Leveraging the Second Strategic Highway Research Program Naturalistic Driving Study: Examining Driver Behavior When Entering Rural High-Speed Intersections

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Pedestrian and Bicycle Safety

FOREWORD

Intersections, particularly stop-controlled intersections in rural areas, provide the setting for a large number of traffic crashes. Factors believed to contribute to these crashes include inadequate surveillance, failure to obey/yield, driver inattention, and speed. In 2005, Congress authorized and funded the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) with the goals of improving safety for motorists and workers, enabling transportation agencies to improve their infrastructure more quickly, targeting resources and enhancing existing processes, and making the system more reliable for travelers.

This research study examined driver stopping and scanning behavior as they approached and entered rural high-speed intersections, producing actionable insights into transportation safety by leveraging the SHRP2 safety databases. This report details the SHRP2 data acquisition process, exploratory analysis, and results. Use of NDS data represents an important addition to the body of knowledge concerning driver behavior at intersections. Secondary objectives include assessing SHRP2's ability to address further questions of safety and increasing awareness and understanding of relevant analysis techniques and methods.

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Director, Office of Safety
Research and Development

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16. Abstract
Overall, 40 percent of crashes in the United States occur at intersections; a total of 57 percent of fatalities from 1997–2004 occurred at stop-controlled intersections, of which 61 percent occurred in rural areas. Factors believed to contribute to these incidents include inadequate surveillance, failure to obey/yield, driver inattention, and speed. This study used naturalistic driving data collected under the second Strategic Highway Research Program to explore drivers' brake and glance patterns on approach to rural high-speed, stop-controlled intersections from the minor route. Brake distance was found to be sufficiently predicted by brake speed (the speed at which the driver was moving upon initial brake activation). At an average brake speed of 61.7 mi/h, participants first applied the brakes at an average distance of 328.7 ft from the intersection. Older participants (ages 45 to 84) applied the brakes farther upstream, especially at higher speeds, than their younger counterparts (ages 18 to 44). The probability of making a complete stop was found to vary significantly with average annual mileage (AAM) and expressed risk associated with performing rolling stops. Participants with higher AAM were found more likely to make complete stops. Intersection approaches were divided into five 98.4-ft segments, and total glance duration to eight regions of interest (ROIs) within each segment were analyzed. Drivers spent nearly the entire approach glancing to the forward ROI until they were 98.4 ft from the intersection. Between 0 and 98.4 ft, drivers spent an average of 5.1 s scanning the intersecting roadway; a total of 86.5 percent of all intersection scanning occurred in the last 98.4 ft of the approach. A novel difference was found among intersection crossings according to the type of stop performed. Drivers who came to a complete (0 mi/h) stop spent just 39.2 percent of their prestop time scanning the intersection, while rolling stoppers spent 74.5 percent. This suggests that complete stoppers focus on getting to the intersection and then stop, scan, and proceed, whereas rolling stoppers scan the intersection prior to arrival so that they can proceed at higher speeds while maintaining a perception of safety.

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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 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		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 (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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

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LIST OF ABBREVIATIONS

AAM	average annual mileage
CT	cross traffic
DUL	data use license
GEE	generalized estimating equation
GLM	generalized linear model
ICWS	intersection conflict warning system
ID	identification
IRB	Institutional Review Board
NDS	naturalistic driving study
PII	personally identifiable information
RID	Roadway Information Database
ROI	region of interest
SHRP2	second Strategic Highway Research Program
SUV	sport utility vehicle
VTTI	Virginia Tech Transportation Institute
QIC	quasilikelihood under the independence model criterion

BACKGROUND

In 2005, Congress authorized and funded the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) with the goals of improving safety and reliability for motorists and workers, enabling transportation agencies to improve their infrastructure more quickly, targeting and efficiently allocating resources, and enhancing existing processes.[1]

The SHRP2 NDS is the largest study of its kind with over 3,100 primary drivers and 3,000 vehicles across 6 sites within the United States. The Virginia Tech Transportation Institute (VTTI) developed the data acquisition systems installed in participating vehicles and continues to house all data acquired throughout the NDS.[2] Data included but were not limited to Global Positioning System coordinates, speed, brake and acceleration behavior, driver demographics, detailed event descriptions, and video feeds to the front and rear of the vehicle and on the driver's face and hands. The accompanying Roadway Information Database (RID) includes detailed roadway data collected on more than 12,000 centerline mi of highways in and around the site, including but not limited to crash histories, traffic and weather conditions, road type, and present signage. Used together, data collected during the NDS and for the RID can be leveraged for a new perspective on driving behaviors.

Intersections provide the setting for a large number of traffic incidents. Overall, 40 percent of crashes in the United States occur at intersections; a total of 57 percent of fatalities from 1997–2004 occurred at stop-controlled intersections, of which 61 percent occurred in rural areas.[3,4] Factors believed to contribute to these incidents include inadequate surveillance, failure to obey/yield, driver inattention, and speed.[5,6] In 2000, researchers in Kansas hypothesized that the majority of such collisions occur because drivers "did not see oncoming vehicles or failed to accurately estimate the speeds of oncoming vehicles on the major roadway."[7](p. 32) A naturalistic environment provides an opportunity for new insight into stopping and scanning behaviors at intersections.

OBJECTIVE

The main objective of this research was to produce actionable insight into transportation safety by leveraging the SHRP2 databases. Specifically, this research aimed to explore and quantify the stopping and scanning behaviors of drivers as they approached and entered rural high-speed intersections. The use of NDS data represents an important addition to the body of knowledge concerning driver behavior at intersections by leveraging the higher degree of ecological validity relative to driving simulators. Secondary objectives include assessing SHRP2's ability to address further questions of safety and increasing awareness and understanding of relevant analysis techniques and methods.

DATA

All data used in this analysis were acquired from the SHRP2 dataset. The following sections detail the data request process, how intersections were selected for inclusion in this analysis, the contents of the static and time-series datasets, and the reduction of video data.

DATA REQUEST PROCESS

The process to request SHRP2 NDS data began with *InSight*, VTTI's Web site for limited data access, message boards, and documentation. *Insight*'s highest user access level, qualified researcher, requires registering for the site, agreeing to the terms of service and privacy policy, and uploading a valid Institutional Review Board (IRB) training certificate. Doing so unlocks the custom query capability, which was used to assess the feasibility of the project by identifying the data components necessary for analysis of stopping and scanning behaviors.

The RID was then used to identify rural high-speed intersections.[8] Geographic information system software was used to interface with the database. The RID provided detailed information on roadway features and identified each road segment with a unique link identification (ID). A set of relevant link IDs was identified and sent to VTTI in exchange for the number of crossings and unique participants who traversed them.

VTTI required three documents to establish a data sharing agreement. First, a detailed research statement was submitted, outlining the study's objectives and proposed analyses. Concurrently, an IRB application was submitted to the principal investigator's home institution. The application described how the study involved human subjects, the research design, expected benefits and potential risks, a risk mitigation plan, as well as how personally identifiable information (PII) would be used. Finally, a data use license (DUL) created by VTTI was filled out and submitted for review. The DUL included a project background and description, a data request scope (summary of dataset being requested and a description of how it ties into the research problem), a data specification (list of the specific data elements requested), biographies of all members of the research team, and a data security plan. All research team members and an institutional representative from the principal investigator's home institution signed the DUL, binding them to the extensive terms and conditions. After some clarification on the data security plan, the director of VTTI then signed the DUL, thereby enacting it.

Because VTTI was handling data requests on an individual basis, a standardized pricing scheme did not exist at the time, so a subcontract was considered the correct course of action. The principal investigator's home institution initiated the process by providing VTTI with a statement of work outlining expectations, timelines, and payments. VTTI responded with a detailed cost estimate, and the two parties agreed to a firm fixed-price subcontract with three milestones to be accomplished within 2 mo: (1) extraction of static and time-series datasets, (2) joint development of a video reduction protocol, and (3) delivery of video-reduced data (eyeglances and traffic presence).

It should be noted that the principal investigator's home institution had two options regarding the reduction of video data. To protect PII, viewing of face videos was restricted to a facility (referred to as the "secure data enclave") on VTTI's campus. Reduction was accomplished entirely by VTTI staff, but the principal investigator's home institution could have reserved time in the enclave and performed the reduction using members of the project team. The principal investigator's home institution considered this option but ultimately chose to subcontract VTTI for the reduction because costs were comparable. Reduction by the principal investigator's home institution staff was subject to non-completion within the constraints of the enclave time.

INTERSECTION SELECTION

Intersections were selected from the RID to be as homogeneous as possible. Through an iterative segmentation process, four Pennsylvania intersections were found to have the desired features and number of crossings sufficient for meaningful analysis. Those desired features include the following:

- A rural setting, which was determined using the U.S. Census Bureau's 2014 TIGER/LINE® shapefiles available to the public from census.gov.
- Four approaches.
- Each approach having exactly one through lane in each direction and no turn lanes.
- A major route with a posted speed limit $\geq$ 50 mi/h.
- Stop-controlled minor route approaches.

After identifying the intersections of interest, a list of link IDs was sent to VTTI for extraction. In return, VTTI provided time-series data on 735 crossings through 7 intersections. However, to be useful to the analysis of intersection-approaching stopping and scanning behaviors, crossings wherein drivers began on the major route were excluded, leaving 461 relevant crossings. A total of 3 sites experienced only 5, 8 and 13 crossings, respectively. After excluding these crossings for lack of sufficient replication to test for site-specific effects and 24 others for incomplete traces (crossings originating at selected intersections), the dataset consisted of 411 crossings through 4 similar intersections. Figure 1 through figure 4 provide satellite imagery for each intersection overlaid with associated crossings.

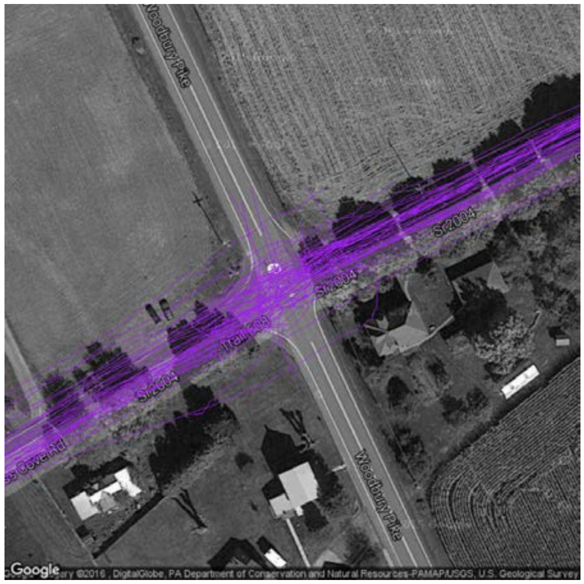

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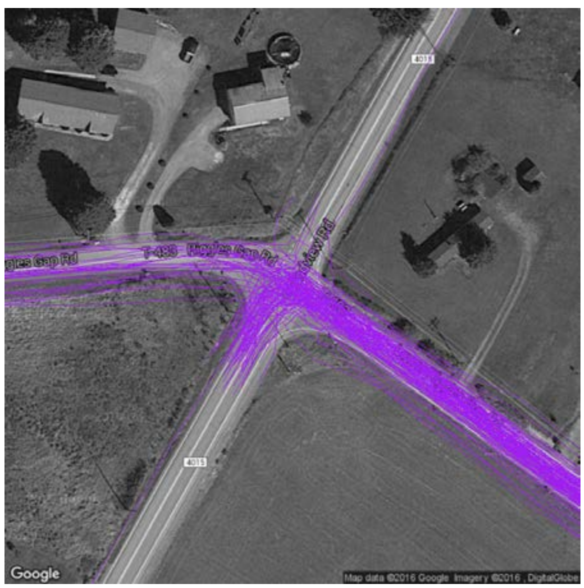
Figure 1. Map. Crossings through intersection 1.[(9)]



Original image: ©2016 Google®; map annotations provided by Leidos.

Figure 2. Map. Crossings through intersection 2.[(10)]

Original image: ©2016 Google®; map annotations provided by Leidos.

Figure 3. Map. Crossings through intersection 3.[(11)]

Original image: ©2016 Google®; map annotations provided by Leidos.

Figure 4. Map. Crossings through intersection 4.[(12)]

The 411 extracted crossings of 4 intersections were performed by 31 unique drivers. Table 1 lists the number of crossings in this final dataset by participant and intersection and highlights the unbalanced nature inherent to naturalistic data.

Table 1. Number of crossings in final dataset by participant and intersection.

Participant	Intersection 1	Intersection 2	Intersection 3	Intersection 4	Total
1	0	0	0	130	130
2	0	50	0	0	50
3	42	0	0	0	42
4	0	38	0	0	38
5	0	36	0	0	36
6	28	0	0	0	28
7	0	0	20	0	20
8	0	0	0	11	11
9	0	0	7	0	7
10	0	0	6	0	6
11	0	0	6	0	6
12	0	0	5	0	5
13	0	0	0	3	3
14	0	0	0	3	3
15	0	0	0	3	3
16	0	0	0	2	2
17	0	0	2	0	2
18	0	0	2	0	2
19	0	2	0	0	2
20	0	0	2	0	2
21	0	1	1	0	2
22	0	0	0	2	2
23	0	1	0	0	1
24	0	0	1	0	1
25	0	0	1	0	1
26	0	1	0	0	1
27	0	0	1	0	1
28	0	0	1	0	1
29	0	1	0	0	1
30	0	0	1	0	1
31	1	0	0	0	1
Total	**71**	**130**	**56**	**154**	**411**

STATIC AND TIME-SERIES DATA EXTRACTION

For each crossing through the selected intersections, numerous static and time-series variables were requested for their relevance to stopping and scanning behaviors.

Static Data

The static data used in this analysis consisted of variables that remained constant throughout the individual crossings. Table 2 lists these variables and their definitions. All static data elements (with the exception of maneuver) were collected via questionnaire prior to participation in the NDS.

Table 2. Static variables and definitions.

Variable	Definition
Gender	The gender with which the participant identifies.
Age group	The age group corresponding to the driver's birthdate.
Average annual mileage (AAM)	The participant's estimated AAM over the past 5 years.
Number of crashes	The number of crashes the participant has been in in the last 3 years.
Level of risk associated with performing a rolling stop	The participant's associated risk with going through a stop sign without stopping.
Tendency to perform a rolling stop	How often the participant reported not making a full stop at a stop sign in the past 12 mo.
Maneuver	The maneuver executed by the driver upon exiting the intersection.

Both genders (male and female) were well represented in the data. Of the 411 crossings, 47.7 percent were made by males, and 52.1 percent were made by females, with the remaining 0.2 percent unspecified. Of the 31 participants, 41.9 percent were male, 54.8 percent were female, and 3.2 percent were unspecified.

Age has been shown to affect both braking distance and scanning patterns.[9–11] Age group was originally quantified in 5-year increments, but because of the scarcity of the data, this was aggregated into two groups: younger (ages 16–44) and older (ages 45–84). Though drivers aged 16–19 years are likely to drive differently than any other age group, only one such participant crossed a qualifying intersection during the study period. The aggregation into two age groups divides the participants almost exactly in half, with 14 participants classified as older and 12 as younger (with two participants missing age data altogether). No effort was made to update age throughout the study because it would change by no more than 2 years, which would likely not result in any change to the binomial aggregation.

AAM was similarly aggregated from 5,000- to 10,000-mi increments. Mileage may reflect driving experience better than age, and greater experience has been shown to correlate with longer glance durations.[16]

The number of crashes was transformed from a count variable (with levels {0, 1, 2 or more} and frequencies {360, 13, 38} respectively) to a binary indicator with 1 used to indicate that the participant had experienced at least 1 crash in the prior 3 years and 0 otherwise, resulting in levels {0, 1} with respective frequencies {360, 51}.

Prior to beginning the study, participants were asked to indicate the risk they associated with performing a rolling stop. The level of risk associated with performing a rolling stop was originally captured on a 7-point scale, with 1 and 7 corresponding to "no greater risk" and "much greater risk," respectively. These responses were aggregated to low (1–2), medium (3–5), and high (6–7). The tendency to perform a rolling stop originally had four possible responses (never, rarely, sometimes, and often) but was aggregated to two: never/rarely and often/sometimes. In a survey of 4,010 American drivers in 2002, 58 percent of respondents considered rolling stops a major threat, while 42 percent admitted to performing them.[(17)]

Drivers' maneuvers were also extracted as a static variable. Because all chosen intersections consisted of exactly four approaches, the three possible values consisted of left turn, right turn, and straight ahead. These values were not aggregated or manipulated in any way.

Several variables described the scene of the crossing, such as weather conditions (raining, clear, etc.), road surface conditions (wet or dry), and the presence of construction. However, these variables exhibited too little variation to warrant analysis.

Time-Series Data

Whereas the static data provide one data point for each crossing, the time-series data consisted of a large variable amount of observations per crossing. Most data were recorded by the onboard data acquisition systems at a rate of 10 Hz (one observation every 0.1 s). Table 3 lists the raw data provided by VTTI used in this analysis as well as the corresponding definitions.

Table 3. Time-series variables and definitions.

Variable	Definition
VTTI timestamp	Integer used to identify one time sample of data.
Latitude	Vehicle position latitude.
Longitude	Vehicle position longitude.
Brake use indicator	Brake usage (0 for inactive and 1 for active).
Speed	Vehicle speed indicated on speedometer collected from network.
Acceleration	Vehicle acceleration (g) in the longitudinal direction versus time.

The VTTI timestamp counted milliseconds within each trip and was used to calculate glance times. Latitude and longitude were used in conjunction with intersection center coordinates to calculate how far drivers were from the intersection at any given moment. The moment when the distance between the driver and the intersection center was minimized was considered the point of arrival at the intersection. Coordinates were provided at a 1-Hz frequency and interpolated to 10 Hz using provided speed data. Interpolated coordinates were not simply linear extensions of existing coordinates but calculated based on minute changes in speed (provided at 10 Hz). The brake use indicator, speed, and acceleration variables were left unaltered and were analyzed using their original definitions.

Eyeglance locations and traffic conditions are data of the time-series variety but not readily extractable like the variables listed in table 3. The following section details the reduction process for these data points.

DATA REDUCTION

In addition to static and time-series data, VTTI staff were commissioned to reduce video from four camera angles (forward, driver face, hands/dash, and rear) to produce useable quantitative data regarding eyeglance locations and traffic presence.

Eyeglance Locations

Due to its very nature, video of participating drivers' faces is considered PII and was therefore not viewable outside of VTTI's secure data enclave. Reductionists viewed the video feeds of the 411 crossings frame by frame and noted when drivers glanced to the 10 regions of interest (ROIs). Examples of glances to each ROI are provided in figure 5 through figure 11 along with descriptions of each in table 4. Note that the example photos shown here depict a VTTI employee and as such do not violate PII protection agreements.

Figure 5. Photo. Example of glance to far left.

Figure 6. Photo. Example of glance to near left.

Figure 7. Photo. Example of glance to road ahead.

©Virginia Tech Transportation Institute.

Figure 8. Photo. Example of glance to rearview.

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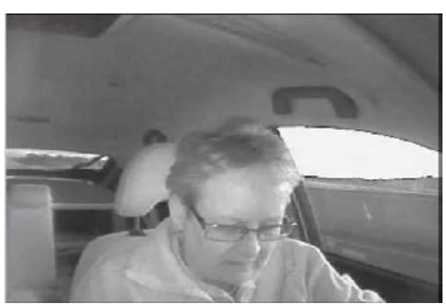
Figure 9. Photo. Example of glance to near right.

©Virginia Tech Transportation Institute.

Figure 10. Photo. Example of glance to far right.



©Virginia Tech Transportation Institute.

Figure 11. Photo. Example of glance to cell phone.

Table 4. Definition of each ROI.

ROI	Definition
Far left	Any glance to the left side mirror or window, including over the driver's left shoulder.
Near left	Any glance out the forward windshield where the driver appears to be looking specifically out the left margin of the windshield (e.g., as if scanning for traffic before turning or glancing at oncoming or adjacent traffic). This glance location includes any time the driver is looking out the windshield but clearly not in the direction of travel (e.g., at road signs or buildings).
Road ahead	Any glance out the forward windshield directed toward the direction of the vehicle's travel. Note that when the vehicle is turning, these glances may not be directly forward but toward the vehicle's heading; such glances are counted as forward glances.
Rearview mirror	Any glance to the rearview mirror or equipment located around it. This glance generally involves movement of the eyes to the right and up to the mirror. This includes glances that may be made to the rearview mirror in order to look at or interact with back seat passengers.
Near right	Any glance out the forward windshield where the driver appears to be looking specifically out the right margin of the windshield (e.g., as if scanning for traffic before turning or glancing at oncoming or adjacent traffic). This glance location includes any time the driver is looking out the windshield but clearly not in the direction of travel (e.g., at road signs or buildings).
Far right	Any glance to the right side mirror or window, including over the driver's right shoulder.
Cell phone	Any glance at a cell phone or other electronic communications device no matter where it is located. This includes glances to cell phone-related equipment (e.g., battery chargers).
Other	Any glance that cannot be categorized using the previous codes. This includes center stack, instrument cluster, passenger, interior object, portable media device, eyes closed, etc.
Transition	Any frame that is between fixations as the eyes move from one fixation to the next. Note that the eyes often fixate while the head is still moving. This category is based on the eyes' fixation rather than the head's movement, unless sunglasses preclude the eyes from being seen.
Unavailable	Unable to complete glance analysis due to an inability to see the driver's eyes/face. This includes no driver, no video, and glance location unknown.

The video's refresh rate was 15 Hz, which resulted in a dataset describing eyeglance locations approximately every 0.07 s. All assigned reductionists had been previously trained in VTTI's eyeglance methodology and tested for accuracy. At the start of this project, assigned reductionists were familiarized with the updated glance location definitions that apply to this project. All reduced data were reviewed by a second-level quality assurance data reductionist; no one performed reviews of their own work. When corrections were identified, the original reductionist would go back to make the changes unless they disagreed with the suggestion. Any remaining disagreements were resolved by a supervisor.

Traffic Presence

Because traffic was considered likely to influence stopping and scanning behaviors, the presence and path of other visible vehicles was also coded by VTTI personnel. Each vehicle was assigned a two-letter code for each frame during which it was visible: the first letter designated the vehicle's approach direction, and the second letter designated the vehicle's departure direction. Table 5 shows the construction of these codes, which are illustrated in figure 12 through figure 16. Note that all directions are from the participant driver's perspective upon arrival at the intersection. These data were later used to indicate the presence of cross traffic (CT) and vehicle queues.

Table 5. Construction of traffic presence codes.

Approach Direction	Departure Direction	Resulting Code
Left	Ahead	LA
	Right	LR
	Driver	LD
	Unknown	LU
Driver	Left	DL
	Ahead	DA
	Right	DR
	Unknown	DU
Right	Driver	RD
	Left	RL
	Ahead	RA
	Unknown	RU
Ahead	Right	AR
	Driver	AD
	Left	AL
	Unknown	AU
Unknown	Ahead	UA
	Right	UR
	Driver	UD
	Left	UL
	Unknown	UU
Unavailable	Unknown	Unavailable

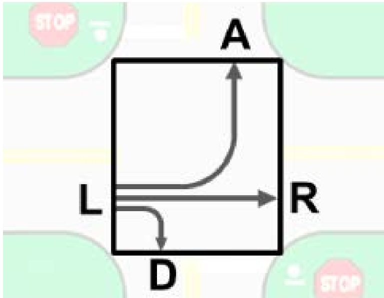


Figure 12. Illustration. Traffic vehicle path approaching from left.

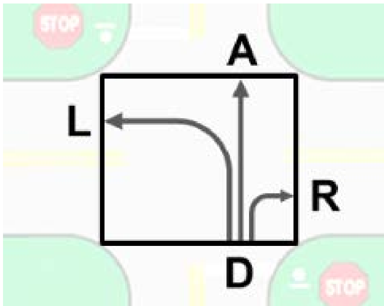


Figure 13. Illustration. Traffic vehicle path approaching from the driver.

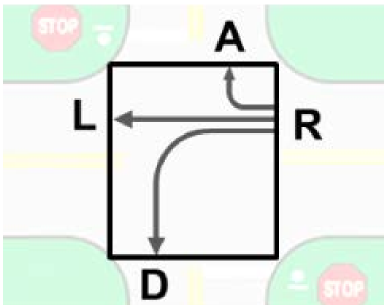


Figure 14. Illustration. Traffic vehicle path approaching from right.

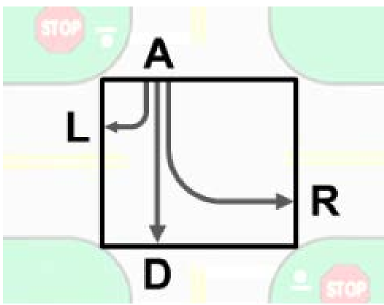


Figure 15. Illustration. Traffic vehicle path approaching from ahead.

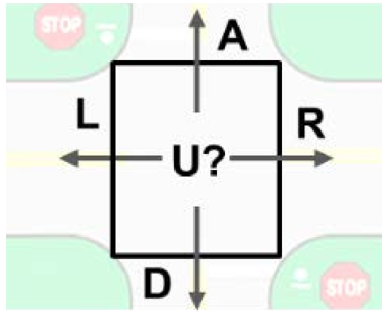


Figure 16. Illustration. Traffic vehicle path approaching from unknown direction.

STATISTICAL ANALYSIS

Four dependent measures of interest were analyzed: brake distance, the probability of a complete stop, glance duration, and scan time allocation. All available observations were used in the analysis of glance duration and scan time allocation, but only crossings without queues were used in brake distance models, and only totally unimpeded crossings were used in complete stop probability models. All modeling was performed using generalized estimating equations (GEEs), where analysis of repeated measures was possible, and generalized linear models (GLMs). The quasilikelihood under the independence model criterion (QIC) and scaled deviance statistics were used to assess GEE and GLM model fit, respectively. Smaller values of both statistics' QIC indicate better fitting models. Wald statistics for type 3 GEE analysis are reported. A value of 0.05 was used as the cutoff for determining *p*-value significance. All reported confidence intervals have been adjusted for simultaneous hypothesis testing.

BRAKE DISTANCE

Data provided on the status of the brake pedal was binary, indicating whether or not the brakes were activated. The distance at which the brake variable first took on the value of 1 was identified as the brake distance. Figure 17 shows the distribution of this distance for the 279 crossings that did not involve vehicle queues.

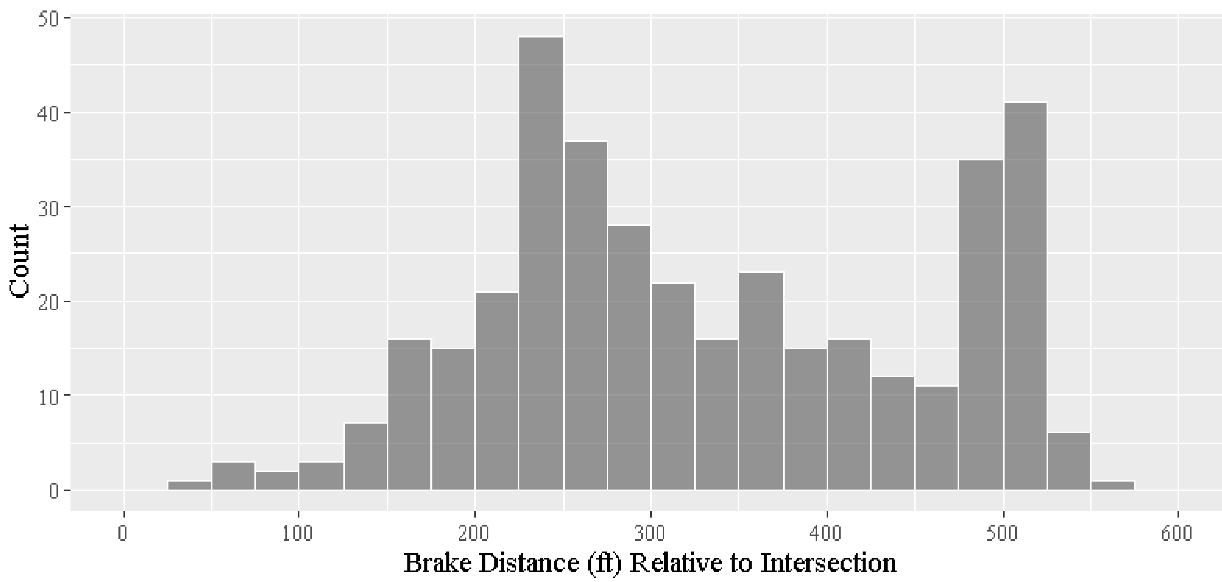


Figure 17. Graph. Brake distance (non-queued crossings only).

Brake distance overall averaged 329.4 ft (with a standard deviation of 115.8 ft) from intersection center. The choice of when to apply the brakes and thus begin to prepare to heed the stop sign is dependent on the presence of a vehicle queue. Logic dictates that if a lead vehicle is present, whether stationary or concurrently approaching the intersection, the driver of the upstream vehicle will be forced to apply the brakes sooner than in the absence of such a vehicle. Median brake distance among queued crossings was 31.5 ft greater than non-queued crossings (332 and 300.5 ft, respectively). In a previous study using an instrumented vehicle, Bao and Boyle found significant differences in brake distance by age: middle-aged drivers braked earlier than younger and older drivers.[13] However, no such difference was observed between older and younger drivers in the present data.

The speed at which drivers were traveling when they first applied the brakes was also identified. Brake distance and brake speed were found to be positively correlated (Pearson correlation coefficient of 0.76). That is, greater brake distances were associated with higher approach speeds. It was hypothesized that drivers who attained a lower minimum speed also applied the brake further upstream of the intersection, but the two measures were very weakly correlated (Pearson correlation coefficient of 0.11).

Method

Brake distance is defined as the distance from the intersection center at which drivers first applied the brakes. Because brake distance was found to be affected by the presence of vehicle queues, 132 such cases were excluded, leaving 279 for analysis. Separate GEEs were estimated for each predictor variable analyzed. These models employed normal response distributions with identity link functions and repeated measures clustered on participants.

Results

Table 6 lists the QIC statistics for these models. The hypothesis that drivers who attain a lower minimum speed also apply the brakes farther upstream of the intersection was tested but failed to improve model fit over the null (296.5 > 286.9).

Table 6. Fit statistics for brake distance models.

Model	QIC
Minimum speed	296.5
Null	286.9
Brake speed + rolling stop risk	285.8
Brake speed + maximum deceleration	279.1
Brake speed + gender	276.8
Brake speed + crash history	276.6
Brake speed + maneuver	275.0
Brake speed + rolling stop tendency	272.6
Brake speed + AAM	265.5
Brake speed + minimum speed	265.3
Brake speed	264.2
Brake speed + age group	256.7

However, a model using brake speed—the speed at which the driver was traveling upon initial brake application—produced a better fit (264.2 < 286.9) and predicted the result shown in figure 18.

$$\text{Brake Distance} = 7.6 \times \text{Brake Speed} - 142.3$$

Figure 18. Equation. Estimated brake distance (ft) as a function of brake speed (mi/h).

Brake distance was measured in feet and speed in miles per hour. Speed at brake application was normally distributed with a mean of 61.7 and standard deviation of 11.5. Figure 19 shows the results of this calculation for selected speeds. Note that the difference in brake distances at 50 and 70 mi/h (the approximate 25th and 75th percentiles, respectively) is a considerable 152.9 ft.

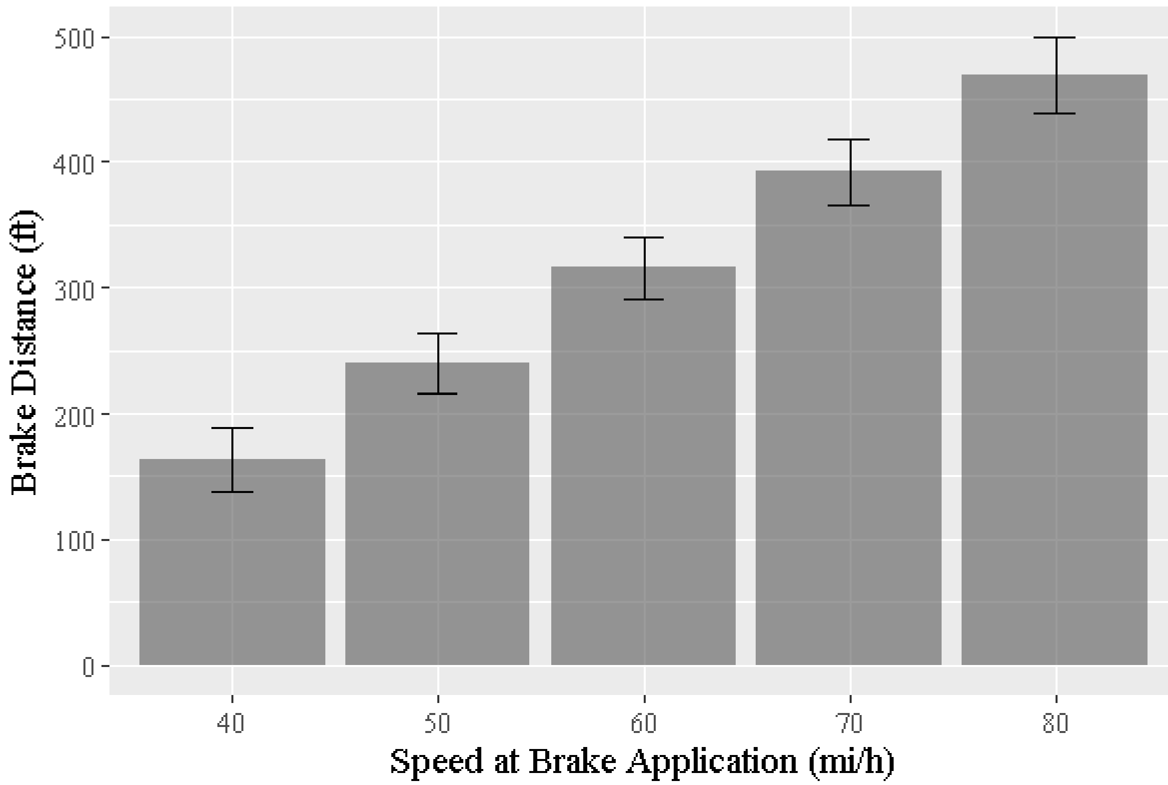


Figure 19. Graph. Mean brake distance by speed at brake point.

The only additional explanatory variable that further improved the model fit was age group (256.7 < 264.2). Figure 20 shows that older drivers (ages 45–84) consistently applied the brakes farther upstream than younger drivers (ages 16–44) and that this difference became more pronounced at higher speeds. At 40 mi/h, the difference in brake distance was negligible, but, at 70 mi/h, the difference was statistically significant at 104 ft. While driver age cannot be controlled by local transportation departments, such differences could precipitate situations in which a younger driver rear-ends an older driver because the former may not expect what he or she might consider an early or unnecessary decrease in speed and may ignore or fail to detect other visual cues indicative of the downstream driver braking. The difference may also be due to engine braking among younger drivers or older drivers enjoying the comfort of a gradual brake from farther upstream.

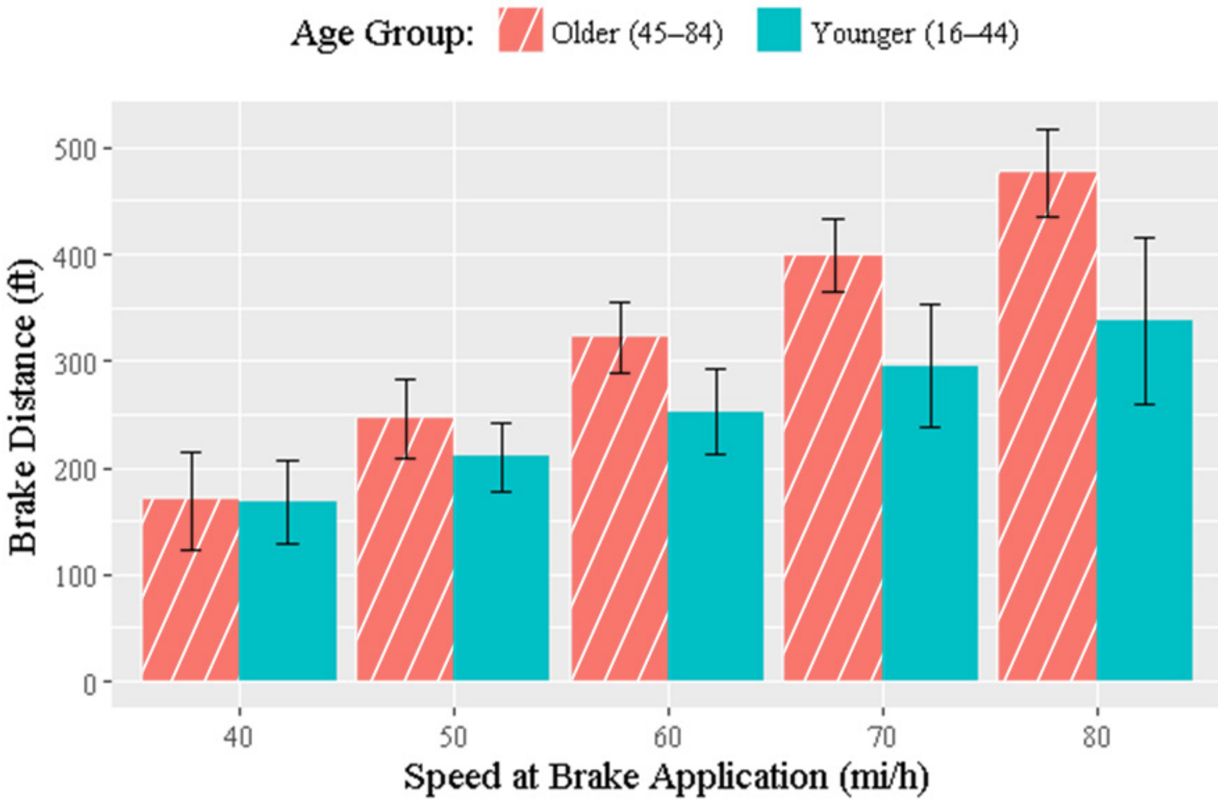


Figure 20. Graph. Mean brake distance by speed at brake point and age.

An attempt was also made to estimate the effect of vehicle classification on brake distance. Of the 279 crossings examined, 96 percent were made in cars, with the remaining crossings executed in pickup trucks (2.5 percent), sport utility vehicles (SUVs) (1.1 percent), and minivans (0.4 percent). Unfortunately, reliable brake pedal status readings were missing from all crossings made with pickup trucks, SUVs, and minivans, making the analysis impossible.

PROBABILITY OF MAKING A COMPLETE STOP

Of the 411 events, 15 were missing speed data, resulting in a total of 396 useable cases. Figure 21 shows the minimum speed attained in each of these crossings as a histogram. The term "minimum speed" (the lowest speed observed in each crossing) is preferred over "stop speed" because the latter implies a minimum speed of 0 mi/h. Indeed, despite the legal requirement to achieve 0 mi/h before proceeding through any intersection, this was only observed in 49.7 percent of cases. In contrast, in an on-road experiment with an instrumented vehicle, Bao and Boyle found that drivers came to a complete (0 mi/h) stop 81 percent of the time when approaching divided highways.[18] Such a strict definition may be naively narrow and subject to instrument sensitivity, so less conservative definitions were also used: 65.9 percent of events included minimum speeds ≤ 3 mi/h, and 82.3 percent of events included minimum speeds ≤ 6 mi/h.

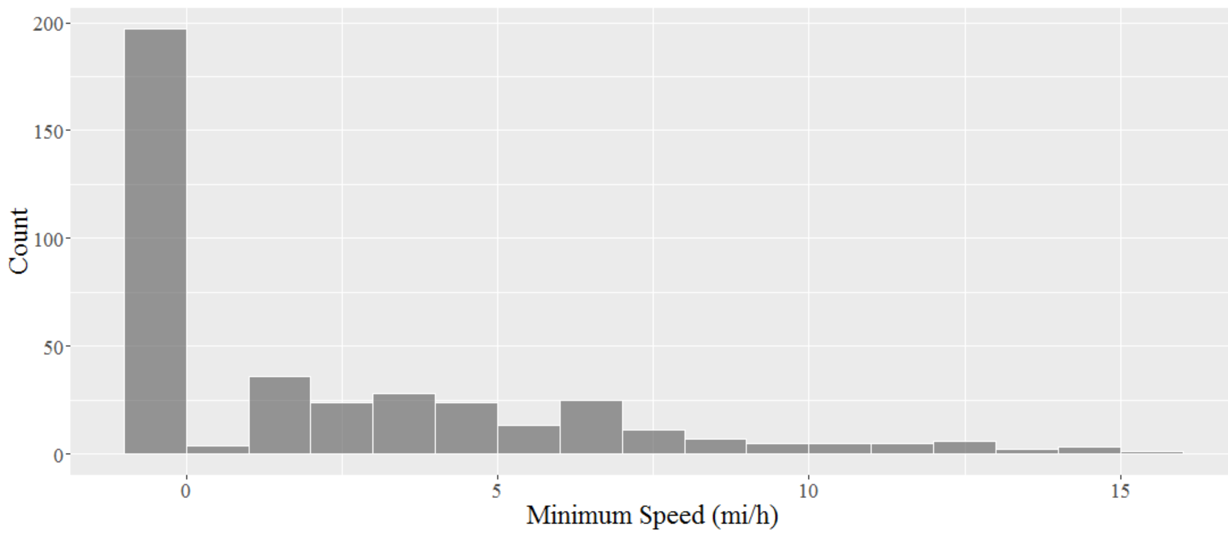


Figure 21. Graph. Minimum speed (all crossings).

The proclivity to make a complete stop—regardless of minimum speed thresholds—is highly dependent on traffic conditions. Previous work by Bao and Boyle found a significant correlation between higher traffic volume and higher probabilities of complete stops.[(18)] This pattern was found in the present dataset as well. Figure 22 shows a boxplot of minimum speed for each of the four possible traffic conditions. The median minimum speed of crossings with no CT or vehicle queues was 4 mi/h. Removal of CT or vehicle queues lowered the median to 2.5 or 0 mi/h, respectively. Those crossings with both CT and vehicle queues exhibited a median minimum speed of 0 mi/h.

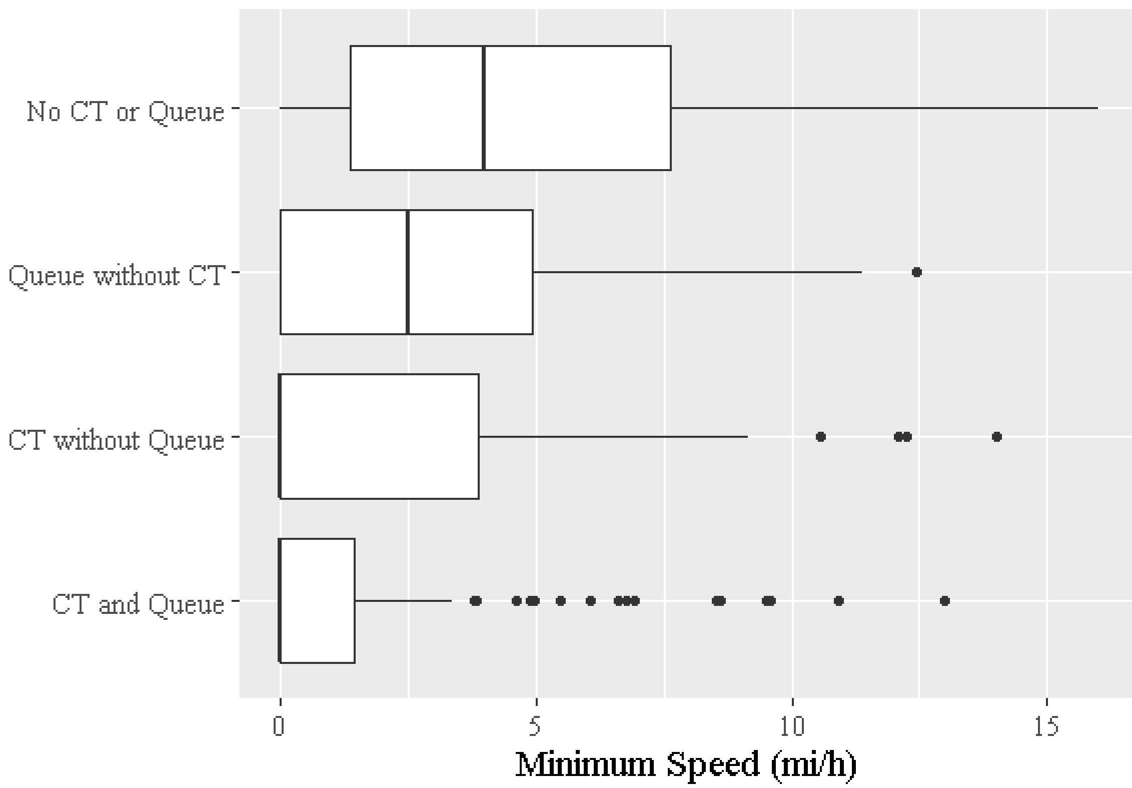


Figure 22. Graph. Minimum speed by traffic condition.

Method

Minimum speed is defined as the minimum speed observed in each crossing. Because minimum speed was found to be affected by the presence of CT and vehicle queues, 332 such cases were excluded, leaving 79 for analysis. The three minimum speed thresholds used to define complete stops (0, 3, and 6 mi/h) were applied to the continuous variable minimum speed to create a binary variable for each. Separate GEEs were estimated for each predictor variable analyzed. These models employed binomial response distributions with logit link functions and repeated measures clustered on participants.

Results

Table 7 lists the QIC statistics for these models (using the 0 mi/h threshold). Four separate models outperformed the null, with AAM yielding the best fit.

Table 7. Fit statistics for complete stop probability models.

Model	QIC
Maximum deceleration	98.5
Age group	97.1
Crash history	96.1
Null	94.0
Gender	88.6
Rolling stop tendency	88.1
Rolling stop risk	72.6
AAM	50.1

Age group failed to produce a better fit than the null model, but AAM surpassed all others, suggesting that the latter better reflects driver experience. Figure 23 shows the probability of making a complete stop (denoted as Pr(Complete Stop)) by AAM for each definition of "complete." Drivers who reported an annual average of 20,000 to 30,000 mi were 9.1 times more likely to make complete stops (0 mi/h) than those driving 10,000 to 20,000 mi ($p < 0.001$). This difference is statistically insignificant at the 3-mi/h threshold; however, too little variation existed under the 6-mi/h threshold, and too few drivers fell into the extreme mileage categories to analyze further.

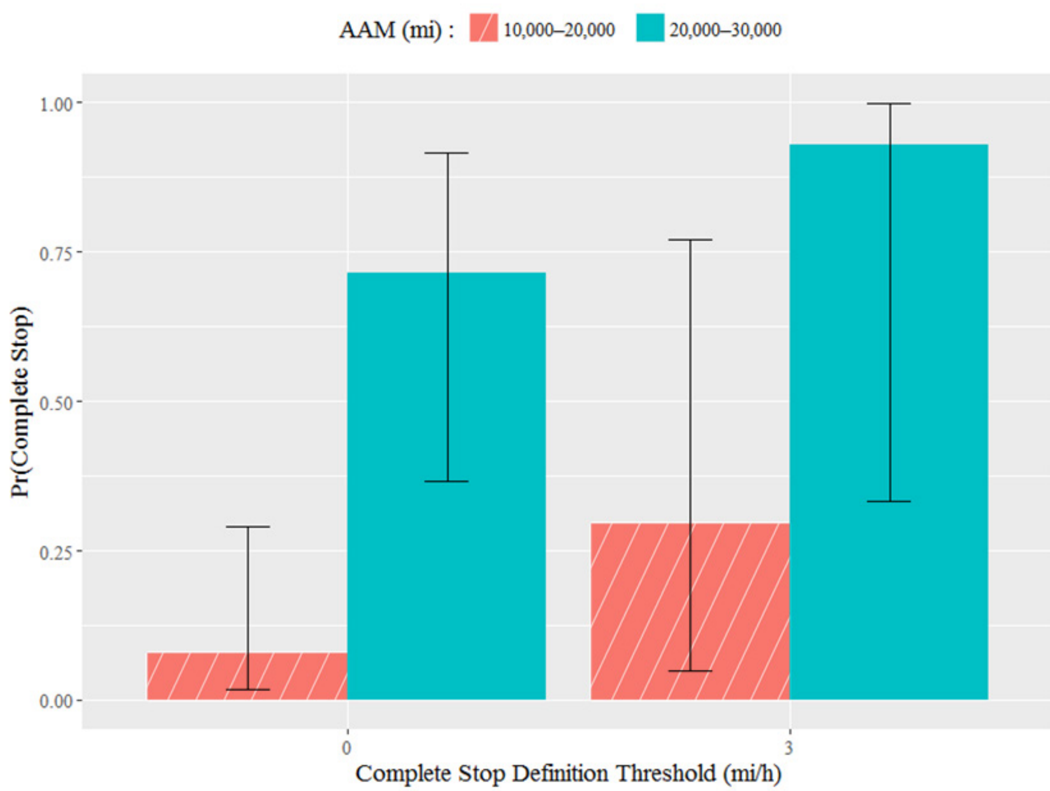


Figure 23. Graph. Probability of making a complete stop by AAM for each definition of "complete."

Participants were asked, “If you were to not make a full stop at a stop sign, how do you think it would affect your risk of crash?” Figure 24 shows that drivers who expressed a high risk associated with performing rolling stops were more likely to perform them. (Note that this graph shows the probability of a rolling stop, which is the complement to the probability of a complete stop.) Those indicating high risk were 6.8 to 14.0 (p = 0.002 to 0.015) times more likely to perform rolling stops (3 and 6 mi/h thresholds, respectively) than those who indicated that doing so only posed a medium risk, although this difference was not statistically significant under the 0-mi/h threshold.

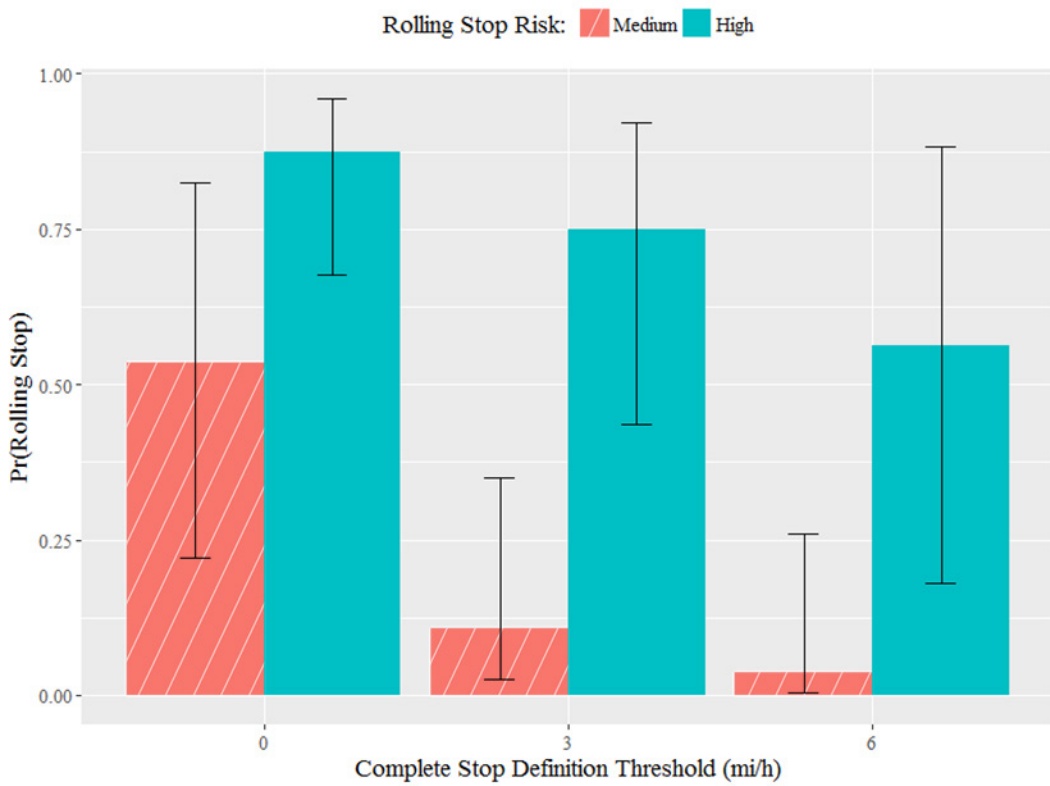


Figure 24. Graph. Probability of making a rolling stop by expressed risk associated with performing a rolling stop for each definition of “complete.”

Participants were also asked, “In the past 12 mo while driving, how often did you not make a full stop at a stop sign?” Figure 25 shows that those who claimed to “never” or “rarely” commit rolling stops were no less likely to do so than those who admitted to doing it “often” or “sometimes” (p > 0.05 for all stop definition thresholds). These two findings indicate a social demand characteristic; participants may have felt inclined to tell transportation researchers that rolling stops are highly risky and that they do the right thing and never or rarely commit them. Regardless, these results strongly suggest that self-assessments concerning such behaviors are unreliable.

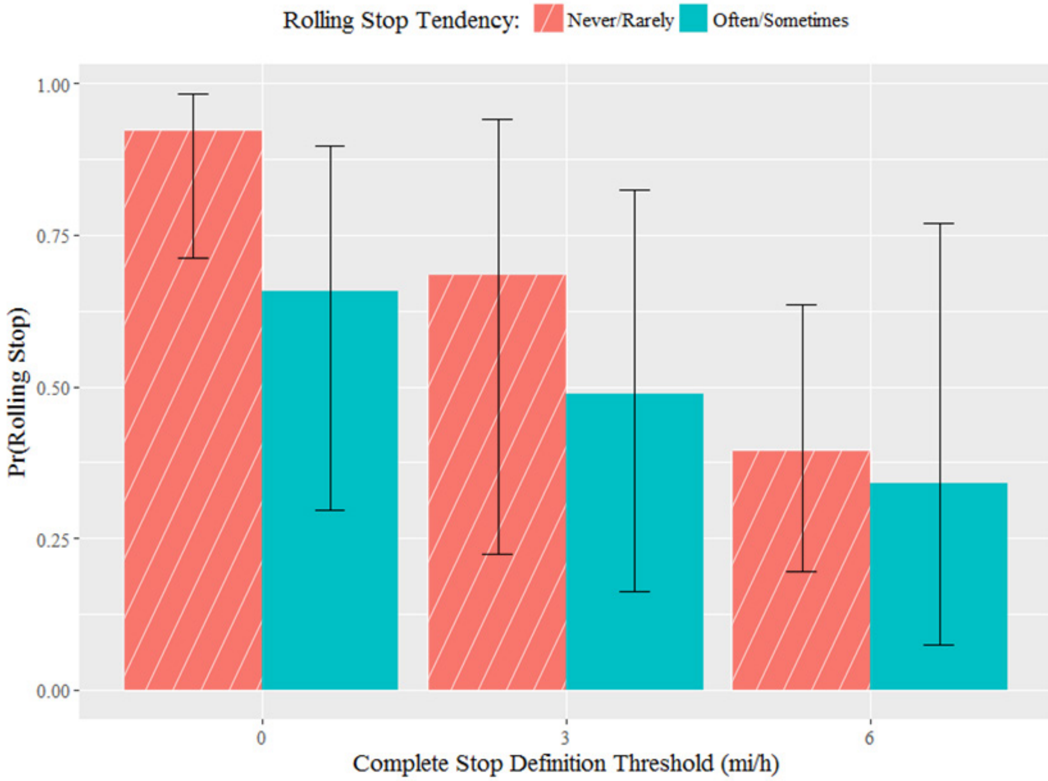


Figure 25. Graph. Probability of making a rolling stop by expressed tendency to perform a rolling stop for each definition of "complete."

GLANCE DURATION

As drivers neared the intersections, they glanced around their surroundings. Figure 26 shows each eyeglance to the eight identified visual ROIs (excluding unavailable and transition). The forward ROI dominates drivers' vision for the majority of the approach, with glances to the left and right becoming more common in the last 197 ft. Overall, glances to the forward ROI accounted for 56.3 percent of total glance time. Excluding the last 197 ft, forward glances account for 83 percent of total glance time, well in line with Brakstone's and Waterson's finding that drivers generally spend 80 percent of their time looking in the forward ROI.(19)

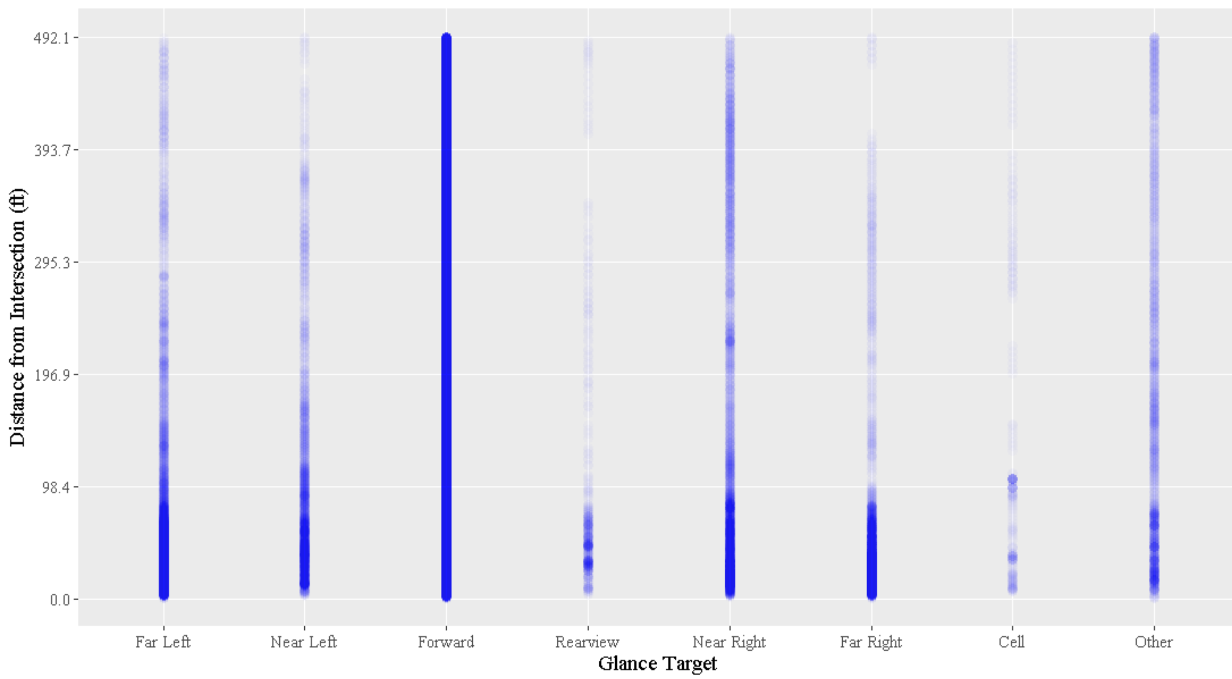


Figure 26. Graph. Discrete eyeglances along intersection approach.

Many prior studies have examined the relationship between single-glance duration away from the road and various safety metrics, generally concluding that two seconds spent glancing away from the roadway significantly increases crash risk. (See references 20–23.) Because this study aimed to describe glance patterns at different points along the approach, a discrete framework had to be implemented. To compare the time that drivers spent glancing at each ROI along the approach, approaches were divided into five 98.4-ft segments, where segment 1 indicated 0–98 ft, 2 indicated 98–197 ft, etc. Because of the speed variation inherent to approaching a stop-controlled intersection (as well as CT and queue presence), this segmentation results in drivers occupying segment 1 the longest. Table 8 shows speed and time statistics for each segment.

Table 8. Mean speed and time spent in each segment.

	Speed (mi/h)		Time (s)	
Segment	Mean	Standard Deviation	Mean	Standard Deviation
1	12.6	9.7	10.8	8.9
2	38.2	10.5	2.7	1.5
3	51.3	10.6	2.1	2.0
4	59.2	9.2	1.7	0.4
5	63.5	9.2	1.6	0.3

Method

VTTI examined video feeds for each crossing and denoted glance targets for each 0.07-s video frame. Each crossing consisted of an approach at least 492.1 ft in length, which was then divided into 98.4-ft segments. (Observations more than 492.1 ft from the intersection were discarded.) Absolute total glance duration for each ROI segment combination was used as the dependent variable. These data were then merged with the time-series data using VTTI's timestamp, which resulted in a dataset with timestamped geospatial coordinates and eyeglance targets (among other variables). Separate GEEs were estimated for each ROI and each predictor variable analyzed. These models employed Poisson response distributions with log link functions and repeated measures clustered on crossings.

Results

Table 9 shows the resulting fit statistics (QIC) for each ROI and model specification. The high incidence of missing values is the result of too few glances to certain ROIs. For example, mean total glance duration to cell was less than 0.05 s for each segment, while mean total glance duration to forward was greater than 1.3 s. This scarcity made models with factors in addition to segment impossible to estimate for several ROIs. Table 9 also shows that the null models outperform several others (produce lower QIC statistics) on several ROIs. The goal of this research, however, was to create a model of glance behavior along the driver's approach to a stop-controlled intersection.

Table 9. Fit statistics (QIC) for glance duration models.

Model	Far Left	Near Left	Forward	Rearview	Near Right	Far Right	Other	Cell
Null	813.5	823.2	616.5	216.5	1,122.2	700.1	795.0	43.3
Segment	647.5	1,142.4	633.4	385.1	1,542.4	786.5	898.6	74.8
Segment + maneuver	660.7	—	671.6	—	1,551.5	—	921.2	—
Segment + traffic conditions	—	—	627.1	—	—	—	962.0	—
Segment + gender	686.9	1,154.4	627.5	—	1,515.6	734.3	985.6	—
Segment + age group	657.3	—	610.6	423.2	1,556.9	—	856.8	—
Segment + AAM	—	—	650.3	—	—	—	—	—
Segment + crash history	659.4	1,142.0	634.4	—	1,583.6	—	906.2	—
Segment + rolling stop risk	594.0	1,069.5	1087.2	—	1,466.7	—	826.0	—
Segment + rolling stop tendency	698.8	1,161.6	657.1	—	1,477.8	741.4	937.9	—
Segment + maximum deceleration	724.7	1,195.9	654.8	—	1,586.6	—	948.3	—
Segment + full stop (0 mi/h)	627.1	1,229.6	632.0	—	1,592.9	794.8	980.7	—
Segment + full stop (3 mi/h)	662.3	1,183.3	638.5	—	1,579.8	769.1	956.6	—
Segment + full stop (6 mi/h)	652.4	—	628.9	—	1,568.2	737.7	917.0	—

—Models were too sparse to estimate (i.e., ROIs that were rarely glanced at and may not coincide with all levels of another model variable).

Table 10 compiles the Wald statistics for type 3 GEE analysis from each ROI's segment-only model, where each row represents one ROI-specific model and the statistics associated with the segment variable. For all ROIs except cell, segment is a highly statistically significant predictor of total glance duration.

Table 10. Wald statistics for segment variable from each ROI's segment model.

ROI	Degrees of Freedom	Chi-Squared	*p*-Value
Far left	4	884.96	< 0.0001
Near left	4	164.45	< 0.0001
Forward	4	544.85	< 0.0001
Rearview	4	63.31	< 0.0001
Near right	4	215.20	< 0.0001
Far right	4	565.45	< 0.0001
Other	4	20.82	0.0004
Cell	4	3.53	0.4559

Figure 27 shows the mean total glance duration estimated for each ROI segment combination. Approaches were divided into five 98-ft segments with segment 1 indicating 0–98 ft from intersection center, segment 2 indicating 98–197 ft, etc. Between 492 and 98 ft from the intersection (segments 5 through 2), the average driver spent very little time glancing directly at the far left (0.24 s total), near left (0.19 s), rearview (0.03 s), near right (0.30 s), and far right (0.08 s). Within 98 ft of the intersection (segment 1), drivers devoted much more time to each (far left was 2.40 s, near left was 0.39 s, rearview was 0.08 s, near right was 0.48 s, and far right was 1.82 s). Among these ROIs, the majority of glance duration (at least 61.5 percent) occurred within 98 ft of the intersection.

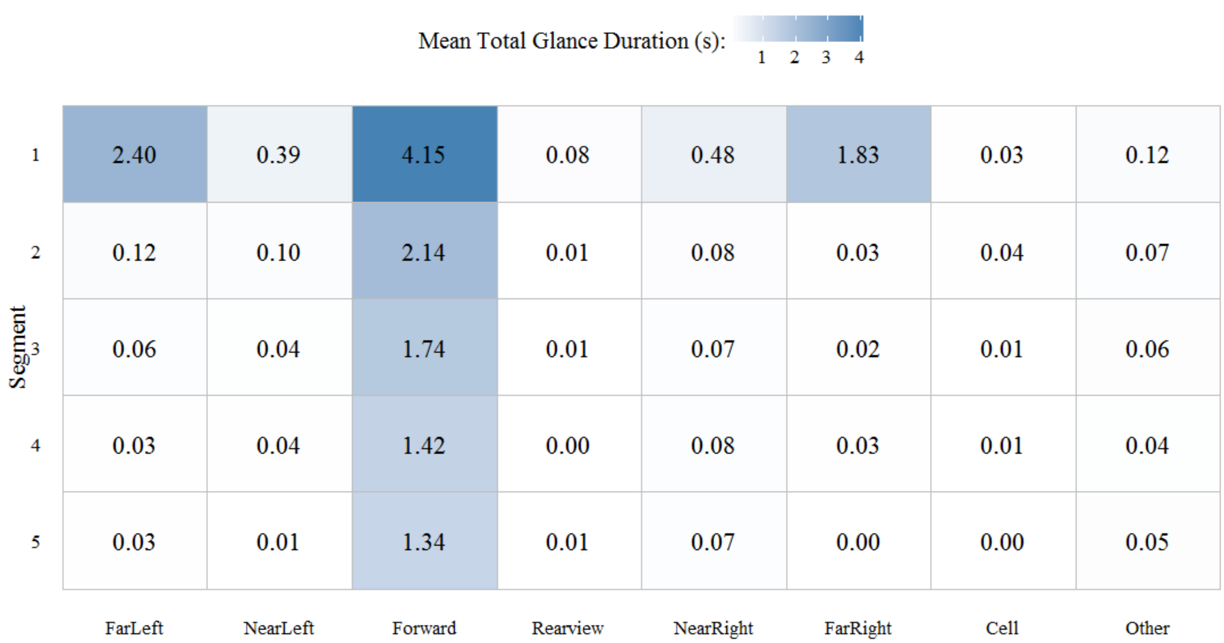


Figure 27. Heat map. Mean total glance duration among all crossings.

A very similar pattern emerged in the absence of CT and vehicle queues, as shown in figure 28. Durations to most ROIs were shorter in the absence of traffic, suggesting that some glance time was attributable to waiting.

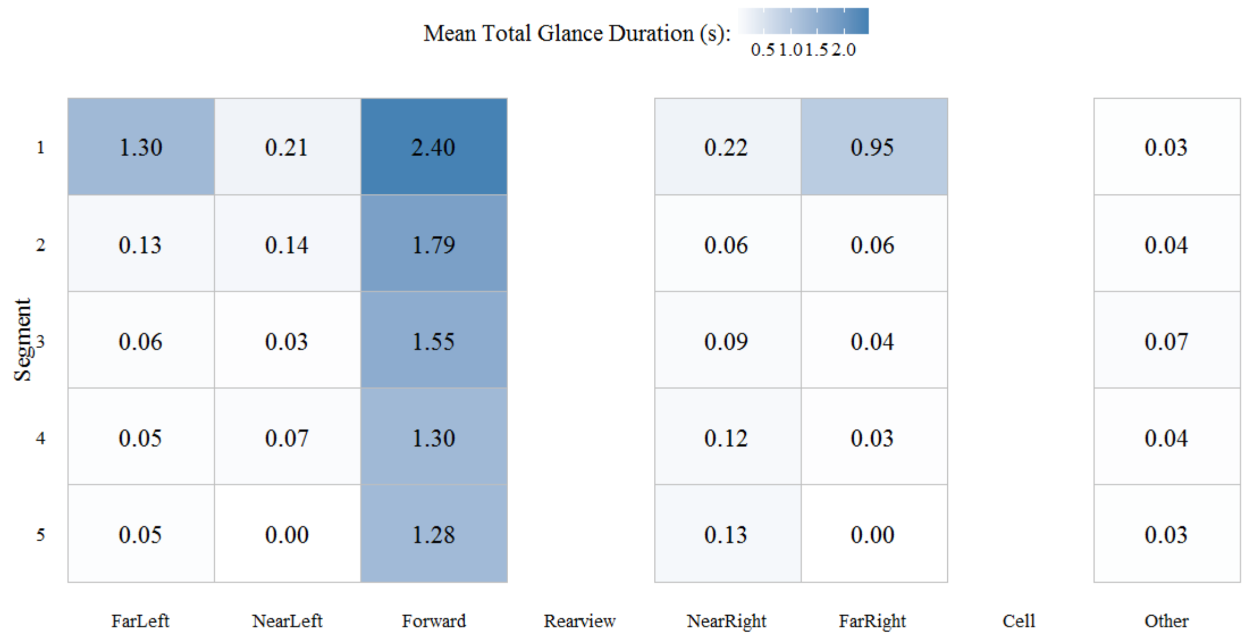


Figure 28. Heat map. Mean total glance durations among crossings with no CT or vehicle queues.

In an effort to analyze glance times along the approach in the context of other explanatory variables, ROIs were collapsed to three classes: forward (unchanged), scanning (the sum of far left, near left, near right, and far right) and other (the sum of rearview, other, and cell). Again, the null models outperformed others on the collapsed ROIs using QIC as the metric for goodness of fit.

Figure 29 presents the mean total glance duration estimated by the segment-only models for the collapsed ROIs. The Wald chi-squared value for segment in each model was highly statistically significant ($p < 0.001$). Drivers spent more time glancing in the forward direction as they approached the intersections (though this could be the result of merely occupying each segment longer as speed decreases), with time in segment 1 significantly greater than all others ($p < 0.001$). Similarly, drivers spent practically no time scanning until 98 ft from the intersection; mean total scanning duration among these segments ranged from 0.1 to 0.3 s and were not statistically different from one another. Total scanning duration in segment 1, however, averaged 5.1 s, a statistically significant ($p < 0.001$) 4.8-s increase over segment 2. As a percentage of the approach, drivers spent 86.5 percent of their time scanning in these last 98 ft. Glance durations to the other ROI remained low and fairly stable, ranging from 0.05 s (segment 4) to 0.23 s (segment 1).

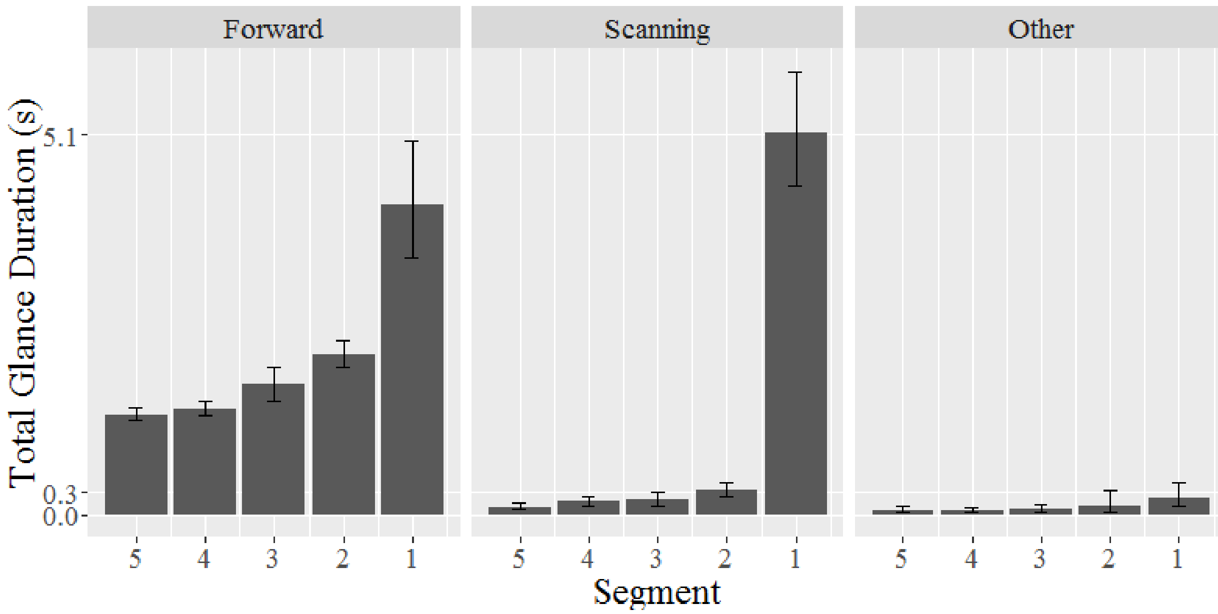


Figure 29. Graph. Estimated mean total glance duration for collapsed ROIs across segments.

A very similar pattern emerged in the absence of CT and vehicle queues, as shown in figure 30. As with the disaggregated data, glance durations to most ROIs were shorter in the absence of traffic, suggesting that some glance time was attributable to waiting.

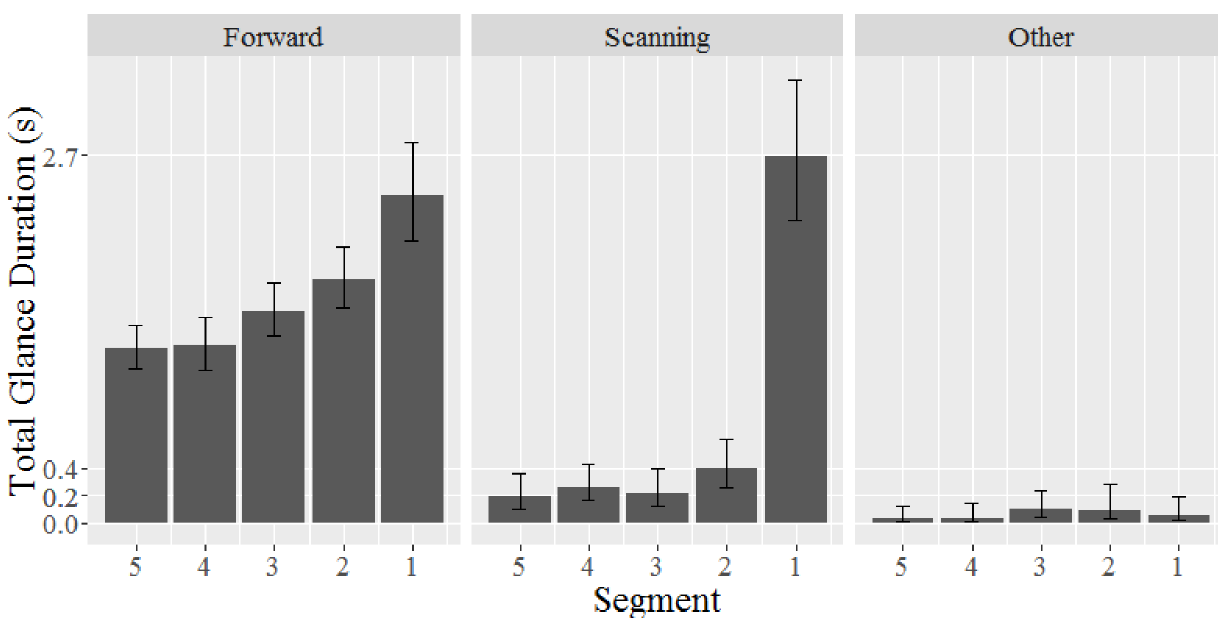


Figure 30. Graph. Estimated mean total glance duration for collapsed ROIs across segments among crossings with no CT or vehicle queues.

SCAN TIME ALLOCATION

"Scan time allocation" refers to how drivers allocated their intersection scanning time relative to stopping. Over the course of this research, two subpopulations were identified: (1) drivers who came to a complete stop and then scanned the intersection before proceeding and (2) drivers who scanned ahead of time, performed a rolling stop, and then proceeded through the intersection.

Method

To formally test the differences among these groups, the moment at which each crossing's minimum speed was attained was used as a before and after delineation. Scan time was calculated as the sum of glance durations to ROIs (far left, near left, near right, and far right) and then expressed as a percentage of total glance time before and after stopping (reaching the crossing's minimum speed). Because the before and after scan percentages are complementary, the prestop scan time percentage was modeled as a function of stop type (complete or rolling using each definition) and one other predictor variable. Separate GLMs were estimated for each using binomial response distributions and logit link functions.

Results

Table 11 lists the scaled deviance and degrees of freedom for the scan time allocation models (for the 0 mi/h definition of a complete stop only). Though the null model fits reasonably well ($P(\chi^2_{395} \geq 34.1) \approx 1$), adding stop type represents a significant improvement ($P\left(\chi^2_{\Delta df} \geq \Delta D\right) = P(\chi^2_1 \geq 13.0) < 0.001$).

Table 11. Fit statistics for scan time allocation models.

Model	Degrees of Freedom	Deviance
Null	395	34.1
Stop type	394	21.1
Stop type + gender	392	21.1
Stop type + age group	386	21.1
Stop type + maximum deceleration	388	21.1
Stop type + crash history	392	21.0
Stop type + maneuver	390	20.8
Stop type + AAM	386	20.8
Stop type + rolling stop tendency	392	20.9
Stop type + rolling stop risk	389	20.4
Stop type + traffic conditions	388	17.8

Prestop scan time differed significantly with stop type ($\chi^2(1) = 4787.5$ and $p < 0.001$ under the 0 mi/h threshold). Those drivers who came to a complete stop spent just 39.2 percent of their prestop time scanning the intersection, while rolling stoppers spent 74.5 percent. This relationship holds for minimum speeds ≤ 3 mi/h ($\chi^2(1) = 3007.37$ and $p < 0.001$) and ≤ 6 mi/h ($\chi^2(1) = 1651.07$ and $p < 0.001$). Figure 31 shows these results graphically. This finding confirms the existence of two distinct intersection-scanning protocols: (1) approach intersection, stop, scan, and proceed and (2) scan intersection during approach, slow, and proceed.

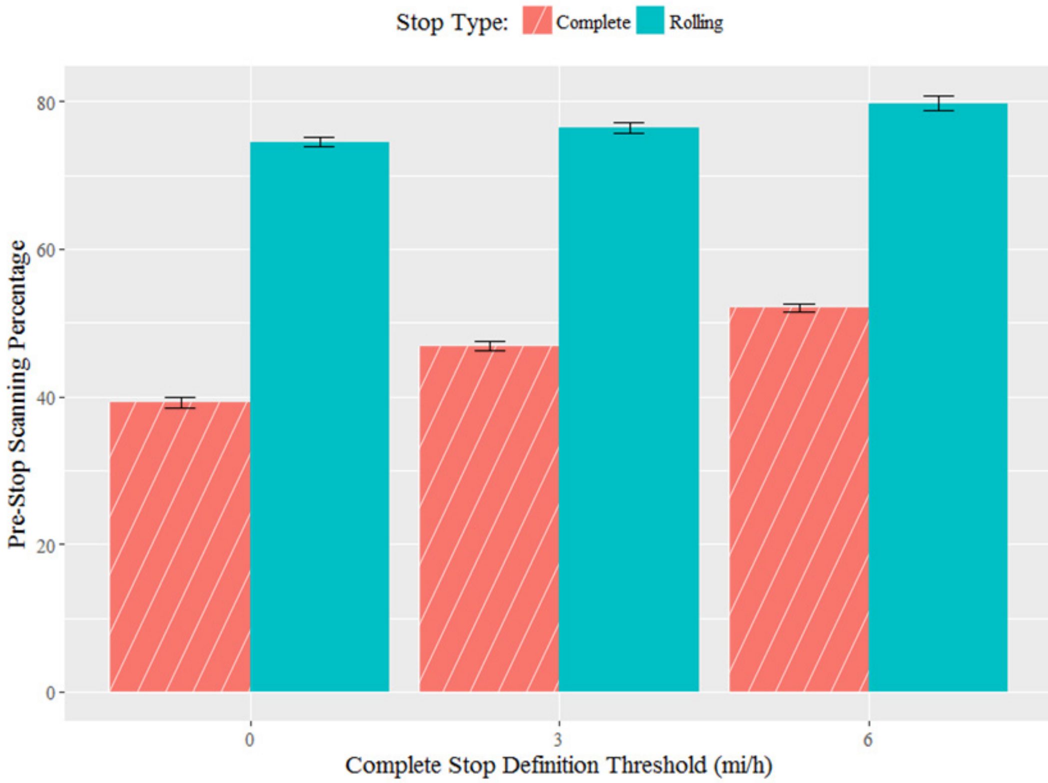


Figure 31. Graph. Prestop scanning percentage by stop type for each definition of "complete."

Further inclusion of prospective predictor variables failed to produce significant improvements (all $P(\chi^2_{\Delta df} \geq \Delta D) > 0.05$), but given the nature of the data, examining this trend under various traffic conditions is worthwhile. A GLM with stop type (based on the 0-mi/h definition), traffic conditions, and the interaction thereof found all terms to be significant predictors of prestop scan time (stop type $\chi^2(1) = 1{,}462.95$ and $p < 0.001$; traffic conditions $\chi^2(3) = 1{,}014.35$ and $p < 0.001$ and interaction $\chi^2(3) = 151.73$ and $p < 0.001$). This significance was robust to all definitions of a complete stop. Figure 32 shows that the largest difference occurred when both CT and vehicle queues were present, with complete stoppers using just 25.1 percent of prestop time for scanning versus 66.0 percent among rolling stoppers. However, even in the absence of any visible traffic, complete stoppers still spent significantly less prestop time scanning (55.0 percent) than rolling stoppers (79.6 percent).

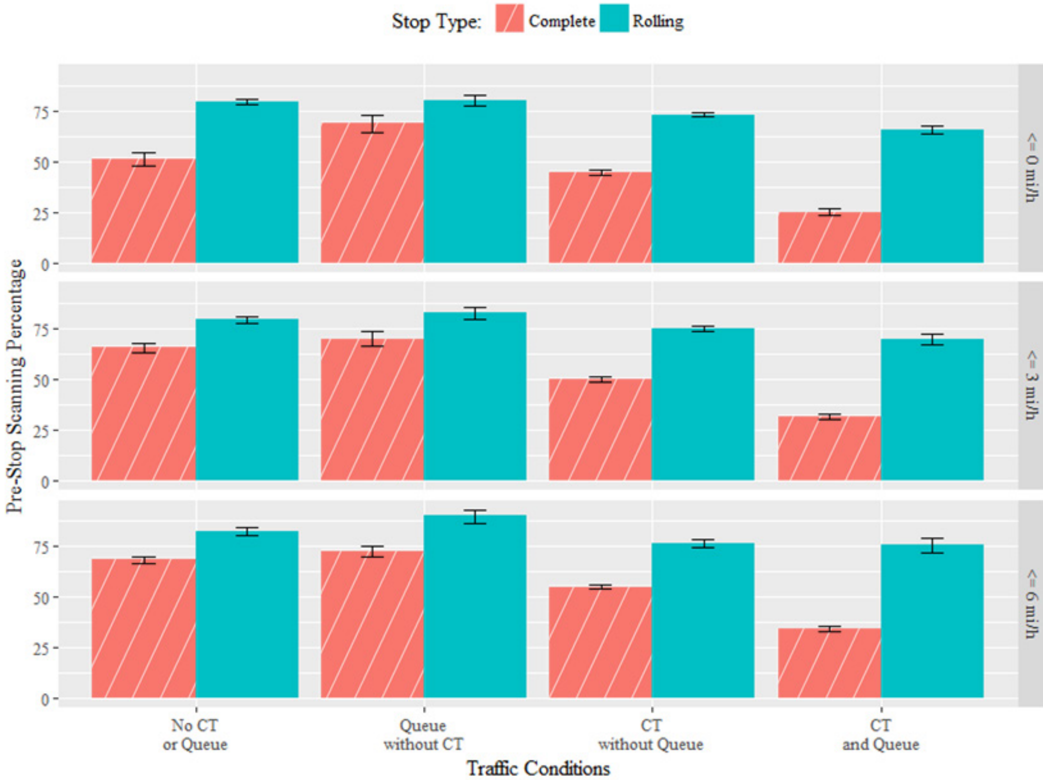


Figure 32. Graph. Prestop scanning percentage by stop type and traffic condition for each definition of "complete."

CONCLUSION AND DISCUSSION

Naturalistic data of drivers approaching rural high-speed, stop-controlled intersections were analyzed for the purposes of modelling stopping and scanning behaviors. Older and younger drivers were found to apply the brakes at different distances from the intersection. This may contribute to rear-end collisions when younger drivers follow older drivers traveling at comparable speeds. However, given that drivers in general were found to focus predominantly on the forward ROI, they would likely use other visual cues related to braking to avoid potential collisions. Local transportation departments are powerless to affect age distribution, but the knowledge of this discrepancy could help explain or prevent such collisions in communities with higher proportions of elderly residents. This difference may also be due to the use of engine braking or driver comfort.

The probability of coming to a complete stop was found to correlate positively with reported AAM, which suggested an experience effect: drivers learned the high value (and negligible cost) of making a complete stop as they drive longer distances. The non-significant relationship with age group suggests that mileage is more reflective of experience than time.

Drivers approaching rural high-speed, stop-controlled intersections spent the last 98 ft of the approach principally engaging in scanning behaviors. This behavior could be leveraged for a variety of applications such as the placement of intersection conflict warning systems (ICWSs) and guide signs. A 2015 assessment of ICWSs examined the effects of sign wording and placement on comprehension using a driving simulator.[(24)] Signs were placed across the intersection for some participants and to the left for others (along the intersecting major route, visible to the driver only after arriving at the stop sign, and visible to the driver when looking approximately 90 degrees to the left). No statistically significant difference in comprehension was detected based on placement. Because the present study found that a significant proportion of drivers did not come to a complete stop prior to entering an intersection, such drivers would likely miss the left-placed sign despite pre-arrival scanning, thus rendering it ineffective. ICWS signs placed across the intersection maximize the probability of detection and thus the probability of conflict avoidance, regardless of scan time allocation.

This study was also meant to assess the SHRP2 database in its capacity to address further questions regarding driver safety. Due to the nature of any NDS, no aspect of driving can be controlled by the researcher; instead, observations must be filtered out to arrive at comparable situations. Though numerous data elements were captured—with varying rates of completeness—few observations may exist across comparable situations. Narrowly defined research topics may find sample sizes insufficient for analysis. For those topics with sufficient sample sizes, the SHRP2 database can be a valuable complement to other research tools such as driving simulators and instrumented vehicles.

This research analyzed 411 crossings of four Pennsylvania intersections. Though this research represents a small fraction of all of the data captured during the NDS, this will likely be the case for future narrowly defined research endeavors. Based on the results of this study, the SHRP2 database should be considered a useful resource for the exploration of driver safety issues. The RID provides ample infrastructure features to explore a wide range of settings (e.g., intersections, curves of specific radii, specific road types, etc.), and vehicular kinematics were recorded at sufficiently high frequency for temporally detailed analysis. However, studies requiring precise eyeglance vectors (e.g., to specific roadside signs) should not rely on head movement-based video reduction. This research did not use any of the radar-enabled data (e.g., headway, time-to-collision, etc.) and therefore cannot comment on the usefulness of such data.

STUDY LIMITATIONS

This project succeeded in modeling driver behavior when approaching to rural high-speed intersections but was limited in two key ways. The number of observations was sufficient for basic analyses but prevented the estimation of more complex models. More than 5.4 million trips were collected as part of the whole NDS, but only 411 of those (less than 0.01 percent) were relevant to this project. Only by loosening the restrictions on intersection selection could this number be increased, but doing so could introduce differences by site, making the ability to make inferences about driver behavior even more difficult. There were several additional intersections identified in the RID that satisfied all criteria for this project, but the minor routes lacked link IDs, thereby making it impossible to request associated crossings. It was possible to expand coverage of the RID to include more rural intersections as defined here, but the authors are aware of no such plans.

The greatest limitation to this study lies in the reduction of eyeglances. Reduction of traffic conditions was relatively straightforward, but eyeglances were plagued by a number of issues. Participants wore sunglasses in 17.3 percent of crossings, so glance targets had to be inferred based on head movements alone. VTTI staff made notes regarding the eyeglance reduction process as well. For 12.2 percent of crossings, notes such as “dark/grainy video,” “bad sun glare,” and “face covered by sun visor” were made. Even under ideal circumstances, however, the reduction of eyeglances based on face video was much less accurate than existing eye-tracking systems common in highway driving simulators and field research vehicles. This report relies on the assumption that head movements correlate to glances to the intersecting roadway, but that is impossible to confirm.

This study was also limited in its ability to assess the effect of daylight on stopping and scanning behaviors. The time of day for each crossing was requested and successfully extracted. However, these times were given in 2-h bins. Such wide bins would have resulted in an unacceptable level of uncertainty regarding the daylight status of many crossings. Future attempts to assess this effect could be addressed by including daylight status in the video reduction protocol.

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