Characteristics of Urban Arterial Crashes Relative to Proximity to Intersections and Injury Severity

Abhishek Das, Anurag Pande, Mohamed Abdel-Aty, and Joseph B. Santos

Intersections of an urban arterial corridor may influence crashes that occur even beyond their physical area. This study examines the effect of the gradual change in the distance of intersection influence on crash characteristics that explain injury severity outcomes of arterial crashes. The approach adopted involves simultaneous estimation of two variables: an ordinal variable representing crash–injury severity and a binary variable representing crash location (intersection versus segment crashes). The dichotomy in crash location is based on the threshold distance of intersection influence. Five sets of bivariate simultaneous models were estimated by using five threshold distances of influence varying from 0 to 200 ft at 50-ft increments. A threshold of 0 ft essentially means that crashes only at the physical area of intersections are treated as intersection crashes. The other four thresholds define crashes 50, 100, 150, and 200 ft from the center of the intersections as intersection crashes. Simultaneous estimation allows accounting for common factors that affect both crash location and injury severity, but are explicitly included in neither model. Effects of these common unknown factors are reflected in the estimated correlation coefficient between the error terms for the two models. The correlation coefficients were found to be significant for influence distances of 150 and 200 ft and insignificant for influence distances 0 through 100 ft. The implications of these results are discussed. Results of the simultaneous estimation also reveal that crashes on the corridor are less severe during afternoon peak traffic conditions and on blacktop surfaces, while segments with a higher speed limit, a wider pavement surface, and a lower-than-median annual average daily traffic are likely to experience more severe crashes. At low-influence distance thresholds (≤50 ft), pavement surface condition (dry pavement) is significant in discriminating intersection crashes from segment crashes, while pavement surface type (blacktop surface) is significant at higher (≥150-ft) thresholds.

Despite their lower prevailing speeds compared with those on freeways and expressways, arterials have a significant proportion of severe and fatal crashes. For example, arterials are the sites of 57% fatal crashes in Florida (*1*). Safety on an arterial corridor may be affected by crash patterns on two seemingly distinct roadway elements: intersections and the segments between the intersections. A study by Abdel-Aty and Wang (*2*) demonstrated a spatial correlation between crash patterns belonging to successive signalized intersections on an urban arterial. It indicated the need to look at a sequence of signalized intersections along a corridor rather than analyzing each intersection as an isolated entity. Crashes on arterial segments joining consecutive intersections would also be a critical part of the analysis for such an approach. There is a potential for achieving better understanding of crash patterns on arterials if the corridors are studied as a whole instead of as disjointed parts (i.e., intersections and segments separately).

An important issue to be addressed for understanding corridor safety as a whole is the difference between the intersection and segment crash patterns, especially as it relates to injury severity. There are significant variations in injury severity patterns that may be partially explained by the separation of crash location from intersections. For example, Abdel-Aty et al. (*3*) found that the prevailing types of fatal or severe crashes at intersections are mostly angle and left-turn crashes, while those on roadway segments farther from the intersections are mostly fixed-object collisions. Hence, if one observes crashes only at the physical area of intersections, crashes will involve a higher proportion of angle or left-turn crashes, or both, which tend to be more severe. However, as the definition of the intersection is changed to include some area in its vicinity (i.e., the influence area for an intersection is defined); rear-end and other groups of crashes will be included in the sample and the severity patterns may be altered.

The influence area for an intersection is characterized by the distance from the center of the intersection along either of the two legs belonging to the corridor under consideration. Crashes within this distance from any intersection (signalized or unsignalized) are categorized as intersection–intersection-related crashes, while crashes beyond it are categorized as segment crashes. This study attempts to understand factors associated with crashes and their severity on a multilane arterial while accounting for the variations resulting from the location of the crashes relative to intersections. This understanding is accomplished by developing different models for different distance thresholds used to define the influence area for intersections. The methodology used in this study also accounts for the correlations between the factors that explain injury severity and the crash location (intersection versus segment) at a particular threshold. The approach adopted here provides a better understanding of the relationship between a crash location's relative proximity to intersections and the severity outcome. It may also improve understanding of how changes to an intersection affect the neighboring segments of the arterial.

Crash data from the SR-816 corridor in Broward County, Florida, were used is this study. The crashes associated with intersections were separated from crashes associated with arterial segments by defining

A. Das, A. Pande, and M. Abdel-Aty, Department of Civil, Environmental, and Construction Engineering, University of Central Florida, 4000 Central Florida Boulevard, Orlando, FL 32816-2450. J. B. Santos, Florida Department of Transportation, State Safety Office, MS #53, 605 Suwannee Street, Tallahassee, FL 32399-0450. Corresponding author: A. Pande, anurag@mail.ucf.edu.

Transportation Research Record: Journal of the Transportation Research Board, No. 2083, Transportation Research Board of the National Academies, Washington, D.C., 2008, pp. 137–144.
DOI: 10.3141/2083-16

a binary variable whose definition changed on the basis of a specified distance of intersection influence. The injury severity of crashes was defined as an ordinal variable. Detailed characterization of these two variables is provided in the next section, along with particulars of the solution approach and modeling methodology. The next section provides details of the data used for analysis, and is followed by the results and conclusions of this investigation.

SOLUTION APPROACH AND MODELING METHODOLOGY

Relationships between the following variables are of interest in this study:

1. A three-level ordinal variable representing the injury severity. The variable is created from the injury severity information available from the Crash Analysis and Reporting (CAR) database of the Florida Department of Transportation (FDOT).
2. A binary variable representing crash location; with its value being 1 for crashes that occurred within the threshold influence distance of an intersection (intersection–intersection-related crashes), and 0 for crashes that occurred outside this influence distance (segment crashes). In this study, the influence distance, (measured from the center of the intersection), was varied in 50-ft increments on arterial corridors. Hence, there would be multiple binary variables that would distinguish between crashes based on their location (i.e., intersection and nonintersection crashes).

An ordered probit modeling framework was used for the first variable because injury severity levels are naturally ordered. Ordered probit modeling has been applied to injury severity in several studies (*4–6*). However, of these studies, only Abdel-Aty (*4*) compared the factors that affect injury severity at different roadway locations, using the ordered probit model to study severity of traffic crashes at roadway sections and at signalized intersections. The analyses for these roadway elements (segments and intersections), however, were carried out independently of each other.

In the preliminary analysis, chi-square tests for association between injury severity and the binary variables representing crash location suggested a possible association between them. Furthermore, the nature and strength of association changed as the definition of the variable representing crash location was varied. (The results from these tests are discussed in detail later.) The straightforward way to assess the impact of crash location (i.e., intersection) on injury severity would be to use the binary variables representing crash location as an independent variable in the ordered probit model for injury severity. However, this binary variable would be related to the variables generally used in the model for injury severity. For example, the crashes under rainy conditions are less likely to occur right at the intersection than at the roadway segment influenced by intersections. Similarly, left-turn or angle crashes are more likely to occur within the physical area of the intersection (compared with segments), and they are also likely to be more severe. To avoid the confounding effects of other variables, it was decided that the models for the crash location (binary dependent variable) and the injury severity (ordinal dependent variable) would be estimated simultaneously. Because the location variable may have been associated with certain variables included in the severity model, its inclusion (i.e., recursive specification) would have also led to problems of correlated independent variables and to biased and inefficient estimates for the coefficients.

Simultaneous estimation of the two models would improve the coefficient estimates by accounting for the correlations between the unmeasured factors. The difference between independent estimation and the simultaneous (bivariate) modeling procedure is that the latter does not assume the errors for the two models to be uncorrelated. The simultaneous estimation procedure also provides the *p*-value for the statistical test on correlation, with the null hypothesis being that the correlation coefficient $\rho = 0$.

MODEL FORMULATION

According to Long (*7*), logit and probit models provide very similar results in relation to the resulting classification and standardized effects for independent variables. However, convergence is more likely for bivariate probit models, even though it may require more computational time (*8*). The model specification for the simultaneously estimated probit model equations is as follows (*9*):

$$Y_1^* = \boldsymbol{X}_1'\boldsymbol{\beta}_1 + \epsilon_1 \tag{1}$$

$$Y_2^* = \boldsymbol{X}_2'\boldsymbol{\beta}_2 + \epsilon_2 \tag{2}$$

where

Y_1^*, Y_2^* = unobserved, latent continuous variables,
$\boldsymbol{X}_1$ = vector of independent variables explaining roadway location of crash,
$\boldsymbol{X}_2$ = vector of independent variables explaining crash–injury severity,
$\boldsymbol{\beta}_1$ = vector of coefficients for independent variables explaining roadway location of crash,
$\boldsymbol{\beta}_2$ = vector of coefficients for independent variables explaining crash–injury severity,
ϵ_1, ϵ_2 = disturbances with the following specifications, and

$$E\left[\epsilon_1 \middle| X_1, X_2\right] = E\left[\epsilon_2 \middle| X_1, X_2\right] = 0$$

$$\mathrm{Var}\left[\epsilon_1 \middle| X_1, X_2\right] = \mathrm{Var}\left[\epsilon_2 \middle| X_1, X_2\right] = 1$$

$$\mathrm{Cov}\left[\epsilon_1, \epsilon_2 \middle| X_1, X_2\right] = \rho$$

The binary and ordinal scale-dependent variables, Y_1 (crash location) and Y_2 (injury severity) are observed when the respective latent variables Y_1^* and Y_2^* fall in certain ranges. The two independent variables observed as discrete categories (i.e., Y_1 and Y_2) are specified below:

$$Y_1 = \begin{cases} 0 & Y_1^* \le 0 \\ 1 & Y_1^* > 0 \end{cases}$$

$$Y_2 = \begin{cases} 0 & Y_2^* \le 0 \\ 1 & 0 < Y_2^* \le \mu \\ 2 & Y_2^* > \mu \end{cases}$$

Equation 1 (specified as a binary probit model) relates crash location with other crash characteristics; while Equation 2 (specified as an ordered probit model) relates injury severity with the independent variables. This formulation allows one to relate crash location with injury severity without confounding the effects of independent variables that relate to both crash location and injury severity. Detailed descriptions of the variables constituting vectors X_1 and X_2 appear in the next section (Table 1).

The estimates for model coefficients may be obtained by using maximum-likelihood estimation. The likelihood function maximized to obtain the model coefficients incorporates the effect of correlation between error terms. The coefficients for the models specified above [(i.e., vectors $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ along with $\rho(u_1, u_2)$ would be estimated by using SAS (*10*)]. The details of maximum likelihood estimation process may be found elsewhere (*9*).

Multiple sets of simultaneous models (corresponding to different thresholds on influence distance) based on the above specification would be estimated for the corridor. The only difference between the sets of simultaneous models would be the definition of Y_1 (i.e., crash location variable). The definition of Y_1 would in turn depend on the threshold selected to separate intersection crashes from segment crashes. The details on these thresholds and the variables used in the analysis appear in the next section.

DATA PREPARATION

The crash data used in this study were from a 9.72-mi corridor of arterial SR-816 in Broward County, Florida. Both signalized and nonsignalized intersections were considered. The intersection density (intersections per mile) for the corridor is 11.32. The total number of crashes involving at least a possible injury on this multilane arterial over the 4-year period (2002 to 2005) was 1,575. Of these crashes, 11.17% were either fatal or involved incapacitating injury. The crash data for this corridor were downloaded from FDOT's CAR database.

Before proceeding further, some data issues require clarification. The issues mainly relate to the recorded crash location and the definition of influence distance. In the database used for this study, each crash was assigned to an intersection (node) nearest its location. The information on the distance of crash location from the node representing the center of the intersection was also available in the database. A careful review of this information showed that a significant number of crashes were reported to have occurred at a milepost associated with the nodes. In other words, the distance between the crash location and the center of the intersection was reported as 0 ft. That reporting does not necessarily mean that all these crashes occurred at the midpoint of the intersection. Significantly, the large number of such crashes essentially implies that most crashes that occurred inside the physical area of the intersection were reported to be 0 ft from the center of the intersection. Furthermore, in the state of Florida, the physical area of the intersection is, by default, considered to be the area within 50 ft of the center of the intersection. Hence, some of the crashes reported to be within 50 ft of the node (representing the intersection) in the database may have been very close to the stop bar.

TABLE 1 Descriptions of Variables

Variable	Categories	Description
Independent Variables		
Traffic condition (based on time of day/day of week)	MPW	Morning peak traffic condition on weekday (7 a.m.–9:30 a.m.)
	APW	Afternoon peak traffic condition on weekday (4 p.m.–7 p.m.)
	FSN	Friday or Saturday night traffic condition (Friday 10 p.m.–Saturday 3:30 a.m.)
	OP	Off peak traffic condition
Sectional AADT	1*	Section AADT ≤ 52,000
	2*	52,000 < Section AADT ≤ 58,000
	3*	58,000 < Section AADT ≤ 64,500
	4*	Section AADT > 64,500
Road surface		Binary (1 = dry surface, 0 = all other cases)
Lighting		Binary (1 = daytime, 0 = nighttime)
Weather		Binary (1 = clear, 0 = all other cases)
Road curvature		Binary (1 = straight, 0 = curve)
Road surface type		Binary (1 = blacktop, 0 = all other cases)
Road condition at time of crash		Binary (1 = no defects, 0 = all other cases)
Vision obstruction		Binary (1 = no obstruction, 0 = all other cases)
Alcohol–drug involvement		Binary (1 = No, 0 = Yes)
Pavement surface width		Width of the pavement (continuous)
Shoulder width1		Width of the shoulder closest to the travel lane (continuous)
Shoulder width2		Width of the shoulder farthest from the travel lane (continuous)
Median width		Width of the median (continuous)
Speed limit		Maximum posted speed limit (continuous)
Dependent Variables		
Crash location ($\mathbf{Y}_1$; location_D)	1	Crashes within the 'D' ft from the center of intersection
	0	Crashes beyond 'D' ft from the center of intersection
Injury severity ($\mathbf{Y}_2$)	2	Crashes resulting in incapacitating injuries or fatalities
	1	Crashes resulting in nonincapacitating injuries
	0	Crashes resulting in possible injuries

*The AADT values from various sections of the corridor have been split into four quartiles.

These crashes, while not strictly at the intersection, would most likely have been influenced by it. Therefore, the first two thresholds for influence distance (to separate intersection crashes from non-intersection crashes) were chosen to be 0 and 50 ft, respectively. The threshold of 0 ft means that the crashes within 50 ft of the center of the intersection were classified as intersection crashes (i.e., only those crashes within the physical area of the intersection). For the model corresponding to distance $D = 50$ ft, the crashes that occurred within the physical area of the intersection and those that occurred within 50 ft of the stop bar were classified as intersection crashes. The successive thresholds were also chosen to be in 50-ft increments (i.e., 100 ft, 150 ft, and so on). As noted earlier, this threshold defines one of the two simultaneously estimated dependent variables ($\boldsymbol{Y_1}$; see previous section).

The selection of thresholds at 50-ft increments is somewhat arbitrary. Therefore, the results from the sets of simultaneous models estimated by using different thresholds needed to be interpreted in relative terms. For example, in the case of the models with a threshold at 100 ft, crashes closer to the intersection were treated as intersection–intersection-related crashes compared with the set of models with a threshold at 150 ft. Table 1 lists the independent (regressors) and dependent variables (responses) used in the study. The last row of Table 1 represents the crash location as a binary variable Location_D, which was 1 for crashes within D ft of the center of the intersections.

Crashes with fatalities and incapacitating injuries were combined into one category (of variable $\boldsymbol{Y_2}$ representing injury severity) for two reasons. First, the relatively small frequency of fatal crashes compared with other injury severity levels could create problems in the analysis. For example, the chi-square tests on contingency tables may not be valid due to low expected cell frequency. Second, the crashes that involved incapacitating injury could easily have been fatal and vice versa, depending on the vulnerability of the subjects involved. In addition, the variables shown in Table 1 were gathered from the long form (complete crash reports) prepared by law enforcement authorities in Florida. The information on crashes involving no injury was likely to be incomplete for this set of crashes (*11*). Therefore, only crashes that involved at least a possible injury were included in this study, and the injury severity was categorized as a three-level ordinal variable.

Some of the binary variables shown in Table 1 had in fact more levels in the original database. Some of the categories belonging to these variables were quite infrequent and were therefore combined. Furthermore, the average annual daily traffic (AADT) of the sections was divided into four quartiles, such that they had close to 25% of the cases in each category. In the analysis, this variable was used as a nominal variable and not as an ordinal variable. The reason was that the categorization may not follow the natural order in the relationship of AADT to injury severity ($\boldsymbol{Y_2}$). All the other variables shown in the table are self-explanatory.

ANALYSIS AND RESULTS

As mentioned earlier, the association between the ordinal variable representing crash–injury severity and the binary variables representing the crash location was first examined with chi-square tests. For reliable assessment of the strength of this association by using the chi-square test, each cell of the contingency table was required to have a minimum expected frequency. With the increase in the influence distance (starting from 0 ft), more crashes got assigned as intersection crashes, and the number of crashes assigned as nonintersection or segment crashes was reduced. Beyond a certain influence distance, the frequency of segment (or nonintersection) crashes becomes too low for the chi-square test statistic to be credible. Therefore, a maximum-allowable influence distance was chosen such that at least 10% of all crashes were assigned as nonintersection crashes. Using this criterion, the maximum-allowable threshold influence distance for SR-816 was found to be 200 ft. Limiting the threshold distance to 200 ft also helped in reducing the chances of having the influence area of one intersection overlap with another. The chi-square test statistics and corresponding p-values for testing associations between $\boldsymbol{Y_1}$ and $\boldsymbol{Y_2}$ (with definition of $\boldsymbol{Y_1}$ varying on the basis of the thresholds of influence distance, $D = 0$ ft through $D = 200$ ft) are shown in Table 2.

Bivariate probit models, formulated earlier in the paper, were then developed for the injury severity ($\boldsymbol{Y_2}$, ordered probit) and the location variable ($\boldsymbol{Y_1}$, binary probit). The bivariate formulation does not assume that the errors in the models being simultaneously estimated are uncorrelated. The significance of the correlation coefficient (ρ) was tested and reported along with the estimated coefficients (and their significance) for independent variables included in the two models. The correlation essentially accounted for the common factors associated with both dependent variables that were not explicitly included in the models. The last column of Table 2 also provides the estimates for ρ and its significance. Table 3 shows the detailed estimates of variables coefficients and their significance along with estimates of error correlation coefficients shown in the last column of Table 2.

Table 2 shows that the significance trend for ρ at various distances of intersection influence is similar to the corresponding significance trend of the chi-square statistic. In Tables 2 and 3, cells with statistically significant parameters (at 90% confidence level) have been highlighted. The values of μ (for converting the estimated latent continuous variable into the categorical injury severity) were also estimated for each of the five injury severity models and are shown in Table 3.

The significance of ρ changed as the influence distance for defining crashes on intersection and segment varied from 0 to 200 ft. For the models developed for intersection influence distances 0, 50, and 100 ft, the ρ values were insignificant. These ρ values indicate that the error terms in the two models were not significantly correlated. However, the correlation coefficient became significant beyond an influence distance of 100 ft. Table 2 also depicts a similar trend for the significance of the chi-square test statistic. This trend in effect means that on average, when intersection crashes are defined such

TABLE 2 Chi-Square Statistics and Estimates of Coefficient of Error Correlation

Influence Distance (ft)	Chi-square (p-value) (from contingency tables)	Correlation Coefficient ρ (p-value) (from bivariate probit models shown in Table 3)
0	4.369 (0.113)	0.053 (0.172)
50	1.354 (0.508)	–0.046 (0.266)
100	1.285 (0.526)	–0.055 (0.201)
150	7.889 (0.019)	–0.135 (0.005)
200	5.950 (0.051)	–0.120 (0.016)

TABLE 3 Five Simultaneous Models for Crash Location and Injury Severity Levels on SR-816

Parameter		*D* = 0 Estimate	*D* = 0 Approx. *p*-Value	*D* = 50 Estimate	*D* = 50 Approx. *p*-Value	*D* = 100 Estimate	*D* = 100 Approx. *p*-Value	*D* = 150 Estimate	*D* = 150 Approx. *p*-Value	*D* = 200 Estimate	*D* = 200 Approx. *p*-Value
Crash Location Model											
Traffic condition	APW	–0.086	0.338	–0.166	0.074	–0.148	0.125	–0.157	0.152	–0.176	0.115
Traffic condition	FSN	–0.090	0.504	–0.057	0.693	–0.076	0.618	–0.228	0.181	–0.222	0.211
Traffic condition	MPW	–0.061	0.625	–0.055	0.671	–0.063	0.638	–0.062	0.685	–0.122	0.424
Traffic condition	OP	0.000		0.000		0.000		0.000		0.000	
Dry road surface		0.276	0.023	0.251	0.050	0.149	0.266	–0.010	0.948	–0.049	0.753
Daylight condition		–0.150	0.039	–0.225	0.004	–0.246	0.003	–0.253	0.008	–0.246	0.013
Clear weather		–0.110	0.298	–0.168	0.139	–0.167	0.157	–0.085	0.521	0.004	0.977
Straight road section		–0.483	0.159	–0.277	0.461	–0.402	0.339	0.016	0.970	0.071	0.870
Blacktop road surface		–0.112	0.245	0.007	0.944	0.064	0.537	0.201	0.080	0.223	0.056
No vision obstruction		–0.042	0.758	0.064	0.647	0.234	0.097	0.094	0.572	0.039	0.820
No alcohol–drug use		–0.080	0.596	0.114	0.472	–0.099	0.570	–0.011	0.954	–0.189	0.394
Injury Severity Model											
Traffic condition	APW	–0.216	0.017	–0.214	0.019	–0.215	0.018	–0.214	0.018	–0.214	0.019
Traffic condition	FSN	0.154	0.229	0.154	0.228	0.154	0.229	0.154	0.229	0.154	0.231
Traffic condition	MPW	0.045	0.710	0.042	0.729	0.040	0.737	0.039	0.745	0.040	0.741
Traffic condition	OP	0.000		0.000		0.000		0.000		0.000	
Dry road surface		0.095	0.425	0.094	0.433	0.093	0.435	0.093	0.433	0.094	0.430
Daylight condition		0.044	0.535	0.044	0.527	0.045	0.520	0.047	0.507	0.047	0.508
Clear weather		–0.021	0.837	–0.020	0.844	–0.020	0.845	–0.021	0.839	–0.021	0.836
Straight road section		–0.020	0.953	–0.019	0.956	–0.016	0.962	–0.018	0.958	–0.017	0.961
Blacktop road surface		–0.221	0.015	–0.223	0.014	–0.223	0.014	–0.224	0.014	–0.223	0.014
No road defects at time of crash		0.029	0.881	0.046	0.812	0.047	0.806	0.072	0.708	0.064	0.742
No vision obstruction		–0.144	0.274	–0.150	0.256	–0.150	0.255	–0.157	0.233	–0.155	0.239
Pavement surface width		0.040	0.018	0.044	0.009	0.044	0.008	0.047	0.005	0.046	0.006
Closest shoulder width		–0.263	0.362	–0.258	0.371	–0.262	0.364	–0.259	0.368	–0.259	0.369
Farthest shoulder width		–0.181	0.370	–0.175	0.388	–0.171	0.399	–0.169	0.405	–0.171	0.399
Median width		–0.013	0.016	–0.013	0.015	–0.013	0.015	–0.013	0.012	–0.013	0.012
Maximum posted speed limit		0.023	0.023	0.021	0.033	0.021	0.033	0.020	0.040	0.020	0.037
AADT (1st quartile)	1	0.329	0.003	0.333	0.002	0.335	0.002	0.326	0.003	0.323	0.003
AADT (2nd quartile)	2	0.226	0.014	0.221	0.017	0.221	0.017	0.209	0.024	0.210	0.023
AADT (3rd quartile)	3	0.044	0.638	0.045	0.631	0.043	0.648	0.028	0.762	0.028	0.762
AADT (4th quartile)	4	0.000		0.000		0.000		0.000		0.000	
No alcohol/drug use		–0.322	0.021	–0.322	0.021	–0.322	0.021	–0.323	0.020	–0.324	0.020
μ (for classification)		0.916	<.0001	0.916	<.0001	0.916	<.0001	0.916	<.0001	0.916	<.0001
Correlation Coefficient											
ρ		0.053	0.172	–0.046	0.266	–0.055	0.201	–0.135	0.005	–0.120	0.016

that they include a smaller influence area (within about 100 ft of intersections for this corridor), severity on the arterial crashes may be modeled independently of crash location. Once again, 100 ft is the distance from the center of the intersection. This distance may also vary from corridor to corridor, depending on intersection density and traffic patterns. As noted earlier, due to data constraints the authors have not been able to develop models for *D* >200 ft and beyond. It may be inferred that the correlation would probably have been significant.

From this point forward, the discussion will be about the factors found to be significant for the two simultaneously estimated models at various threshold distances. The crash location (Y_1) models for various threshold values (*D*) show the factors that help discriminate between intersection crashes and segments crashes. The models of crash–injury severity (Y_2) for various threshold values (*D*) in Table 3 show the factors that relate significantly with the ordinal variable. Figure 1 shows the significant parameters for the ordinal model of crash–injury severity in the form of bubble plots. The size of the

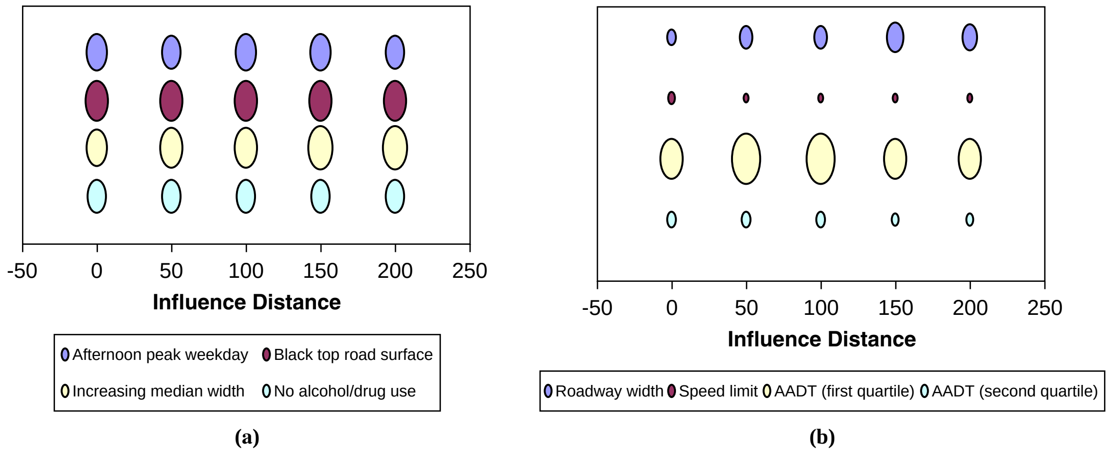

FIGURE 1 Significant parameters for model of crash injury severity: factors with (*a*) negative coefficients and (*b*) with positive coefficients.

bubbles in the plots reflects the relative significance of these parameters with respect to each other. In addition, the bubbles within a plot may be compared horizontally but not vertically. Figure 1*a* shows the effect of the factors that decrease the severity of the crash (i.e., negative coefficients), and the Figure 1*b* shows those that increase the severity (i.e., positive coefficients).

Figure 1 and Table 3 illustrate that weekday afternoon peak-period (APW, Table 1) conditions, blacktop pavement surface, and an increase in median width decreased the severity of crashes on SR-816 (Figure 1*a*). No alcohol or drug use also had the same effect, which essentially means that alcohol or drug involvement increased the severity of the crashes. During afternoon peak periods, the speeds are generally lower due to congestion; therefore, crashes are likely to be less severe. Likewise, larger median width may reduce the chances of severe crossover head-on collisions. It explains the significantly negative coefficient for median width. A similar result for severity of peak-hour crashes at intersections was found by Abdel-Aty and Keller (*11*). Presence of a median was also found to reduce the severity of crashes in that study.

Blacktop surfaces were found to affect severity negatively in all five models ($D = 0$ ft through $D = 200$ ft). This variable was also significant for separating intersection versus segment crashes when intersection crashes included the crashes that occurred within 150 and 200 ft of the intersections (models for $D = 150$ ft and $D = 200$ ft in Table 3; see also Figure 2). For the other three values of D (defining intersection crashes as only those that occur within 0, 50, and 100 ft of intersections), this variable was not significant in the crash-location model. These crashes were not only less severe (*11*, *12*) but were also likely to be more frequent in the segment within 150 to 200 ft from intersections. The findings also seem to corroborate the findings of a study that asphalt pavements may lead to a higher frequency of peak-period crashes (*13*). Crashes on blacktop surfaces with an asphalt base seem to have higher frequencies during peak periods and within 150 to 200 ft of intersection, indicating that these pavement surfaces might increase the odds of rear-end crashes. It may in turn be the reason for the negative coefficient of the variable representing blacktop surfaces with asphalt base in the injury severity model (because rear-end crashes tend to be less severe).

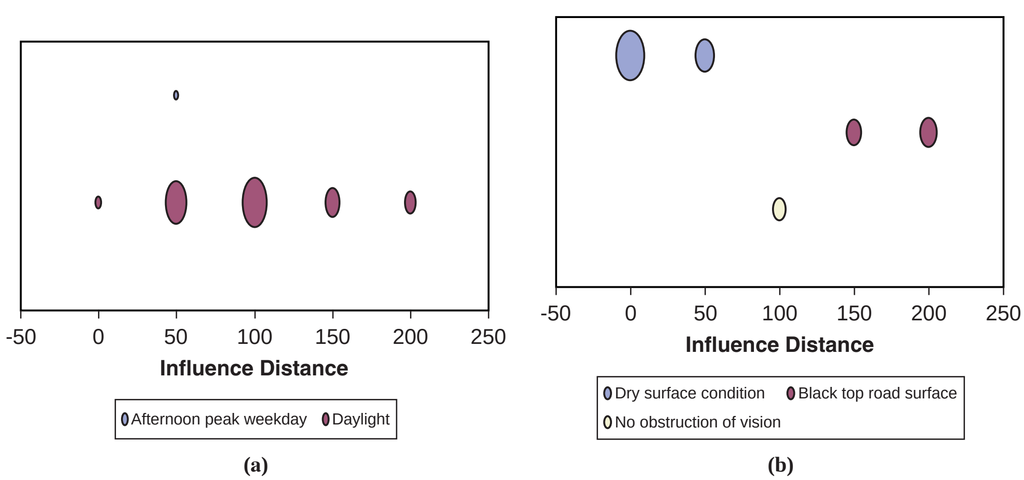

FIGURE 2 Significant parameters of model for crash location: factors with (*a*) negative coefficients and (*b*) with positive coefficients.

The findings also show that increases in roadway width and speed limit increase the severity of crashes. AADT below the median value (the first and second quartiles) were also positively associated with the severity (Figure 1*b*). Among the factors positively influencing injury severity, lower AADT was the most significant. The effect of roadway width became more profound when the influence distance was greater than zero.

Figure 2 depicts significant parameters for five binary crash location models, each estimated simultaneously with the corresponding injury severity model. The coefficients of the model are shown in Table 3. The size of the bubbles once again reflects the relative significance of the parameters. Some parameters have no corresponding bubble at certain values of D (i.e., intersection influence distances). This observation indicates that, if crashes at intersections are defined on the basis of this influence distance, then the corresponding parameters do not contribute to discriminating the crash location. Figure 2*a* shows the effect of the factors that decreased the likelihood of a crash being within a particular distance from an intersection (negative coefficients), while Figure 2*b* depicts those that increased it (positive coefficients).

Figure 2 and Table 3 show that, during the afternoon peak period on weekdays, the likelihood of a crash occurring within 50 ft of the intersection was less than during the off-peak traffic conditions. While this difference was insignificant at influence distances of 100, 150, and 200 ft (no corresponding bubble in Figure 2*a*), the p-value was much closer to .10 (Table 3). This difference between afternoon peak weekdays (APW, Table 1) and off peak (OP, Table 1) conditions was insignificant if one examined the relative likelihood of a crash occurring within the physical area of an intersection (influence distance = 0 ft). The reason for this insignificant difference is probably that, during the afternoon peak hours, drivers expect congestion and expect to slow down or stop as they approach an intersection. This behavior reduces the likelihood of crashes that prevail in the vicinity of intersections. The modeling results also show that the variable representing normal daylight was significant in separating crashes at intersections and segments regardless of the specified influence distance. However, the significance was more profound if the influence area of intersections was defined as 50 and 100 ft. While it is hard to conclude definitively, the smaller coefficient of this variable at influence distances D = 150 ft and D = 200 ft might have been caused by the dilemma zone phenomenon.

Of the variables with positive coefficients (Figure 2*b*), blacktop road surface was significant for separating intersection crashes from segment crashes if the influence distance is 150 or 200 ft. The implications of this result were discussed earlier. A dry surface condition also augmented the likelihood of a crash to occur at the physical area of an intersection or within 50 ft of it. The significance was more profound for the physical area of the intersection than for the case when the influence distance was 50 ft. This situation can essentially be interpreted as follows: if the influence area of the intersection was increased, then the weather conditions' ability to discriminate between intersection and segment crashes diminished. It might be due to wet-weather crashes that were more prevalent on approaches to intersections. A result that was not clearly understood was that the variable representing vision obstruction was found to be significant in identifying intersection crashes from segment crashes with the influence distance at 100 ft. The variable was not significant at any other influence distance and p-values were not even on the margin. This might be a peculiar issue with the specific corridor, such as a few intersections with vision obstruction problems along the corridor or the demographics of Broward County, with a sizeable proportion of older drivers.

CONCLUDING REMARKS

Understanding safety on urban arterials is a complex problem because it is affected by interactions between traffic patterns on intersections and the segments connecting them. Implementation of certain safety improvements at intersections may lead to unanticipated changes in safety or operational performance of nearby segments or vice versa. Hence, an improved understanding for safety may be achieved if consecutive intersections on arterial corridors are examined as a whole, along with the segments connecting them, instead of as isolated entities. The analysis presented in this paper, focusing on injury outcomes of crashes, was an effort in that direction.

More specifically, the researchers simultaneously examined the crash characteristics that explain the location (intersection crashes versus segment crashes) and the severity of crashes. The analysis was carried out by simultaneous estimation of models for crash location and injury severity at five values of intersection influence distances. These values varied from $D = 0$ through $D = 200$ ft at 50-ft increments. The value of D (influence distance) essentially represents the distance from the center of an intersection along the corridor to the point at which the crashes are categorized as intersection related. Simultaneous estimation of crash location and injury severity models allowed accounting for correlation between errors of the two models. The correlation was likely the result of common unknown factors that affected both these variables but were not explicitly included in either model.

The model for crash location variable indicated that, during peak hours, crashes were less likely to occur at or in the vicinity of intersections. It was also found that an increase in the pavement surface width and speed limits expectedly increased the severity of the crashes. Lower AADT values were also positively associated with crash severity. It may be inferred that certain conditions that make the task of driving easier (higher roadway width, low AADT) can lead to increased severity of crashes.

The results obtained in this study may be specific to the corridor under consideration. It may be expected, however, that similar results (for example, the influence distance threshold beyond which the error correlation coefficient becomes significant) would be obtained from corridors with comparable intersection density. The results also suggest that for corridors with higher intersection density (i.e., more closely spaced intersections) the errors may not be correlated and hence crash location and injury severity may be modeled independently of each other. This inference is based on insignificant correlation between errors for the simultaneous models developed corresponding to $D = 0$, 50, and 100 ft. In contrast, arterials on which intersections are fewer and farther between, injury severity models for the corridor need to account for crash location (i.e., intersection versus segment crashes). These inferences need to be validated with analysis of data from more arterial corridors.

ACKNOWLEDGMENTS

The authors thank the Florida Department of Transportation for funding the research presented here. The authors also thank the anonymous reviewers for their insightful comments, which resulted in a significantly improved paper.

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The Safety Data, Analysis, and Evaluation Committee sponsored publication of this paper.