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Analysis of Stopping Behavior at Rural T-Intersections Using Naturalistic Driving Study Data

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Abstract

Rural intersections account for around 30% of crashes in rural areas and 6% of all fatal crashes, representing a significant but poorly understood safety problem. Crashes at rural intersections are also problematic since high speeds on intersection approaches are present which can exacerbate the impact of a crash. Additionally, rural areas are often underserved with EMS services which can further contribute to negative crash outcomes. This paper describes an analysis of driver stopping behavior at rural T-intersections using the SHRP 2 Naturalistic Driving Study data. Type of stop was used as a safety surrogate measure using full/rolling stops compared to non-stops. Time series traces were obtained for 157 drivers at 87 unique intersections resulting in 1277 samples at the stop controlled approach for T-intersections. Roadway (*i.e.* number of lanes, presence of skew, speed limit, presence of stop bar or other traffic control devices), driver (age, gender, speeding), and environmental characteristics (time of day, presence of rain) were reduced and included as independent variables. Results of a logistic regression model indicated drivers were less likely to stop during the nighttime. However presence of intersection lighting increased the likelihood of full/rolling stops. Presence of intersection skew was shown to negatively impact stopping behavior. Additionally drivers who were traveling over the posted speed limit upstream of the intersection approach were less likely to stop at the approach stop sign.

Keywords

Naturalistic Driving Study Data, Intersection, Safety, Rural, Stopping Behavior

1. Introduction

1.1. Background

Rural intersections account for 30% of crashes in rural areas and 6% of all fatal crashes, representing a significant but poorly understood safety problem. Crashes at rural intersections are particularly problematic when high speeds on intersection approaches are present. 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 [1]. EMS response times in rural areas are 1.6 to 2 times longer than in urban areas [2] [3], and fatal injury crash rates are two times higher in rural than in urban areas [1] [4].

Inappropriate gap selection has been found to be a major contributing cause of crashes at rural intersections. In a study conducted in 2003 [5] [6], inappropriate gap selection accounted for 56% of all right-angle crashes at rural Minnesota through-stop intersections. Right-angle collisions, the result of drivers selecting a gap that is too small or failing to observe traffic control, account for between 36% to 50% of crashes at intersections on high-speed divided highways, while such collisions account for only 28% of crashes at intersections on other types of roads [7].

Drivers failing to stop on the minor approach have been found to account for 25% of right angle crashes [6]. Retting *et al.* [8] found that crashes where drivers failed to stop at stop signs were more likely to result in injuries than crashes where drivers stopped. Characteristics correlated to failure to yield right of way include age [9] [10], speeding, vision obstruction, and inattention/distraction [11].

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 [12] [13] [14] [15]. Barua *et al.* [16] evaluated crashes at rural undivided intersections in Alberta, Canada, and found that crash risk is higher during the fall than the winter (possibly due to harvesting), at nighttime, at offset intersections, at T-intersections, and on horizontal or sag curves. Leckrone *et al.* [17] 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 a lower likelihood of a severe crash. Additionally, they found that the crash risk was lower at T-intersections than at intersections with four approaches.

1.2. Objective

The Second Strategic Highway Research Program (SHRP2) conducted a large-scale naturalistic driving study (NDS) using instrumented vehicles, which provides a significant amount of on-road driving data for a range of drivers. The present study utilized data from the SHRP2 NDS as well as the SHRP2 Roadway

Information Database (RID) to observe driver behavior at rural intersections firsthand 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. The overarching objective of this study was to better understand how drivers react at rural intersections. This paper summarizes results of analyses to assess stopping behavior at T-intersections (3-approaches). Type of stop was used as a surrogate for intersection safety. It was assumed a full/rolling stop was less likely to result in a conflict or crash than a non-stop. The purpose of the analysis was to better understand driver behavior at rural intersections so that agencies can better address intersection crashes.

2. Description of Data

The second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) data is the largest dataset of its kind. The participating states were Florida, Indiana, New York, North Carolina, Pennsylvania and Washington (six US states). The vehicles of naïve drivers were equipped with a Data Acquisition System which included various sensors which extracted kinematic vehicle data such as speed, acceleration, GPS data, and radar. Four cameras were positioned to collect video from the forward roadway, rear roadway, driver face, and over the driver's shoulder. Over the three years of the study approximately 3400 participants drove 5 million trips logging over 30 million data miles.

The SHRP2 Roadway Information Database (RID) was collected simultaneously with the NDS. Mobile data collection was conducted on over 12,500 center line mile across the six NDS states. Existing roadways and supplemental data were also acquired from public and private sources. These data came from several sources including the NDS states' Department of Transportation (DOT), Highway Performance Monitoring System (HPMS), covering most roadways for each study state.

Data Reduction

A set of rural intersections within the six States covered by the SHRP2 NDS (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) was identified using the RID and other sources such as Google Earth. These intersections were selected 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, two-way stop-controlled, and T-intersections.

Ultimately, 87 minor stop controlled T-intersections were utilized in the mode. Time series traces, forward roadway video, and static driver characteristics (e.g., age, gender) were requested and provided by the subcontractor that archives the SHRP2 NDS data. These data were reduced, and 1277 time series traces reflecting a range of driver ages and genders were viable and were utilized in the analysis. Time series traces provide kinematic vehicle data, such as speed, acceleration, and global positioning system (GPS) location, at 0.1-second intervals and represent one driver trip through one intersection.

Roadway characteristics (such as skew angle, number of approaches, and type of countermeasure) were extracted from the RID or Google Street View and were confirmed for each time series trace using the forward roadway video. Environmental characteristics (such as time of day and ambient conditions) and the presence of opposing vehicles were also reduced from the forward roadway video.

Roadway features, such as the location of a stop sign or advance warning sign, were identified and mapped to vehicle position within each of the time series traces. As a result, the distance of the vehicle from a particular characteristic, such as an upstream advance warning sign, could be determined. Data were reduced along the corresponding approach from the location of the stop sign to 600 meters upstream and approximately 5 meters downstream. The maximum speed within that distance was identified, 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 meters. An example of intersection characteristics present is shown in **Table 1**.

Additionally, the stopping behavior was coded by determining minimum speed within 5 meters upstream or downstream of the stop location. Type of stop was then coded using the following criteria:

- Full stop: speed was reduced to approximately zero.
- Rolling: vehicle speed was greater than zero but less than approximately 2.24 m/s (5 mph).
- Non-stop: vehicle speed was greater than approximately 2.24 m/s (5 mph).

3. Methodology

3.1. Variables Utilized

The dependent variable was type of stop. Initially, models were developed using full, rolling, and no-stop as separate dependent variables. The models for full and rolling stops were similar and the number of full stops was small. As a result, full stop and rolling were combined (n = 821) and compared against no-stops (n

Table 1. Description of intersection characteristics.

Characteristic	Count
Skew	36
Intersection lighting	21
Bacons	6
Limited sight distance	28
Advance intersection warning sign	57
Double stop signs	15
Stop bar	14
Turn lane	4
Lane width < 10 feet	22

= 456). The model included 1277 time series traces at T-intersections. This represented 157 unique drivers at 87 unique intersections. Data were reduced only for the stop-controlled approach. 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 also included as a random effect. Metrics for independent variables are provided in **Table 2**. Categorical independent variables are shown in **Table S1** which is provided as **Supplementary Material**.

3.2. Approach

Ordered logit models [18], 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 type of stop include full, rolling, 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, these data are well suited for analysis using 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 is the vector of variables determining the discrete ordering, β is the vector of estimable parameters, and ε is a random disturbance term. With the use of this equation, the observed safety level outcome y for each driver is defined as

$$y = 1 \text{ if } z \leq \mu\_0$$
$$y = 2 \text{ if } \mu_0 < z \leq \mu_1$$
$$y = 3 \text{ if } \mu_1 < z \leq \mu_2$$
$$y = \ldots$$
$$y = 1 \text{ if } z \geq \mu_{I-1}$$

Table 2. Independent variables with all traces.

Variable	Description	Min.	Max.	Mean	Std. Deviation
MinSpeed	minimum speed within 5 m of stop bar (m/s)	0	11.65	1.80	1.73
Angle	skew angle between incoming and departure approach	55.46	161.00	101.89	18.90
MajorLane	major approach lanes	2	4	2.12	0.45
LaneWidth	average lane width (m)	2.44	3.66	3.14	0.27
SpeedLimit	speed limit (m/s) of minor approach	11.18	24.59	18.88	3.03
MaxSpeed	maximum speed (in m/s) within the 600 meters upstream of the intersection	10.44	32.50	22.44	3.51
YrsDriving	number of years the driver has been driving	0	67	33.78	19.03
Age	Driver age	17	89	51.32	19.17

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 μ_0 equal to zero results in the outcome probabilities

$$P(y=i)=\Phi(\mu_i-\beta X)-\Phi(\mu_{i+1}-\beta X) \quad (2)$$

where, μ_i and μ_{i+1} represent the upper and lower thresholds for response category i, and $\Phi(.)$ 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 utilized 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 evaluated to determine whether they needed to be included in the model. Once the best fit models were found, the model assumptions were tested. It was 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 if one type of stop differed greatly from the others. It was found that the no-stop data differed from the data for the other two stop types. Therefore, it was 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 was used to model binary responses (in this case, no stop versus full/rolling stop). Mixed effects models have two components, fixed and random. The fixed effects are included to explain the relationship between the dependent variable (in this case, stopping behavior) and a set of independent variables. The 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.

Note that 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 the random variables α_i and γ_i, which follows a Bernoulli distribution for the probability of no stop, p_i.

$$\log\left(p_i/\left(1-p_i\right)\right)=\beta_0+B_1x_1+\cdots+\beta_nx_n+\alpha_i+\gamma_i \tag{3}$$

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

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

One of the benefits of the logistic regression model is that the output of the model is easily interpreted odds ratios. Odds ratios are the probability that an event happens in relation to the probability that it 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. There is a direct relationship 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:

$$\operatorname{logit}(p)=\log(\text{odds})=\log(p/q) \tag{4}$$

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 using the logit function as the response variable. The logit transformation allows for a linear relationship between the response variable and the coefficients, as follows:

$$\operatorname{logit}(p)=a+bX \tag{5}$$

or

$$\log\left(\frac{p}{q}\right)=a+bX\ . \tag{6}$$

Equation (6) can be expressed as an odds ratio by eliminating the log. This is done by taking e to the power for both sides of the equation 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 non-informative, the convergence of the chains were assessed using trace plots and R values, and the model fit was assessed using posterior predictive checks.

4. Results

A binomial mixed effects logistic regression model was developed with the dependent variable having possible values of full/rolling stop or no-stop. This was done 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 final model was developed using the top fifteen 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 the independent variables. It does not provide insights about the mechanism of the model, and for this 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*.

The best fit model is shown in Table 3. Since the model's implementation is Bayesian, the table does not present p-values but rather 90% credible intervals, which indicate that the corresponding parameter lies within that interval with a probability of 90%. If zero is included within the credible interval, it means that zero is a likely value for the parameter (*i.e.*, that variable might not be significant).

The model shows the likelihood of not stopping. Positive values indicate an increase in not stopping. Drivers who were traveling over the posted speed limit (speeding) were 2.23 times more likely to not stop than drivers traveling at or below the speed limit. Values less than zero indicate they are less likely to not

Table 3. Independent variables for final model for stopping behavior at two-way stop-controlled intersections with all traces.

Variable	Estimate	Est. Error	l-90% CI	u-90% CI	Odds Ratio
Intercept	−4.017	1.060	−5.824	−2.340	0.018
Major approach vehicle	−2.100	0.218	−2.462	−1.749	0.122
Lighting	−0.843	0.478	−1.649	−0.071	0.430
TOD = Day (baseline = dawn/dusk)	−0.906	0.5201	−1.774	−0.048	0.404
TOD = Night (baseline = dawn/dusk)	−0.470	0.546	−1.368	0.419	0.625
Speeding	0.804	0.338	0.257	1.353	2.235
*Skewed = Left (baseline = no)	1.208	0.725	0.016	2.403	NA
*Skewed = Right (baseline = no)	0.736	0.965	−0.870	2.281	NA
*Right movement (baseline = left)	4.675	0.970	3.172	6.372	NA
*Advanced Warning	2.914	0.877	1.560	4.451	NA
Skew − Movement = Left − Right (baseline = no − left)	−2.480	1.118	−4.317	−0.659	NA
Skew − Movement = Right − Right (baseline = no − left)	−0.529	1.006	−2.190	1.089	NA
*Right movement − Advanced warning (baseline = left movement − no advanced warning)	−2.833	0.956	−4.490	−1.315	0.059
Random Effects					
Approach ID	0.282	0.220	0.021	0.703	
Driver ID	1.665	0.252	1.294	2.115	

stop. The inverse of values less than zero can be used to describe the likelihood of stopping. For instance, when a vehicle was present on the major approach, drivers were 0.111 times less likely to not stop. Alternatively, they were 1/0.122476 = 55.53 times more likely to engage in 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/dusk.

Interactions were present between intersection skew and turning movement and between turning movement and presence of an advance intersection warning sign. These relationships can be better described graphically. Figure 1 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 in the x-axis.

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

Figure 2 shows the relationship between presence of an advance intersection warning sign, turning movement, and the probability of a driver not stopping.

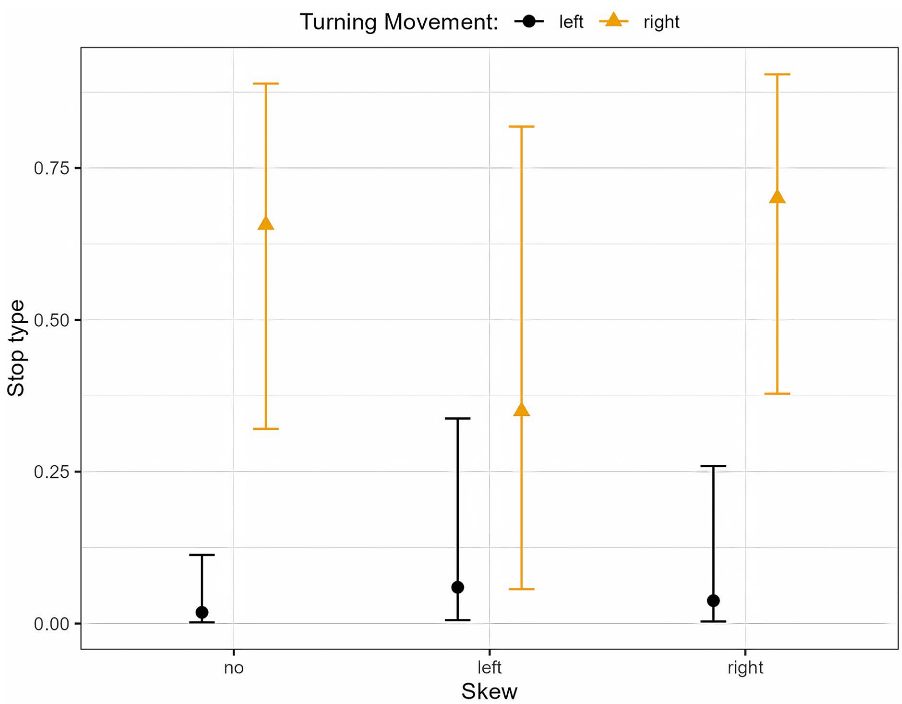

Figure 1. Interaction between turning movement and intersection skew for T-intersections.

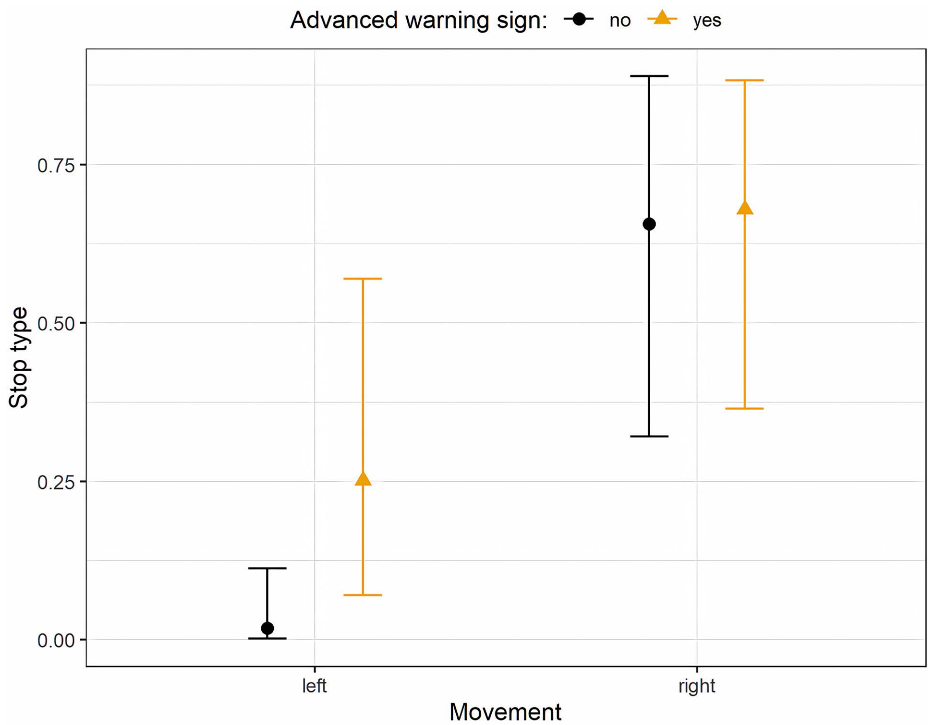

Figure 2. Interaction between turning movement and presence of an advance warning sign for T-intersections.

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% 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, it should be noted that advance signing and other countermeasures are placed at locations where a problem with safety or driver behavior already exists. 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.

5. Discussion

5.1. Summary

Stopping behavior at rural T-intersection approaches was modeled using the SHRP 2 naturalistic study data. Logistic regression was used to model intersection behavior using type of stop (full/rolling versus no-stop) as the dependent variable. Type of stop was used as a surrogate for intersection safety. It was assumed a full/rolling stop was less likely to result in a conflict or crash than a non-stop. The purpose of the analysis was to better understand driver behavior at rural intersections so that agencies can better address intersection crashes.

The most influential variable in terms of the odds ratio was the presence of a vehicle on the major approach at the time of the arrival of the subject vehicle at the stop bar.

Daytime and nighttime driving were associated with a higher likelihood of a rolling/full stop than driving at dawn or dusk. As a result, nighttime driving is more problematic than daytime. However, the model also indicated presence of lighting was associated with a higher likelihood of a rolling/full stop. This suggests improved visibility increases driver recognition of the presence of an intersection.

Interactions were present between intersection skew and turning movement. Left-turning drivers were more likely to not 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. Results suggest intersection reconfiguration may have a positive safety impact.

Left-turning drivers were more likely to not stop when an advance warning sign was present, which was noted in both models. This result was unexpected, since the purpose of the signing is to warn drivers of an upcoming intersection. However, it should be noted that advance signing and other countermeasures are placed at locations where a problem with safety or driver behavior already exists. 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.

Driver behavior was also a major contributing factor. Drivers who were traveling over the posted speed limit upstream of the T-intersections were 2.24 times more likely to not stop than drivers traveling at or below the speed limit upstream of the intersection. This suggests speed management could have positive impacts on intersection behavior as well.

5.2. Conclusions

This study showed naturalistic driving study data can be used to better understand driver behavior at rural intersections. In particular, the results were able to show a relationship between upstream speed and stopping behavior. This type of information is not available in crash data showing the utility of NDS. Other driver characteristics, such as distraction and glance location, were also included in the model. These characteristics showed up as relevant in models for all-way stop intersections (which is the subject of another paper) but not for the model for T-intersection described in this paper. Distraction and glance location could only be reduced for a subset of the traces modeled due to resource constraints. As a result, a larger sample size could show the impact of these characteristics.

Additionally, the results show key intersection characteristics such as lighting improved stopping behavior. Other intersection characteristics, such as skew were correlated with drivers not stopping. This provides information for agencies in addressing rural intersection crashes.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Supplementary Material

Table S1. Categorical independent variables for stopping model at T-intersections with all traces.

Variable	Description	Counts
Movement	turning movement	left = 461, right = 817, through = 0
Following	subjective measure of following	close = 60, following = 47, not following = 1170
TOD	time of day	dawn/dusk = 32, day = 1077, night = 168
Weather	ambient conditions	clear = 1,158, raining = 119
Overhead	overhead flashing beacon	yes = 74, no = 1203
Lighting	intersection lighting	yes = 337, no = 940
Skewed	skew and direction from perspective driver	left = 128, no = 625, right = 524
RightLane	right turn lanes present on minor approach	yes = 1226, no = 51
LeftLane	left turn lanes present on minor approach	yes = 1226, no = 51
Sight	estimate of intersection sight distance	good = 118, limited = 237, somewhat_limited = 922
AdvisorySpeed	advisory speed limit upstream	yes = 105, no = 1172
AdvancedWarning	advance intersection warning sign	yes = 751, no = 526
AdvancedType	type of advance warning sign	none = 526, w2-2* = 21, w3-1* = 371, w2-2* = 5, w3-1a = 301
DoubleWarning	double advance warning signs	yes = 88, no = 1189
Enhancements	intersection warning signs	yes = 27, no = 1250
DoubleStop	double stop signs	yes = 177, no = 1100
TransverseRumble	transverse rumble strips	yes = 35, no = 1242
Beacon	flashing overhead or stop sign beacon	yes = 74, no = 1203
Stop Bar	stop bar	yes = 147, no = 1130
Channelization	channelization at the intersection	yes = 43, no = 1234
Median	divided median on the major approach	yes = 22, no = 1255
MedianType	type of median	no = 1255, painted = 8, raised = 14
Grade	qualitative assessment of grade	downhill = 583, flat = 317, uphill = 377
Splitter	presence of a splitter island	yes = 87, no = 1190
Speeding	max driver speed > speed limit	yes = 1049, no = 228
SpeedingAbove5	max speed > 2.24 m/s (5 mph) over the speed limit	Yes = 826, No = 451
SpeedingAbove10	max 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 seconds of the subject vehicle entering the intersection	Yes = 457, No = 820
IsectAngle	angle of incoming approach to the outgoing approach treated as a categorical variable	90 degree = 625 <90 degree = 103 >90 degree = 549
AgeCategorical	Driver age	Age < 25 years = 139 25 ≤ Age < 60 = 779 Age ≥ 65 years = 359