SPEEDING ACROSS TEXAS:
IDENTIFYING HIGH-RISK LOCATIONS USING PROBE DATA

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ABSTRACT

Speeding contributes to one-third of all motor vehicle fatalities in the U.S., making it crucial to understand speeding behaviors for traffic safety. This work compares a random sample of 15.7 million vehicle speeds in November 2024 to posted speed limits (PSLs) at 1.04 million roadway points across the Texas network, and reviews 12 non-infrastructure strategies to ensure greater PSL compliance.

Least-squares and logistic regression models control for design variables, congestion, and land use to examine how average speeds and shares of vehicles exceeding the PSL vary by time of day, day of week, and setting. Results indicate that speeding is most common during late-night hours and on weekends, especially on roads with lower PSLs (30 and 40 mph), where 43% of drivers exceeded the limit. Almost half the probe vehicles exceed the PSL and 20% exceeded it by more than 15% (e.g., by more than 9 mph in a 60 mph zone) between 3 a.m. and 5 a.m. each day. PSL and access control were the top predictors of average traffic speed, with a 1 mph increase in PSL leading to a 0.75 mph rise in average speed and full access control (freeway-type setting) increasing average speeds by 0.37 mph – everything else constant. Urban settings and weekend variables were also impactful. This paper also emphasizes the effectiveness of non-infrastructure speed management strategies, highlighting the effectiveness of speed cameras, with enforcement and signal retiming also playing key roles in ensuring safe, legal speed choices. This work provides insights to help transportation agencies identify targeted enforcement locations and implement more effective speed management policies.

KEYWORDS: Speed, Speeding, INRIX, Safety, Non-infrastructure countermeasures

BACKGROUND

Speeding on public roadways is a common behavior worldwide (Alonso et al., 2013; WHO, 2019). Pires et al. (2020) surveyed over 35,000 road users across 32 countries, with Americans and Canadians reporting the most speeding on freeways (71.6%), and Asian countries (Japan, South Korea, and India) reporting the lowest (46.4%). The American Automobile Association (AAA, 2022) found that 63% of US drivers believed they would be cited for traveling 15 mph over the posted speed limit (PSL) on freeways, with half reporting having engaged in such speeding during the month prior to the survey. Beyond survey data, of 12 million vehicles measured at 677 sites across the U.S., more than half of arterial-using vehicles were found to exceed PSLs, with 16% to 19% exceeding the limit by 10 mph or more on freeways, arterials, and collector roads (De Leonardis et al., 2018). State-level investigations also support these results: for example, Skszek (2004) found that 46% to 69% of vehicles were exceeding the limit on 55 mph-PSL highways in Arizona. Waymo's 10-day study periods on urban streets in San Francisco and Phoenix (with over one-million speed observations) found that almost half the visible/nearby moving vehicles were exceeding the PSL. Of the vehicles observed, 6% were driving 10 mph or more above the limit on rather low-speed roadways—with PSLs of 40 mph or less (Waymo, 2023). That is an exceedance of 25% or more of the limit, but most police units will not ticket until 5 or 10 mph above the PSL on such roadways and streets (Kockelman and Ma, 2018).

In the U.S., over the past two decades, speeding has contributed to one-third of all motor vehicle fatalities. In 2022 alone, more than 300,000 people were injured and 12,151 were killed in speeding-related crashes, accounting for 9% of traffic injuries and 29% of fatalities (NCSA, 2024). Figure 1 presents the state-level percentages of speeding-related traffic fatalities across the U.S. in 2022, with Texas, California, and North Carolina having the highest numbers of such fatalities, with totals of 1,521, 1,403, and 660 speeding-related roadway deaths, respectively. Speeding imposes significant societal costs, including loss of life, vehicle damage, medical expenses, insurance claims, and other economic burdens. According to a report by NHTSA (Blincoe et al., 2022), crashes result in annual economic-only and comprehensive costs of approximately $1,300 and $4,100 per American.

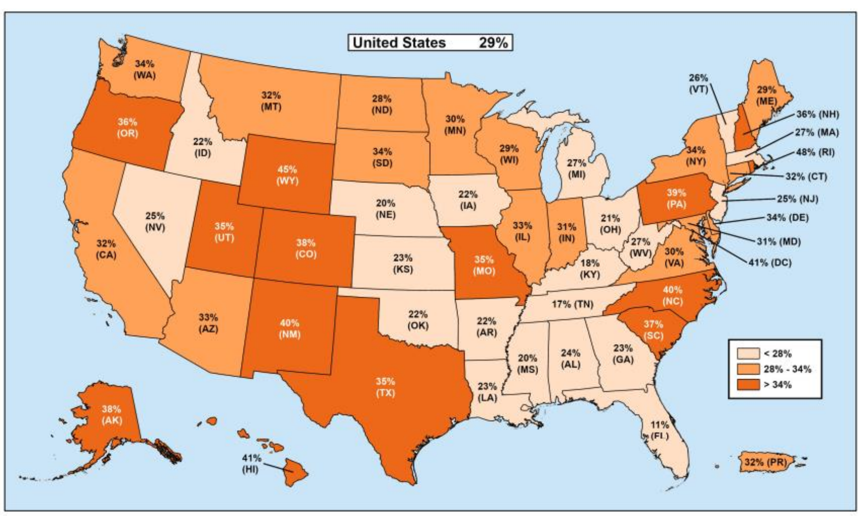


Figure 1: Percentage of Speeding-Related Traffic Fatalities by State in 2022 (Source: NCSA, 2024)

Operating speeds are highly associated with both the occurrence and severity of crashes, making speeding a significant concern. Evans (2004) investigated the relationship between crash rates and vehicle speeds, indicating that a 1% increase in speed resulted in a 4% increase in fatal crash rates and a 4–12% increase in occupant fatality rates. Rósen et al.'s (2011) review of others' investigations found that only 10% of pedestrians survived 60 mph collision speeds, fewer than 50% survived 50 mph speeds, and nearly all survived 12 mph or lower crash speeds (with roadway vehicles, of various body types). Kockelman et al.'s (2006) NCHRP report examined drivers' speed choices, crash rates, injury severity, and PSLs. It was found that injury severity increases notably with higher PSLs. Crash fatalities rose by 28% when PSLs increased from 55 mph to 65 mph, and by 13% when going from 65 mph to 75 mph. The probability of fatal injury rose by 24% in the first setting and by 12% in the higher-limit setting. Similarly, Rosén and Sander (2009) concluded that the average fatality risk at 30 mph is more than five times the risk at 18 mph, and more than twice the risk at 25 mph.

Given the safety benefits of understanding vehicle speeds and speeding behavior, several studies (Zolali et al., 2021; Gargoum and El-Basyouny, 2016) have been consistently conducted on this topic. Malaghan et al. (2022) developed speed prediction models for 77 km of two-lane rural highway sections using continuous speed profile data for heavy passenger vehicles. They identified curve radius, degree of curvature, and preceding tangent length as key factors influencing vehicle speeds on curves. Theeuwes et al. (2024) investigated the effects of road design on drivers' speed choices in the Netherlands and found that the presence of separate bike lanes, central line markings, asphalt surfaces (compared to pavers), multiple lanes, and one-way roads were associated with higher speeds. Existing research on speeding typically focuses on two major aspects: drivers' perceptions of speeding and the factors influencing speeding behavior (Horvath et al., 2012; Schroeder et al., 2013; Truelove et al., 2017; Kockelman and Ma, 2018; Peterson et al., 2021). Mannering (2009) collected 988 responses regarding drivers' perceptions of speeding and concluded that enforcement plays a crucial role in shaping safety perceptions, with drivers' beliefs about safe speeds closely related to the speeds at which they expected to receive speeding tickets. Kim et al. (2022) developed a proportional ordered logit model to examine characteristics associated with speeding, using data from a survey of 2,930 licensed drivers. They found that among demographic variables, driver age was the most significant determinant, with younger drivers being more likely to speed. Additionally, the interaction between educational attainment and engagement in aggressive driving was also associated with speeding behavior. Large-scale naturalistic driving studies are another commonly approach for analyzing speeding behaviors. For example, Perez et al. (2021) analyzed recorded vehicle data from 3,500 drivers over a three-year period. Results showed that age and gender significantly influenced the likelihood of speeding: drivers aged 16 to 24 were 1.5 times more likely to speed than those over 80. Road type and PSLs also had an effect; the odds of speeding in zones with PSLs of 10 to 20 mph were 9.5 times higher than in zones with PSLs of 60 mph or more.

However, few studies have quantitatively examined speeding behavior across roadway networks. De Leonardis et al. (2018) analyzed average free-flow speeds across various roadway types and found that under free-flow traffic conditions, more than half (56%) of vehicles on arterial roads likely exceeded the speed limit, with 16–18% exceeding it by more than 10 mph across 677 sites during a 24-hour period in 2015. A limitation of this study is that average roadway speeds do not intuitively capture individual speeding behavior. To address this, probe vehicle data are often used to quantify the distribution and frequency of speeding (Hong et al., 2014). Eboli et al. (2017)

conducted a speed analysis using continuous speed data collected via smartphone-equipped vehicles driven by 27 participants on a rural two-lane road. Similarly, Richard et al. (2020) analyzed approximately 5.4 million trips from 3,539 passenger vehicle drivers over a 12 to 24-month period. They concluded that driving 10 mph over PSLs was common, with average maximum speeds ranging from 12 to 15 mph above the PSL. However, due to limitations in obtaining accurate PSL data, their study focused only on higher-speed roadways—even though speeding often occurs on local roads with lower PSLs (Perez et al., 2021).

In summary, the main limitations of existing speeding research include the absence of individual-level speed data, small sample sizes, and unreliable PSL information. Currently, no studies have examined vehicle speeds and speeding behavior under near-real conditions at a regional scale. Gaining a better understanding of broader speeding patterns can offer valuable insights for law enforcement and support stakeholders in implementing proper and cost-effective countermeasures (Mears and Lindsey, 2016; FHWA, 2024). To reduce speeding behaviors and protect all road users, infrastructure treatments, including speed humps, chicanes, curb extensions, and non-infrastructure strategies, such as variable speed limits and speed enforcement, have been proven to be effective in many research studies and documents (Shin et al., 2009; Fitzpatrick et al., 2014; Markovich, 2020; New York City, 2023). Compared to infrastructure countermeasures, non-infrastructure ones are less costly, can be deployed more quickly, and are easily adapted to various conditions. Several evaluations (Kockelman et al., 2021; FHWA, 2018, 2024) have assessed the effectiveness of physical countermeasures. Among these, curb ramps, speed trailers, bollards, and raised center medians were found to be the most effective, with CMFs ranging from 0.93 to 0.95. However, the impacts of potential non-infrastructure strategies on operating speeds have not yet been sufficiently studied.

To address these gaps, this paper uses INRIX trip trajectory data from individual vehicles to analyze speed and speeding patterns by time of day and day of the week across the entire Texas road network. To better understand speeding behavior, this study develops an ordinary least squares (OLS) model and a binomial logistic model to estimate the effects of road characteristics and land use patterns on speed and speeding choices. After that, the research identifies high-risk speeding locations and compares them with crash data to inform enforcement and policy interventions. Following the identification of high-risk locations, this study categorizes existing non-infrastructure strategies into three groups: operational, technological, and policy- and education-oriented, and summarizes their associated benefits on operating speeds to support policymakers in implementing more effective strategies.

DATA DESCRIPTION

This section provides an overview of the PSL dataset, INRIX speed data, and crash data used in this study, along with a summary of their key characteristics.

Speed Limit Data

PSLs are determined based on many factors, including road design and sight distance, roadside development and driveways, traffic signals, and the presence of parking and pedestrians (Fitzpatrick et al., 2021). Various publicly available datasets, such as OpenStreetMap (OSM), state-level datasets, and commercial datasets—including HERE and TomTom—provide PSL information. While the state-level dataset (TxDOT Roadway Inventory, TxDOT, 2025) is missing PSLs for 70% of centerline miles—particularly among lower functional classifications such as local roads and minor collectors, where PSLs are often below 30 mph—this study uses commercial datasets that offer better coverage for these roads, where speeding most commonly occurs. Figure 2 shows the PSL dataset coverage by road class, indicating that most local roads have PSLs of 25 mph or 30 mph.

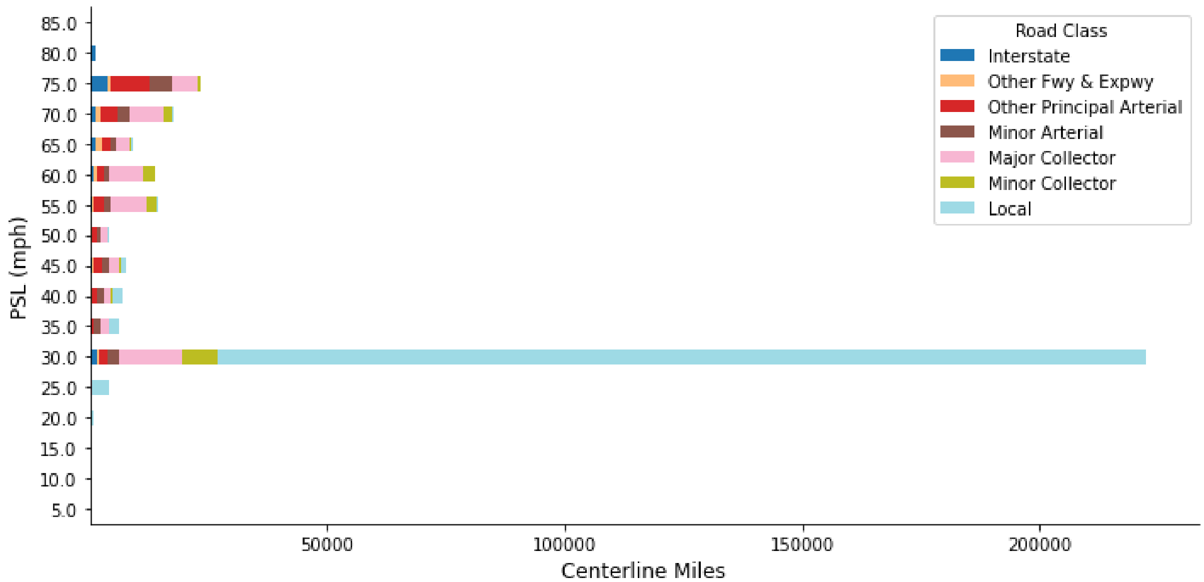


Figure 2. Texas' Centerline-Miles by PSL and Road Class in the PSL dataset

This study also compared the PSL dataset against ground-truth PSLs obtained from speed limit signs identified in Google Street View across all road types. For the comparison, 20 segments were randomly selected for each of TxDOT's 7 functional classification defined, resulting in a total of 140 segments covering approximately 100 centerline-miles across Texas. Figure 3 indicates that for interstates and other freeways and expressways, the PSL dataset accurately captures about 95% of road segments. On average, the dataset achieved 85.5% accuracy for exact PSL matches (with most PSL errors occurring on local roads and within a 10 mph range), which increased to 94.3% when allowing a ±5 mph tolerance. Therefore, this dataset is considered relatively reliable for identifying speeding patterns and modeling speeding behaviors across all road types.

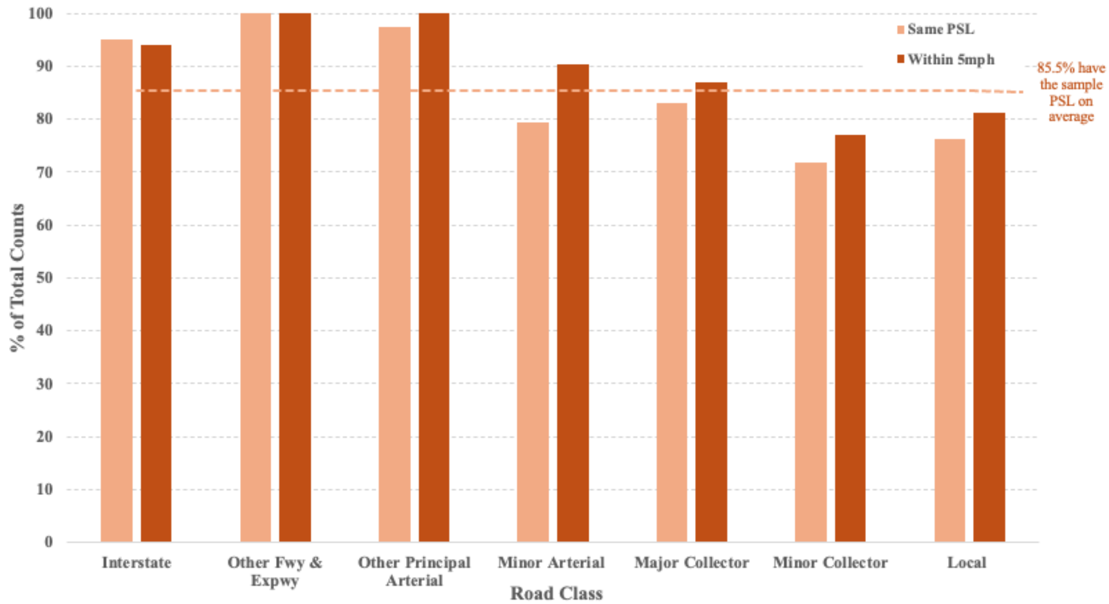


Figure 3. Shares of Segments (n=20 segments for each roadway type across Texas) where PSL Agreed with Actual PSL (or came within 5 mph)

Speed Data

Without the need for roadside equipment, mobile traffic sensors–such as probe vehicles equipped with GPS tracking devices–can collect real-time, network-wide traffic data at lower costs. Because of this, their use has grown rapidly in recent years. Probe vehicle data have proven useful for tracking traffic volumes and congestion (Sharma et al., 2017; Olszewski et al., 2018), estimating travel times (Zheng and Van Zuylen, 2013), and modeling vehicle speeds (Haghani et al., 2009; Ou et al., 2011; Kim and Coifman, 2014; Lobo et al., 2018). Several commercial vendors, including INRIX, HERE, TomTom, and NAVTEQ, provide real-time traffic data (e.g., speeds, traffic volume, traffic time) for a variety of applications. This study uses INRIX trip trajectory data from individual vehicles to calculate mean, median, 85th percentile, and 95th percentile speeds, as well as the shares of INRIX vehicles that are 15% to 30% above the PSL every hour of the November study week.

INRIX's 2024 trip data provide 2 to 4 million vehicle trajectories per day in Texas (for a state population of 31M, with more than 60M vehicle-trips per day), along with trip distance and duration (between engine on and off points), trip start and end times, and detailed trajectory tracking. Since INRIX data relies on connected vehicles equipped with in-vehicle GPS systems, it exhibits sample bias—primarily capturing light-duty vehicles. Additionally, the data cannot illuminate month-to-month variations in network use due to random fluctuations in sampling rates (Mori and Kockelman, 2024). This paper focuses on the available INRIX data to analyze speed and speeding behavior and does not further address this bias. Table 1 summarizes the key attributes included in the dataset. Given the large volume of data, this study focuses on a one-week sample—from November 4 to November 10, 2024 (the most recent period available under TxDOT's license)—for analysis. Each trajectory record includes the speed of a specific vehicle as it travels along each road segments, allowing for detailed analysis of speed variations across different segments.

Table 1: Overview of INRIX Trip Trajectory Data for Texas

Field	**Description**	**Example**
Trip_id	Trip's unique identifier	bc65817ea62f3f95f2b85e49b2305326
Device_id	Device's unique identifier	29453ce0e8a896c9556534f0d6081c74
Provider_id	Provider's unique identifier	1700002963a49da13542e0726b7bb758
Trip_raw_distance_m	Cumulative distance of raw points in meters relative to start of trajectory	10145.247308 *(= 6.304 miles)*
Trip_raw_duration_millis	Cumulative duration of raw points in milliseconds relative to start of trajectory	525261 *(= 8.754 minutes)*
Start_utc_ts	Trip's start in Unix epoch time	1730749269541 *(= November 4, 2024 13:41:10 CST)*
End_utc_ts	Tip's end in Unix epoch time	1730749794802 *(= November 4, 2024 13:49:55 CST)*
Timezone	Trip's start time zone	America/Chicago
Trajectories	Segment ID, index in the trajectory, length, entry time, exit time, speed, and segment attributes	[{'traj_idx': 0, 'solution_segments': array([{'segment_id': '104631619_0', 'segment_idx': 0, 'length_m': 451.033, 'start_utc_ts': 1730749269541.0, 'end_utc_ts': 1730749283945.0, 'speed_kph': 38.25701485585533},...])}]

Crash Data

TxDOT's Crash Records Information System (CRIS) (2025) is a statewide automated database that includes all reported motor vehicle traffic crashes, with details such as crash time, location, facility type, and other characteristics. In this study, the CRIS Query Tool was used to collect all crashes that occurred in Texas in 2024. A total of 633,634 crashes were reported across the state; among these, 59,459 records were missing location information and were therefore excluded from the analysis. Figure 4 shows the spatial distribution of reported crashes, while Figure 5 presents the temporal distribution of all crashes and severe crashes (including fatalities and suspected serious injuries). Crashes are concentrated within city boundaries and occur most frequently between 4 p.m. and 7 p.m. on weekdays—a period that clearly overlaps with peak commuting hours. In contrast, fatalities and severe crashes occur primarily on weekends, particularly late at night on Fridays and Saturdays and early in the morning on Saturdays and Sundays. Of all reported crashes, 27% were speeding-related. This study includes all crashes to identify high-risk locations and ultimately improve roadway safety.

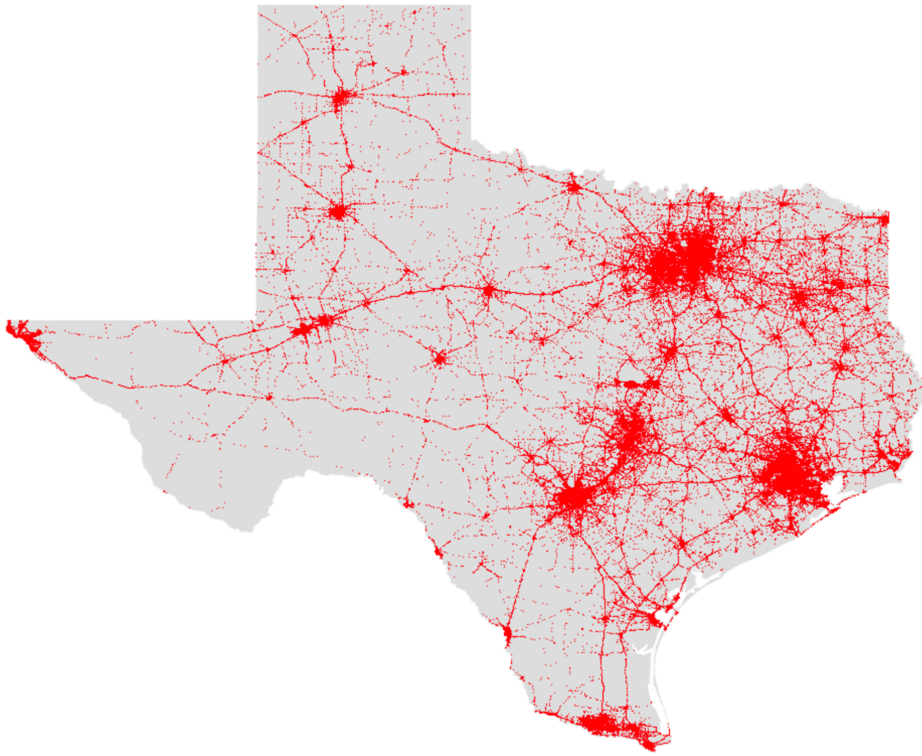


Figure 4. Spatial Distribution of Texas' Recorded Crashes in 2024

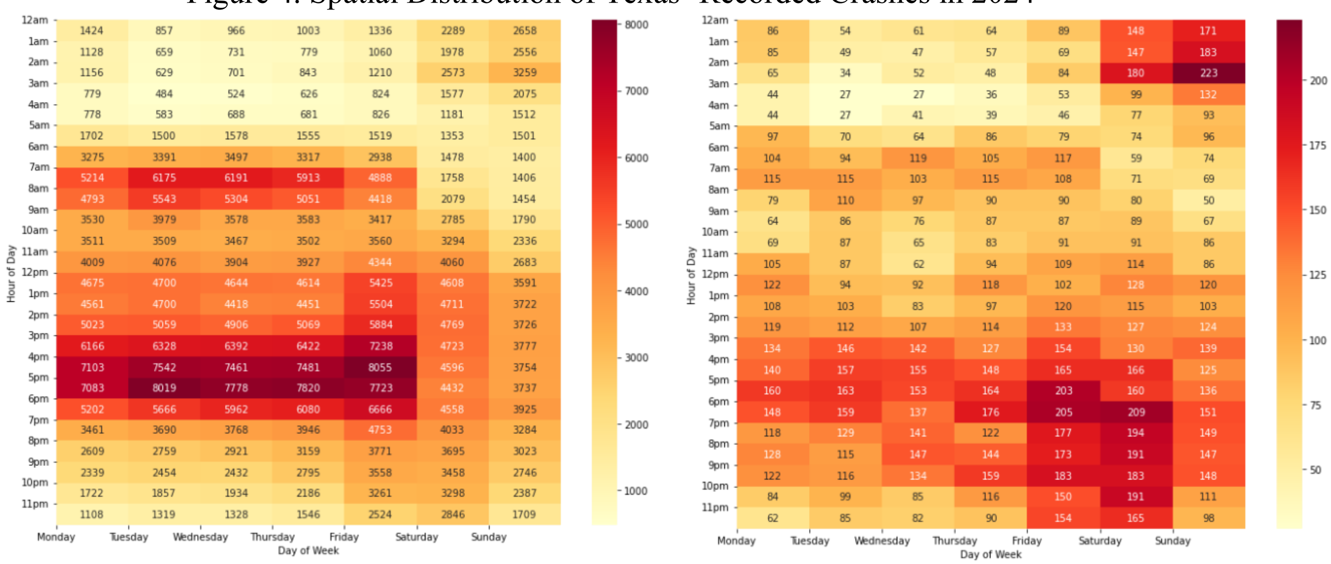


Figure 5. Number of Texas' Reported Crashes (left) and Severe Crashes (right) by Time of Day and Day of Week in 2024

METHOD

Vehicle speed data were extracted from individual trajectory records and segmented by time of day based on when each vehicle entered a specific segment. All Texas road segments in the INRIX database were integrated with PSLs to quantify vehicle speeding behavior. Speeding was measured at the segment level and was represented by the percentage of vehicles exceeding the PSL, as well as the percentages exceeding it by more than 15% and 30%.

OLS and binomial logistic model (Kriswardhana et al., 2020) were used to estimate the dependence of segment-level vehicle speeds (average speed, 85^{th} percentile speed, and 95^{th} percentile speed) and segment-level vehicle speeding (percentages of vehicles exceeding the PSL, exceeding it by more than 15%, and exceeding it by more than 30%) on various roadway and land use attributes, respectively. The formula for the binomial logistic model is provided below:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

where p = percentage of vehicles exceeding the PSL, or exceeding it by more than 15% or 30% (depending on the model run). Practical significance was assessed by increasing each covariate by one standard deviation (SD) in each speed record and calculating the ratio of average vehicle speeds (average speed, 85^{th} percentile speed, and 95^{th} percentile speed) after to that before the increase. It helps evaluate the magnitude of each variable's impact. A positive value indicates an increase in speed, while a negative value indicates a decrease.

Since the segment-level speed data totals approximately 25 million speed records per day across the state, a random 25% sample of those records was used each day during the week of November 4 to November 10, 2024, to infer daily patterns. A total of 39.7 million records were extracted, and observations with 95th percentile speeds below 5 mph (due to road interruptions or other issues) were removed, resulting in a sample size of 39.1 million records for analysis. The TxDOT Roadway Inventory Dataset (2025) and the EPA Smart Location Database (2021) were used to obtain roadway attributes and land use characteristics. Missing data were also excluded from the analysis, and the final dataset included 15.7 million speed records. Table 2 presents summary statistics for the dataset of speed observations and related characteristics. Other explanatory variables (like lane width, time of day, road class) were not statistically significant and so are not shown in the final model results.

Table 2: Summary Statistics for Texas Speed and Associated Roadway Data (n=15.72M vehicle-points)

Variable	**Description**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Avg speed	Average vehicle speed within the segment during the hour (miles/hour = mph)	35.57	31.81	17.85	1.22	123.88
85^{th} speed	85^{th} percentile vehicle speed within the segment during the hour (mph)	39.03	36.05	18.91	0.23	123.88
95^{th} speed	95^{th} percentile vehicle speed within the segment (mph)	40.41	37.72	19.57	5.00	123.88
% over PSL	Percentage of vehicles driving over PSLs within the segment during the hour	0.31	0	0.38	0	1
% over 15PSL	Percentage of vehicles driving over PSLs by more than 15% within the segment during the hour	0.14	0	0.3	0	1
% over 30PSL	Percentage of vehicles driving over PSLs by more than 30% within the segment during the hour	0.08	0	0.23	0	1
Weekend	1 if observed during weekends; 0 otherwise	0.26	0	0.44	0	1
Daylight	1 if observed during daylight (7 a.m. to 6 p.m. in November 2024); 0 otherwise	0.46	0	0.5	0	1

Urban	1 if the segment is in an urban area (population > 5,000); 0 otherwise	0.75	1	0.43	0	1
School	1 if the segment is in school zone; 0 otherwise	0	0	0.04	0	1
Two-Way	1 if the segment is two-way; 0 one-way	0.91	1	0.28	0	1
Full Control	1 if the segment has full access control (e.g., freeway); 0 otherwise	0.06	0	0.23	0	1
Partial Control	1 if the segment has partial access control; 0 otherwise	0.01	0	0.1	0	1
Median	1 if the segment has a median (a two-way left-turn lane is not considered as a median here); 0 otherwise	0.13	0	0.34	0	1
Med Width	Width of the median (ft)	5.43	0	23.19	0	770
# Lanes	Number of lanes per direction on the segment	1.25	1	0.53	1	12
Curve	1 if the segment has a curve; 0 otherwise	0.13	0	0.33	0	1
Curve Degree	Degree of the curve	3.59	0	14.10	0	179.7
Counts per Lane	Number of vehicles per lane per direction on this segment during the hour	2.77	5.28	1	0.06	238
PSL	PSL of the segment (mph)	41.60	35	14.83	5	85
Pop Density	Population density per acre (residents/acre) in the nearest block group	3.29	1.74	4.25	0	107.97
Job Density	Jobs per acre in the nearest block group	2.78	0.34	11.90	0	270.62
Network Density	Total road network density per square miles	13.17	11.60	10.01	0.14	55.84
Ped Road Density	Facility miles of pedestrian-oriented links per square miles	8.94	7.24	7.52	0	53.88
Intersection Density	Street intersection density per square miles	55.65	36.09	61.41	0	864.31
PedIntersect Density	Pedestrian-oriented intersections having 4 or more legs per square miles	16.27	5.43	27.96	0	320.88
Walkability	Walkability index score out of 20	8.27	7.67	3.87	1	20

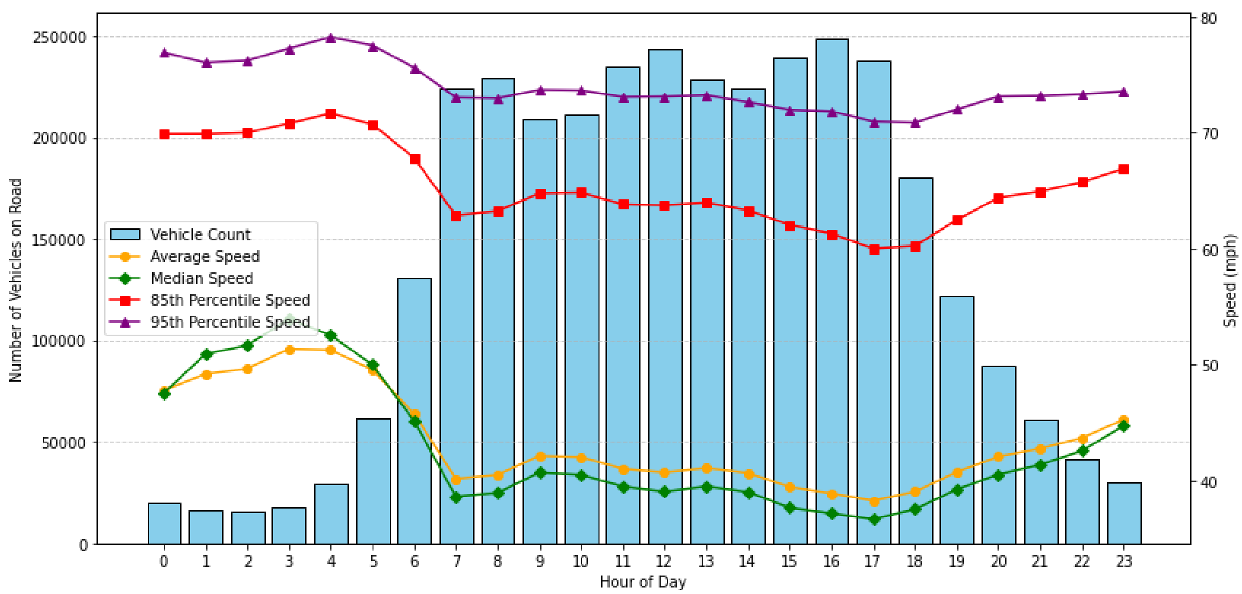
Sources: Speed data are from INRIX dataset. Road attributes and detailed specifications are from TxDOT's Roadway Inventory Dataset (2025). And land use data are from the US EPA's Smart Location Database (2021).

RESULTS

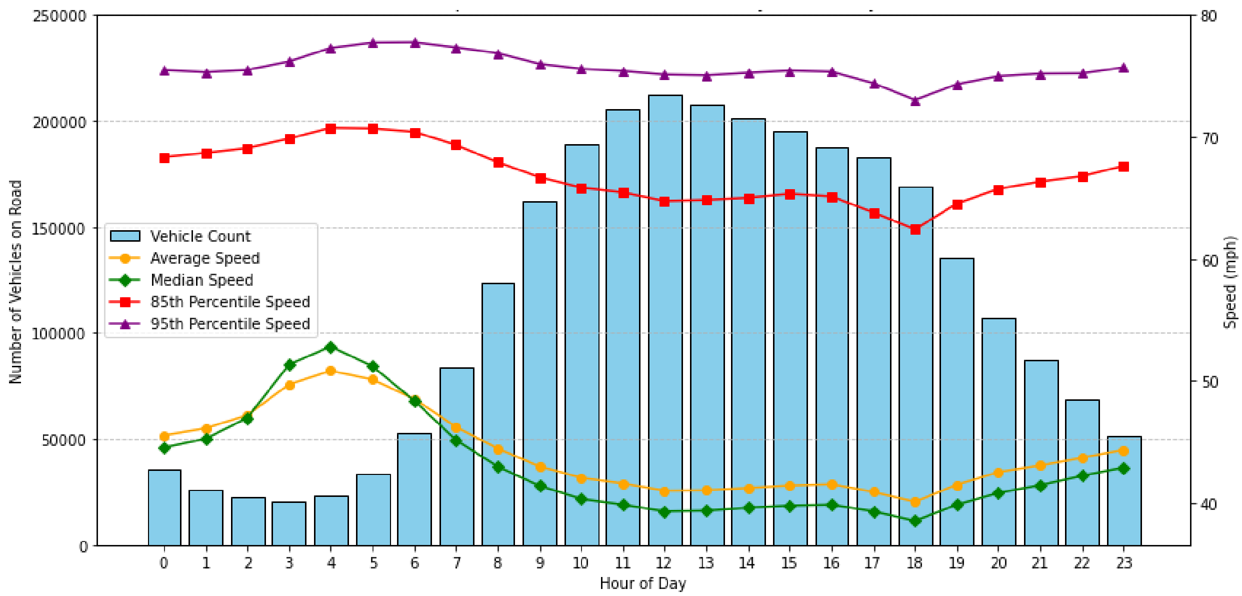
This section analyzes vehicle speeds by time of day on both weekdays and weekends, as well as speeding patterns by time of day and day of week, to better understand speeding behavior across the Texas road network. Models predicting speeds and the share of vehicles exceeding the PSL are then presented to illustrate how roadway characteristics and land use attributes affect vehicle speeds and speeding behavior. High-speeding locations are identified and compared with crash data to highlight risky locations for further study.

Speed and Speeding Data

Figure 6 presents the number of vehicle trips and corresponding speeds throughout the day for two specific dates: Monday, November 4, 2024, and Saturday, November 9, 2024. On Monday, 3.3 million vehicles were recorded, while Saturday saw 2.8 million. Notably, nighttime traffic volumes were significantly higher on the weekend compared to the weekday. Peak traffic volumes on the weekday occurred between 7 and 9 a.m. and 4 to 6 p.m., aligning with typical commute hours. On the weekend, traffic peaked in the noon hour (12 to 1 p.m.), likely reflecting midday activities such as lunch outings. Vehicle speeds generally exhibited an inverse relationship with traffic volume. Speeds were highest during nighttime hours, particularly between 12 a.m. and 5 a.m., with 95th percentile speeds reaching 78 mph on both days. A sharp increase in speed was observed between 2 and 4 a.m., while a noticeable decline occurred during weekday commute periods. Additionally, high speeds were more common on weekends than on weekdays.



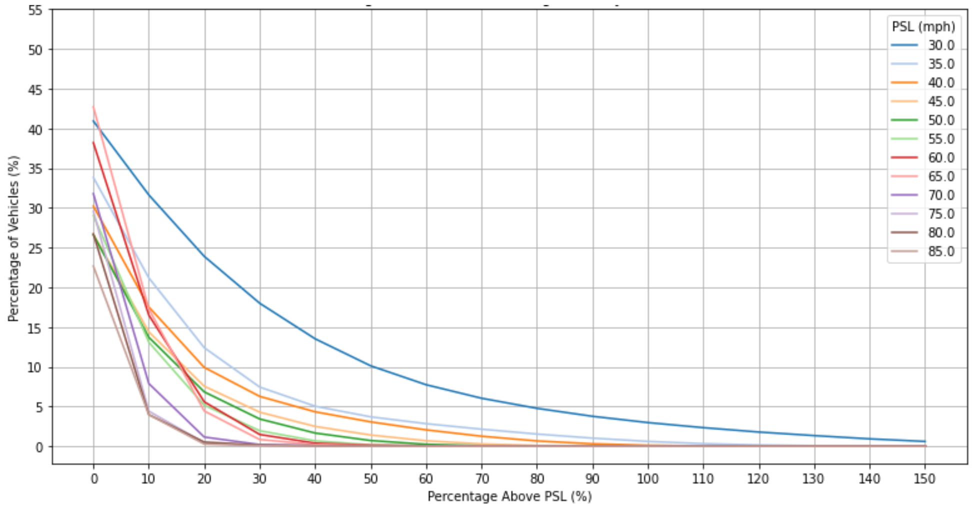
(a)



(b)

Figure 6: INRIX Vehicles and Speed Percentiles on Texas Roads by Time of Day on (a) Monday, November 4 & (b) Saturday, November 9, 2024

Speeding across road types by time of day and day of week can be analyzed by integrating speed data with roadway characteristics. Figure 7 shows the share of vehicles exceeding PSLs on Monday, November 4, 2024. Speeding appeared most common on roads with 30 and 40 mph PSLs, with nearly 43% vehicles exceeding those PSLs, on average. On 30 mph roads, approximately 32% of vehicles exceeded the limit by at least 10%, with 17% traveling more than 30% above the PSL. Similarly, approximately 23% of vehicles exceeded the limit by 10% on 35 mph roads. While roads posted above 60 mph saw 15% of vehicles exceeding PSLs by 10%, lower-speed roads (below 60 mph) experienced even higher exceedance rates, with a larger share of drivers significantly surpassing the limits. This trend is particularly concerning, since these roads often pass through residential and commercial areas with higher pedestrian and bicyclist activity. These are settings where speeding greatly increases crash severity risk. Figure 8 summarizes the percentage of vehicles driving over PSLs, and by more than 15% and 30% by day of week during the sample week. With the total traffic volume decreased during weekends, speeding peak was even higher. Throughout the week, the overall speeding pattern was similar for both weekdays and weekends. However, the percentage of aggressive driving varied by hour, with the highest rates occurring between 3 a.m. and 5 a.m. each day. During this time window, nearly half of all vehicles were driving over the PSLs, and 20% were exceeding the limits by more than 15%. On weekends, 7% more vehicles were speeding during the same hour compared to weekdays, despite traffic volume being approximately 46,000 vehicles lower.



PSL (mph)	# Vehicles
30	10271263
35	5639300
40	5699179
45	6604499
50	2598601
55	3692396
60	4180739
65	5264662
70	3165900
75	2157788
80	107928
85	7620

Figure 7: Percentage of Vehicles Exceeding PSLs (on Monday, November 4, 2024)

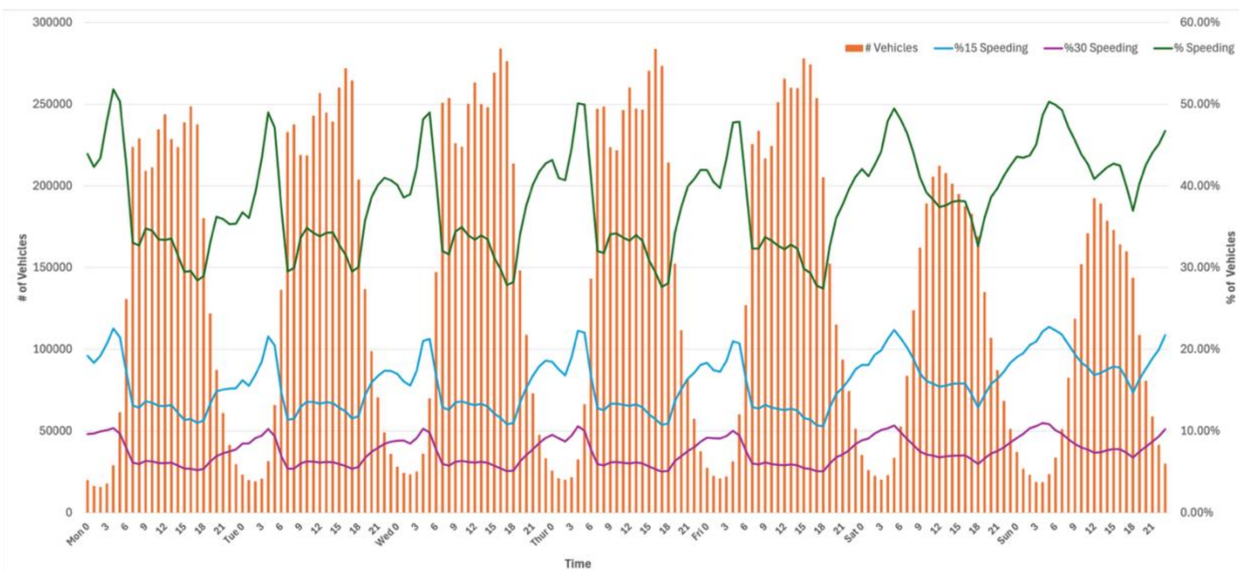


Figure 8: Number of Vehicles and Speeding Percentages on Texas Roads by Day of Week (Nov 4 to Nov 10, 2024)

Speed Model Results

Table 3 presents regression model estimates for average speed, 85th percentile speed, and 95th percentile speed per hour on road segments, based on 15.7 million INRIX speed data. Across all models, PSL settings were the most significant variable, with a 1 mph increase in PSL associated with an increase of 0.75 mph in average speed, 0.80 mph in 85th percentile speed, and 0.81 mph in 95th percentile speed, underscoring that driving speeds are highly correlated with PSL settings. Increasing PSL variable by 1 SD increases average speeds, 85th percentile speeds and 95th percentile speeds by almost 30%. Roadway access control also impacted speeds, particularly average speeds. Full access control increased speeds by 9.3% to 15.4%, and partial access control raised speeds by 8.5% to 10.3%, relative to roads with no access control. In contrast, urban roads reduced vehicle speeds significantly, with rural segments increasing average speeds by 14.4%.

Temporal and lighting conditions exhibited consistent effects across models. On average, vehicles travelled 1.66 mph faster on the weekend than on the prior weekdays and 0.29 mph faster under daylight conditions. Geometric characteristics also influenced speeds. For instance, two-way roads were associated with 6.0% to 7.6% lower speeds, while the presence of a school zone lowered speeds by 0.5% to 1.9%. The presence of median decreased average speeds by 0.82% but increased 85th and 95th percentile speeds by 1.2% and 2%, suggesting that medians slow general traffic while encouraging faster driving among higher-speed vehicles. Curve features for on-system roads—including the presence of curves and their degree—affected speeds modestly. The presence of curve was associated with a 2.0% to 2.4% increase in speed, while a higher curve degree reduced speeds by approximately 0.5%.

Additionally, built environment and land use characteristics had small effects on speeds. One SD higher population and job densities reduced speeds by 0.4% and 0.9%, respectively, on average. Walkability scores were linked to 1.4% to 2.4% reductions in speeds, indicating that denser regions with more pedestrian activities tend to have lower speeds of vehicles. Pedestrian-related roadway and intersection density also contributed to slower speeds, with pedestrian road density reducing speeds by 4.1% to 4.5% and pedestrian intersection density by 0.03% to 0.14%.

Table 3: OLS Model Estimates for Average, 85th Percentile, and 95th Percentile Speeds

Variable	Y = Avg speed in INRIX			Y = 85th Percentile speed			Y = 95th Percentile speed		
	Coef.	Std Err	Pract. Sign	Coef.	Std Err	Pract. Sign	Coef.	Std Err	Pract. Sign
Constant	13.326	0.023		12.874	0.024		12.927	0.025	
Weekend	1.658	0.006	4.66%	1.452	0.007	3.72%	1.363	0.007	3.37%
Daylight	0.291	0.006	0.82%	0.112	0.006	0.29%	0.068	0.006	0.17%
Urban	-5.107	0.009	**-14.36%**	-4.140	0.009	**-10.60%**	-3.807	0.010	**-9.42%**
School	-0.658	0.073	-1.85%	-0.349	0.076	-0.89%	-0.188	0.078	-0.46%
Two-Way	-2.120	0.012	**-5.96%**	-2.664	0.013	**-6.82%**	-3.074	0.013	**-7.61%**
Full Control	5.472	0.016	**15.38%**	3.995	0.017	**10.24%**	3.744	0.018	**9.26%**
Partial Control	3.663	0.031	**10.30%**	3.441	0.032	**8.81%**	3.417	0.033	8.46%
Median	-0.298	0.013	-0.84%	0.466	0.014	1.19%	0.803	0.014	1.99%
Med Width	0.009	0.000	0.55%	0.009	0.000	0.56%	0.010	0.000	0.58%
# Lanes	-2.286	0.006	-3.41%	-1.726	0.007	-2.34%	-1.479	0.007	-1.94%
Curve	0.698	0.012	1.96%	0.892	0.012	2.28%	0.987	0.013	2.44%
Curve Degree	-0.013	0.000	-0.5%	-0.015	0.000	-0.52%	-0.015	0.000	-0.51%
Counts per Lane	0.154	0.000	4.88%	0.284	0.000	8.20%	0.356	0.000	**9.92%**
PSL	0.749	0.000	**31.23%**	0.796	0.000	**30.22%**	0.808	0.000	**29.64%**
Pop Density	-0.035	0.001	-0.42%	-0.038	0.001	-0.41%	-0.043	0.001	-0.46%
Job Density	-0.029	0.000	-0.97%	-0.029	0.000	-0.89%	-0.028	0.000	-0.82%
Network Density	0.119	0.001	3.34%	0.129	0.001	3.30%	0.138	0.001	3.41%
Ped Road Density	-0.196	0.001	-4.14%	-0.225	0.001	-4.34%	-0.241	0.002	-4.48%

Intersection Density	0.001	0.000	0.17%	0.002	0.000	0.36%	0.003	0.000	0.38%
PedIntersect Density	-0.000	0.000	-0.03%	-0.002	0.000	-0.14%	-0.002	0.000	-0.11%
Walkability	-0.225	0.001	-2.44%	-0.170	0.001	-1.68%	-0.144	0.001	-1.38%
N_{obs}			15,722,918			15,722,918			15,722,918
R^2			0.604			0.622			0.622
Log-Lik			-6.033e+07			-6.089e+07			-6.143e+07
Note: All covariates with p-values over 0.10 were removed.									

Speeding-Shares Model Results

The speeding-shares model analyzes several factors influencing the percentage of vehicles exceeding PSLs per hour across three thresholds: any speeding, speeding by more than 15%, and speeding by more than 30%. Table 4 presents the model estimates based on 15.7 million speed observations combined with PSL information. Roadway access control, weekends, and urban settings were the most significant variables affecting speeding behavior. The percentage of speeding vehicles increased by 5.57% on weekends for speeding, and by 0.85% for speeding over 15%. In contrast to the speed models, more speeding occurred during nighttime hours. Urban roadways consistently led to reductions in speeding shares, with decreases of 9.42%, 1.35%, and 0.22% at the three thresholds, respectively.

Roadway features also influenced speeding rates. Two-way roads were associated with a 7.52% lower share of speeding vehicles compared to one-way roads, while fully access-controlled roads were linked to increased speeding rates: 8.91% for speeding, declining to 0.22% for extreme speeding. Partially controlled roads showed similar patterns, with 7.55% increase in speeding behaviors. The presence of medians, roadway curvature, and traffic volumes had relatively small effects. Built environment characteristics, such as population and job density, slightly reduced the share of speeding by 0.33% and 0.15%, respectively. Other factors like network density, pedestrian road density, and walkability also showed small but consistent negative impacts, suggesting that denser, more pedestrian-friendly areas experience lower levels of speeding.

Comparing the speed and speeding-shares models reveals that various factors influence driving behavior in different ways. Both PSL and roadway access control had strong impacts on operating speeds and the percentage of vehicles driving over PSLs, though they had a more direct influence on vehicle speeds. In contrast, temporal variables, particularly weekends and lighting conditions, exhibited a stronger influence on the likelihood of speeding. This suggests that aggressive driving is more common at night and on weekends. Geometric and environmental characteristics such as curves, medians, population density, and walkability showed modest impacts across models, though urban environments consistently reduced speeding, possibly due to stricter enforcement and local traffic regulations. These findings suggest that interventions targeting speeding may benefit from focusing on temporal patterns and enforcement strategies, while speed management efforts may be more effectively addressed through roadway design and PSL adjustments.

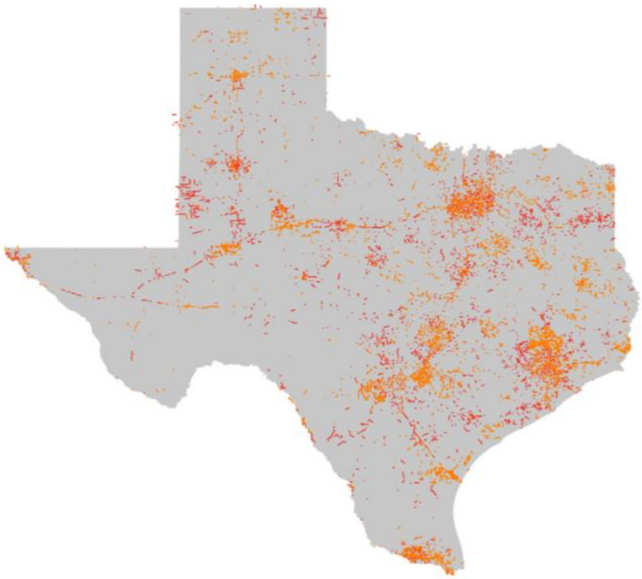
Table 4: Binomial Logistic Model Estimates for Speeding Shares (Y = % vehicles)

Variable	**Y = % over PSL in INRIX**			**Y = % over PSL by 15%**			**Y = % over PSL by 30%**		
	Coef.	Std Err	Pract. Sign	Coef.	Std Err	Pract. Sign	Coef.	Std Err	Pract. Sign

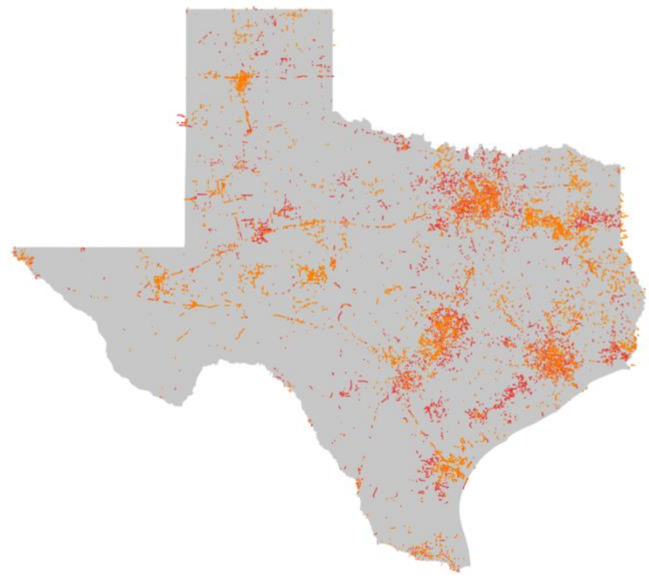
Constant	1.645	0.002		3.673	0.002		5.944	0.003	
Weekend	0.395	0.001	**5.57%**	0.419	0.001	0.85%	0.393	0.001	0.08%
Daylight	-0.084	0.000	-1.39%	-0.065	0.001	-0.17%	-0.037	0.001	-0.01%
Urban	-0.496	0.001	**-9.42%**	-0.440	0.001	**-1.35%**	-0.613	0.001	**-0.22%**
School	-0.204	0.004	-3.54%	-0.421	0.008	**-1.28%**	-0.620	0.012	**-0.22%**
Two-Way	-0.407	0.001	**-7.52%**	-1.078	0.001	**-4.58%**	-1.643	0.002	**-1.08%**
Full Control	0.704	0.001	**8.91%**	1.316	0.001	**1.85%**	1.793	0.002	**0.22%**
Partial Control	0.589	0.002	**7.55%**	0.790	0.003	**1.37%**	1.013	0.004	**0.17%**
Median	0.159	0.001	2.44%	0.332	0.001	0.7%	0.611	0.002	0.12%
Med Width	0.000	8.23e-06	0.01%	0.001	1.14e-05	0.0%	0.002	1.66e-05	0.0%
# Lanes	-0.163	0.000	-2.78%	-0.231	0.001	-0.64%	-0.360	0.001	-0.11%
Curve	0.013	0.001	0.21%	0.149	0.001	0.34%	0.308	0.001	0.07%
Curve Degree	5.188e-05	1.79e-05	0.0%	0.001	2.32e-05	0.0%	-0.000	3.1e-05	-0.0%
Counts per Lane	0.008	8.32e-06	0.13%	0.012	1.11e-05	0.03%	0.020	1.58e-05	0.01%
PSL	-0.027	0.000	-0.44%	-0.089	3.12e-05	-0.23%	-0.153	5.54e-05	-0.04%
Pop Density	-0.021	0.000	-0.33%	-0.025	0.000	-0.06%	-0.027	0.000	-0.01%
Job Density	-0.009	0.000	-0.15%	-0.012	3.44e-05	-0.03%	-0.014	4.73e-05	-0.0%
Network Density	0.030	5.94e-05	0.48%	0.043	7.68e-05	0.1%	0.053	0.000	0.01%
Ped Road Density	-0.035	0.000	-0.57%	-0.059	0.000	-0.15%	-0.082	0.000	-0.02%
Intersection Density	-0.001	1.22e-05	-0.02%	-0.001	1.66e-05	-0.0%	-0.001	2.38e-05	-0.0%
PedIntersect Density	0.000	0.000	0.0%	-0.000	2.18e-05	-0.0%	-0.001	3.16e-05	-0.0%
Walkability	-0.033	0.000	-0.54%	-0.040	0.000	-0.1%	-0.060	0.000	-0.02%
N_{obs}			15,722,918			15,722,918			15,722,918
Pseudo R^2			0.728			0.954			0.978
Log-Lik			-2.191e+07			-1.492e+07			-9.548e+06
Note: All covariates with p-value more than 0.10 were removed.									

High-Speeding-Shares Locations

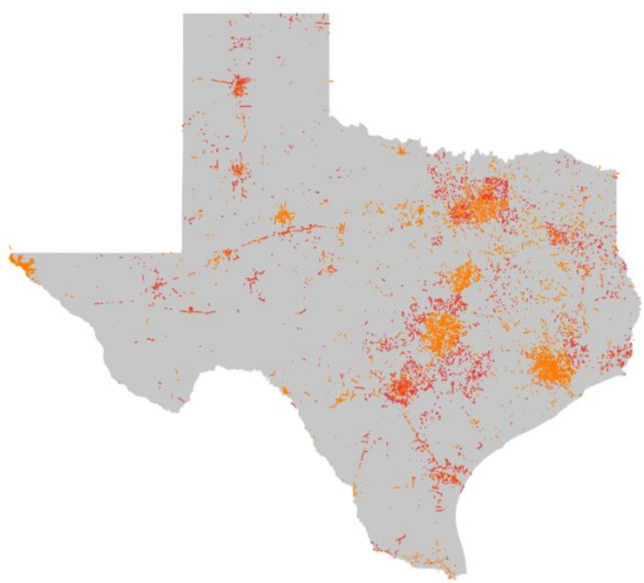
Based on speed data collected during the sample week, this study identified the top 20,000 road segments with the highest frequency of speeding behaviors across Texas at four specific times of day: 8 a.m., 12 p.m., 6 p.m., and 12 a.m., as illustrated in Figure 9. Compared to Figure 4, high-speeding locations largely overlapped with crash-prone areas, particularly around major cities (Dallas, Houston, San Antonio, Austin). Vehicles primarily exceeded limits in urban regions throughout the day, while extreme speeding behaviors were more concentrated in rural areas. Late-night speeding was more geographically clustered, suggesting potential priority areas for targeted speed management. In contrast, daytime speeding appeared to be closely associated with high traffic volume locations.



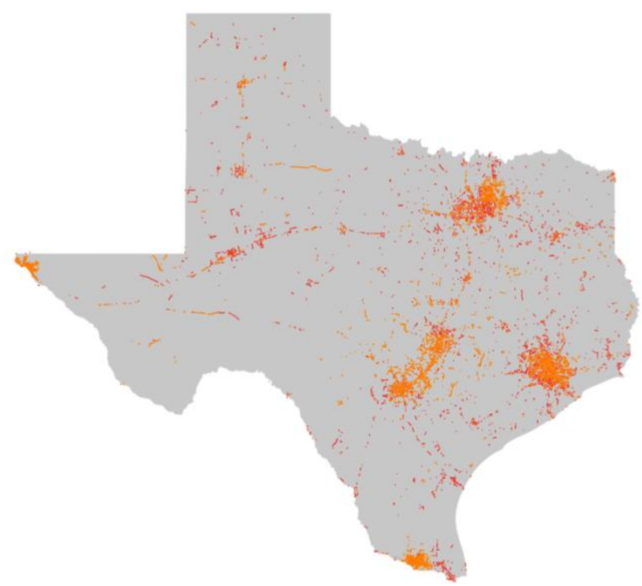
(a) 8 a.m.



(b) 12 p.m. (Noon)



(c) 6 p.m.



(d) 12 a.m. (Midnight)

Figure 9: Top 20k Segments with Speeding (orange) and Speeding over 15% above PSL (red) across Texas

LITERATURE REVIEW OF NON-INFRASTRUCTURE COUNTERMEASURES

Building on the speeding results and high-risk location identification, this section focuses on the next step for implementing speed management countermeasures. It focuses on operational, technological, policy, and education-oriented non-infrastructure strategies, and summarizes existing literature on their effects on operating speeds.

Operational Countermeasures

Operational strategies manage vehicle speeds by implementing enforcement (e.g., speed cameras, police/patrol enforcement, and high-visibility enforcement), controlling traffic operations (e.g., speed limit settings, signal timing, and phase changing), and other strategies. These types of countermeasures regulate or optimize vehicle and pedestrian movements at specific locations, offering greater precision. In the short term, operational countermeasures are more flexible and effective and are therefore commonly implemented by transportation agencies.

Speed cameras, including fixed cameras, point-to-point (P2P) systems, and mobile cameras, are discussed extensively in the literature regarding their effectiveness in reducing average speeds, the number of speeding vehicles over PSLs, and speed-related crash counts (Christie et al., 2003; Champness et al., 2005; De Pauw et al., 2014; Montella et al., 2015). By using multiple cameras and detectors along a stretch of road, P2P camera systems extend the detection range and can more accurately calculate the average speed of vehicles. On the other hand, unlike fixed and P2P speed cameras, which have limited sight distances and are site-specific, mobile units are portable and can be easily relocated. In real-world, permanent cameras exist in the US, mainly in New York City (NYC), Los Angeles, Chicago and many other big cities. As of January 2025, the NYC Department of Transportation (2024) has over 2,200-speed enforcement cameras in 750 school zones operating 24/7. Vehicle owners are quickly alerted via email to each violation and fined \$50 (typically paid online). This speed-management program has resulted in 94 percent fewer PSL violations since 2014. Likewise, in the City of Portland, Oregon's Bureau of Transportation implemented a traffic safety program along key corridors in 2016 (FHWA, 2024). The city began with a 30-day warning period, during which speeding drivers received warning letters only. After this period, official citations with \$160 fines for exceeding PSLs by more than 10 mph were issued by mail. The program resulted in 40% to 75% fewer PSL violations depending on location and 65% to 96% fewer drivers exceeding the PSL by more than 10 mph. Nowadays, Portland is still using these speed cameras as part of its Vision Zero initiative to eliminate fatalities and serious injuries.

Stationary and mobile police enforcement are both widely used in patrol operations. Nazif-Munoz et al. (2014) carried out a quantitative study on the impact of traffic law reform, police enforcement, and road infrastructure investment using data from 13 regions collected between 2000 and 2012. They developed structural equation models, considering traffic fatalities, severe injuries, and crashes as dependent variables. The findings indicated that the presence of police enforcement led to a 60% reduction in pedestrian fatalities and a 12.1% decrease in pedestrian crashes, making it significantly more effective than traffic law reform and road infrastructure investment.

Additionally, strategies such as lowering PSLs, implementing variable speed limits (VSL) (congestion-responsive and weather-responsive VSL), and adopting city-wide PSLs have also been proposed as feasible and effective solutions. In practice, the U.S. and many European countries have been working for a long time to lower PSLs and, in turn, reduce the number of accidents and casualties. The effectiveness of these strategies in decreasing crashes is well-documented in several studies, as listed in Table 5 (Waiz et al., 1983; Wong et al., 2005; European Data Journalism Network, 2023). A study by Waiz et al. (1983) examined car-pedestrian incidents in Zurich over a two-year period before and after lowering PSLs from 60 km/h to 50 km/h across the city. The analysis showed a 16% reduction in car-pedestrian injuries, a 20% decrease in pedestrian injuries, and a 25% decline in fatalities.

Basic traffic signal timing plays an important role in managing traffic flow and protecting all road users. For instance, Safe Waves, a signal timing strategy that uses shorter cycles (66 seconds for AM peak and 84 seconds for PM peak), reduced coordination zones, pedestrian recall in areas with moderate pedestrian demand, undersized phases where demand is low, and adjusted offsets—was tested over three weekdays on a suburban arterial with a 40 mph PSL in Danvers, MA (Furth et al., 2024). It reduced the number of vehicles exceeding PSLs by 79% overall. Other pedestrian-specific signal timing strategies, such as leading pedestrian intervals (LPIs) and No Turn on Red (NTOR), are also used to protect vulnerable road users and reduce crashes (Fayish and Gross, 2010; Chen et al., 2013; Joshua, 2022).

Table 5 summarizes existing literature examining the relationship between operational countermeasures and operating speeds. In conclusion, speed cameras have significant effects in reducing operating speeds and speeding violations, with substantial research supporting these findings. On the other hand, traffic operation-related measures, such as signals and PSL settings, have a relatively minor impact on speeds and are less studied.

Table 5. Studies on the Relationship Between Operational Strategies and Speeds

Study Description	**Method**	**Study Characteristic**	**Change in Travel Speed**
Speed Camera			
Mountain (2004) assessed the effect of 62 fixed speed cameras at various locations across the UK.	Before-after	• 30 mph PSLs	• Average speeds fell by 13.4% • 85th percentile speeds fell by 15.2% • % vehicles exceeding PSLs fell 35% points
De Pauw et al. (2014) investigated speed effects of fixed speed cameras on motorways in Belgium.	Before-after	• 75 mph PSLs	• Average speeds fell by 4 mph
Shin et al. (2009) analyzed the impact of a fixed camera program on one urban freeway in Scottsdale, Arizona.	Generalized least square estimation	• 6.5-mile segment	• Average speeds fell by 12.3%
New York City (2024) examined the effectiveness of fixed cameras installed in 750 school zones.	Before-after	• $50 flat fine	• % vehicles exceeding PSLs fell by 94% since 2014
Portland, Oregon BOT (FHWA, 2024) evaluated a fixed camera program along key corridors in 2016.	Before-after	• $160 fine for speeding 10+ mph over PSLs	• % vehicles exceeding PSLs fell 40% to 75% points • % vehicles speeding 10+ mph over PSLs fell 65% to 96% points
Montella et al. (2015) analyzed a P2P system on a urban motorway in Italy.	Before-after	• 50/43 mph PSLs for light/heavy vehicles	• Average speeds fell by 9.8% and 4.8% for light and heavy vehicles • 85th percentile speeds fell by 14.1% and 8.4% for light and heavy vehicles
Ragnøy (2011) implemented P2P enforcement trials at three sites in Norway.	Before-after	• 50 mph PSLs	• Average speeds fell by 8.5%

De Pauw et al. (2014) examined the P2P enforcement at four locations on a three-lane motorway in Belgium.	Before-after	• 75 mph PSLs • 7.5-mile study segment for each location	• Average speeds fell by 4.8% • % vehicles exceeding PSLs fell 74% points • % vehicles speeding 10+ mph over PSLs fell 86% points
Champness et al. (2005) conducted speed experiments at seven highway sites in Queensland.	Before-after	• 62 mph PSLs	• Average speeds fell by 3.7 mph • 85th percentile speeds fell by 4.3 mph • % vehicles exceeding PSLs fell 37% points
Patrol Enforcement			
Armour (1986) investigated speed impacts of police presence along two-lane urban streets in New South Wales.	Before-after	• 37 mph PSLs	• % vehicles exceeding PSLs fell 70% points
Walter et al. (2011) tracked speed changes along a 6-mile corridor on the highway in London.	Before-after		• 85th percentile speeds fell by 3.4 mph
Vaa (1997) experimented a 6-week police enforcement on a 21-mile road in Norway.	Before-after	• 37 to 50 mph PSLs	• Average speeds fell by 0.6 to 3 mph
Speed Limit Setting			
Switzerland (1996) decreased PSLs on motorways and examined the change of operating speeds.	Before-after	• PSLs decreased from 80 to 75 mph	• Average speeds fell by 3 mph
Elvik et al. (2004) explored the relationship between changes in operating speeds and PSLs.	Meta-analysis	• 98 studies • PSLs decreased by 5 mph	• Average speeds fell by 1 to 2 mph
Kockelman et al. (2006) tested safety impacts of PSL increases on high-speed roads in Washington State, Southern California and Austin, Texas.	Before-after	• PSLs increased from 65 to 75 mph and from 55 to 65 mph	• Average speeds rose by 3 mph
Wyoming DOT (2010) examined speed effectiveness of one weather-responsive VSL system along the corridor.	Before-after	• 65/75 mph PSLs for winter/summer	• Average speeds fell by 4.7 to 7.5 mph in winter
Brussels Times (2021) assessed safety effects of a region-wide PSL settings for five months in Belgium.	Before-after	• 19 mph PSLs	• Average speeds fell by 7% to 19%
Traffic Operations			
Furth et al. (2024) tested "Safe Wavers" (a signal timing strategy) for 3-weekday periods on suburban arterial in Danvers, Massachusetts.	Before-after	• 40 mph PSLs	• % vehicles exceeding PSLs fell up to 15% points

Technological Countermeasures

Besides transportation agencies, manufacturers are actively integrating new safety-related features and designs into the vehicles themselves. Technologies such as intelligent speed assistance (ISA), speed governors and limiters, automated emergency braking (AEB), and vehicle front-end geometry design are discussed in this section, focusing on their effectiveness in controlling operating speeds.

ISA, a speed-related alert system that informs drivers of the speed limit and warns them when they exceed it, has been shown to improve the effectiveness of vehicles in reducing speeding (Oei et al., 2002; Van Der Pas et al., 2014; De Vos et al., 2023), as listed in Table 4. By controlling speeds, ISA helps reduce speeding-related crashes. According to Lai et al. (2012), the universal adoption of intervening ISA could reduce serious road traffic injuries by up to 29%. Different forms of ISA contribute to varying levels of accident reduction, and mandatory dynamic ISA has the most significant impact, potentially preventing 36% of injury accidents and 59% of fatal accidents (Carsten and Tate, 2005). Starting in July 2024, the European Union requires all newly launched vehicles to be equipped with ISA (European Commission, 2019), but it can be easily over-ridden by drivers (Rowe et al., 2021). Besides, various vehicle trackers have been widely adopted for personal use. For example, the LandAirSea 54 GPS Tracker provides location updates every 3 seconds, along with historical playback and speed alerts. It requires a one-time installation fee of $14.95 and a monthly fee of $9.95, which is relatively cheap and can enhance driving safety.

Table 6. Studies on the Impact of ISA on Vehicle Speeds

Study Description	**Method**	**Study Characteristic**	**Safety Impact**
Reagan et al. (2013) tested an auditory and visual advisory alerting system in Michigan.	Before-after	• 35 mph PSLs	• Time spent driving 1 to 4 mph over PSLs fell by 10%
Albert et al. (2007) evaluated speed benefits of equipping light goods vehicles with speed limiters.	Traffic simulation	• 62 and 75 mph speed limiters	• Average speeds fell by 10%
Várhelyi and Mäkinen (2001) examined the effects of in-car speed limiters on urban and rural roads.	Before-after	• 19 to 75 mph PSLs	• Average speeds fell by 16.7%

The AEB system detects potential collisions ahead and can automatically apply or assist in braking to prevent a crash. Cicchino (2022) conducted quasi-induced exposure analyses on police-reported crashes from 18 states between 2017 and 2020, accounting for drivers, vehicles, and environmental risk factors when evaluating the effects of AEB with pedestrian detection. The results showed that AEB reduced half of reported crashes. On the other hand, geometric design for vehicles, especially embedded safety-related features, is important for road users. Monfort et al. (2024) analyzed 121 pedestrian crashes between 2015 and 2021 to examine the relationship between vehicle design and pedestrian injury severity. The vehicles involved had an average speed of 45 km/h and an average model year of 2009. Using a Poisson model, the study found that vehicles with a lower leading-edge height (less than 89 cm) were associated with a 28% reduction in pedestrian injury severity scores (ISS) compared to those with a higher leading-edge height (greater than 89 cm). Additionally, vehicles with flatter bumper leads (<65°) had 34% lower pedestrian ISS than those with a bumper lead angle greater than 65°. However, AEB systems and geometric design have not been proven to impact operating speeds.

Policy- and Education-Oriented Countermeasures

Lastly, speed management is a collaborative effort involving governments, local communities, public campaigns, and citizens. This section discusses policy- and education-oriented countermeasures (including monetary incentives, Neighborhood Speed Watch programs, driver training, and other strategies) while exploring their feasibility in reducing speeding violations. Although most research has examined their effectiveness through small-scale pilot projects or simulator studies, these efforts still offer valuable insights into their feasibility and applicability.

To directly control driver behaviors, Reagan et al. (2013) tested a monetary incentive system in Michigan, involving a total of 50 participants over a 4-week period. Participants received an initial amount of $25, which decreased by 3¢ per 6 seconds for driving 5 to 8 mph over the PSL and 6¢ per 6 seconds for exceeding the PSL by 9 mph or more. Bonus amounts were visually displayed and updated in the assigned vehicles. Results revealed that the incentive system led to significant reductions in speeding. In 25 mph PSL zones, the average speed decreased by approximately 6.5% (1.6 to 1.8 mph), and the time spent driving above the PSL decreased by 11% to 13%. On the other hand, driver training has a longer-lasting effect (Brown et al., 2025). Crundall et al. (2010) examined the relationship between commentary training and driver performance using a driving simulator. The study divided 40 learners into two groups, and the experimental group received a classroom introduction in commentary training and a two-hour on-road training session. This work analyzed their behaviors (e.g., speed, braking) when encountering driving hazards. Observation results indicated that trained drivers responded to hazards more quickly and reduced their speed more significantly compared to untrained drivers.

Many apps are also designed to help parents monitor their children's driving behavior and detect risky driving, as teenagers are known for driving aggressively. The University of Minnesota (Creaser et al., 2015) developed the Teen Driver Support System (TDSS), which provides real-time feedback and reports monitored behaviors to parents if risky driving persisted for a relatively long time. To assess its effectiveness, they divided 300 newly licensed teen drivers into three groups: control group (received no feedback), partial TDSS group (received in-vehicle feedback only), and full TDSS group (received both in-vehicle feedback and parental notifications). Final results over 52 weeks showed that the full TDSS group had the lowest percentage of miles spent speeding, reducing speeding by 7% compared to the control group and 2% compared to the partial TDSS group.

Campaigns and neighborhood programs encourage all possible road users and residents to enhance road safety as well. A one-month test conducted by Blume et al. (2000) assessed the effectiveness of the Neighborhood Speed Watch program in reducing speeds on two local roads in Massachusetts, with PSLs of 25 mph and 30 mph, respectively. Speed results on these two local roads, shows a 1 to 2 mph reduction in average speeds and a 5-mph reduction in 85^{th} percentile speeds. Additionally, the percentage of vehicles exceeding PSL declined from 17.9% to 14.1% after the intervention. Few speed campaigns were adequately evaluated in terms of their impact on actual speed behaviors. For instance, Van Schagen et al. (2016) monitored speeds of 10 million vehicles over a 16-week anti-speeding campaign conducted at twenty locations in the Netherlands, with ten locations of 50 km/h PSLs and ten of 30 km/h PSLs. In this campaign, posters were placed at half of each group of locations to remind drivers of the speed limit. Results showed that average speeds on 30 km/h roads fell by 7.6 km/h with local posters installed.

As policy- and education-oriented countermeasures are often evaluated through pilot projects or case studies, their overall effectiveness on a larger scale remains unclear and requires further investigation for better implementation.

CONCLUSIONS

This study provides a comprehensive analysis of vehicle speeds and speeding behaviors across Texas using 15.7 million sampled vehicle speeds in November 2024. Speed data were merged with detailed PSL and land use information into both speed and speeding models, and ordinary least squares (OLS) and binomial logistic regression models illuminate how temporal, geometric, and environmental characteristics influence speed choices.

Key findings reveal that PSL and roadway access control are the most influential predictors of vehicle speeds. A 1 mph increase in PSL was associated with a 0.75 mph increase in average speed, 0.80 mph in 85th percentile speed, and 0.81 mph in 95th percentile speed. Full access control raised average speeds by 15.4%. In contrast, speeding behavior, particularly extreme speeding, was more sensitive to temporal and contextual conditions. Nighttime and weekend periods saw increased speeding rates, with up to 50% of vehicles exceeding PSLs and 20% exceeding them by more than 15% between 3 a.m. and 5 a.m. on weekends. These patterns were especially prevalent on lower-speed roads (30–40 mph) in pedestrian-dense urban areas, where over 30% of drivers were observed speeding. Built environment features such as urban settings, walkability, and pedestrian-oriented infrastructure were associated with both lower travel speeds and reduced speeding rates, suggesting that denser, pedestrian-friendly environments discourage speeding.

In addition, while traditional physical countermeasures are well-evaluated using CMFs and benefit-cost analyses, non-physical strategies lack a comprehensive framework to guide researchers and practitioners. This paper provides a systematic overview to support future efforts in speed management. Among all non-infrastructure countermeasures, speed cameras are the most effective in reducing speeds and are well studied.

However, this work is limited by its reliance on a single week of connected vehicle data, which may underrepresent certain driving populations. It also does not account for variables such as weather, enforcement activity, or real-time traffic conditions. Future work will expand this analysis over longer periods and broader driver samples, integrating additional variables. This study lays the groundwork for future research using probe vehicle data and offers valuable insights for policymakers in developing targeted speed management and enforcement strategies. Besides, new non-physical strategies for speed management continue to emerge and will be the focus of future work. For example, Li et al. (2024) proposed a smartphone-based approach with computer-vision-based speed estimation and vehicle identification (like vehicle make, model, and color, plus license plate reading). Several machine-learning approaches, including SVM, random forests, artificial neural networks, and time-series-based models, were tested to classify three speed cases: accelerating, decelerating, and maintaining constant speeds. All approaches yielded 90% to 95% accuracy in identifying speed changes among 188 cases. Although acoustic-based “cameras” (which “see” sounds to produce image for speed inference) are still under development to assist law enforcement, existing research suggests it is quite feasible. Of course, the legality of implementation (with standard cameras for vehicle identification) remains in doubt in many US states (GHSA, 2024).

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