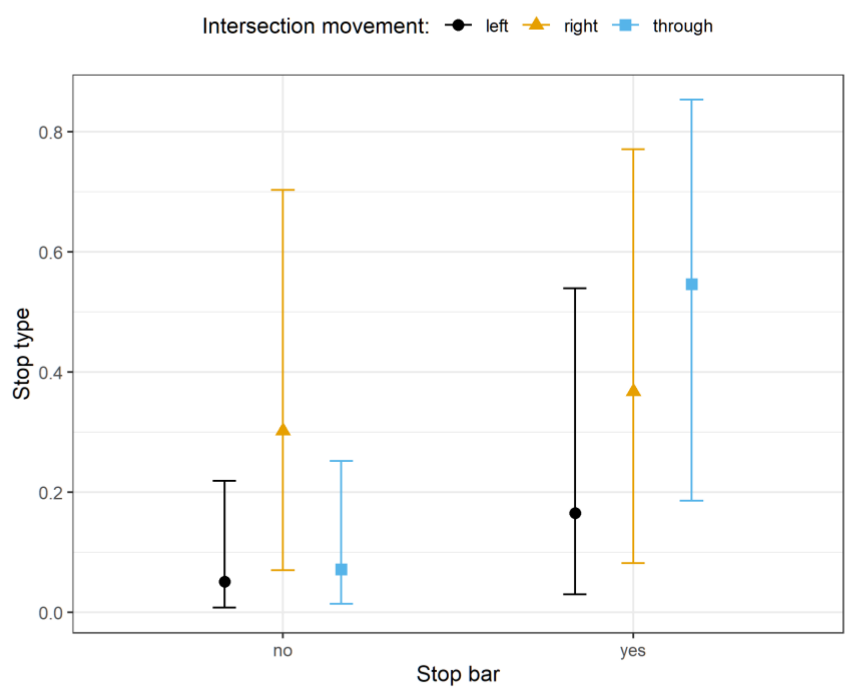


Figure 25. Graph. Interaction between turning movement and presence of a stop bar for two-way stop-controlled intersections (all traces).

As shown in figure 24, the probability of not stopping was greater for all movements when the intersection was skewed left (skew is from the perspective of the driver). The probability of not stopping was lowest for right-turning drivers at intersections with no skew. For left-turning drivers, the probability of not stopping was very low and was similar for intersections with no skew and those with right skew, although more variability was present for intersections with no skew. Additionally, in all cases, a right turn resulted in a higher probability of not stopping.

Figure 25 illustrates the probability of not stopping when a stop bar was present (yes) versus not present (no). As the figure shows, left-turning and through drivers had a low probability of not stopping when no stop bar was present (approximately 5 percent and 8 percent, respectively) but a much higher probability of not stopping when a stop bar was present (approximately 18 percent and 55 percent for left-turning and through vehicles, respectively). However, a significant amount of variance was found when the stop bar was present. The probability of not stopping was also higher for right-turning drivers when a stop bar was present. However, there was a significant amount of overlap in the credible sets for right-turning drivers in the presence or absence of a stop bar.

Model with Kinematic Driver Variables

Similar to the model for stopping behavior at two-way stop-controlled intersection approaches using all traces, a logistic regression model with mixed effects was fitted for only those traces with kinematic variables coded. A final model was selected using these kinematic variables and the top 15 most important variables as determined by a random forest analysis using all traces.

The model was fit in *R* using the package "brms." The best-fit model is shown in table 19 through table 21.

Table 19. Dependent variable for final model for stopping behavior at two-way stop-controlled intersections with kinematic driver variables.

Variable	Possible Values
Type of stop	0 = full or rolling stop, 1 = no stop

Table 20. Independent variables for final model for stopping behavior at two-way stop-controlled intersections with kinematic driver variables.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^	Odds Ratio
Intercept	−1.209	0.595	−2.252	−0.296	0.299
Skewed = No (baseline = left)	−1.128	0.587	−2.101	−0.185	0.324
Skewed = Right (baseline = left)	−1.127	0.557	−2.061	−0.238	0.324
Movement = Right (baseline = left)	1.543	0.521	0.736	2.435	4.679
Movement = Through (baseline = left)	0.007	0.501	−0.809	0.841	1.007
Major approach vehicle	−0.895	0.362	−1.490	−0.311	0.409
Stop bar	1.051	0.462	0.341	1.855	2.858

Table 21. Random effects for final model for stopping behavior at two-way stop-controlled intersections with kinematic driver variables.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^
Approach ID	0.649	0.381	0.086	1.326
Driver ID	1.089	0.505	0.298	1.961

Right-skewed intersections and non-skewed intersections were both 1/0.3237 = 3.09 and 1/0.3241 = 3.09 times more likely, respectively, to result in a rolling/full stop compared to left-skewed intersections. Moreover, when a vehicle was on the major approach, drivers were 1/0.4087 = 2.45 times more likely to engage in a rolling/full stop.

However, drivers making a right turn were 4.68 times more likely not to stop compared to drivers making a left turn. The results for through movements were similar to those for left turns. Drivers at intersection approaches with stop bars were 2.86 times more likely not to stop at the intersection.

DISCUSSION

This chapter describes the analysis of stopping behavior at two-way stop-controlled intersections, which includes intersections with a major through approach and two minor stop-controlled approaches. In all cases, the minor stop-controlled approach was two-lanes.

An initial analysis was conducted that demonstrated that the data for rolling stop and full stop exhibited similar patterns, and therefore these types of stops were combined into a single class. The likelihood of no stop versus a full or rolling stop was modeled at the approaches for two-way stop-controlled intersections. Logistic-mixed-effects regression was used to model the probability (odds) of a driver's making no stop. Two separate models were developed. One model included all traces, and one included the subset of traces in which kinematic driver behaviors were reduced. Overall, the two models provided similar results.

It was found in both models that the presence of vehicles on a major approach significantly affected a driver's stopping behavior at these types of intersections. That result was expected because drivers often have to stop to wait for conflicting vehicles on the major approach to pass and may not stop if conflicting vehicles are not present.

It was also found that the movement a driver makes at an intersection has an effect on the driver's probability of stopping. Vehicles turning right are more likely not to stop than are vehicles turning left or going through. That is to be expected because a driver turning right has to assess gap size in traffic from only one direction and needs less time than when assessing gap size in traffic from two directions, which drivers turning left or going through an intersection must do.

Additionally, the model that included all traces showed that drivers who engage in riskier behavior upstream in the form of speeding by 2.24 m/s (5 mph) or more over the posted speed limit are more likely to take risks at an intersection in terms of being more likely not to stop.

Intersection skew was also found to be statistically significant characteristic affecting stopping behavior. An interaction was found between intersection skew and turning movement in the model that included all traces. For all turning movements, the probability of not stopping was greatest when left skew was present (skew is from the perspective of the driver). For right-turning drivers, the probability of not stopping was lowest at an intersection with no skew. For left-turning drivers, the probabilities of not stopping were similar when no skew or right skew was present, although more variability was evident when no skew was present. Skew was also a relevant variable for the model that included only traces in which kinematic driver characteristics had been reduced. Stopping behavior was similar when right skew and no skew were present, with drivers much more likely to engage in a rolling/full stop in those cases.

Like intersection skew, presence of a stop bar was found to be a relevant intersection characteristic in the model that included all traces. An interaction was similarly found between presence of a stop bar and turning movement. Left-turning and through drivers were more likely not to stop when a stop bar was present. The probability of not stopping was also higher for right-turning drivers when a stop bar was present, but a significant amount of overlap was found in the credible sets for right-turning drivers in the presence or absence of a stop bar.

This result may be due to bias at the sites where these countermeasures are present. That is, guidance often recommends using stop bars on the minor approaches of intersections that are not currently being recognized by some approaching motorists. Therefore, these countermeasures may be present especially at those intersections where there is already a propensity for drivers not to stop.

The model of all traces, unfortunately, did not identify any other roadway countermeasures that affect the probability of a driver engaging in a full/rolling stop versus no stop at intersections. This is likely due to the large sample size of drivers and intersections, which makes it difficult to pinpoint the exact effect of any one roadway feature.

CHAPTER 6. ANALYSIS OF STOPPING MODEL AT T-INTERSECTIONS

The research team modeled stopping behavior at T-intersection approaches similarly to the analysis conducted for two-way stop-controlled intersections (chapter 5). The T-intersections in this study typically involved single two-lane stop-controlled approaches intersecting two-lane major approaches but did include a few four-lane divided intersections.

DATA USED

The team reduced data as noted in chapter 3, including the coding of stopping behavior as either full stop, rolling stop, or no stop. Additionally, as noted in chapter 5, rolling stops and full stops were combined. As a result, the likelihood of no stop versus a full or rolling stop was modeled at approaches for two-way stop-controlled intersections.

As noted in chapter 3, kinematic driver characteristics were coded only for a subset of viable time series traces. To capitalize on all available data, the team developed two different models. The first model included all available time series traces on the minor approach of a T-intersection, and the second included only time series traces on the minor approach of a T-intersection for which kinematic variables had been reduced.

VARIABLES USED FOR T-INTERSECTIONS

Table 22 through table 25 summarize data used in the development of a binomial mixed-effects logistic model for all viable time series traces at T-intersection approaches. As the tables show, the model comprised 87 unique T-intersections with 157 unique drivers. A total of 1,277 time series traces were used.

Table 22. Dependent variable (binary) for stopping model at T-intersections with all traces.

Variable	Counts
Type of stop (0 = full or rolling stop, 1 = No Stop)	0 = 821, 1 = 456 (total number of traces = 1,277)

Table 23. Random factors for stopping model at T-intersections with all traces.

Factor	Count
Intersection ID	Unique ID = 87
Driver ID	Unique ID = 157
State ID	Unique ID = 5

Table 24. Continuous independent variables for stopping model at T-intersections with all traces.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
MinSpeed	Minimum speed within 5 m (16 ft) of the intersection (m/s)	0	11.65	1.80	1.73
Angle	Angle between incoming and departure approach	55.46	161.00	101.89	18.90
MajorLane	Number of major approach lanes	2.00	4.00	2.12	0.45
LaneWidth	Average lane width (m)	2.44	3.66	3.14	0.27
SpeedLimit	Speed limit (m/s) of the upstream approach	11.18	24.59	18.88	3.03
MaxSpeed	Maximum speed (in m/s) within the 600 m (1,969 ft) upstream of the intersection	10.44	32.50	22.44	3.51
YrsDriving	Number of years the driver has been driving	0	67.00	33.78	19.03
Age	Age of the driver when the trip occurred	17.00	89.00	51.32	19.17

Table 25. Categorical independent variables for stopping model at T-intersections with all traces.

Variable	Description	Counts
Movement	Vehicle movement (left, right, or through)	Left = 461, right = 817, through = 0
Following	Subjective measure of whether the subject vehicle was following another vehicle on the approach	Close = 60, following = 47, not following = 1,170
Time of day	Time of day at which the trip occurred	Dawn/dusk = 32, day = 1,077, night = 168
Weather	Ambient conditions	Clear = 1,158, raining = 119
Overhead	Presence of an overhead flashing beacon	Yes = 74, no = 1,203
Lighting	Presence of lighting at the intersection	Yes = 337, no = 940
Skewed	Presence of skew and direction from perspective of the approach vehicle	Left = 128, no = 625, right = 524
RightLane	Presence of right turn lanes on minor approach	Yes = 1,226, no = 51
LeftLane	Presence of left turn lanes on minor approach	Yes = 1,226, no = 51

Variable	Description	Counts
Sight	Estimate of sight distance as driver approaches the intersection	Good = 118 Limited = 237 Somewhat_limited = 922
AdvisorySpeed	Presence of advisory speed limit upstream	Yes = 105, no = 1,172
AdvanceWarning	Presence of advance warning sign	Yes = 751, no = 526
AdvanceType	Type of advance warning sign	None = 526, "W2-2"* = 21, "W3-1"* = 371, "W2-2"* = 5, "W3-1A" = 301
DoubleWarning	Presence of double advance warning signs	Yes = 88, no = 1,189
Enhancements	Presence of intersection warning signs	Yes = 27, no = 1,250
DoubleStop	Presence of double stop signs at approach	Yes = 177, no = 1,100
TransverseRumble	Presence of transverse rumble strips	Yes = 35, no = 1,242
Beacon	Presence of flashing overhead or stop sign beacon	Yes = 74, no = 1,203
Stop Bar	Presence of a stop bar	Yes = 147, no = 1,130
Channelization	Presence of channelization at the intersection	Yes = 43, no = 1,234
Median	Divided median on the major approach	Yes = 22, no = 1,255
MedianType	Type of median (no, painted, raised, grass)	No = 1,255, painted = 8, raised = 14
Grade	Qualitative assessment of approach grade	Downhill = 583, flat = 317, uphill = 377
Splitter	Presence of a splitter island	Yes = 87, no = 1,190
Speeding	Maximum speed > speed limit	Yes = 1,049, no = 228
SpeedingAbove5	Maximum speed > 2.24 m/s (5 mph) over the speed limit	Yes = 826, no = 451
SpeedingAbove10	Maximum speed > 4.47 m/s (10 mph) over the speed limit	Yes = 573, no = 704
Gender	Driver gender	Male = 752, female = 525
MajorApproachVeh	Presence of vehicle on perpendicular major approach within 3 s of subject vehicle's entrance into the intersection	Yes = 457, no = 820
IsectAngle	Angle of incoming approach to the outgoing approach treated as a categorical variable	90 degrees = 625 <90 degrees = 103 90 degrees = 549

Variable	Description	Counts
AgeCategorical	Age when trip was collected treated as a categorical variable	Age <25 yr = 139 25 ≤ age <65 = 779 Age ≥65 yr = 359

*MUTCD sign designation.

Stopping behavior was the dependent variable, and the likelihood of a particular type of stop was modeled. A unique Intersection ID was assigned to each intersection and used as a random-effects variable in the model to account for repeated samples at the same intersection. Similarly, a unique Driver ID was assigned to each driver and used as a random-effects variable. The corresponding State was also assigned a unique State ID and included as a random effect.

Table 26 through *mutcd sign designation.

provide the same information for the model with the subset of traces for which glance location and distraction were coded. As the tables show, the model consisted of 209 time series traces representing 71 unique intersections and 96 unique drivers.

Table 26. Dependent variable (binary) for stopping model at T-intersections with kinematic driver variables.

Variable	Counts
Type of stop (0 = full or rolling stop, 1 = No Stop)	0 = 132, 1 = 77 (total number of traces = 209)

Table 27. Random factors for stopping model at T-intersections with kinematic driver variables.

Factor	Count
Intersection ID	Unique ID = 71
Driver ID	Unique ID = 96
State ID	Unique ID = 5

Table 28. Continuous independent variables for stopping model at T-intersections with kinematic driver variables.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
MinSpeed	Minimum speed within 5 m (16 ft) of the intersection (m/s)	0.00	7.26	1.82	1.72
Angle	Angle between incoming and departure approach	−55.46	160.95	96.55	18.12
MajorLane	Number of major approach lanes	2.00	4.00	2.14	0.47
LaneWidth	Average lane width (m)	2.44	3.66	3.09	0.26
SpeedLimit	Speed limit (m/s) of the upstream approach	11.18	24.59	19.38	3.40
MaxSpeed	Maximum speed (in m/s) within the 600 m (1,969 ft) upstream of the intersection	11.15	32.50	21.55	3.69
YrsDriving	Number of years the driver has been driving	0.00	67	34.44	18.38
Age	Age of the driver when the trip occurred	18.00	89.00	51.93	18.49

Table 29. Categorical independent variables for stopping model at T-intersections with kinematic driver variables.

Variable	Description	Counts
Movement	Vehicle movement (left, right, or through)	Left = 78, right = 131
Following	Subjective measure of whether the subject vehicle was following another vehicle on the approach	Following = 6, not following = 203
Time of day	Time of day at which the trip occurred	Day = 170, dawn/dusk and night = 39
Weather	Ambient	Clear = 198, raining = 11
Lighting	Presence of lighting at the intersection	Yes = 56, No = 153
Skewed	Presence of skew and direction from perspective of the approach vehicle	Left = 38, no = 120, right = 51
RightLane	Presence of right-turn lanes on minor approach	Yes = 10, no = 163
LeftLane	Presence of left-turn lanes on minor approach	Yes = 10, no = 163
Sight	Estimate of sight distance as driver approaches the intersection	Good = 28, limited = 181
AdvisorySpeed	Presence of advisory speed limit upstream	Yes = 27, no = 182
AdvanceWarning	Presence of advance warning sign	Yes = 137, no = 72

Variable	Description	Counts
AdvanceType	Type of advance warning sign	No = 72, “W2-2”* = 3, “W3-1”* = 97, “W2-2”* = 2, “W3-1A”* = 26
DoubleWarning	Presence of double advance warning signs	Yes = 19, no = 190
Enhancements	Presence of intersection warning signs	Yes = 4, no = 205
DoubleStop	Presence of double stop signs at approach	Yes = 46, no = 163
TransverseRumble	Presence of transverse rumble strips	Yes = 7, no = 202
Beacon	Presence of flashing overhead or stop sign beacon	Yes = 20, no = 189
Stop Bar	Presence of a stop bar	Yes = 36, no = 173
Channelization	Presence of channelization at the intersection	Yes = 9, no = 200
Median	Divided median on the major approach	Yes = 10, no = 199
MedianType	Type of median (no, painted, raised, grass)	No = 199, painted = 7, raised = 3
Grade	Qualitative assessment of approach grade	Downhill = 88, flat = 98, uphill = 23
Splitter	Presence of a splitter island	Yes = 21, no = 188
Speeding	Max speed > speed limit	Yes = 148, no = 61
SpeedingAbove5	Max speed > 2.24 m/s (5 mph) over the speed limit	Yes = 98, no = 111
SpeedingAbove10	Max speed > 4.47 m/s (10 mph) over the speed limit	Yes = 58, no = 151
Gender	Driver gender	Male = 97, female = 112
MajorApproachVeh	Presence of vehicle on perpendicular major approach within 3 s of subject vehicle’s entrance into the intersection	Yes = 86, no = 123
IsectAngle	Angle of incoming approach to outgoing approach treated as a categorical variable	90 degrees = 625, <90 degrees = 103, >90 degrees = 549
AgeCategorical	Age when trip was collected treated as a categorical variable	Age <25 yr = 27 25 ≤ age <65 = 127 Age ≥65 yr = 55
Violations	Number of moving-violation citations the driver has received	0 = 156, 1 = 42, 2 or more = 11
CrashExperience	Number of crashes the driver has been involved in	0 = 157, 1 = 50, 2 or more = 2

*MUTCD sign designation.

Table 30. Kinematic driver variables for stopping model at T-intersections with kinematic driver variables.

Variable	Description	Counts
ScanDist	Distance upstream (in 50-m (164-ft) increments) at which the driver began scanning	Mean = 63.40 m (208.0 ft), standard deviation = 63.64 m (208.8 ft)
Non_forward_100_to_250	Whether a driver engaged in glances away from roadway-related glance locations within 100–250 m (328–820 ft) upstream of the intersection	Yes = 45, no = 166
Non_forward_100	Whether a driver engaged in glances away from roadway-related glance locations within 100 m (328 ft) upstream of the intersection	Yes = 46, no = 165
Distract100_to_250	Whether a driver was engaged in a distraction within 100–250 m (328–820 ft) upstream of the intersection	Yes = 5, no = 206
Distract100	Whether a driver was engaged in a distraction within 100 m (328 ft) upstream of the intersection	Yes = 2, no = 209

Independent variables are listed in table 24, table 25, table 28, and table 29 and included intersection characteristics such as lane width, intersection angle, types of signs present, approach grade, approach speed limit, and countermeasures; driver characteristics such as age and gender; and environmental factors such as pavement surface condition and time of day.

ANALYSIS AND RESULTS OF STOPPING BEHAVIOR AT T-INTERSECTIONS

Model With All Viable Traces

As in the analysis of two-way stop-controlled intersections, an ordinal mixed-effects logistic regression model was initially run, with the dependent variable being type of stop and the possible values being full stop < rolling stop < no stop. However, the model was found to violate the proportional odds ratio assumption. Therefore, a binomial mixed-effects logistic regression model was developed using the “brm()” function of the “brms” package in *R*, with the dependent variable having possible values of full/rolling stop or no stop. Relevant interactions (e.g., overhead flashing beacons at night) were tested to determine whether they needed to be included in the model.

The final model was developed using the top 15 most important variables as determined by a random forest analysis. A random forest analysis is a machine-learning regression technique that considers complex relationships between dependent and independent variables. The technique does not provide insights about the mechanism of the model, and for that reason, a random forest was not used as the final model. Random forests can, however, provide a ranking of the most important variables. The random forests were fitted using the package “randomForest” in *R* (Liaw and Wiener 2002).

Table 31 through table 33 show the output for the model that used all available traces.

Table 31. Dependent variable (binary) for final model for stopping behavior at T-intersections with all traces.

Variable	Possible Values
Type of stop	0 = Full or Rolling Stop, 1 = No Stop

Table 32. Independent variables for final model for stopping behavior at T-intersections with all traces.

Variable	Estimate	Estimated Error	l-90% CI	u-90% CI	Odds Ratio
Intercept	−4.01703	1.060037	−5.82447	−2.34043	0.018006
Major approach vehicle	−2.09984	0.217672	−2.46203	−1.74865	0.122476
Lighting	−0.84333	0.477592	−1.64891	−0.07062	0.430276
Time of day = Day (baseline = dawn/dusk)	−0.90578	0.520118	−1.77384	−0.04788	0.404227
Time of day = Night (baseline = dawn/dusk)	−0.46952	0.545999	−1.36786	0.419049	0.625302
Speeding	0.80423	0.337859	0.256913	1.352656	2.234969
*Skewed = Left (baseline = no)	1.208337	0.724874	0.015615	2.403369	N/A
*Skewed = Right (baseline = no)	0.735617	0.964712	−0.86967	2.280603	N/A
*Right movement (baseline = left)	4.674667	0.970267	3.172007	6.371623	N/A
*AdvanceWarning	2.914015	0.877019	1.560457	4.450883	N/A
Skew—Movement = Left—Right (baseline = no—left)	−2.4802	1.118168	−4.31654	−0.6593	N/A
Skew—Movement = Right—Right (baseline = no—left)	−0.52869	1.006361	−2.19049	1.086718	N/A
*Right movement—advance warning (baseline = left movement—no advance warning)	−2.83335	0.956121	−4.4903	−1.31538	0.058816

*Interaction term.
CI = confidence interval.

Table 33. Random effects for final model for stopping behavior at T-intersections with all traces.

Variable	Estimate	Estimated Error	l-90% CI	u-90% CI
Approach ID	0.282134	0.219924	0.020734	0.703328
Driver ID	1.665425	0.251735	1.294402	2.115476

The model indicated that when a vehicle was present on the major approach, drivers were 1/0.122476 = 55.53 times more likely to engage in a rolling/full stop. When lighting was present at the intersection, drivers were 2.32 times more likely engage in a rolling/full stop. Time of day was also significant. Drivers were 2.47 times more likely during the daytime and 1.60 times more likely at night to engage in a rolling/full stop than at dawn/dusk. Drivers who were traveling over the posted speed limit (speeding) were 2.23 times more likely not to stop than drivers traveling at or below the speed limit.

Interactions were present between intersection skew and turning movement and between turning movement and presence of an advance intersection warning sign. Figure 26 shows the credible sets for the interaction between turning movement and intersection skew. The probability of not stopping is represented on the *y*-axis, and skew is represented on the *x*-axis.

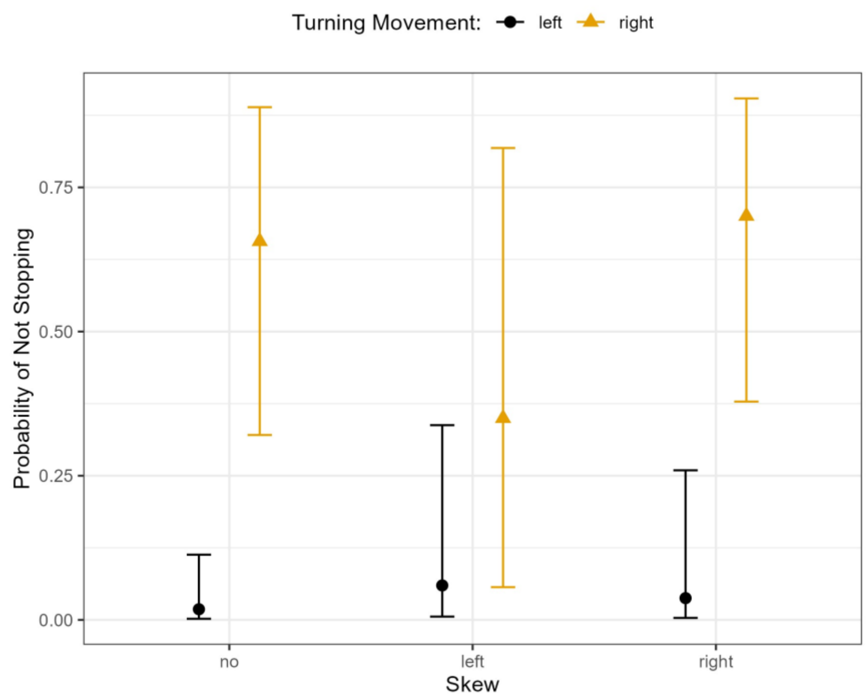


Figure 26. Graph. Interaction between turning movement and intersection skew for T-intersections (all traces).

As the figure shows, left-turning drivers had a low probability of not stopping for all skew scenarios, including left skew, right skew, and no skew (skew direction is from the perspective of the driver). However, drivers were more likely not to stop when left skew was present.

Right-turning drivers were more likely not to stop when either no skew (62 percent) or right skew (70 percent) was present. They were less likely not to stop (approximately 28 percent) when left skew was present. However, the credible sets are rather large.

Figure 27 shows the relationship between presence of an advance intersection warning sign, turning movement, and the probability of a driver's not stopping.

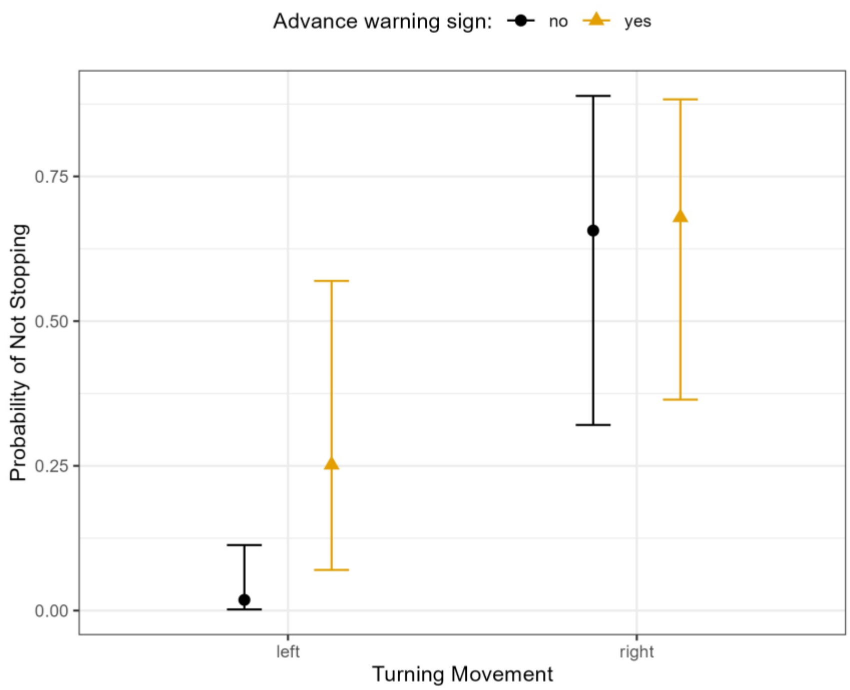


Figure 27. Graph. Interaction between turning movement and presence of an advance warning sign for T-intersections (all traces).

As the figure shows, right-turning vehicles at T-intersections had a high probability of not stopping regardless of the presence of advance signing. Left-turning drivers had a low probability of not stopping when no advance signing was present but a 25-percent probability of not stopping when advance signing was present. This result was unexpected, since the purpose of the signing is to warn drivers of an upcoming intersection. However, advance signing and other countermeasures are placed at locations where problems with safety or driver behavior already exist, and as a result, the presence of countermeasures may be a surrogate for a problem location. In such cases, a before-and-after analysis may yield more representative results.

The random effects variables initially included Driver ID, Intersection ID, and State ID, but only Driver ID and Approach ID were found to be statistically significant.

Model With Kinematic Driver Variables

Similar to the model for stopping behavior at two-way stop-controlled intersection approaches using all the traces, a logistic regression model with mixed effects was fitted for only those traces with kinematic variables coded. A final model was selected using these kinematic variables and the top 15 most important variables as determined by a random forest analysis using all traces.

The model was fit in *R* using the package "brms." The best fit model is shown in table 34 through table 37.

Table 34. Dependent variable (binary) for final model for stopping behavior at T-intersections with kinematic driver variables.

Variable	Possible Values
Type of stop	0 = Full or Rolling Stop, 1 = No Stop

Table 35. Number of observations for final model for stopping behavior at T-intersections with kinematic driver variables.

Data	Observations
Number of observations	209
Driver ID	96
Intersection ID	71
State ID	5

Table 36. Independent variables for final model for stopping behavior at T-intersections with kinematic driver variables.

Variable	Estimate	Estimated Error	l-90% CI	u-90% CI	Odds Ratio
Intercept	−4.40335	3.388411	−10.288	0.418656	0.012236
Major approach vehicle	−4.84651	1.337685	−7.29174	−2.99327	0.007856
Lighting	−5.19606	2.068733	−8.89416	−2.42416	0.005538
Time of day = Day (baseline = dawn/dusk)	−3.42966	2.02796	−6.98925	−0.39056	0.032398
Time of day = Night (baseline = dawn/dusk)	−2.58571	2.082133	−6.17215	0.613768	0.075342
MaxSpeed over SpeedLimit	4.007764	1.773139	1.804454	7.312556	55.02369
Any non-roadway during last 100 m	−1.64302	1.195097	−3.85102	−0.00256	0.193395
*Right movement (baseline = left)	5.667047	2.738439	1.905542	10.32973	N/A
*Advance warning	5.023487	2.476217	1.680504	9.408294	N/A
*Skewed = Left (baseline = no)	2.607832	2.106428	−0.53252	6.190962	N/A
*Skewed = Right (baseline = no)	3.700455	2.744372	−0.35509	8.42835	N/A
*Skewed—movement = Left—Right (baseline = no—left)	−6.26958	3.569167	−12.3589	−1.43464	N/A

Variable	Estimate	Estimated Error	l-90% CI	u-90% CI	Odds Ratio
*Skewed—movement = Right—Right (baseline = no—left)	−2.28292	2.912618	−7.18842	2.117906	N/A
*Right movement—advance warning sign (baseline = left—no advance warning sign)	−4.57002	2.688823	−9.24778	−0.8164	N/A

*Interaction term.
N/A = not applicable.

Table 37. Random effects for final model for stopping behavior at T-intersections with kinematic driver variables.

Variable	Estimate	Estimated Error	l-90% CI	u-90% CI
Approach ID	1.286621	1.082755	0.097185	3.342346
Driver ID	4.188647	1.65287	2.11845	7.163766

The results indicated that when a vehicle was present on the major approach, drivers were 1/0.007856 = 127.29 times more likely to engage in a rolling/full stop. When intersection lighting was present, drivers were 1/0.00554 = 180.57 times more likely to engage in a rolling/full stop. When drivers were traveling over the posted speed limit upstream of the intersection, they were 55.02 times more likely not to stop. These odds ratios are higher than expected, likely due to sample size.

Drivers who had engaged in a non-roadway-related glance within 100 m (328 ft) prior to their arrival at the stop bar were 5.17 times more likely to engage in a rolling/full stop. This result was unexpected, since glances away from the roadway are often associated with distractions. However, a driver who is glancing at multiple locations, even locations not related to the roadway, may be more likely to be alert.

Interactions were present between intersection skew and turning movement and between turning movement and presence of an advance intersection warning sign. Figure 28 shows the credible sets for the interactions between turning movement and intersection skew. The probability of not stopping is represented on the *y*-axis, and skew is represented on the *x*-axis. In all cases, the credible sets are large, indicating a significant amount of variance, and the researchers suggest that readers therefore interpret the variance with caution.

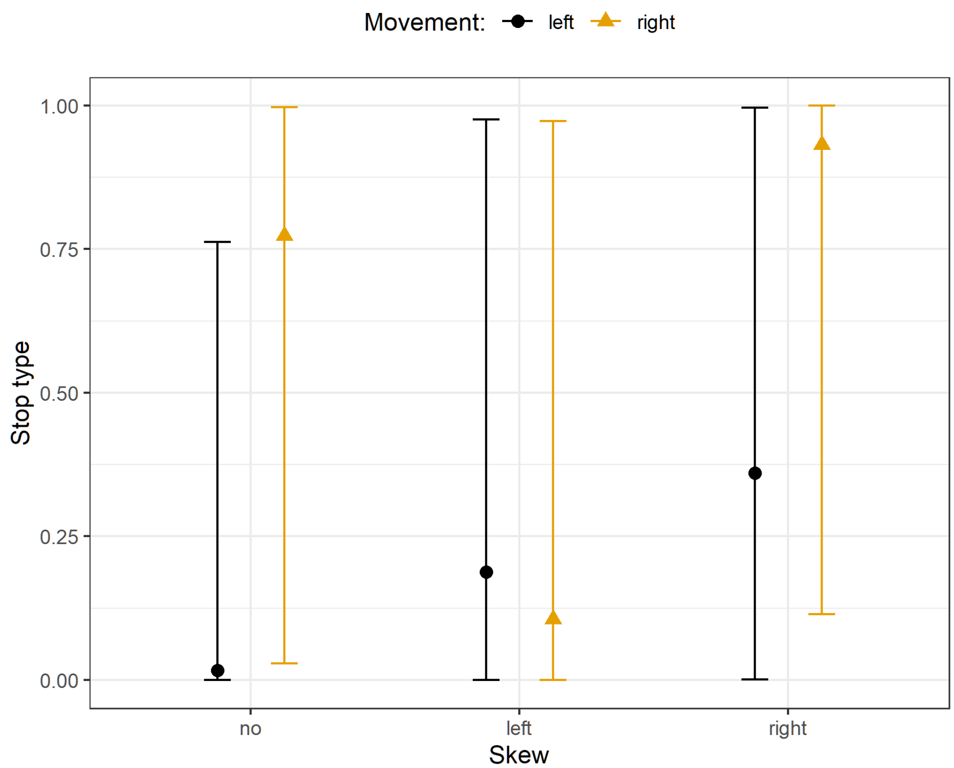


Figure 28. Graph. Interaction between turning movement and presence of a stop bar for T-intersections (traces with kinematic driver variables).

As the figure shows, when no skew or right skew was present, right-turning drivers had a high probability of not stopping (> 75 percent). However, when the intersection was skewed left from the perspective of the driver, right-turning drivers had a much lower probability of not stopping (approximately 13 percent). That result may be due to the fact that when no skew or right skew is present, drivers have better sight distance and feel more comfortable proceeding. Left skew may limit sight distance, causing drivers to stop in order to scan the intersection. Left-turning drivers were much more likely not to stop in the presence of left skew (18 percent) or right skew (37 percent) than no skew (3 percent).

The interaction between presence of an advance intersection warning sign, turning movement, and the probability of not stopping is shown in figure 29.

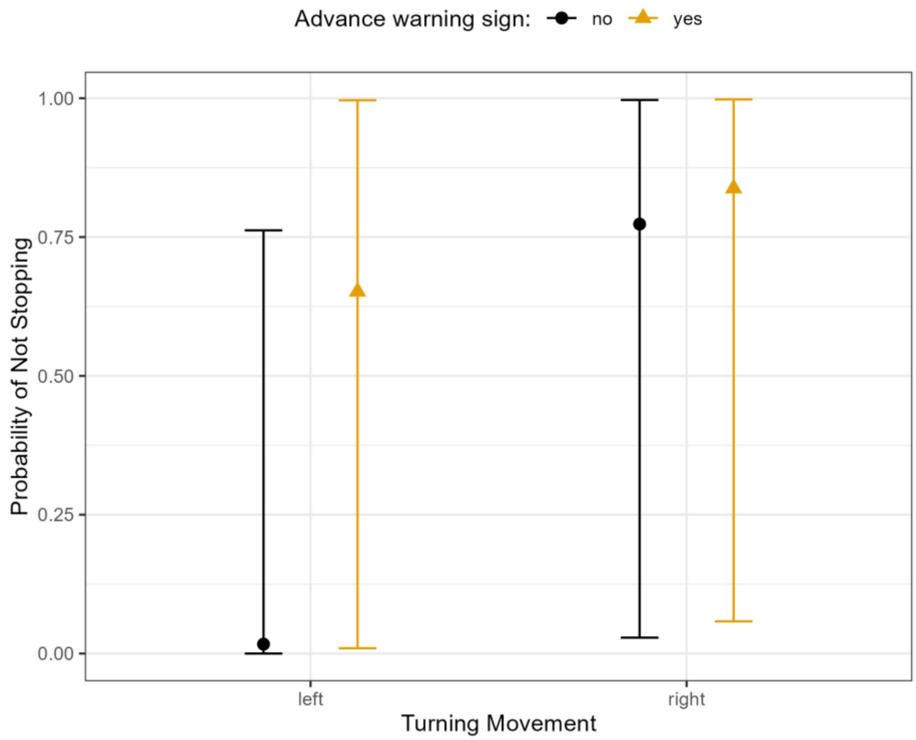


Figure 29. Graph. Interaction between turning movement and presence of an advance warning sign for T-intersections (traces with kinematic driver variables).

As the figure shows, left-turning drivers were much less likely not to stop when no advance signing was present versus when advance signing was present (3 percent versus 62 percent, respectively). Right-turning drivers behaved similarly regardless of the presence of advance signing.

DISCUSSION

Stopping behavior at T-intersection approaches was modeled similarly to the analysis conducted for two-way stop-controlled intersections (chapter 5). Based on the results of that analysis, the data for rolling and full stop were combined for this analysis. The T-intersections in this study typically involved a single two-lane stop-controlled approach intersecting a two-lane major approach.

The likelihood of drivers' making no stop versus a rolling/full stop was modeled at T-intersection approaches. Logistic mixed-effects regression was used to model the probability (odds) of a driver making no stop at a T-intersection. Two separate models were developed. One included all traces, and one included the subset of traces in which kinematic driver behaviors were reduced.

Overall, the results were consistent for both models. The most influential variable in terms of the odds ratio was the presence of a vehicle on a major approach at the time of the arrival of the subject vehicle at the stop bar. Daytime driving and nighttime driving were associated with a higher likelihood of a rolling/full stop than driving at dawn or dusk. Presence of lighting was also associated with a higher likelihood of a rolling/full stop. Drivers traveling over the posted speed limit were more likely not to stop than drivers traveling at or below the speed limit upstream of the intersection. In all cases, right-turning vehicles were more likely not to stop than left-turning vehicles, which may be due to the fact that left-turning vehicles need to yield to both directions of traffic.

Interactions were present between intersection skew and turning movement. Left-turning drivers were more likely not to stop when any type of skew was present than when no skew was present.

Interactions were also present between presence of an advance intersection warning sign and turning movement. Right-turning vehicles at T-intersections had a high probability of not stopping regardless of the presence of advance signing. Left-turning drivers were more likely not to stop when an advance warning sign was present, which was noted in both models. That result was unexpected, since the purpose of the signing is to warn drivers of an upcoming intersection. However, advance signing and other countermeasures are placed at locations where a problem with safety or driver behavior already exist, and as a result, the presence of a countermeasure may be a surrogate for a problem location. In these cases, a before-and-after analysis may yield more representative results.

CHAPTER 7. ANALYSIS OF STOPPING MODEL AT ALL-WAY STOP-CONTROLLED INTERSECTIONS

Stopping behavior at all-way stop-controlled intersections was modeled similarly to the analysis conducted for two-way stop-controlled intersections (chapter 5). The all-way stop-controlled intersections in this study typically involved four approaches.

DATA USED

Data were reduced as noted in chapter 3. The reductions included coding stopping behavior as either full, rolling, or no stop. Additionally, as noted in chapter 5, rolling and full stops were combined. As a result, the likelihood of no stop versus a full or rolling stop was modeled at all approaches to all-way stop-controlled intersections.

As noted in chapter 3, kinematic driver characteristics were coded only for a subset of viable time series traces. To capitalize on all available data, the team developed two different models. The first included all available time series traces at all-way stop-controlled intersection approaches, and the second included only time series traces at all-way stop-controlled intersection approaches for which kinematic variables had been reduced.

VARIABLES USED FOR ALL-WAY STOP-CONTROLLED INTERSECTIONS

Table 38 through table 41 summarize data used to develop a binomial logistic regression model for all viable time series traces at all-way stop-controlled intersection approaches. As the tables show, the model included 46 unique all-way stop-controlled intersections with 276 unique drivers. A total of 3,959 time series traces were used.

Table 38. Dependent variable (binary) for stopping model at all-way stop-controlled intersections with all traces.

Variable	Counts
Type of stop (0 = Full or Rolling Stop, 1 = No Stop)	0 = 2,619, 1 = 1,340 (total number of traces = 3,959)

Table 39. Random factors for stopping model at all-way stop-controlled intersections with all traces.

Factor	Count
Intersection ID	Unique ID = 46
Driver ID	Unique ID = 276
Approach ID	Unique ID = 148
State	Unique ID = 5

Table 40. Continuous independent variables for stopping model at all-way stop-controlled intersections with all traces.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
MinSpeed	Minimum speed within 5 m (16 ft) of the intersection (m/s)	0	12.21	1.83	1.62
MajorLane	Number of major approach lanes	2.00	4.00	2.23	0.64
LaneWidth	Average lane width (m)	2.44	4.27	3.24	0.30
SpeedLimit	Speed limit (m/s) of the upstream approach	11.18	24.59	18.60	3.55
MaxSpeed	Maximum speed (in m/s) within the 600 m (1,969 ft) upstream of the intersection	10.02	36.09	21.00	3.94
YrsDriving	Number of years the driver has been driving	0	69.00	33.78	16.05

Table 41. Categorical independent variables for stopping model at all-way stop-controlled intersections with all traces.

Variable	Description	Counts
Movement	Vehicle movement	Left = 1,069, right = 507, through = 2,383
Following	Subjective measure of whether the subject vehicle was following another vehicle	Closely following = 133, following = 494, not following = 3,332
Time of day	Time of day in which the trip occurred	Dawn/dusk/night = 969, day = 2,990
Weather	Pavement condition	Clear = 3,635, raining = 324
Overhead	Presence of an overhead flashing beacon	Yes = 1,094, no = 2,865
Lighting	Presence of lighting at the intersection	Yes = 1,192, no = 2,767
Skewed	Presence of skew from perspective of the approach vehicle	Left = 559, no = 2,463, right = 937
Approaches	Number of intersection approaches	3 = 164, 4 = 3,795
RightLane	Presence of right turn lanes on minor approach	Yes = 915, no = 3,044
LeftLane	Presence of left turn lanes on minor approach	Yes = 426, no = 3,533
Sight	Estimate of sight distance as driver approaches the intersection	Good = 487, somewhat limited = 1,559, limited = 1,913
AdvanceWarning	Presence of advance warning sign	Yes = 2,589, no = 1,370
AdvanceType	Type of advance warning sign	No = 1,370, W3-1 or W3-1a* = 11, W3-1* = 2,523, W3-1a* = 55
DoubleWarning	Presence of double advance warning signs	Yes = 831, no = 3,128

Variable	Description	Counts
Enhancements	Presence of intersection warning signs	Yes = 378, no = 3,581
DoubleStop	Presence of double stop signs at approach	Yes = 695, no = 3,264
TransverseRumble	Presence of transverse rumble strips	Yes = 253, no = 3,706
Beacon	Presence of flashing overhead or stop sign beacon	Yes = 1,145, no = 2,814
Stop Bar	Presence of a stop bar	Yes = 2,648, no = 1,311
OnPavement	presence of on-pavement signing	Yes = 494, no = 3,465
Channelization	Presence of channelization at the approach	Yes = 517, no = 3,442
Median	Divided median on the major approach	Yes = 0, no = 3,959
MedianType	Type of median (no, painted, raised, grass)	No = 3,959
Grade	Qualitative assessment of approach grade	Downhill = 722, flat = 2,972, uphill = 266
Speeding	Max speed within 600 m (1,969 ft) of intersection > speed limit	Yes = 3,193, no = 766
SpeedingAbove5	Max speed > 2.24 m/s (5 mph) over the speed limit	Yes = 1,596, no = 2,363
SpeedingAbove10	Max speed > 4.47 m/s (10 mph) over the speed limit	Yes = 779, no = 3,180
Gender	Driver gender	Male = 2,133, female = 1,826
Opposite	Presence of vehicle on any other approach within 3 s of the subject vehicle's approach to the intersection	Yes = 1,635, no = 2,324
AgeCategorical	Age when trip was collected	Age <25 yr = 228; 25 ≤ age <65 = 3,071; age ≥65 yr = 660

*MUTCD sign designation.

Stopping behavior was the dependent variable, and the likelihood of a particular type of stop was modeled. A unique Intersection ID was assigned to each intersection and used as a random effects variable in the model to account for repeated samples at the same intersection. Similarly, a unique ID was assigned to each approach; a unique Driver ID was assigned to each driver; and both were also used as random effects variables. The corresponding State was also assigned a unique State ID and included as a random effect.

Table 42 through *mutcd sign designations.

table 46 provide the same information for the model that included only time series traces with kinematic driver variables. As the tables show, the model included 44 unique all-way stop-controlled intersections with 151 unique drivers and a total of 368 time series traces.

Table 42. Dependent variable (binary) for stopping model at all-way stop-controlled intersections with kinematic driver variables.

Variable	Counts
Type of stop (0 = Full or Rolling Stop, 1 = No Stop)	0 = 217 1 = 151 (total number of traces = 368)

Table 43. Random factors for stopping model at all-way stop-controlled intersections with kinematic driver variables.

Factor	Count
Intersection ID	Unique ID = 44
Driver ID	Unique ID = 151
Approach ID	Unique ID = 128
State	Unique ID = 5

Table 44. Continuous independent variables for stopping model at all-way stop-controlled intersections with kinematic driver variables.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
MinSpeed	Minimum speed within 5 m (16 ft) of the intersection (m/s)	0.00	12.21	2.30	2.29
MajorLane	Number of major approach lanes	2.00	4.00	2.19	0.58
Approach	number of lanes on the perpendicular major approach	2.00	3.00	2.01	0.12
LaneWidth	Average lane width (m)	2.44	3.66	3.26	0.31
SpeedLimit	Speed limit (m/s) of the upstream approach	11.18	24.59	18.46	3.96
MaxSpeed	Maximum speed (in m/s) within the 600 m (1,969 ft) upstream of the intersection	11.29	31.59	21.54	3.98
YrsDriving	Number of years the driver has been driving	0.00	69.00	32.53	19.70
Reaction Point, in meters	Distance, in meters, where drivers showed a reaction to the intersection by decreasing speed	−499.5	−26.61	−193.07	113.67

Table 45. Categorical independent variables for stopping model at all-way stop-controlled intersections with kinematic driver variables.

Variable	Description	Counts
Movement	Vehicle movement	Left = 57, right = 48, through = 263
Following	Subjective measure of whether the subject vehicle was following another vehicle	Closely following = 0, following = 45, not following = 323
Time of day	Time of day in which the trip occurred	Dawn/dusk/night = 93, day = 275
Weather	Pavement condition	Clear = 340, raining = 28
Overhead	Presence of an overhead flashing beacon	Yes = 136, no = 232
Lighting	Presence of lighting at the intersection	Yes = 114, no = 254
Skewed	Presence of skew from perspective of the approach vehicle	Left = 76, no = 218, right = 74
Approaches	Number of intersection approaches	3 approaches = 34, 4 approaches = 334
RightLane	Presence of right turn lanes on minor approach	Yes = 83, no = 285
LeftLane	Presence of left turn lanes on minor approach	Yes = 30, no = 338
Sight	Estimate of sight distance as driver approaches the intersection	Good = 71, somewhat limited = 169, limited = 128
AdvanceWarning	Presence of advance warning sign	Yes = 262, no = 106
AdvanceType	Type of advance warning sign	No = 106, "W3-1"* and "W3-1a"* = 6, "W3-1"* = 251, "W3-1a"* = 5
DoubleWarning	Presence of double advance warning signs	Yes = 92, no = 276
Enhancements	Presence of intersection warning signs	Yes = 43, no = 325
DoubleStop	Presence of double stop signs at approach	Yes = 72, no = 296
TransverseRumble	Presence of transverse rumble strips	Yes = 30, no = 338
Beacon	Presence of flashing overhead or stop sign beacon	Yes = 150, no = 218
Stop Bar	Presence of a stop bar	Yes = 251, no = 117
OnPavement	presence of on-pavement signing	Yes = 55, no = 313
Channelization	Presence of channelization at the approach	Yes = 31, no = 337
Median	Divided median on the major approach	No = 368
MedianType	Type of median (no, painted, raised, grass)	No = 368

Variable	Description	Counts
Grade	Qualitative assessment of approach grade	Downhill = 58, flat = 294, uphill = 16
Speeding	Max speed within 600 m (1,969 ft) of intersection > speed limit	Yes = 318, no = 50
SpeedingAbove5	Max speed > 2.24 m/s (5 mph) over the speed limit	Yes = 202, no = 166
SpeedingAbove10	Max speed > 4.47 m/s (10 mph) over the speed limit	Yes = 96, no = 272
Gender	Driver gender	Male = 156, female = 212
Opposite	Presence of vehicle on any other approach within 3 s of the subject vehicle approaching the intersection	Yes = 149, no = 219
AgeCategorical	Age when trip was collected	Age <25 yr = 48; 25 ≤ age <65 = 210; age ≥65 yr = 110

*MUTCD sign designations.

Table 46. Kinematic driver variables for stopping model at all-way stop-controlled intersections with kinematic driver variables.

Variable	Description	Counts
ScanDist	Distance upstream (in 50-m increments) at which the driver began scanning	Mean = 52.69, standard deviation = 38.07
Distract100_to_250	Whether a driver was engaged in a distraction within 100–250 m (328–820 ft) upstream of the intersection	Yes = 6, no = 362
Distract100	Whether a driver was engaged in a distraction within 100 m (328 ft) upstream of the intersection	Yes = 0, no = 368
Non_forward_100_to_250	Whether a driver engaged in glances away from roadway-related glance locations within 100–250 m (328–820 ft) upstream of the intersection	Yes = 78, no = 290
Non_forward_100	Whether a driver engaged in glances away from roadway-related glance locations within 100 m (328 ft) upstream of the intersection	Yes = 58, no = 310

The independent variables listed in table 40, table 41, table 44, and table 45 included intersection characteristics (lane width, intersection angle, types of signs present, approach grade, approach speed limit, and presence of countermeasures), driver characteristics (age and gender), and environmental factors (pavement surface condition and time of day).

ANALYSIS AND RESULTS OF STOPPING BEHAVIOR AT ALL-WAY STOP-CONTROLLED INTERSECTIONS

Model With All Viable Traces

As in the analysis of two-way stop-controlled intersections, an ordinal mixed-effects logistic regression model was initially run, with the dependent variable being type of stop and the possible values being full stop to rolling stop to no stop. However, the model was found to violate the proportional odds ratio assumption. Therefore, a binomial mixed-effects logistic regression model was developed, with the dependent variable having possible values of full/rolling stop or no stop. Development of the model used the "brm()" function of the "brms" package in *R*. Relevant interactions (e.g., overhead flashing beacons at night) were tested to determine whether they needed to be included in the model.

The final model was developed using the top 15 most important variables as determined by a random forest analysis. A random forest analysis is a machine-learning regression technique that considers complex relationships between the dependent and independent variables. The technique does not provide insights about the mechanism of the model, and for that reason, a random forest was not used as the final model. Random forests can, however, provide a ranking of the most important variables. The random forests were fitted using the package "randomForest" in *R* (Liaw and Wiener 2002).

Table 47 through table 49 show the final model results for stopping behavior at all-way stop-controlled intersections with all traces. The odds ratios are relevant only when no interactions exist.

Table 47. Dependent binary variable for final model for stopping behavior at all-way intersections with all traces.

Variable	Possible Values
Type of stop	0 = Full or rolling stop, 1 = no stop

Table 48. Independent variables for final model for stopping behavior at all-way intersections with all traces.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^	Odds Ratio
Intercept	−1.053	0.410	−1.71242	−0.38261	0.34874
Opposite	−2.029	0.114	−2.21463	−1.83979	0.131484
SpeedingAbove10	0.616	0.198	0.295099	0.942578	1.851461
*Movement = Right (baseline = left)	2.315	0.534	1.452	3.215	N/A
*Movement = Through (baseline = left)	−0.033	0.425	−0.726	0.689	N/A
*Stop Bar	0.254	0.519	−0.614	1.109	N/A
*Beacon	−1.045	0.653	−2.114	0.041	N/A

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^	Odds Ratio
*Movement—stop bar = Right—yes (baseline = left—no)	−1.555	0.659	−2.650	−0.496	N/A
*Movement—stop bar = Through—yes (baseline = left—no)	−0.083	0.553	−1.003	0.809	N/A
*Movement—beacon = Right—yes (baseline = left—no)	1.368	0.800	0.068	2.696	N/A
*Movement—beacon = Through—yes (baseline = left—no)	0.622	0.649	−0.450	1.651	N/A

*Interaction term.

Table 49. Random effects for final model for stopping behavior at all-way intersections with all traces.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^
Approach ID	0.540	0.177	0.237	0.828
Driver ID	2.057	0.202	1.748	2.408

Negative values for the estimates indicate an increased probability of a full or rolling stop, while positive values indicate the probability of no stop.

When one or more vehicles were present on an opposing approach within 3 s of the subject driver's reaching the intersection, the subject driver was 7.60 times more likely to stop at the intersection. This finding was expected because drivers are generally more likely to stop when conflicting vehicles are present.

A correlation between speeding and likelihood of a stop was also found. Drivers who were traveling 4.47 or more m/s (10 mph) over the posted speed limit upstream of the intersection were 1.85 times more likely not to stop than drivers who were not speeding.

Interactions were present between turning movement and presence of a stop bar and between turning movement and presence of a beacon. Figure 30 shows the credible sets for the interaction between turning movement and presence of a stop bar. The probability of not stopping is represented on the *y*-axis, and turning movement is shown on the *x*-axis.

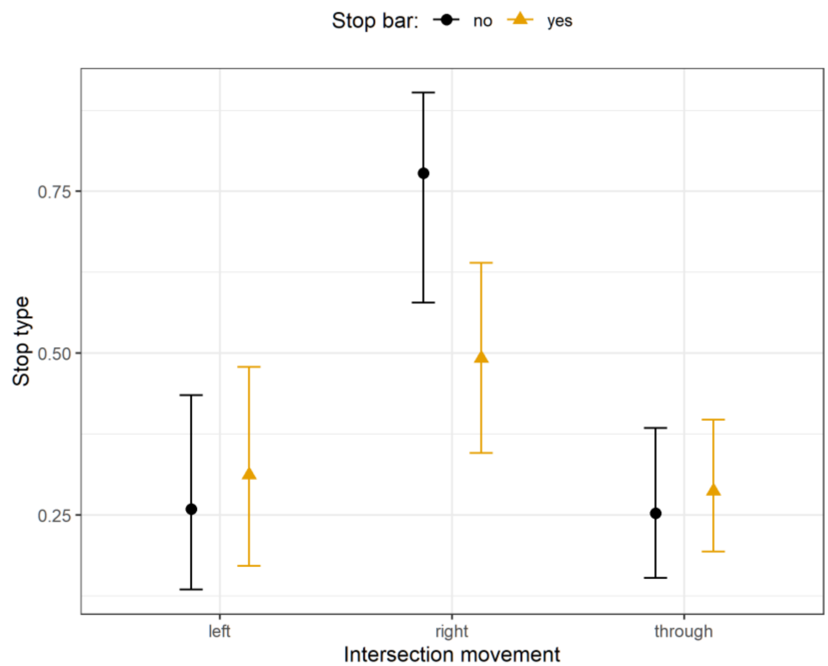


Figure 30. Graph. Interaction between turning movement and presence of a stop bar for all-way stop-controlled intersections (all traces).

The probabilities of a left-turning driver's not stopping when a stop bar was present versus not present were similar (25 percent and 30 percent, respectively). Similarly to left-turning vehicles, through vehicles had similar probabilities of not stopping in the presence or absence of a stop bar (25 percent and 28 percent, respectively), and the percentages are similar to those for left-turning vehicles. Right-turning vehicles were much more likely not to stop when no stop bar was present (> 75 percent) compared with when a stop bar was present (approximately 50 percent).

The interaction between turning movement and presence of a beacon is shown in figure 31.

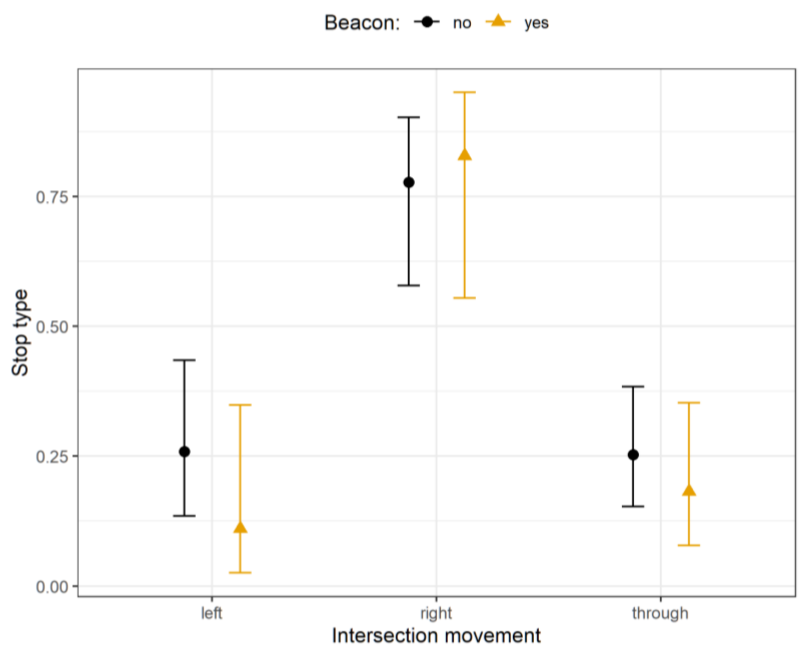


Figure 31. Graph. Interaction between turning movement and presence of a beacon for all-way stop-controlled intersections (all traces).

For right-turning vehicles, the probability of not stopping in either the presence or absence of a beacon was greater than 75 percent, with drivers slightly more likely not to stop when a beacon was present. However, there was significant overlap in the credible sets. Through drivers were slightly more likely not to stop when no beacon was present (25 percent) than when a beacon was present (18 percent). Significant overlap was present in the credible sets. Finally, left-turning drivers were much more likely not to stop when no beacon was present (26 percent) than when a beacon was present (11 percent). Overall, the presence of a beacon appears to have an impact on the stopping behavior of left-turning and through drivers.

Model With Kinematic Driver Variables

Table 50 through table 52 show the model developed for time series traces at all-way stop-controlled intersections that included kinematic driver variables.

Table 50. Dependent variable (binary) for final model for stopping behavior at all-way stop-controlled intersections with kinematic driver variables.

Variable	Possible Values
Type of stop	0 = Full or rolling stop, 1 = no stop

Table 51. Independent variables for final model for stopping behavior at all-way stop-controlled intersections with kinematic driver variables.

Variable	Estimate	Estimated Error	Lower-90% CI^	Upper-90% CI^	Odds Ratio
Intercept	−4.648	2.105	−8.488	−1.668	0.010
Opposite	−3.258	0.690	−4.484	−2.247	0.038
SpeedingAbove10	1.863	0.682	0.823	3.067	6.443
*Movement = right (baseline = left)	8.034	2.913	4.006	13.307	N/A
*Movement = through (baseline = left)	4.145	2.115	1.106	7.993	N/A
*Stop bar	3.916	2.279	0.524	8.019	N/A
*Beacon	−3.186	1.811	−6.210	−0.458	N/A
*Distraction_100 m	−1.477	0.838	−2.895	−0.163	N/A
*Nonroadway_100–250 m	−0.874	0.627	−1.933	0.124	N/A
*Movement—stop bar = Right—yes (baseline = left—no)	−7.208	3.032	−12.723	−2.787	N/A
*Movement—stop bar = Through—yes (baseline = left—no)	−2.921	2.332	−6.994	0.649	N/A
*Movement—beacon = Right—yes (baseline = left—no)	5.3125	2.379	1.664	9.447	N/A
*Movement—beacon = Through—yes (baseline = left—no)	2.008	1.763	−0.757	4.966	N/A
*Distraction_100 m—Nonroadway_100–250 m (baseline = no—no)	2.638	1.293	0.605	4.853	N/A

*Interaction term.

Table 52. Random effects for final model for stopping behavior at all-way stop-controlled intersections with kinematic driver variables.

Variable	Estimate	Estimated Error	Lower-90% CI	Upper-90% CI
Approach ID	0.783	0.556	0.072	1.849
Driver ID	3.297	0.888	2.080	4.948

As table 50 through table 52 show, the presence of a vehicle on the opposite approach resulted in higher odds of a driver's engaging in a rolling/full stop (1/0.038454 = 26.01) than when a vehicle was not present. When drivers were traveling 4.47 or more m/s (10 or more mph) over the posted speed limit upstream of the intersection, they were 6.44 times more likely not to stop.

Interactions were present between several variables, as illustrated in figure 32 and figure 33 using credible sets. The relationship between presence of a stop bar, turning movement, and probability of not stopping is shown in figure 32.

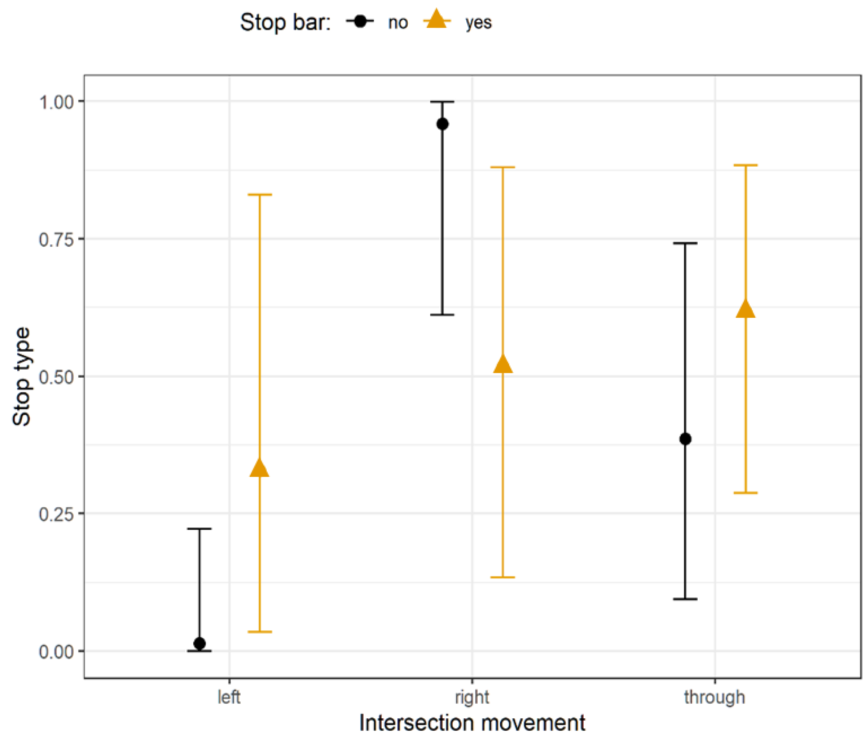


Figure 32. Graph. Interaction between turning movement and presence of a stop bar for all-way stop-controlled intersections (traces with kinematic driver variables).

As the figure shows, through drivers were more likely not to stop when a stop bar was present (61 percent) than when a stop bar was not present (37 percent). However, there was significant overlap in the credible sets. Left-turning vehicles had a very small probability of not stopping when no stop bar was present but a 32-percent chance of not stopping when one was present. Most right-turning drivers did not stop when no stop bar was present, but only 50 percent did not stop when a stop bar was present.

The relationship between presence of a beacon, turning movement, and probability of not stopping is shown in figure 33.

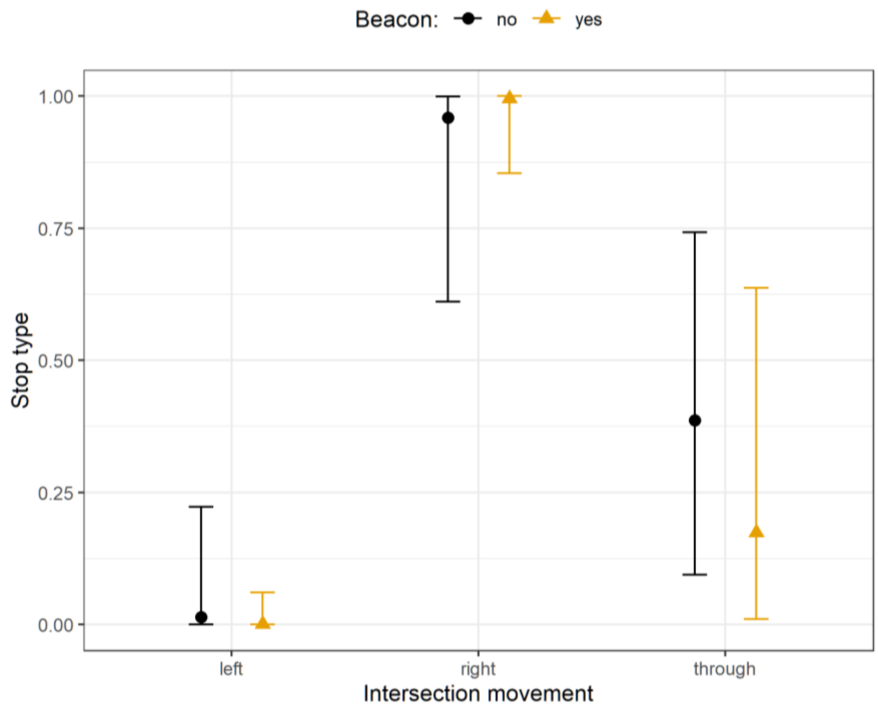


Figure 33. Graph. Interaction between turning movement and presence of a beacon for all-way stop-controlled intersections (traces with kinematic driver variables).

Drivers making a through movement had a 32-percent probability of not stopping when no beacon was present but a 19-percent chance of not stopping when a beacon was present. However, there was significant overlap in the credible sets. Right-turning drivers had a high probability of not stopping in either the presence or absence of a beacon. However, less variance was observed in the probability of not stopping when a beacon was present, suggesting that drivers were slightly more likely not to stop when a beacon was present. Left-turning vehicles had a low probability of not stopping in the presence or absence of a beacon. Much less variance was observed when a beacon was present, suggesting that drivers were less likely not to stop when a beacon was present.

Finally, an interaction was found between whether a driver engaged in a non-roadway-related glance (see chapter 3 for definition) within 100–250 m (328–820 ft) upstream of an intersection and whether the driver was engaged in a distraction within 100 m (328 ft) of the intersection. Although the interaction is complicated to explain, in general the relationship suggests that drivers who divert their attention away from the roadway multiple times are more likely not to stop. However, the credible sets are quite large, so the team suggests that readers interpret the results with caution.

DISCUSSION

Stopping behavior at all-way stop-controlled intersection approaches was modeled similarly to the analysis conducted for two-way stop-controlled intersections (chapter 5). Based on the results of that analysis, the data for rolling and full stop were combined for this analysis. All the two-way stop-controlled intersections in the analysis were rural.

The results of both models showed that vehicles turning right at an intersection were more likely not to stop than vehicles turning left or going straight. That result was expected, since a right turn has fewer conflict points than other turning movements do, and drivers making right turns may feel more comfortable not stopping. Additionally, when right-turn channelization was present, drivers may have had to only yield rather than stop.

Both models showed a correlation between speed and likelihood of a stop, in that drivers traveling 4.47 or more m/s (10 or more mph) over the posted speed limit were much more likely not to stop. Both models also showed that when one or more vehicles were present on an opposing approach within three seconds of the subject driver reaching the intersection, the subject driver was more likely to stop at the intersection. That result was expected, since drivers are generally more likely to stop when conflicting vehicles are present.

An interaction was present between turning movement and presence of a stop bar. In the model that included all traces, left-turning and through vehicles did not differ significantly in terms of stopping behavior when a stop bar was present versus when one was not present. The model that included only traces with kinematic driver behaviors reduced indicated that left-turning and through vehicles were more likely not to stop when a stop bar was present. Both models found that right-turning drivers were much more likely not to stop when no stop bar was present compared with when a stop bar was present.

An interaction was also present between turning movement and presence of a beacon. Right-turning vehicles were slightly more likely not to stop when a beacon was present. In both models, through drivers were more likely not to stop when no beacon was present than when a beacon was present. Both models also showed that left-turning drivers were much more likely not to stop when no beacon was present compared with when a beacon was present. Overall, presence of a beacon appeared to have a positive impact on the stopping behavior of left-turning and through drivers.

Finally, an interaction was present between whether a driver engaged in a non-roadway-related glance within 100–250 m (328–820 ft) upstream of an intersection and whether a driver was engaged in a distraction within 100 m (328 ft) of the intersection. Although the interaction is fairly complicated to explain, in general the relationship suggests that drivers who divert their attention away from the roadway multiple times are more likely not to stop. However, the credible sets are quite large, so the researchers suggest that readers interpret the results with caution.

CHAPTER 8. ANALYSIS OF INTERSECTION CRASHES

The most promising outcome of the SHRP2 NDS data has been the ability to assess crash and near-crash events firsthand in order to identify such factors as driver distraction, which heretofore could not be observed. However, once crashes are disaggregated by roadway type and other factors, the available sample size is smaller than might be expected, and a rigorous analysis cannot be completed using NDS data alone. As a result, stopping behavior and the point at which drivers react to an upcoming intersection were used as surrogate measures to more fully assess rural intersection safety.

DATA USED

Rural-intersection-related safety-critical events (crash, near crash, and crash relevant) were identified in the *InSight Data Access Website: SHRP2 Naturalistic Driving Study* (VTTI 2019) by setting "Traffic Control" to "Stop Sign" and setting "Locality" to "open country, open residential, or moderate residential." The team removed events in which roadway surfaces were snowy or icy because stopping behavior may have been compromised. Additionally, events in which intersection configuration could not be determined or in which configuration was highly unusual were removed. Further, only events in which the subject driver was at fault were retained. The result comprised 38 safety-critical events.

The team gave the event IDs of the 38 safety-critical events to the subcontractor that archives the SHRP2 NDS data, and the subcontractor returned a set of 214 baseline events at the intersections where those events had occurred. The subcontractor reduced glance locations and secondary tasks for the baseline events. The reaction point just prior to each event was determined using the reaction point before the crash or near-crash point (both of which were determined by the subcontractor). For baseline events, the event point was defined as the point at which a vehicle crossed the stop bar at stop-controlled approaches and the point at which a vehicle began making a turn at approaches without stop control. Distractions that occurred 5 s prior to an event point were coded by the subcontractor, as noted in chapter 3. Type of stop was also coded using the definition described in chapter 3. And speed at the same point was extracted.

All other data used were the same as those described in chapter 3.

ANALYSIS AND RESULTS OF SAFETY-CRITICAL EVENTS

The data were insufficient for developing a statistical model. As a result, the team used a simple statistical analysis to evaluate the data. The team disaggregated the data by events that had occurred at a stop-controlled approach where drivers would have been expected to stop (19 safety-critical events and 111 baseline events) and by events that had occurred at a major street approach with no traffic control (also 19 safety-critical events and 103 baseline events). Further disaggregation by type of intersection (e.g., two-way versus T-intersection) or by type of driver was not practical due to sample size.

Figure 34 shows stopping behavior for events at stop-controlled approaches.

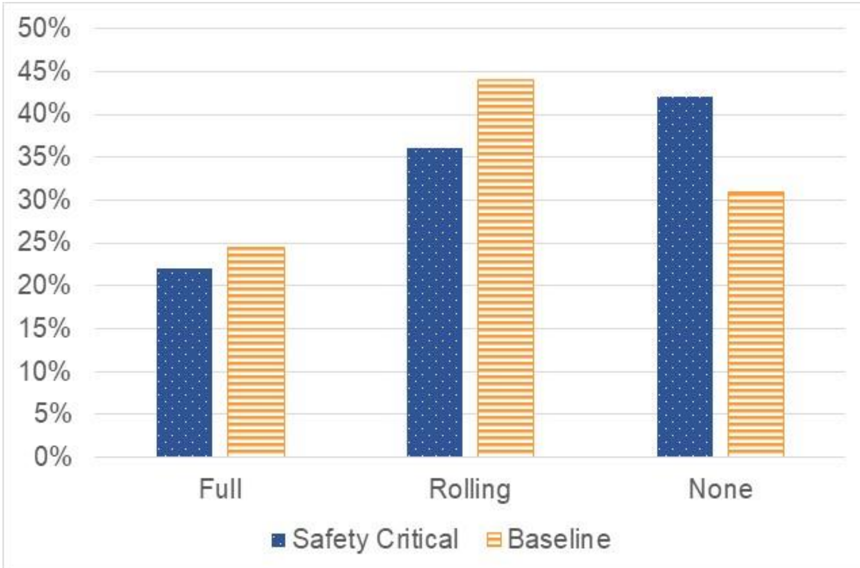


Figure 34. Graph. Stopping behavior at stop-controlled approaches by type of event.

As the figure shows, 21 percent of safety-critical events involved a full stop versus 25 percent of baseline events. Similarly, 37 percent of safety-critical events involved a rolling stop compared with 44 percent of baseline events. Finally, drivers in 42 percent of safety-critical events did not stop compared with drivers in 32 percent of baseline events.

Simple odds ratios were calculated for several characteristics. For events on a major approach, the odds of experiencing any type of distraction in the 5 s before a crash or near-crash event were 1.52 times those of a baseline event, with a 95 percent CI of 0.57–4.11. For a crash or near-crash event on a stop-controlled approach, the odds of being engaged in a distraction were 3.56 higher (CI = 0.85–7.68). The odds of a driver's not stopping in a crash or near-crash event were 1.65 higher (CI = 0.61–4.47) than in a baseline event.

The analyses suggest that drivers involved in crashes at rural intersections were more likely to have been distracted or to have engaged in unsafe stopping behaviors. However, none of the results are statistically significant because the CI includes 1. The wide CI is likely due to the small sample size of crash and near-crash events.

CHAPTER 9. CONCLUSIONS

This study used traces of drivers' behaviors upstream of and through rural minor stop-controlled intersections from the SHRP2 NDS database to evaluate drivers' behaviors at rural intersections (VTTI 2019). The research team developed models for where drivers began reacting upstream of an intersection, for drivers' stopping behaviors, and for the roadway, environmental, and driver features that influenced those reactions and behaviors.

The researchers hoped the study could assess the effect of roadway features and countermeasures on driver behavior; however, the approach taken was likely too broad. The variety of roadway features and countermeasures included in the 199 unique intersections that were used for this study made it too difficult to isolate the effect of any single feature or countermeasure. However, the researchers identified various features in the models developed as part of this study, which may affect driver behavior at rural intersections. The features are intersection skew, presence of stop bars, on-pavement signing presence, presence of beacons, and presence of advance intersection warning signs. Researchers in future projects could study each of those countermeasures through the use of SHRP2 NDS data by taking a more targeted approach that would include a variety of intersections that are very similar except for the presence or absence of countermeasures of interest. In the same manner, researchers could also study other intersection features that did not show up as significant in this research project—likely due to the inclusion of too many potential factors.

Additionally, the models were able to identify the role driver behaviors such as scanning and engaging in distraction play in a driver's negotiation of a rural intersection. Scanning at a high rate within 200 m (656 ft) of an intersection was associated with drivers' being more likely to come to a full stop, whereas drivers who did a high amount of scanning in the 100 m (328 ft) upstream of the intersection were actually less likely to stop, which may have been due to their assessing for potential conflicts and when none were present, traveling through the intersection without stopping. Researchers can use those findings related to driver behavior in their development of education related to traveling through rural intersections. For instance, informing drivers that although they may scan an intersection in the 100 m (328 ft) leading up to its approach, vehicles traveling on the mainline of most rural intersections are traveling 24.5 m/s (80 ft/s) every second, and therefore a driver could easily misjudge a gap. Researchers could also use—in education to detract from distracted driving—the quantified increased risk of being involved in a crash or near-crash event when distracted (1.5–3.6× depending on major or minor approach).

ACKNOWLEDGMENTS

The team thanks the Iowa DOT for funding a pilot stage of this research and thanks the staff of the Center for Transportation Research and Education at Iowa State University for assistance. The research team also thanks the TAC members of the Iowa DOT for their guidance.

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Recommended citation: Federal Highway Administration,
Evaluating the Relationship Between the Driver and the Roadway to Address Rural Intersection Safety by Using SHRP2 Naturalistic Driving Study Data and the Roadway Information Database
(Washington, DC: 2024) https://doi.org/10.21949/1521585

HRSO-20/07-04(WEB)E