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Understanding Dallas District Pedestrian Safety Issues



Prepared for Dallas District
Texas Department of Transportation

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BACKGROUND

From 2007 to 2016, pedestrian fatalities increased 27 percent nationally, while all other traffic fatalities decreased 14 percent. In 2016, Texas had the ninth highest pedestrian fatality rate in the United States at 2.44 per 100,000 population. In a review of the U.S. counties with the highest number of pedestrian fatalities in 2016, Dallas County had the fourth highest number of pedestrian fatalities with 84. The top three counties were Los Angeles County, CA (265 pedestrian fatalities), Maricopa County, AZ (133 pedestrian fatalities), and Harris County, TX (128 pedestrian fatalities). Texas had three counties within the top 10 counties with the highest number of pedestrian facilities with — as noted previously — Harris County being third, Dallas County being fourth, and Bexar County being eighth (68 pedestrian fatalities).

Similar to the rest of the United States, pedestrian crashes (both total crashes and high-severity crashes — crashes with fatal and incapacitating injuries) have been increasing in the Texas Department of Transportation's (TxDOT's) Dallas District over the last 10 years, as shown in Figure 1. The district's population has also grown by 19 percent over the same time period, which could have contributed to the increase in these types of crashes or, at the least, made it harder to reduce them. Although pedestrian-related crashes represent only 3 percent of the total crashes, they tend to result in more serious injuries because pedestrians are roadways' more vulnerable users. In fact, Figure 2 shows that pedestrian fatal crashes are about 20 percent of total fatal crashes, and the trend is increasing.

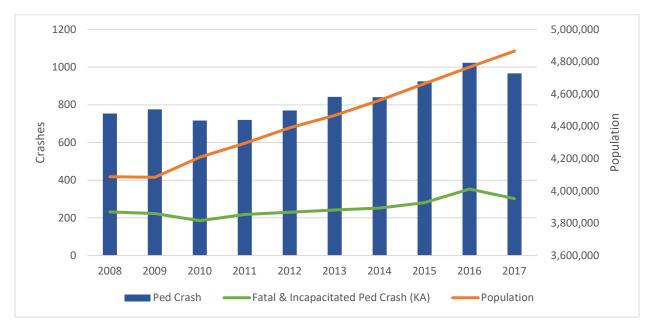


Figure 1. Dallas District Pedestrian Crashes in 2008–2017.

¹ Governors Highway Safety Association. *Pedestrian Traffic Fatalities by State*. February 28, 2018. https://www.ghsa.org/sites/default/files/2018-03/pedestrians 18.pdf.



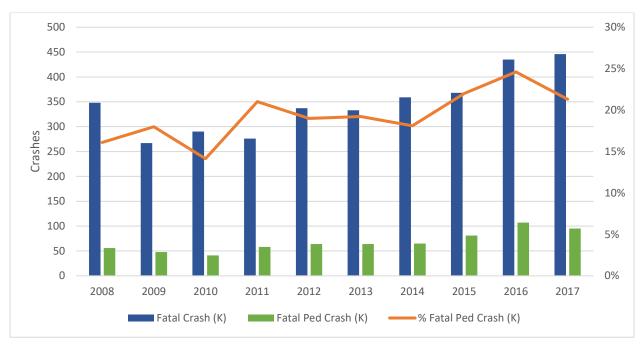


Figure 2. Dallas District Fatal Crashes versus Pedestrian Fatal Crashes in 2008–2017.

For this reason, TxDOT's Dallas District requested that the Texas A&M Transportation Institute (TTI) investigate these types of crashes to better understand the issue. This in-depth analysis provides a deeper understanding of the circumstances and factors leading to these crashes, which can lead to identifying potential countermeasures.

This analysis examined:

- How population/demographics relate to pedestrian crashes.
- Where the crashes are occurring:
 - o Counties.
 - o Cities.
 - o Roadway classification (freeway or non-freeway).
 - On- or off-state highway system.
 - o Intersections or non-intersection areas.
- When crashes are occurring:
 - During daylight.
 - In the dark.
- The behaviors on the part of motorists and/or pedestrians that are associated with the crashes.
- Freeway and intersection hot spots.

Crash Data

For this study, TTI wanted an extensive database to explore the pedestrian safety issues. Extensive datasets provide more reliable insights, especially given the infrequency and random

nature of pedestrian crashes. All fatal to possible injury (KABC) pedestrian-related crashes (i.e., involving person type 4: pedestrian) for the Dallas District from 2008 to 2017 were extracted from TxDOT's Crash Record Information System (CRIS). Only crashes that were identified as TxDOT reportable were included in the analysis. *TxDOT reportable* is defined as a crash occurring on a public roadway and resulting in death or injury or \$1,000 in damage. In total, 8,332 crashes were extracted for the evaluations focusing on the Dallas District.

Population

Figure 3 compares the number of pedestrian crashes relative to their respective population from 2008 to 2017 in the three most populous counties in Texas, according to American Community Survey 2017 population estimates. Pedestrian crashes, as defined in the previous section, were extracted for each county from the CRIS database. Harris County had the highest number of crashes of any county in Texas during this period; however, as Figure 3 shows, Harris County had the lowest crash rate at 243 crashes per 100,000 population. Bexar County, with a smaller population than Dallas but with a similar number of crashes (6,096 versus 6,707), had 328 crashes per 100,000 population. Dallas County with 267 crashes per 100,000 population had a slightly higher crash rate than Harris County but a lower crash rate than Bexar County.

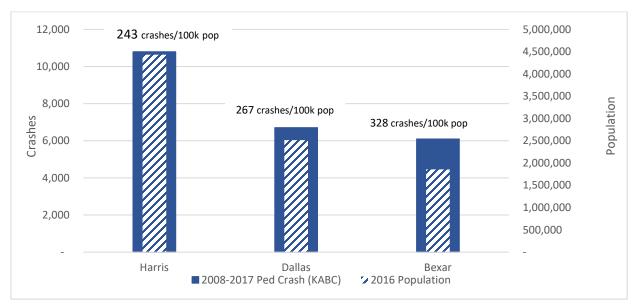


Figure 3. 2016 Population and 2008–2017 Pedestrian Crashes for Harris, Dallas, and Bexar Counties.

Dallas County Demographics

The 2008–2017 pedestrian crashes (KABC) in Dallas County show an overrepresentation of males involved in pedestrian crashes compared to females (Figure 4). In terms of race and ethnicity, Figure 5 shows that Blacks are highly overrepresented in pedestrian crashes in Dallas County.

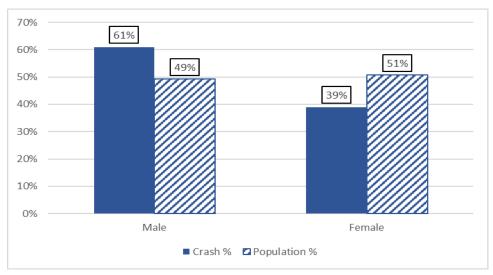


Figure 4. Dallas County Gender.

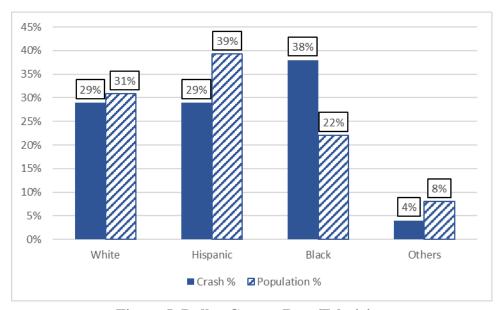


Figure 5. Dallas County Race/Ethnicity.

Focus Cities

The increase in pedestrian fatalities and injuries has not gone unnoticed at the national level. In 2015, the Federal Highway Administration (FHWA) designated Texas as a focus state and five cities within it as focus cities for reducing pedestrian fatalities. These cities are Austin, Dallas, Fort Worth, Houston, and San Antonio. With this designation, these cities have become places of interest for reducing pedestrian fatalities and injuries with additional resources, such as training and technical assistance, that have been provided to these states and cities by FHWA to combat the problem. Figure 6 compares the number of pedestrian crashes for these five cities relative to

its population. Figure 6 shows that Dallas ranks third in the number of pedestrian crashes and in population but ranks second in the pedestrian crash rate with 350 crashes per 100,000 population.

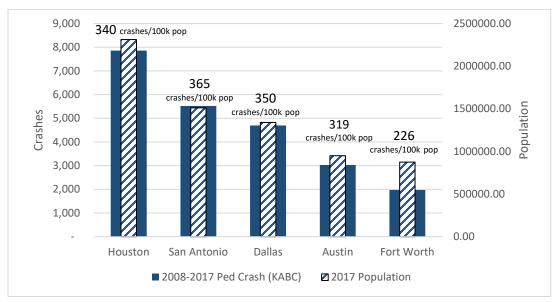


Figure 6. Five Focus Cities in Texas.

City of Dallas Demographics

Figure 7 shows the percentage of population by gender for the city of Dallas. Similar to the county, there is an overrepresentation of males involved in pedestrian crashes. In terms of race and ethnicity, Figure 8 shows that, at the city level, Hispanics are overrepresented compared to their proportion of the city population.

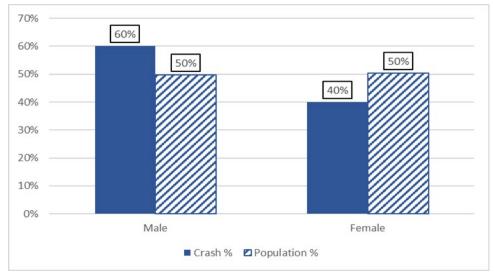


Figure 7. City of Dallas Gender.



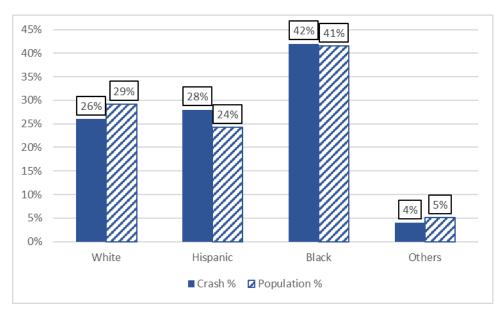


Figure 8. City of Dallas Race/Ethnicity.

It is not known if these overrepresentations are simply a function of exposure (i.e., Hispanics walk more than other racial or ethnic groups) or if actual behavior is different among one or both of these groups. This does, however, highlight the groups that could most benefit from educational and outreach campaigns.



OVERVIEW OF DALLAS DISTRICT PEDESTRIAN CRASHES

Dallas District Crash Location (County, Freeway Related, and On or Off System)

Figure 9 shows a crash tree diagram that highlights the general findings of the analysis. The seven-county Dallas District had 8,332 pedestrian-related crashes from 2008 to 2017. Starting at the district level, the crashes were split by county. The majority of the crashes (i.e., 6,707 [80 percent]) occurred in Dallas County. Of those, 4,696 (70 percent) occurred in the city of Dallas. Therefore, the focus of the analysis is on the pedestrian-related crashes that occurred in the city of Dallas.

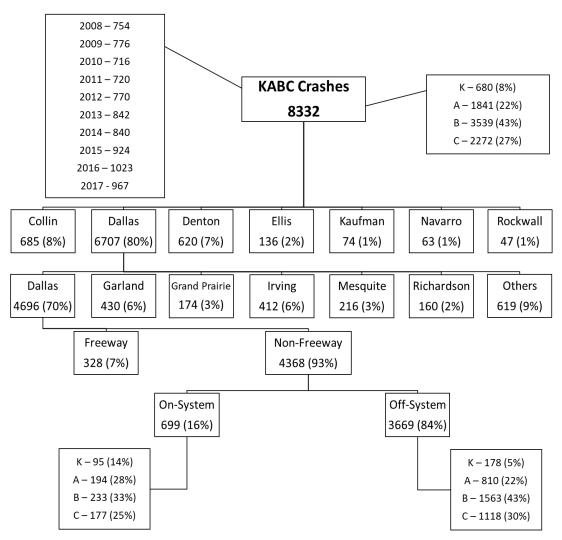


Figure 9. Crash Tree Diagram Characteristics of Dallas District Pedestrian Crashes (1).

TTI sought to distinguish between those crashes occurring on access-controlled highways, such as freeways and tollways, and those occurring on the city street (non-access-controlled) network. This was done to better understand the interactions between pedestrians and motorists in a



typical street environment as opposed to non-traditional pedestrian and motorist interaction on a limited-access highway (i.e., freeway). Of the 8,332 pedestrian-related crashes in the city of Dallas, 328 (7 percent) occurred on freeways.

Of the pedestrian crashes on city of Dallas freeways, 128 (39 percent) were fatal. These crash reports were reviewed to gain a better understanding of fatal pedestrian crashes on high-speed facilities. Table 1 shows why the pedestrian was at the crash location. Some of the reasons recorded included crossing the roadway, lying down, standing, walking, previous crash, stalled vehicle, and retrieving items from the roadway. These reasons were classified into "intended" or "unintended" pedestrians based on similar research² done on high-speed facilities. *Unintended pedestrians* are defined as people that had not intended to be a pedestrian and were struck while outside their vehicle, such as attending to a broken-down vehicle or flat tire, being there after a previous crash, or working.

Table 1. Distribution of Freeway Fatal Crashes in City of Dallas by Reason the Pedestrian Was at the Crash Location Based on Crash Reports.

Why Was the Pedestrian at the Crash Location?	Intended	Un- intended*	Not Stated	Total
Crossing roadway	38			38
Walking or lying down in traffic	11			11
Standing in traffic	6			6
Walking or lying down on median, shoulder, or				
off the road	3			3
Fleeing police	2	1		3
Suicide	2			2
Commuting/moving from one place to another	1			1
Standing on median, shoulder, or off the road	1			1
Unknown	1		2	3
Previous crash		10		10
Retrieving items from road		1		1
Stalled vehicle		20		20
Unconscious			1	1
Working		3		3
Missing reports				25
Total	65	35	3	128

^{*}The pedestrian was associated with leaving a vehicle or was working.

² Fitzpatrick, K., V. Iragavarupu, M. Brewer, D. Lord, J. Hudson, R. Avelar, and J. Robertson. *Characteristics of Texas Pedestrian Crashes and Evaluation of Driver Yielding at Pedestrian Treatments*. TxDOT Report FHWA/TX-13/0-6702-1, May 2014.



Researchers determined that 65 pedestrians (51 percent) intended to be on the freeway as opposed to 35 (27 percent) that did not intend to be there. The dataset had 25 missing reports (20 percent), and the unintended pedestrian coded as "fleeing police" first exited his car before being fatally struck as he was crossing the freeway. These results were unexpected because pedestrians are legally prohibited from walking on freeways. The study also did not support the statewide study, which found that only 5 percent (24 of 474) of the fatal freeway pedestrian crashes were not associated with a vehicle. However, the current study also found that 68 percent of the crash reports did not include the reason why the pedestrian was at the crash location. Researchers suspect that the sample size may need to be expanded by going outside Dallas and/or including other crash severities to get a more accurate representation.

Table 2 and Table 3 show how many pedestrians and/or drivers, respectively, in these crashes were under alcohol or drug influence. Overall, 30 pedestrians (23 percent) involved were "under the influence" as compared to 9 drivers (7 percent) involved. These findings are not conclusive because at least half of the pedestrians and drivers involved were flagged as "unknown" for alcohol/drug influence (50 percent of pedestrians and 60 percent of drivers), but the findings do point to a factor that could be contributing to these types of crashes.

Table 2. Freeway Fatal Crashes: Influence of Alcohol/Drugs for Pedestrians.

Influence of Alcohol/Drugs (Pedestrian)	Intended	Un- intended	Not Stated	Total
Unknown	37	24	2	64
Alcohol or "had been drinking"	10	4		14
Drugs	7	3		10
Not under influence	6	3	1	10
Both alcohol and drugs	5	1		6
Missing reports				25
Total	65	35	3	128

Table 3. Freeway Fatal Crashes: Influence of Alcohol/Drugs for Drivers.

Influence of Alcohol/Drugs (Driver)	Intended	Un- intended	Not stated	Total
Unknown	52	22	3	78
Not under influence	12	4		16
Alcohol but within limits		1		1
Drugs	1			1
Alcohol or "had been drinking"		7		7
Both alcohol and drugs		1		1
Missing reports				25
Total	65	35	3	128



Of the 4,368 pedestrian crashes that did not occur on a freeway (93 percent), 699 (16 percent) were on TxDOT system roads, and the remaining 3,669 (84 percent) were off system. Although there were fewer on-system road crashes, they had higher percentages of fatal crashes than the off-system road crashes (14 percent versus 5 percent) and suspected serious injury crashes (28 percent versus 22 percent). This is likely due to the fact that on-system roads typically have higher traffic volumes, more travel lanes (i.e., wider cross sections and thus more pedestrian exposure), and higher posted/operating speeds.

Characteristics of Non-freeway Dallas District Crashes

TTI then analyzed the pedestrian-related crashes in more detail to identify characteristics of city of Dallas non-freeway crashes. The bottom half of the tree diagram (Figure 10) summarizes the location of the Dallas pedestrian-related crashes relative to intersections, the presence of traffic control devices (e.g., a stop light, stop sign, pedestrian hybrid beacon, or other pedestrian-only signal), lighting conditions (e.g., dark or daylight), and time of day (e.g., day or night).

The highest percentage of non-freeway crashes occurred at non-intersection locations with 388 (56 percent) and 1,738 (47 percent) for on-system and off-system roads, respectively. The top three contributing factors leading to these crashes, as reported, were identified. "Pedestrians failed to yield the right of way to vehicle" was cited for a quarter of the non-intersection (also called midblock) crashes. However, for intersection and intersection-related crashes on off-system roads, the top contributing factor was "vehicle failure to yield the right of way to a pedestrian". These results seem intuitive because non-intersection crashes would typically involve a pedestrian crossing outside a crosswalk, where a pedestrian crossing should yield the right of way to a vehicle. In addition, off-system road intersections would typically have more pedestrian traffic and situations where motorists would need to legally yield to pedestrians.

The most common traffic control at intersection crashes was a signal light, which included 125 on-system (45 percent) and 642 off-system (38 percent) intersections. Stop signs were the second most common traffic control type. However, there was a higher percentage of off-system crashes where it was stop controlled (4 percent on system versus 12 percent off system).

Lighting conditions and the time of day were other factors considered. A higher percentage of pedestrian crashes occurred in dark lighting conditions. The non-intersection-related crashes on the on-system roads had the most and highest percentage with 238 (61 percent). In fact, 224 crashes (58 percent) also occurred in nighttime conditions, between 7 p.m. and 6 a.m.



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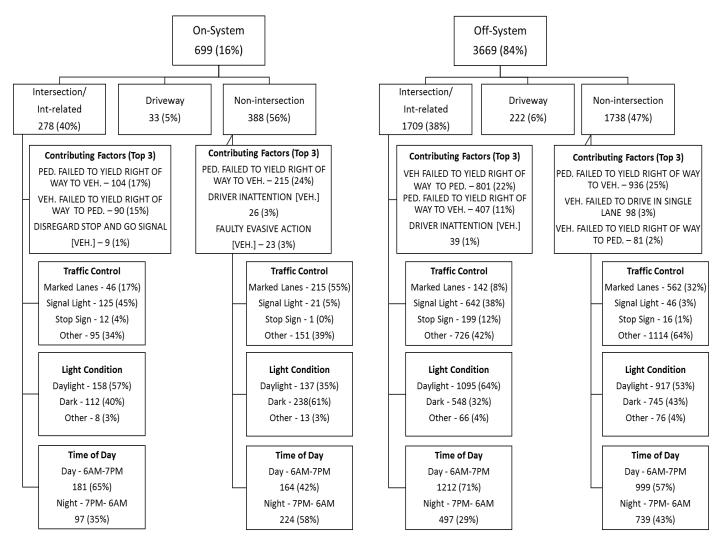


Figure 10. Crash Tree Diagram Characteristics of Dallas District Pedestrian Crashes (2).



ANALYSIS OF CITY OF DALLAS PEDESTRIAN CRASHES

The next step of the analysis was to examine the crashes with respect to their location. TTI started with the dataset containing 8,332 pedestrian-related crashes as described previously. The coordinates for 217 crashes (3 percent) were missing, so TTI used various techniques to geocode them based on available information such as street name, intersecting street, block number, etc., to develop a dataset that was as complete as possible. From the crashes TTI geocoded, 208 crashes (96 percent) were locatable, while nine crashes were not, resulting in 8,323 pedestrian-related crashes available for analyses. As expected, the majority (60 percent) were on off-system roads. By crash severity, 2 percent were fatal, 29 percent incapacitating, 37 percent non-incapacitating, and 32 percent possible injury.

Freeway Crash Clusters

Given the effort required, TTI performed spatial analysis of the pedestrian crashes within only the city of Dallas. The crashes were divided between freeway and non-freeway crashes. This step was necessary to avoid mixing freeway main lane crashes located on an overpass/underpass with crashes located below/above it on an arterial/frontage road. This section discusses the findings for freeways, while the following section discusses non-freeway crashes.

Based on the spatial distribution of freeway crashes, a 300-foot radius buffer was applied to each crash. A cluster was formed if two or more crash buffers intersected. In other words, two crashes that are within 600 feet (0.11 miles) from each other would form a cluster. This distance seemed reasonable given that the stopping sight distance is 645 feet for a design speed of 65 mph. This method identified 59 clusters where two or more pedestrian crashes occurred. The clusters were ranked by crash frequency and by crash rate (per million vehicle miles traveled). The maximum annual average daily traffic (AADT) used to calculate the crash rate for each cluster was from TxDOT's 2017 Roadway Highway Inventory Network Offload (RHINO) data. Table 4 lists the top 10 freeway clusters by crash frequency, and Table 5 lists them by crash rate. The complete rankings can be found in Appendices A and B, respectively.

TxDOT is building a pedestrian bridge at the highest crash rank cluster, which had an average of one pedestrian crash per year (sixth by the crash rate rank). This cluster is also shown in Figure 11.



Table 4. Freeway Crash Clusters by Frequency.

ID	Crashes	AADT	Miles	Crash Rate	Crash Rank	Crash Rate Rank	Hwy.	From	То
117	10	133,174	0.455	0.45	1	6	IH 30	W. of St. Francis	E. of Dilido
86	7	76,959	0.824	0.30	2	17	IH 45/ US 175	Grand	Pennsyl- vania
118	6	133,174	0.187	0.66	3	2	IH 30	W. of Chevrolet	LP 12
167	6	210,326	0.227	0.34	4	13	IH 35E	S. of Royal	N. of Royal
78	5	76,959	0.389	0.46	5	5	US 175	N. of Warren	Dathe
169	5	175,683	0.299	0.26	6	28	IH 635	S. of Skillman	N. of Royal
161	5	175,683	0.317	0.25	7	29	IH 635	Plano	E. of Plano
62	5	202,307	0.322	0.21	8	37	IH 35E	Brooklyn	Storey
45	4	70,348	0.255	0.61	9	3	US 175	Masters	Cade
98	4	166,672	0.204	0.32	10	16	IH 30	W. of 3rd	W. of 1st

Table 5. Freeway Crash Clusters by Crash Rate.

ID	Crashes	AADT	Miles	Crash Rate	Crash Rank	Crash Rate Rank	Hwy.	From	То
52	3	68,401	0.161	0.75	17	1	US 175	W. of LP 12	E. of LP 12
118	6	133,174	0.187	0.66	3	2	IH 30	W. of Chevrolet	LP 12
45	4	70,348	0.255	0.61	9	3	US 175	Masters	Cade
34	2	72,668	0.144	0.52	32	4	US 175	W. of Silverado	Silverado
78	5	76,959	0.389	0.46	5	5	US 175	N. of Warren	Dathe
117	10	133,174	0.455	0.45	1	6	IH 30	W. of St. Francis	E. of Dilido
48	2	85,384	0.143	0.45	33	7	US 67	Kiest	IH 35E
150	2	113,875	0.117	0.41	34	8	IH 35W	S. of LP 12	Hightech
61	2	84,039	0.174	0.37	35	9	IH 45	S. of Pine	N. of Overton
82	3	134,306	0.173	0.35	18	10	LP 12	N. of IH 30	IH 30



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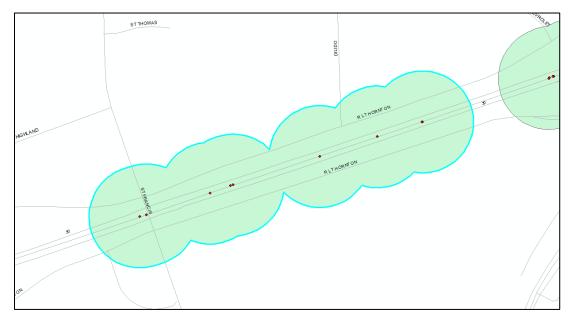


Figure 11. IH 30 Freeway Crash Cluster Example.

Non-freeway Safety Analysis Approach

Traditional hot-spot analysis is based on historical crash patterns over a roadway network or a geographic area. This approach is effective in identifying where crashes have occurred and the associated risk factors at those locations. But it does not account for other locations with the same (or more) risk factors that have not (yet) experienced crashes. Therefore, the hot-spot approach typically results in fewer sites or does not identify sites where pedestrian incidents could occur. Given the infrequency of pedestrian-related crashes and the desire to identify locations that are susceptible to pedestrian crashes, another approach was desired for this analysis.

TTI sought an approach that combines the relative crash risk, in terms of pedestrian and vehicular exposure, along with the historical crash patterns for the safety analysis of intersections. Thus, the team compiled available datasets from various sources including the City of Dallas, TxDOT, the North Central Texas Council of Governments (NCTCOG), Dallas County Appraisals, Dallas Area Rapid Transit, HERE (formerly Navteq), and the U.S. Census Bureau to perform the analysis.

Crash Risk Factors

Pedestrian crashes have many different types of potential risk factors, such as the number of pedestrians and vehicles, crossing distance, lack of pedestrian refuge islands, high vehicle operating speeds, pedestrian generators such as schools or libraries, alcohol sources such as bars or liquor stores, transit stops, land use, and others. The variable with the most influence on the prediction of crashes is exposure; therefore, TTI explored options for collecting exposure data (described in the next section). Although the vehicular exposure is extensively available, the pedestrian exposure is seldom available. FHWA developed a *Guide for Scalable Risk Assessment*



Methods for Pedestrians and Bicyclists that describes methods to assess pedestrian and bicyclist risk at various geographic scales.³ A tool was developed to estimate pedestrian exposure based on household surveys at a regional level. The tool showed a 15 percent increase in the number of pedestrian trips in the north central Texas region between 2009 and 2016. However, a more microscopic-level exposure estimate, such as at the intersection level, was desired for this analysis. Therefore, TTI estimated pedestrian exposure, recognizing that these types of crashes cannot occur without interaction between pedestrians and vehicular traffic.

The literature provided insights into the types of variables that are associated with pedestrian crossing demand such as demographics, the number of lanes, area type, and the presence of sidewalks. The team also used their engineering judgment and consideration of variables that could be derived from using geographic information systems (GIS). GIS layers of approximately 1,500 signalized and 14,500 stop-controlled intersections within the city of Dallas were developed. Each intersection was spatially joined with various datasets to develop the exposure estimates. Pedestrian exposure could not easily be estimated for segments (i.e., between intersections) because of the complexities of attributing variables to each segment. Therefore, this study focused on estimating pedestrian volumes for intersections.

Table 6 lists the variables considered. Intersection characteristics, such as the presence in the central business district (CBD); adjacent land use as it relates to commercial, single and multifamily, industrial, and vacant land uses; the presence of light-rail transit (LRT) stops; the presence of bus stops; the presence of sidewalks; and the presence of special generators within 300 feet of the intersection, were explored. The CBD was defined as the area enclosed by IH 35E, SP 366, IH 345, and IH 30. Figure 12 shows some of these variables.

Table 6. Variables Considered for Predicting Pedestrian Exposure.

No.	Variables Considered
1	Within the CBD
2	Adjacent land uses
3	Number of K-12 schools within ¼, ½, and 1 mile
4	Number of higher education schools within ¼, ½, and 1 mile
5	Population density
6	LRT stops
7	Bus stops
8	Intersection control: traffic signals versus stop controlled
9	Number of lanes
10	Sidewalks
11	Special generators
12	Maximum posted speed limit

15

³ Federal Highway Administration. *Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists*. Publication No. FHWA-SA-18-032, July 2018. https://safety.fhwa.dot.gov/ped_bike/tools_solve/fhwasa18032/.



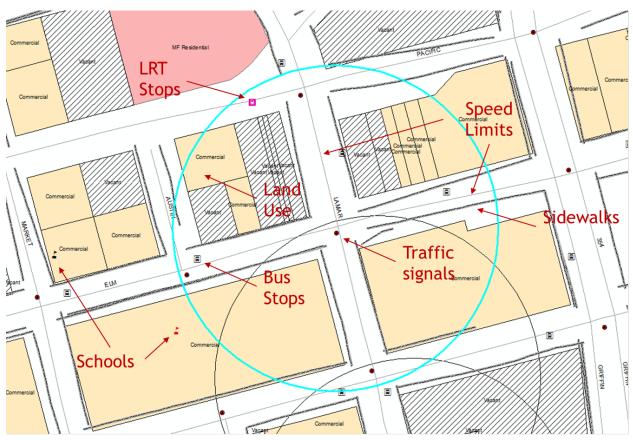


Figure 12. Variables Considered for Exposure Estimate.

Given the number of potential pedestrians around schools, a variable that reflects the proximity of schools (K-12 and higher education) was created. Schools within ½, ½, and 1 mile of each intersection and along the available street network were counted. Because pedestrians may avoid higher-speed streets, the maximum posted speed limit for the intersection approaches was also considered. Obtaining the posted speed limit can be a labor-intensive task. Therefore, TTI explored other sources for posted speed limit including using data available from HERE. However, a number of local streets did not have posted speed limit data within the HERE database. These streets are likely subject to statutory speed limits, which are established by state legislatures for specific types of roadways such as 25–30 mph for residential urban streets. ⁴ These speed limits are enforceable by law and are applicable even if the speed limit sign is not posted. HERE provided a speed category value in addition to posted speed limits. The speed category classifies the general speed trend of a roadway and represents a combination of factors besides the posted speed limit (e.g., physical restrictions and access characteristics). Therefore, it can differ from the speed limit. For example, a speed category of 6 is defined as speeds from

⁴ Federal Highway Administration. *Speed Limit Basics*. Publication No. FHWA-SA-16-076, undated. https://safety.fhwa.dot.gov/speedmgt/ref mats/fhwasa16076/fhwasa16076.pdf.



21 mph to 30 mph. To be conservative, the upper limit of the speed category range was assumed for approaches that were missing speed limits.

Developing Pedestrian Exposure Models for Dallas

Obtaining pedestrian volumes for an entire city is difficult and expensive. Direct demand models are statistical models that are developed based on observed volumes at a sample of locations and are linked to nearby context such as land use, street type, and other variables to estimate facility-specific pedestrian volumes. Pedestrian counts were available for 54 observed signalized intersections in Dallas as part of a TxDOT Traffic Safety Grant, Developing a Crash Analysis Tool to Address Pedestrian Safety. These counts were collected for two hours per site. They were extrapolated to 24 hours based on a 24-hour count at an intersection in downtown Dallas. Additionally, the City of Dallas provided 142 observed pedestrian counts at stop-controlled intersections. These counts were collected as part of traffic signal warrant studies. Most of them were collected over eight hours, so they were also extrapolated to 24 hours based on a 24-hour count at a stop-controlled intersection near downtown Dallas. Table 7 and Table 8 show the ranges of the variables for signalized and stop-controlled intersections, respectively.

Table 7. Descriptive Statistics for Traffic Signal Variables (n=54).

Variable	Mean	Min.	Max.	Std.
				Dev.
CBD (1=yes; 0=no)	0.19	0.00	1.00	0.39
Schools within 1 mile	5.02	0.00	13.00	3.28
Percent commercial and multifamily	71%	0%	100%	23%
land use				
Number of bus stops within 300 feet	2.67	0.00	7.00	1.57
Max. speed limit of all approaches	34.54	30.00	45.00	5.69
Special generator (1=yes; 0=no)	0.11	0.00	1.00	0.32
Observed pedestrian volume (daily)	1,167.09	25.00	6,982.00	1,569.06

Table 8. Descriptive Statistics for Stop-Controlled Variables (n=142).

Variable	Mean	Min.	Max.	Std.
				Dev.
CBD (1=yes; 0=no)	0.01	0.00	1.00	0.08
Schools within 1 mile	3.30	0.00	13.00	2.48
Percent commercial and multifamily	40%	0%	100%	32%
land use				
Number of bus stops within 300 feet	1.29	0.00	4.00	1.10
Max. speed limit of all approaches	31.09	20.00	50.00	3.68
Special generator (1=yes; 0=no)	0.01	0.00	1.00	0.12
Observed pedestrian volume (daily)	143.93	1.00	1201.00	194.44

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TTI used a negative binomial regression model to predict the pedestrian crossing volumes based on similar research.⁵ As an initial step, separate regression models were developed to estimate the pedestrian volumes at signalized and stop-controlled intersections. Researchers examined different functional forms with various combinations of variables, and the form shown in the following equation reflects the findings from several preliminary regression analyses:

$$V = e^{b_0 + b_{sch} \times N_{sch} + b_{co+mf} \times p_{co+mf} + b_{psl} \times PSL_{max} + b_{cbd} \times I_{cbd} + b_{spl} \times I_{spl} + b_{bus} \times N_{bus}}$$
 Equation 1

where:

V = predicted pedestrian volume at an intersection.

 N_{sch} = number of schools within 1 mile.

 p_{co+mf} = proportion of surrounding area with commercial and multifamily development.

 PSL_{max} = maximum posted speed limit on all legs of the intersection.

 I_{cbd} = indicator variable for the CBD (1.0 if it is CBD; 0.0 otherwise).

 I_{spl} = indicator variable for a special generator (1.0 if a special generator is present; 0.0

if absent).

 N_{bus} = number of bus stops within 300 feet. b_i = calibration coefficient for variable i.

Table 9 shows the intersection variables used in the model along with the estimates and statistics.

Parameter Signalized Intersections Stop-Controlled Intersections Std. Error Est. Est. p-value Std. Error p-value Intercept (b_0) 7.1061 1.1549 < 0.0001 4.1588 0.6128 < 0.0001 Number of schools within 1 mile 0.1097 0.0477 0.0213 0.1892 0.0338 < 0.0001 (b_{sch}) Commercial and multifamily 2.0964 0.4821 < 0.0001 1.2957 0.2411 < 0.0001 proportion (b_{co+mf}) Posted speed limit (b_{psl}) -0.0750.0281 0.0080 -0.031 0.0177 0.0773 CBD indicator (b_{chd}) 1.6020 0.3721 < 0.0001 0.9459 0.8773 0.2809 Number of bus stops (b_{bus}) 0.2479 0.0722 -0.211 0.0766 0.0058 0.0006 Special generator indicator (b_{spl}) 1.0989 0.0057 0.1423 0.6429 0.8249 0.3977 < 0.0001 0.7564 Dispersion parameter (δ) 0.5465 0.0977 0.0835 < 0.0001

Table 9. Pedestrian Crossing Volume Model Variables

Note: bold plus italicized value means the variable is not significant at 5% level

A positive estimated value in Table 9 indicates that the pedestrian volume increases with an increase in the variable value (and vice versa). Both models showed a similar trend with respect to every variable, except for the number of bus stops variable. For signalized intersections, the

⁵ Munira, S., and I. Sener. *Data Mining to Improve Planning for Pedestrian and Bicyclist Safety*. UTC Safe-D 01-003, October 2017.



number of bus stops variable is counterintuitive (i.e. the pedestrian volume increases as the number of bus stops decrease). This result is due to the smaller sample size and low variability in the data variable. In addition, half of the variables in the stop-controlled intersection model are not statistically significant at a 5 percent significant level. This result is also attributed to the small sample size. To overcome the sample size issue, the team combined the data for signalized and stop-controlled intersections and developed one combined model with an indicator variable representing the intersection type. The functional form used is as follows:

$$V = e^{b_0 + I_{sig} + b_{sch} \times N_{sch} + b_{co+mf} \times p_{co+mf} + b_{psl} \times PSL_{max} + b_{cbd} \times I_{cbd} + b_{spl} \times I_{spl} + b_{bus} \times N_{bus}}$$
Equation 2

where:

 I_{sig} = indicator variable for signalized intersection (1 if signalized; 0 otherwise).

Table 10 shows the combined model estimates and statistics. Applying the signal indicator variable, the pedestrian volume at signalized intersections can be estimated using the following equation:

$$V_{sig} = e^{6.268 + 0.157 \times N_{sch} + 1.431 \times p_{co+mf} - 0.058 \times PSL_{max} + 0.968 \times I_{cbd} + 1.257 \times I_{spl} + 0.0487 \times N_{bus}}$$
Equation 3

The pedestrian volume at stop-controlled intersections can be estimated using the following equation:

$$V_{stop} = e^{5.305 + 0.157 \times N_{sch} + 1.431 \times p_{co+mf} - 0.058 \times PSL_{max} + 0.968 \times I_{cbd} + 1.257 \times I_{spl} + 0.0487 \times N_{bus}}$$
 Equation 4

where:

 V_{sig} = sum of daily pedestrian volumes (pedestrians/day) crossing all intersection legs at a signalized intersection.

 V_{stop} = sum of daily pedestrian volumes (pedestrians/day) crossing all intersection legs at a stop-controlled on a minor approach intersection.



Table 10. Estimated Parameters for the Combined Pedestrian Volume Model.

Parameter	Est.	Std. Error	p-value
Intercept ($m{b_0}$)	5.3048	0.5157	<0.0001
Indicator variable for the signalized intersection (I_{sig})	0.9630	0.1787	<0.0001
Number of schools within 1 mile ($m{b}_{sch}$)	0.1566	0.0272	<0.0001
Commercial and multifamily proportion ($oldsymbol{b}_{co+mf}$)	1.4305	0.2250	<0.0001
Posted speed limit ($m{b}_{psl}$)	-0.0578	0.0148	0.0001
CBD indicator ($m{b}_{cbd}$)	0.9682	0.3178	0.0026
Special generator indicator ($m{b}_{spl}$)	1.2568	0.3458	0.0004
Number of bus stops ($m{b}_{bus}$)	0.0487	0.0565	0.3895
Dispersion parameter ($oldsymbol{\delta}$)	0.7693	0.0717	<0.0001

Note: bold plus italicized value means the variable is not significant at 5% level

For signalized intersections, Figure 13 illustrates the relationship between observed pedestrian volumes and predicted volume, as obtained from the calibrated model in Equation 3. Two locations had predicted volumes higher than the maximum observed value for the 54 sites (6,982 pedestrians/day). However, they were retained because the observed volumes are expected to be more disperse than predicted volumes. Based on the negative binomial distribution properties, given a prediction and corresponding dispersion parameter, a probability of occurrence can be established for a confined region of the range of the response variable (volumes). This effectively establishes the maximum and minimum values for the corresponding confining realizations (i.e., observed values volumes) that can be typically expected, can be determined with a certain confidence level. In other words, given a predicted value, a range of typically observed values are expected to either be established above or below the prediction with a spread around the point prediction, with an associated probability from the negative binomial distribution. The width of such a region is determined by the dispersion parameter of the corresponding distribution.

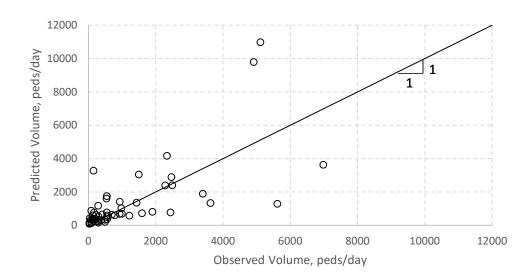


Figure 13. Observed versus Predicted Pedestrian Volumes for Signalized Intersections.

For stop-controlled intersections, Figure 14 illustrates the relationship between observed pedestrian volume and predicted volume, as obtained from the calibrated model shown in Equation 4. The one location with predicted volumes higher than the maximum observed value for the 142 sites (1,201 pedestrians/day) was retained.

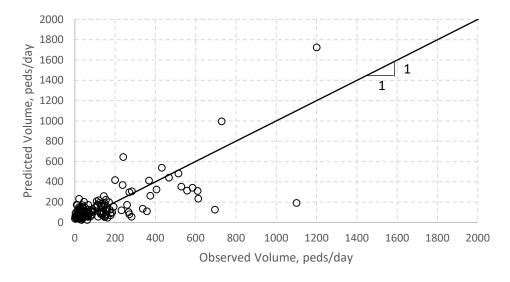


Figure 14. Observed versus Predicted Pedestrian Volumes for Stop-Controlled Intersections.

Model Validation

The calibrated model was validated by using a leave-one-out cross validation (LOOCV) technique. LOOCV is a technique that allows validating predictive models over the same dataset used for model development. This approach is well suited for situations when the data are scarce,

but the approach is computationally more demanding than classical validation (where the data are partitioned in a subset to fit the model and a subset to validate). Under the LOOCV protocol, the models are fitted to the largest possible subset of data (a subset of size n-1, where n is the number of independent data available) that will still allow a single fair comparison of the prediction power of the model (i.e., on the single data point left outside for model fitting). The comparison between the model prediction and the single observation not used for model fitting is then a fair assessment of the model's prediction performance because it is a comparison independent of the modeling process. With the LOOCV protocol, the model under evaluation is fitted *n* times, each producing an independent assessment of the prediction performance of the model. More details and sample applications of this technique can be found elsewhere. Figure 15 shows no bias, a cloud of points around the 1:1 blue line, and negative binomial scedasticity as expected. Therefore, researchers concluded that the model predictions performed adequately.

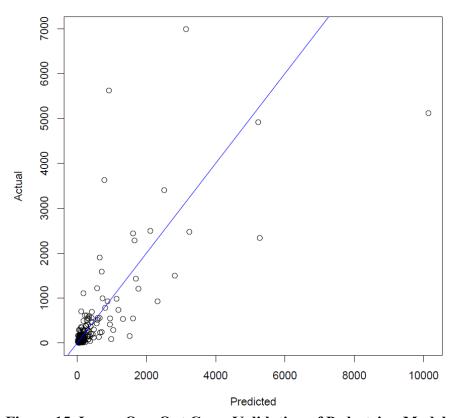


Figure 15. Leave-One-Out Cross Validation of Pedestrian Model.

⁶ Avelar R., K. Dixon, and P. Escobar. "Evaluation of Intersection-Related Crash Screening Methods Based on Distance from Intersection". Patricia F. Waller Award: Outstanding Paper in Safety and System Users. *Transportation Research Record*, the Journal of the Transportation Research Board. No. 2514 / 2015. pp. 177-186. ISSN 0361-1981. DOI 10.3141/2514-19.

⁷ James, G., D. Witten, T. Hastie, and R. Tibshirani (2017). *An Introduction to Statistical Learning*. Springer.

Model Transferability

Model transferability is an important check before using the calibrated model elsewhere. Pedestrian counts were also available at 12 intersections outside the Dallas city limits. Researchers used these intersections to test the model and predict the pedestrian volumes at them.

The comparison of pedestrian predicted and observed volumes is shown in Figure 16. Although the prediction is in the reasonable limits, the predicted values are slightly higher than the observed volumes when the pedestrian count is less than 250 per day. An adjustment factor was then developed for these intersections by dividing the sum of observed counts by the sum of predicted counts at these intersections. This factor was multiplied with the predicted counts to get the adjusted values, represented by the triangles in Figure 16. The unadjusted model values are represented by circles. This check revealed a few interesting findings:

- Since the observed counts are short term, it is unknown if they are biased.
- The model may not be accurate for predicting counts at intersections with low pedestrian activity and therefore may need an adjustment factor for low-volume intersections.
- The model may need to be adjusted when applied to intersections outside the city limits, such as with an indicator variable that differentiates intersections inside the city limits to others (similar to the CBD indicator variable).
- The model may need an adjustment factor when transferring to other geographic locations.

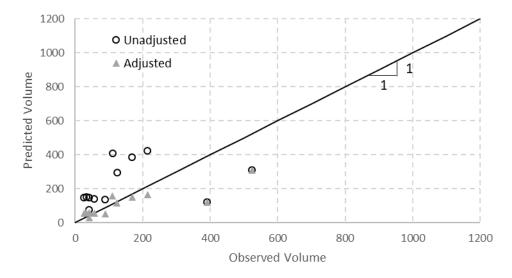


Figure 16. Predicted versus Observed Pedestrian Volume at Dallas County Sites.

Using Pedestrian Volume Model for City of Dallas Intersections

The model was then applied to the signalized and stop-controlled intersections in the city of Dallas. A heatmap was created to show the level of daily pedestrian activity (volumes) within the city of Dallas as shown in Figure 17. As expected, the locations with the highest estimated



pedestrian volumes are within the urban core, particularly in the CBD, uptown, west Dallas, and Oak Cliff areas.

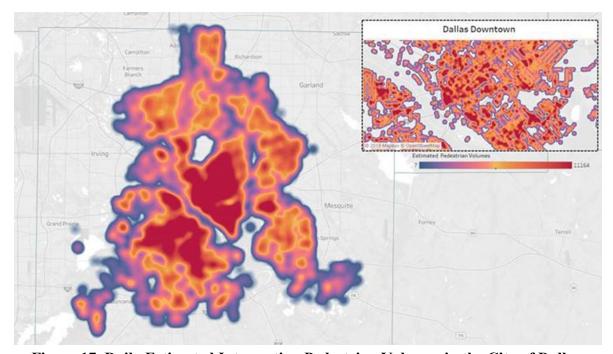


Figure 17. Daily Estimated Intersection Pedestrian Volumes in the City of Dallas.

Vehicle Exposure Data for Dallas

Vehicular exposure was determined for each intersection by averaging available AADT for the two major approached and the two minor approaches of each intersection. TxDOT's 2017 RHINO data were used to compile the approach volumes. Most AADTs were for 2017, but some were for 2016. More than half the city's intersections are off the state highway system, so the reliability of the AADTs on these roadways is unknown. Therefore, a cursory check was done with available data provided by NCTCOG. A check of 41 random off-system roadway 2017 AADTs found that they were within a 10 percent error of observed counts, on average, which seemed reasonable.

Predicting Crashes at Intersections

Researchers used the previous intersection variables along with the following variables to develop a safety performance function (SPF) for signalized and stop-controlled intersections within the city of Dallas:

- AADT on major and minor streets (2017 RHINO).
- Crashes within 300 feet of an intersection (snapped to the nearest intersection).

The SPF is a statistical model that predicts the mean crash frequency for similar locations with the same characteristics. The *Highway Safety Manual* (HSM) includes the SPF for signalized intersections and non-stop-controlled intersections. However, the HSM SPFs are not based on



Texas data. Therefore, it is necessary to calibrate for local conditions, which requires a significant amount of effort. The HSM also recommends developing jurisdiction-specific SPFs whenever possible. The SPF for the number of pedestrian crashes for Dallas signalized and stop-controlled intersections is shown as follows with the corresponding variable coefficients in Table 11 and Table 12, respectively. All the signalized intersection coefficients presented are statistically significant at the 5 percent level. All the stop-control intersection coefficients are significant at the 5 percent level except the ratio of minor AADT to major AADT variable. This variable is significant at the 10 percent level, and researchers decided to keep it in the model because it is intuitive and in line with the signalized intersection results.

$$N_{ped} = exp\left(b_0 + b_{tot}AADT_{tot} + b_{ratio}\frac{_{AADT_{min}}}{_{AADT_{maj}}} + b_{ped}V + b_{co+mf}p_{co+mf} + b_{bus}n_{bus}\right)$$
 Equation 5

Where:

 N_{ped} = number of KABC pedestrian crashes.

 $AADT_{tot}$ = sum of major-street AADT and minor-street AADT.

 $AADT_{min}$ = minor-street AADT. $AADT_{maj}$ = major-street AADT.

V = sum of daily pedestrian volumes (pedestrians/day) crossing all intersection legs.

 p_{co+mf} = proportion of commercial and multifamily land use.

 n_{bus} = number of bus stops within 300 feet of the center of the intersection.

 b_i = calibrated coefficients.

Table 11. Signalized Intersection Crash Prediction Model Variables.

Parameter	Est.	Std. Error	t-stat	p-value
Intercept (b_0)	-4.9065	0.6867	-7.14	<0.0001
Total AADT (b_{tot})	0.2926	0.05863	4.99	<0.0001
Ratio of minor AADT to major AADT (b_{ratio})	0.0517	0.02375	2.18	0.030
Pedestrian crossing volume (b_{ped})	0.2146	0.04145	5.18	<0.0001
Number of bus stops (b_{bus})	0.2557	0.02719	9.40	<0.0001
Commercial and multifamily proportion (b_{co+mf})	0.8517	0.1444	5.90	<0.0001
Dispersion parameter (δ)	0.9474	0.07826	12.11	<0.0001

Table 12. Stop-Controlled Intersection Crash Prediction Model Variables.

Parameter	Est.	Std. Error	t-stat	p-value
Intercept (b_0)	-6.1712	0.4157	-14.9	<0.0001
Total AADT (b_{tot})	0.3274	0.0506	6.5	<0.0001
Ratio of minor AADT to major AADT (b_{ratio})	0.069	0.0426	1.6	0.1063
Pedestrian crossing volume (b_{ped})	0.2159	0.0561	3.9	0.0001
Number of bus stops (b_{bus})	0.2914	0.0276	10.6	<0.0001



Commercial and multifamily proportion (b_{co+mf})	1.0589	0.1256	8.4	<0.0001
Dispersion parameter (δ)	1.495	0.1449	10.3	<0.0001

Note: bold plus italicized value means the variable is not significant at 5% level

The calibrated signalized and the stop-controlled models were graphed to compare the predicted and observed crash frequency. In general, the plotted data indicate that the models provide a reasonable estimate of predicted crash frequencies as shown in Figure 18 and Figure 19, respectively.

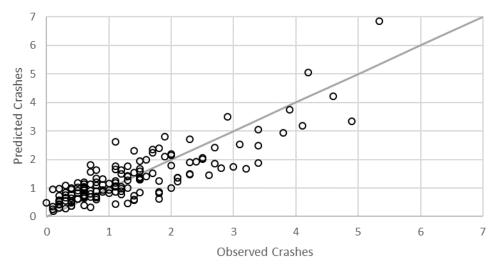


Figure 18. Observed versus Predicted Pedestrian Crashes for Signalized Intersections.

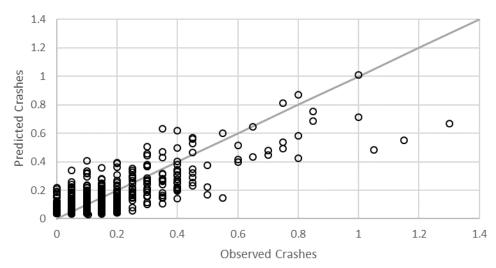


Figure 19. Observed versus Predicted Pedestrian Crashes for Stop-Controlled Intersections.



Combining Exposure with Crashes at Intersections

The empirical Bayes (EB) method was used to estimate the expected number of crashes at an intersection based on the observed crashes and the predicted crashes (from SPF). This method produces the most reliable results because it accounts for regression to the mean, changes in traffic volume, and temporal effects. With the inclusion of the overdispersion parameter, k, as the weighted adjustment factor decreases, more emphasis is placed on the observed crashes rather than the predicted crashes.

TTI researchers developed a safety risk index by dividing the expected crashes at an intersection (from the EB method) with the predicted crashes (from the SPF). An index value of less than 1 indicates a low risk because the expected number of crashes at an intersection is less than the predicted number of crashes for similar intersections. This safety risk index provides a network selection tool because it is based on historical crashes at intersections and on the relative risk associated with the intersection even if there were no observed crashes. Figure 20 and Figure 21 show safety index distributions for signalized and stop-controlled intersections, respectively. Per TxDOT's request, only the on-system intersections were included in this part of the analysis so that the Dallas District's priorities could be identified for the next phase of the study, that is, development of possible countermeasures.

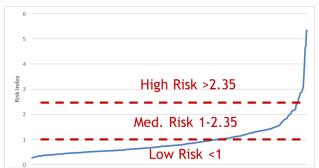


Figure 20. Safety Risk Index for Signalized Intersections (On System Only).

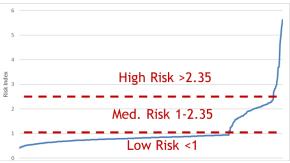


Figure 21. Safety Risk Index for Stop-Controlled Intersections (On System Only).

Researchers divided the distribution into three general risk categories based on the inflection points in the distributions: low (\leq 1.0), medium (1.01–2.35), and high (>2.35). The risk index categories are also shown in Figure 20 and Figure 21 for signalized and stop-controlled intersections, respectively.

There were 19 high-risk signalized intersections, as listed in Table 13. Figure 22 shows their locations along with the other risk categories. Most of the high-risk signals are along State Loop 12 (also known as Buckner, NW Highway, or Great Trinity Forest). For example, there is a small cluster between Highway 342 and IH 45 in south Dallas and another one in east Dallas, just north of IH 30. Other locations include along the IH 635, US 75, and IH 35E frontage roads.



Table 13. High-Risk Dallas Signalized Intersection.

			0				
Street 1	Street 2	Est.	Maj.	Min.	Obs.	Exp.	Risk
		Ped.	ADT	ADT	Crash	Crash	Index
I DI IMPOD	CL :II	Vol.	20.524	400	_	2.40	5.06
LBJ WBSR	Skillman	102	29,531	499	7	2.40	5.36
Corinth	Morrell	162	11,362	4,488	9	4.43	5.33
Buckner	John West	409	23,840	10,522	10	6.07	4.73
Great Trinity Forest	Jim Miller	134	22,693	9,994	12	8.08	4.71
Community	Northwest	298	46,032	2,679	11	7.72	4.11
Scyene	St. Augustine	240	18,616	1,570	8	5.28	3.58
Bonnie View	Great Trinity Forest	123	27,030	340	7	4.76	3.12
Central SBSR	Lemmon	144	50,655	18,708	4	1.89	3.00
Bonnie View	LBJ EBSR	65	10,822	810	3	0.97	2.92
Great Trinity Forest	Wadsworth	67	27,030	340	4	1.98	2.92
Central NBSR	Mockingbird	117	39,590	21,049	4	2.04	2.85
Bonnie View	Ledbetter	730	27,030	10,049	10	8.11	2.79
Coit Road	IH 635 WB FR	232	40,336	22,476	5	3.20	2.71
Buckner	Grovecrest/Mattison	424	34,964	340	6	4.24	2.67
Buckner	Chenault	277	23,840	340	5	3.39	2.53
Forest Lane	Central SBSR	268	42,122	15,453	6	4.39	2.52
Good Latimer Expressway NBSR	Al Lipscomb Way	325	7,920	3,897	3	1.47	2.45
Ann Arbor	R. L. Thornton NBSR	391	11,808	5,598	3	1.56	2.37
Buckner	Рорру	519	39,140	340	4	2.56	2.37



es, Time and Resources

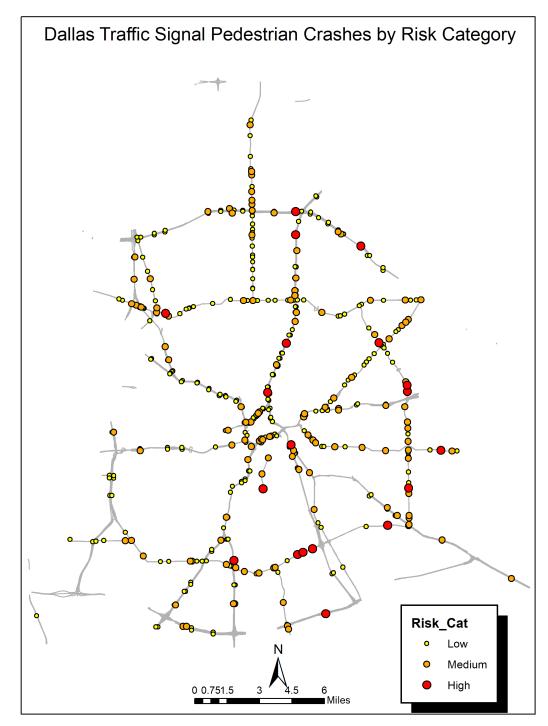


Figure 22. Dallas Traffic Signal Pedestrian Crashes by Risk.

There were 23 high-risk stop-controlled intersections, as listed in Table 14.



Table 14. High-Risk Dallas Stop-Controlled Intersection.

Street 1	Street 2	Est. Ped.	Maj.	Min.	Obs.	Ехр.	Risk
		Vol.	ADT	ADT	Crash	Crash	Index
E. Ledbetter Drive	Corrigan Drive	256	27,030	340	6	2.92	5.60
W. Northwest Highway	Starlight Road	190	46,032	340	6	3.02	5.46
E. Ledbetter Drive	Corrigan Avenue	100	27,030	340	4	1.13	5.30
S. Buckner Boulevard	Norvell Drive	198	38,087	340	5	2.23	5.14
Great Trinity Forest Way	Stoneport Drive	160	27,328	340	6	3.33	4.99
S. Lancaster Road	Arden Road	51	14,244	340	3	0.48	4.76
Great Trinity Forest Way	Cranfill Drive	94	27,030	934	4	1.58	4.61
Harry Hines Boulevard	Storey Lane	56	26,296	2,146	3	1.01	3.97
Great Trinity Forest Way	S. Murdeaux Lane	98	22,693	340	3	1.18	3.72
S. Central Serv. NB	Jordan Street	72	931	340	2	0.20	3.69
N. Central Serv. NB	Bonner Drive	149	16,747	340	3	1.21	3.67
W. Northwest Highway	Kendale Drive	160	46,032	340	4	2.33	3.49
Great Trinity Forest Way	Hillburn Drive	51	22,693	1,541	3	1.47	3.28
Great Trinity Forest Way	Hillburn Drive	46	32,400	340	2	0.59	3.11
Preston Road	Berry Trail	63	54,102	340	2	0.67	2.99
East Grand Avenue	Coronado Avenue	42	36,440	340	2	0.71	2.92
W. Northwest Highway	Starlight Road	234	46,032	340	3	1.73	2.89
E. Ledbetter Drive	Kildare Avenue	39	29,581	340	2	0.76	2.86
S. Walton Walker Serv. NB	Preakness Lane	88	3,802	340	2	0.78	2.83
East Grand Avenue	and Avenue Philip Avenue		36,440	340	2	0.83	2.75
Marvin D. Love Serv. SB	Glennlyons Drive	203	10,014	340	2	0.85	2.73
Great Trinity Forest Way	Satinwood Drive	109	22,693	340	2	0.92	2.62
S. Buckner Boulevard	Tillman Street	359	34,964	340	3	2.07	2.40

Figure 23 shows their locations along with the other risk categories. The high-risk stop-controlled intersections are more concentrated along State Loop 12 in south Dallas, between west of Highway 342 and IH 45, and southeast Dallas, between Stoneport Drive and US 175.



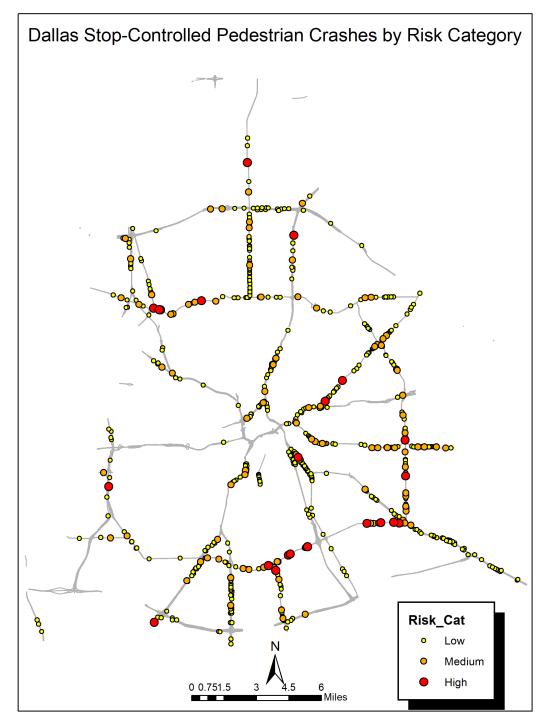


Figure 23. Dallas Stop-Controlled Pedestrian Crashes by Risk.



CONCLUSIONS

As in the rest of the United States, pedestrian crashes (both total crashes and those crashes with fatal and incapacitating injuries) have been increasing in TxDOT's Dallas District over the last 10 years. Therefore, TxDOT requested that TTI investigate these types of crashes to better understand the circumstances and factors leading to them in the Dallas District.

Overall, Dallas County had 266 crashes per 100,000 population, which was slightly higher than Harris County but lower than Bexar County, between 2008 and 2017. Males involved in pedestrian crashes are overrepresented compared to females (Figure 4). In terms of race and ethnicity, Figure 5 shows that Blacks are highly overrepresented in pedestrian crashes. The city of Dallas ranks second with 350 crashes per 100,000 population out of the five federally designated Texas focus cities. Similar to Dallas County, the city of Dallas has an overrepresentation of males involved in pedestrian crashes (Figure 7). In terms of race and ethnicity, Figure 8 shows that Hispanics are overrepresented in pedestrian crashes in the city of Dallas.

More specific findings include the following:

- The seven-county Dallas District had 8,332 pedestrian-related crashes (KABC) from 2008 to 2017:
 - o 6,707 (80 percent) occurred in Dallas County.
 - o 4,696 (70 percent) occurred in the city of Dallas.
- 328 crashes (7 percent) in the city of Dallas occurred on freeways:
 - o 129 (39 percent) were fatal pedestrian crashes.
 - o 65 (51 percent) of the pedestrians in fatal crashes intended to be on the freeway. *Unintended pedestrians* are people that had not intended to be a pedestrian and were struck while outside their vehicle, such as attending to a broken-down vehicle or flat tire, being there after a previous crash, or working.
- 4,368 pedestrian crashes (93 percent) in the city of Dallas did not occur on a freeway:
 - o 699 (16 percent) were on system roads, and 3,669 (84 percent) were off system.
 - o 388 (56 percent) and 1,738 (47 percent) occurred at non-intersection locations for on-system and off-system roads, respectively.
 - o "Pedestrians failed to yield the right of way to vehicle" was the most reported contributing factor for non-intersection crashes (about 25 percent).
 - o "Vehicle failed to yield the right of way to pedestrian" was the most reported contributing factor for intersection or intersection-related crashes (22 percent off system and 17 percent on system).
 - The most common traffic control at intersection crashes was a signal light, 125 (45 percent) on system and 642 (38 percent) off system.
 - A high percentage of the pedestrian crashes occurred in dark lighting conditions.
 Non-intersection-related crashes on on-system roads had the most and highest percentage with 238 (61 percent).



- 59 crash clusters, where two or more pedestrian crashes occurred on city of Dallas freeways within 600 feet of another crash, were identified. The top 10 freeway clusters by crash frequency and per monthly vehicle miles traveled are listed in Table 4 and Table 5, respectively. TxDOT recently constructed a pedestrian bridge at the highest crash frequency cluster, which had an average of one pedestrian crash per year (sixth by the crashes per monthly vehicle miles traveled).
- Using a comprehensive evaluation of the city and regression models, pedestrian crashes were predicted for Dallas signalized and stop-controlled intersections. Each intersection was categorized as being high, medium, and low risk for pedestrian crashes.
 - o There were 19 high-risk signalized intersections as listed in Table 13. Figure 22 shows their locations along with the other risk categories. Most of the high-risk signals are along State Loop 12 (also known as Buckner, NW Highway, or Great Trinity Forest). For example, there is a small cluster between Highway 342 and IH 45 in south Dallas and another one in east Dallas, just north of IH 30. Other locations include along the IH 635, US 75, and IH 35E frontage roads.
 - O There were 23 high-risk stop-controlled intersections as listed in Table 14. Figure 23 shows their locations along with the other risk categories. The high-risk stop-controlled intersections are more concentrated along State Loop 12 in south Dallas, between west of Highway 342 and IH 45, and southeast Dallas, between Stoneport Drive and US 175.



RECOMMENDATIONS

This analysis provides the Dallas District with a foundational understanding of the demographics, geographic areas, roadway facilities, and causal and risk factors associated with its pedestrian crashes. Through data mining and direct demand modeling, researchers were able to estimate pedestrian exposure and ultimately identify freeway and non-freeway hot spots. The non-freeway hot spots were derived by using a comprehensive examination that identified high-risk intersections by their control type (signals or stops). TTI recommends completing the study by examining the hot spots more closely, developing countermeasures, and then prioritizing the sites for implementation of the countermeasures. The proposed approach could include:

- Review available crash reports.
- Perform site visits or review available intersection characteristics and aerial photographs.
- Develop crash diagrams.
- Develop possible countermeasures.
- Develop cost estimates.
- Prioritize countermeasures for implementation.

One possible tool that could be used in this process is FHWA's Pedestrian and Bicycle Analysis Tool (PBCAT). PBCAT is designed to assist agencies in selecting countermeasures to improve pedestrian and bicyclist safety. The application includes links to two FHWA websites that feature a number of proven countermeasures that may be used to mitigate specific crash types. The website provides practitioners with the latest information available for improving the safety and mobility of pedestrians and bicyclists and includes interactive tools. Countermeasures are provided for 12 crash groups as shown in Figure 24.

Finally, future research is recommended to test the transferability of the pedestrian volume model and the safety performance functions on a larger sample size and in other urban areas such as Fort Worth, Houston, San Antonio, Austin, or other similar metropolitan areas.



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COM	nterme	asures strian Far	way Desi Nay Desi Inters	ign gn Traffi	_{Jesign} Calmin Traffi	o Manag	gement other
rash Group Cov	γε.	K0.	///	-//0	110	213.	000
1. Dart/Dash	•	•		•	•	•	•
2. Multiple Threat/Trapped	•	•	•	•		•	•
3. Unique Midblock	•	•		•		•	•
4. Through Vehicle at Unsignalized Location	•	•	•	•	•	•	•
5. Bus-Related	•	•		•		•	•
6. Turning Vehicle	•	•	•	•	•	•	•
7. Through Vehicle at Signalized Location	•	•	•	•	•	•	•
8. Walking Along Roadway	•	•				•	•
9. Working or Playing in Roadway	•	•		•	•	•	•
10. Non-Roadway	•	•		•		•	•
11. Backing Vehicle	•	•		•		I I I	•
12. Crossing an Expressway	•					•	•

Source: Federal Highway Administration. *PBCAT Manual 2.0*. Figure 95, p. 77, March 2006.

Figure 24. Pedestrian Countermeasures by Crash Groups.



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APPENDIX A: FREEWAY CRASH CLUSTERS BY FREQUENCY

	Curches	ADT	0.031	Court Bata	Crash	Crash Rate		F	
ID	Crashes	ADT	Miles	Crash Rate	Rank	Rank	Hwy	From	To
117	10	133174	0.455	0.45	1	6	IH30	W. of St. Francis	E. of Dilido
86	7	76959	0.824	0.30	2	17	IH45/US17		Pennsylvania
118	6	133174	0.187	0.66	3	2	IH30	W. of Chevrolet	LP 12
167	6	210326	0.227	0.34	4	13	IH35E	S. of Royal	N. of Royal
78	5	76959	0.389	0.46	5	5	US175	N. of Warren	Dathe
169	5	175683	0.299	0.26	6	28	IH635	S. of Skillman	N. of Royal
161	5	175683	0.317	0.25	7	29	IH635	Plano	E. of Plano
62	5	202307	0.322	0.21	8	37	IH35E	Brooklyn	Storey
45	4	70348	0.255	0.61	9	3	US175	Masters	Cade
98	4	166672	0.204	0.32	10	16	IH30	W. of 3rd	W. of 1st
93	4	151606	0.242	0.30	11	18	IH45	Hickory	S. of Corinth
105	4	152216	0.242	0.30	12	19	IH30	Bank	Fitzhugh
51	4	202307	0.240	0.23	13	31	IH35E	S. of Krueger	N. of Saner
193	4	231824	0.242	0.19	14	43	US75	IH635	S. of IH635
89	4	184587	0.351	0.17	15	50		E E. of Jefferson	Industrial
96	4	224804	0.307	0.16	16	51	IH35E	Pacific	S. of Commerce
52	3	68401	0.161	0.75	17	1	US175	W. of LP12	E. of LP12
82	3	134306	0.173	0.35	18	10	LP12	N. of IH30	IH30
81	3	118329	0.210	0.33	19	14	IH30	E. of Cockrell Hill	Bastille
134	3	135038	0.186	0.33	20	15	IH35E	N. of Mockingbird	S. of Mockingbird
192	3	174538	0.163	0.29	21	21	IH635	E. of US75	E. of Schroeder
80	3	118329	0.251	0.28	22	23	IH30	W. of Hampton	E. of Hampton
171	3	169680	0.180	0.27	23	26	US75	S. of North Haven	Royal
176	3	170868	0.197	0.24	24	30	IH35E	S. of IH635	N. of IH635
158	3	175683	0.208	0.23	25	33	IH635	E. of Plano	W. of Kingsley
99	3	272996	0.145	0.21	26	39	IH35E	N. of Woodall	S. of Woodall
153	3	210326	0.198	0.20	27	42	IH35E	S. of Walnut Hill	Composite
72	3	202307	0.218	0.19	28	44	IH35E	N. of 7th	Church
170	3	208492	0.215	0.18	29	45	IH35E	S. of Crown	Bixel
109	3	272996	0.233	0.13	30	57	IH35E	HiLine	S. of HiLine
77	3	184587	0.353	0.13	31	58	IH35E	Dodd	Perimeter
34	2	72668	0.144	0.52	32	4	US175	W. of Silverado	Silverado
48	2	85384	0.143	0.45	33	7	US67	Kiest	IH35E
150	2	113875	0.117	0.41	34	8	IH35W	S. of LP12	Hightech
61	2	84039	0.174	0.37	35	9	IH45	S. of Pine	N. of Overton
107	2	133174	0.117	0.35	36	11	IH30	W. of Winfield	E. of Winfield
74	2	76959	0.203	0.35	37	12	US175	Eugene	Pine
113	2	133174	0.139	0.30	38	20	IH30	Jim Miller	E. of Jim Miller
115	2	133174	0.148	0.28	39	22	IH30	E. of Jim Miller	W. of St. Francis
21	2	168956	0.120	0.27	40	24	IH20	E. of Mtn. Creek	W. of Legters
16	2	94884	0.214	0.27	41	25	US67	S. of Camp Wisdom	N. of Camp Wisdom
110	2	133174	0.156	0.26	42	27	IH30	W. of Lawnview	E. of Lawnview
29	2	115591	0.210	0.23	43	32	IH20	W. of Dowdy Ferry	E. of Dowdy Ferry
165	2	210326	0.116	0.22	44	34	IH35E	S. of Walnut Hill	Composite
43	2	117896	0.213	0.22	45	35	IH35E	S. of Overton	N. of Fairshop
114	2	133174	0.191	0.22	46	36	IH30	E. of Ferguson	W. of Rena
129	2	221214	0.118	0.21	47	38	IH35E	S. of Record Crossin	Sleepy Hollow
35	2	123875	0.216	0.20	48	40	IH35E	S. of LP12	N. of LP12
157	2	175683	0.153	0.20	49	41	IH35E	S. of Walnut Hill	N. of Manana
201	2	239431	0.126	0.18	50	46	IH635	DNT	W. of Noel
186	2	204029	0.155	0.17	51	47	IH635	W. of Greenville	Greenville
6	2	153165	0.209	0.17	52	48	IH20	W. of Hwy342	E. of Hwy342
179	2	170868	0.189	0.17	53	49	IH635	Josey	Nelda
191	2	216260	0.164	0.15	54	52	IH635	Flagstone	Merit
112	2	214246	0.171	0.15	55	53	US75	Woodall	Flora
195	2	216260	0.175	0.14	56	54	IH635	Hillcrest	E. of Hilcrest
64	2	202307	0.173	0.14	57	55	IH35E	Crawford	E. of Marsalis
202	2	239431	0.161	0.14	58	56	IH635	W. of Spurling	E. of Spurling
126	2	221214	0.205	0.14	59	59	IH35E	Wayside	Inwood
120	2	221214	0.203	0.12	33	33	11133L	vvaysiuc	



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APPENDIX B: FREEWAY CRASH CLUSTERS BY CRASH RATE

					Crash	Crash Rate			
ID	Crashes	ADT	Miles	Crash Rate	Rank	Rank	Hwy	From	То
52	3	68401	0.161	0.75	17	1	US175	W. of LP12	E. of LP12
118	6	133174	0.187	0.66	3	2	IH30	W. of Chevrolet	LP 12
45	4	70348	0.255	0.61	9	3	US175	Masters	Cade
34	2	72668	0.144	0.52	32	4	US175	W. of Silverado	Silverado
78	5	76959	0.389	0.46	5	5	US175	N. of Warren	Dathe
117	10	133174	0.455	0.45	1	6	IH30	W. of St. Francis	E. of Dilido
48	2	85384	0.143	0.45	33	7	US67	Kiest	IH35E
150	2	113875	0.117	0.41	34	8	IH35W	S. of LP12	Hightech
61	2	84039	0.174	0.37	35	9	IH45	S. of Pine	N. of Overton
82	3	134306	0.173	0.35	18	10	LP12	N. of IH30	IH30
107	2	133174	0.117	0.35	36	11	IH30	W. of Winfield	E. of Winfield
74	2	76959	0.203	0.35	37	12	US175	Eugene	Pine
167	6	210326	0.227	0.34	4	13	IH35E	S. of Royal	N. of Royal
81	3	118329	0.210	0.33	19	14	IH30	E. of Cockrell Hill	Bastille
134	3	135038	0.186	0.33	20	15	IH35E	N. of Mockingbird	S. of Mockingbird
98	4	166672	0.204	0.32	10	16	IH30	W. of 3rd	W. of 1st
86	7	76959	0.824	0.30	2	17	IH45/US175		Pennsylvania
93	4	151606	0.242	0.30	11	18	IH45	Hickory	S. of Corinth
105	4	152216	0.242	0.30	12	19	IH30	Bank	Fitzhugh
113	2	133174	0.139	0.30	38	20	IH30	Jim Miller	E. of Jim Miller
192	3	174538	0.163	0.29	21	21	IH635	E. of US75	E. of Schroeder
115	2	133174	0.148	0.28	39	22	IH30	E. of Jim Miller	W. of St. Francis
80	3	118329	0.251	0.28	22	23	IH30	W. of Hampton	E. of Hampton
21	2	168956	0.120	0.27	40	24	IH20	E. of Mtn. Creek	W. of Legters
16	2	94884	0.214	0.27	41	25	US67		N. of Camp Wisdom
171	3	169680	0.180	0.27	23	26	US 75	S. of North Haven	Royal
110	2	133174	0.156	0.26	42	27	IH30	W. of Lawnview	E. of Lawnview
169	5	175683	0.299	0.26	6	28	IH635	S. of Skillman	N. of Royal
161	5	175683	0.317	0.25	7	29	IH635	Plano	E. of Plano
176	3	170868	0.197	0.24	24	30	IH35E	S. of IH635	N. of IH635
51	4	202307	0.240	0.23	13	31	IH35E	S. of Krueger	N. of Saner
29	2	115591	0.210	0.23	43	32	IH20	W. of Dowdy Ferry	E. of Dowdy Ferry
158	3	175683	0.208	0.23	25	33	IH635	E. of Plano	W. of Kingsley
165	2	210326	0.116	0.22	44	34	IH35E	S. of Walnut Hill	Composite
43	2	117896	0.213	0.22	45	35	IH35E	S. of Overton	N. of Fairshop
114	2	133174	0.191	0.22	46	36	IH30	E. of Ferguson	W. of Rena
62	5	202307	0.322	0.21	8	37	IH35E	Brooklyn	Storey
129	2	221214	0.118	0.21	47	38	IH35E	S. of Record Crossing	
99	3	272996	0.145	0.21	26	39	IH35E	N. of Woodall	S. of Woodall
35	2	123875	0.216	0.20	48	40	IH35E	S. of LP12	N. of LP12
157	2	175683	0.153	0.20	49	41	IH35E	S. of Walnut Hill	N. of Manana
153	3	210326	0.198	0.20	27	42	IH35E	S. of Walnut Hill	Composite
193	4	231824	0.242	0.19	14	43	US75	IH635	S. of IH635
72	3	202307	0.218	0.19	28	44	IH35E	N. of 7th	Church
170	3	208492	0.215	0.18	29	45	IH35E	S. of Crown	Bixel
201	2	239431	0.126	0.18	50	46	IH635	DNT	W. of Noel
186	2	204029	0.155	0.17	51	47	IH635	W. of Greenville	Greenville
6	2	153165	0.209	0.17	52	48	IH20	W. of Hwy342	E. of Hwy342
179	2	170868	0.189	0.17	53	49	IH635	Josey	Nelda
89	4	184587	0.351	0.17	15	50		E. of Jefferson	Industrial
96	4	224804	0.307	0.16	16	51	IH35E	Pacific	S. of Commerce
191	2	216260	0.164	0.15	54	52	IH635	Flagstone	Merit
112	2	214246	0.171	0.15	55	53	US75	Woodall	Flora
195	2	216260	0.175	0.14	56	54	IH635	Hillcrest	E. of Hilcrest
64	2	202307	0.190	0.14	57	55	IH35E	Crawford	E. of Marsalis
202	2	239431	0.161	0.14	58	56	IH635	W. of Spurling	E. of Spurling
109	3	272996	0.233	0.13	30	57	IH35E	HiLine	S. of HiLine
77	3	184587	0.353	0.13	31	58	IH35E	Dodd	Perimeter
126	2	221214	0.205	0.12	59	59	IH35E	Wayside	Inwood .