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Did Operating Speeds During COVID-19 Result in More Fatal and Injury Crashes on Urban Freeways?

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Abstract

Impacts of the COVID-19 pandemic in the transportation arena included less traffic, higher speeds, and higher fatal and injury crash frequencies. Many news media reported on speeding and its impact. However, the majority of these reporting are based on partial or incomplete information. The current study aims to understand the association between speed and crash on the freeways of Dallas (Texas) by collecting data from the National Performance Management Research Dataset, the Texas Department of Transportation's (TxDOT's) roadway inventory, and TxDOT's crash database for 2018–2020. The results show decreasing traffic volume, increasing average operating speed, and increasing fatal and severe crash frequencies per 100 million vehicle miles traveled during 2020 (April–November). This study developed 8-month- and daily-level safety prediction models for fatal and injury crashes. The 8-month-level dataset contains speed measures as an aggregate for the 8-month period. The daily-level database includes operating speeds and fatal and injury crashes at the daily level where segments experiencing fatal and injury crashes were temporally matched with the same segment with the same day of the week and with no fatal and injury crash occurrences. For the 8-month models, average operating speed and speed variability are positively associated with fatal and injury crash frequencies during the COVID period. This association was also found for daily-level models. The findings of this study can help transportation agencies in developing strategies (for example, posted speed limit reconsideration, additional enforcement at specific locations) for crash reduction.

Keywords

data and data science, speed data, safety, speeding

To minimize the spread of COVID-19, many social distancing measures—such as "shelter-in-place" orders, halting of non-essential business operations, and limitations of in-person gatherings—were taken in 2020 (*1*). For example, Texas experienced 38 COVID-19-related orders and amendments, and Dallas County alone experienced 49. The majority of the orders started within the first two months of the pandemic (mid to late March 2020). Some examples of the State's orders included temporarily closing schools, requiring travelers to self-quarantine if flying in from areas experiencing substantial community spread, and defining essential services and activities. Other examples of the state orders included direction on the three-phased reopening approach occurring between April and June 2020 before fully reopening in March 2021. Dallas County orders included limitations on community and recreational gatherings, Stay Home Stay Safe restrictions from late March to early August 2020, and continued face mask requirements in certain public space as of August 2021. These restrictions affected people's daily lives, including their travel and driving patterns. In fact, vehicle miles traveled (VMT) of the interstate highways in the U.S.A. dropped drastically from mid-March 2020 to its lowest point of 50% at the beginning of April 2020, according to the Federal Highway Administration's (FHWA's) Office of Highway Policy Information (*2*, *3*).

This extensive and prolonged disruption in travel patterns has recently gained much research interest. For

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example, with traffic demand lower than "normal" (or pre-COVID) conditions, roadway crash frequency decreased in comparison to previous years, reinforcing that motor vehicle crash occurrence (*4*, *5*) is a function of risk and exposure (i.e., VMT). The recently published studies above revealed similar but slightly conflicting results on speed–crash association. The varying results may be because of many reasons, such as different study sites and different study periods. However, none of the studies above primarily focused on the impact of the COVID-19 pandemic on high-speed facilities, such as freeways.

In Texas Department of Transportation's (TxDOT's) Dallas District (Collin, Dallas, Denton, Ellis, Kaufman, Navarro, and Rockwall Counties), there has been a 13%–50% decrease in crashes between April and November of 2020 compared to 2019. Moreover, the statewide fatal crashes decreased initially but increased above the 2017–2019 average by mid-May, only to drop below it again in early July 2020. The 2020 Dallas District fatal crashes, however, stayed above 2019 numbers between April and November. The general hypothesis is that the increase in Dallas District's fatal crashes is likely caused by higher operating speeds, particularly on freeways. It is important to note that there was a decrease in VMT during the pandemic, which directly resulted from the various county-specific shelter-in-place orders, such as Dallas County's Stay Home Stay Safe restrictions and the State's phased reopening of essential businesses and activities from "retail-to-go" to operating up to 25% and 50% of capacity. A macroscopic look at the average freeway speeds in Dallas County shows higher operating speeds throughout the day in April as compared to the more typical freeway speed profiles found in February. However, robust statistical analysis is needed to determine more definitive conclusions from these observations. Other societal factors related to the pandemic, such as mental health (i.e., risky behavior) and enforcement, could also have contributed to the increase in higher speeds, more severe crashes, or both, as discussed in the conclusion.

Discussions clearly indicate that there is a need for a study that can explore drivers' speeding behavior, travel patterns, and their association with traffic crashes. This study aims to better understand the impact of COVID-19 on traffic safety by exploring the associations between operating speed and fatal and severe injury crashes on freeways in the Dallas, Texas, metro area before and during the pandemic. More specifically, this study examines the following three research questions.

- **RQ1:** Were operating speeds higher on freeways during 2020 (April–November) as compared to previous years?
- **RQ2:** Were those higher operating speed measures associated with more fatal and injury crashes during 2020 with consideration of other influential factors?
- **RQ3:** Were 5-minute operational speed measures more useful for assessing the speed–crash relationship when analyzed at a 24-hour (daily) interval rather than annually?

This research could further contribute to the transportation safety community by providing insights into the roadway safety implications (i.e., fatal and severe injury crashes) during the pandemic. This could help transportation agencies to mitigate the ongoing and future impacts of the pandemic, or other conditions where travel patterns on high-speed facilities, such as freeways, are severely disrupted for an extended period of time.

Literature Review

The association between speed and traffic crashes does not produce a conclusive result (see Table 1). It is worth mentioning that rural areas are more often in these studies than the urban environment. Some studies indicate a positive association between operating speeds and traffic crash frequencies. On the other hand, other studies conclude a negative association. This is mostly caused by the study design, data availability, data integration, segment- and temporal-based clusters, the overall accuracy of operating speed measures, and availability of other real-time exposure variables, such as rainfall and traffic volume. COVID-19 has made this inconclusive outcome more interesting. As the travel restrictions during the earlier days of COVID-19 and the work from home (WFH) culture made disruptions in travel and driving patterns, this association requires more careful investigation. The scope of the current literature review is limited to speed–crash association-related studies during 2020–2021, as these studies explore this association with regard to the COVID-19 pandemic.

Table 2 provides a brief overview of the studies conducted recently to explore the speed–crash association during COVID-19. A general overview of the studies shows that the majority of the studies provided descriptive analysis to explore crash, speed, and driver behavior during COVID-19. As the traffic volume dropped, less traffic encouraged higher travel speed (*13*, *20*, *21*, *24*). Over speeding (i.e., operational speed is more than 10 mph or so from the posted speed limit [PSL]) is considered a factor of increased risk of being involved in a crash, particularly with more severe crashes (*4*, *13*, *14*). However, crashes are affected by many other factors and complicated psychosocial reasons other than speed. Gao et al. (*13*) found, using New York City crash data, that

Table 1. Key Studies on the Speed–crash Relationship

Study	Finding	Roadway facility	Operating speed effect on crashes
Gargoum and El-Basyouny (*6*)	Increase in operational speed is associated with increase in crashes.	Urban roadways	↑
Vadeby and Forsman (*7*)	There is a negative association between operational speed and traffic crashes.	Rural roadways	↓
Yu et al. (*8*)	The severity of crashes measured by the KABC/total crash ratio is increasing by increasing the operational speed differential.	Urban roadways	↑
Dimaiuta et al. (*9*)	For non-congested roadways, posted speed limit is associated with traffic flow and safety. No significant associations were found for uncongested scenarios.	Rural roadways	↑→
Banihashemi et al. (*10*)	Lower mean speed (operational) is associated with higher crash frequency.	Urban roadways	↓
Das and Geedipally (*11*)	Operational speed variability on rural roadways is associated with crash frequencies at annual level. At daily level, daily operating speed measure is associated with daily crash frequencies. This association is inconclusive for annual-level analysis for rural roadways.	Rural roadways	↑→
Dutta and Fontaine (*12*)	Rural facility types were examined; increases in different operational speed measures were positively correlated with an increase in crash frequency on most facility types except rural interstates.	Rural roadways	↑

Note: ↑ means positive association, ↓ means negative association, and →means no association. KABC = fatal and injury(where, K= fatal, A= severe injury, B= moderate injury, and C= minor injury).

the number of fatalities increased during the pandemic, even though the number of crashes decreased. Qureshi et al. (*15*) determined that property damage only (PDO) and minor injury crashes were reduced during the pandemic. However, fatal and severe injury crashes did not change much, and the study period could have affected the study results. Some published studies that used only March and April data reached different conclusions. For example, a study conducted by Katrakazas et al. (*5*) concluded by only using the March 2020 crash data that the total number of crashes and the fatal crashes all decreased. This study also found evidence of frequent harsh acceleration and braking during COVID-19 compared to pre-COVID periods. Several studies produced descriptive statistics of fatal and injury crash reduction (*16*, *17*, *22*, *23*). A study conducted in Connecticut showed an increase in the single vehicle crash rate during COVID-19. A UK-based study (*19*) showed an increase in operating speeds in rural areas. The number of drivers traveling 15 mph above the limit also increased on countryside roads. An Alabama study (*25*) identified an emerging pattern of "new normal" within-day travel behavior. The findings from COVID-19-related studies indicate the need for a robust exploration of driving and travel patterns and their associations with traffic crashes. A New York-based study (*26*) was performed using survival analysis by exploring the effects of human mobility changes caused by the pandemic on injury-related crashes.

Methodology

For this study, the research team used three datasets for the freeways of the seven counties in Dallas District: (1) 2018–2020 crash data from the Crash Records Information System (CRIS); (2) 2019 roadway geometry data from the Road-Highway Inventory Network Offload (RHiNO); and (3) 5-min interval operating speed data from the National Performance Management Research Dataset (NPMRDS). The data collection was limited to 8 months (April–November) for each of the

Table 2. COVID-19-related Key Studies

Ref.	Location	Research problem	Approach/modeling	Key findings
Inada et al. (*4*)	Japan	Speed–crash association during COVID-19	Time series forecasting	More speed-limited violations during COVID-19.
Katrakazas et al. (*5*)	Greece	Driver behavior and safety during COVID-19	Descriptive statistics	Reduced traffic volume, slight increase in operating speeds, frequent harsh acceleration and braking.
Gao et al. (*13*)	New York and Seattle	Impact of COVID-19 on transportation system	Descriptive statistics	Crashes were low because of low traffic; fatalities were up, possibly because of higher speeds.
Aarts and Van Schagen (*14*)	Not applicable	Speed–crash association during COVID-19	Literature review	High speed was associated with more severe crashes.
Qureshi et al. (*15*)	Missouri	Lockdown and traffic crashes	Descriptive statistics	Fatal and injury crashes are unchanged compared to earlier years. Minor injury and no injury crashes decreased.
Catchpole and Naznin (*16*)	Australia	Impact of COVID-19 on fatal crashes	Descriptive statistics	Decline in fatal crashes during the COVID-19 pandemic was significantly smaller than the decline in motor vehicle use.
Calderon-Anyosa and Kaufman (*17*)	Peru	Impact of COVID-19 lockdown policy on homicide, suicide, and fatal traffic crashes	Descriptive statistics	All forms of external death presented a sudden drop after the lockdown, with the most severe drop in fatal traffic crashes.
Doucette et al. (*18*)	Connecticut	Impact of COVID-19's stay-at-home order on traffic crash patterns	Descriptive statistics	Single vehicle crash rates significantly increased by 2.29 times.
Owen et al. (*19*)	UK	Impact of lockdown on traffic flow and speeds	Bayesian approach	Clear changes were seen on all roads, but the increase in speeds on rural roads was more marked. Meanwhile, the number of drivers travelling 15 mph above the limit also increased on countryside roads.
Pishue (*20*)	U.S.A.	Effect of COVID-19 on interstate and highway crashes	Descriptive statistics	Overall VMT dropped at onset of COVID-19 with major metropolitan areas yet to recover. Lower VMT was associated with less traffic congestion and higher speeds.
Saladié et al. (*21*)	Spain	COVID-19 lockdown and reduction of traffic crashes	Descriptive statistics and hot-spot maps	Mobility reduction was higher when compared with crash reduction.
Rapoport et al. (*22*)	Canada	Impact of COVID-19 on motor vehicle injuries and fatalities in older adults	Descriptive statistics	Reduction in driver injuries and fatalities in in older adults
Shilling and Waetjen (*23*)	California	Impact of COVID-19 on crashes	Descriptive statistics	Fatal and injury crashes were reduced by 50%. For certain roadways, maximum and average operating speeds increased slightly. Although the difference is few mph.
Li et al. (*24*)	China	Urban road congestion patterns during COVID-19	Singular value decomposition	Identified three spatiotemporal variations in traveling patterns: stable, major variations, and variation in commuting trips. Spatial-level speeds increased during the lockdown because of low traffic.
Shirani-bidabadi et al. (*25*)	Alabama	Within-day travel speed patterns	Unsupervised data mining	A new travel speed pattern at end of travel restriction order was identified.
Dong et al. (*26*)	New York	Understand safer mobility policies	Survival analysis	Provide new insights by exploring the effects of human mobility changes caused by the pandemic on injury-related crashes.

Note: VMT = vehicle miles traveled.

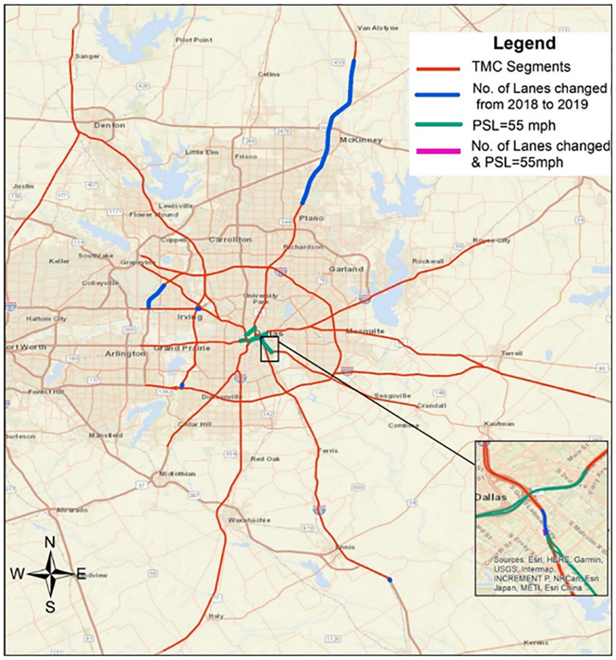

Figure 1. Selected freeway corridors in Dallas for this study.
Note: TMC = traffic message channel; PSL = posted speed limit.

years of 2018–2020 (see Figure 1 for the roadway network used for this analysis). This study used only 8 months of data because of the availability of crash data until November of 2020 (when the study was conducted). The following section describes the overall methods for data conflation to traffic message channel (TMC) segments, traffic volume estimation for 2020, descriptive statistics of the key variables, variable selection, and developed models for 8-month data and daily data.

Data Conflation

The data conflation procedure has six steps (see Figure 2):

- Step 1: conflate RHiNO on the NPMRDS directional network;
- Step 2: conflate HERE (HERE is a technology company, https://www.here.com/) links on the conflated NPMRDS network;
- Step 3: assign CRIS crashes to the conflated NPMRDS network;
- Step 4: manually check the quality of CRIS crash assignments;
- Step 5: determine appropriate speed measurement variables for 8-month, daily, and hourly level data; and
- Step 6: determine appropriate traffic volume for 8-month, daily, and hourly level data.

Step 1: Conflate Roadway Inventory Data and NPMRDS. The roadway inventory data for Dallas area freeways were collected from the RHiNO database. The directional 2019 NPMRDS network for Dallas area freeways is collected from the NPMRDS website (https://npmrds.ritis.org/analytics/). RHiNO segments were conflated to NPMRDS segments using ArcGIS software. Each segment in the conflated NPMRDS network has a TMC code and a corresponding RHiNO segment.

Step 2: Conflate HERE Link on the Conflated NPMRDS Network. HERE data contains PSL information. Although PSLs are provided in the RHiNO roadway inventory, HERE data was used as a cross-check of PSLs. HERE links are conflated to the conflated NPMRDS network produced in Step 1. Note that TMC segments with PSLs of 55 mph were removed because of the small sample size.

Step 3: Assign CRIS Crash Data to the Conflated NPMRDS Network. Crash data from three 8-month periods (April–November, 2018–2020) were collected from CRIS. Crash events were assigned to RHiNO and TMC segments in the conflated NPMRDS network by using the ArcMap near function. Each crash event was assigned to a RHiNO and TMC segment, by direction, and within 10 ft from the crash event. For each unique TMC segment, this study summarized the number of crashes by different severity levels (K: fatal, A: incapacitating injury, B: non-incapacitating injury, C: possible injury, and O: not injured and unknown) for 2018, 2019, and 2020 separately.

Step 4: Manual Quality Check to Assign Crashes to NPMRDS Segments. The research team manually checked about 35,500 crashes to ensure they were assigned to the appropriate RHiNO and TMC segments. These crashes were initially assigned in the previous step (i.e., GIS functions), but a quality check was necessary because of crash proximities to interchanges and ramps, or the crash direction was not clear or intuitive. This study performed quality control while assigning crashes to the relevant segment.

Step 5: Determine Appropriate Speed Measurement Variables for 8-month- and Daily-level Data. Speed measurement variables are calculated based on the 5-min raw speed data collected from NPMRDS. The speed measurement variables included in the 8-month-level data are SpdAve, SpdStd, Spd85, SpdAveDay, SpdAveNight, SpdAve MTWT, SpdAveFSS, SpdFFAve, and SpdFF85. Table 3 shows the definition of the speed measures used for the 8-month-level data. The speed measurement variables included in the daily-level data are SpdAveDaily,

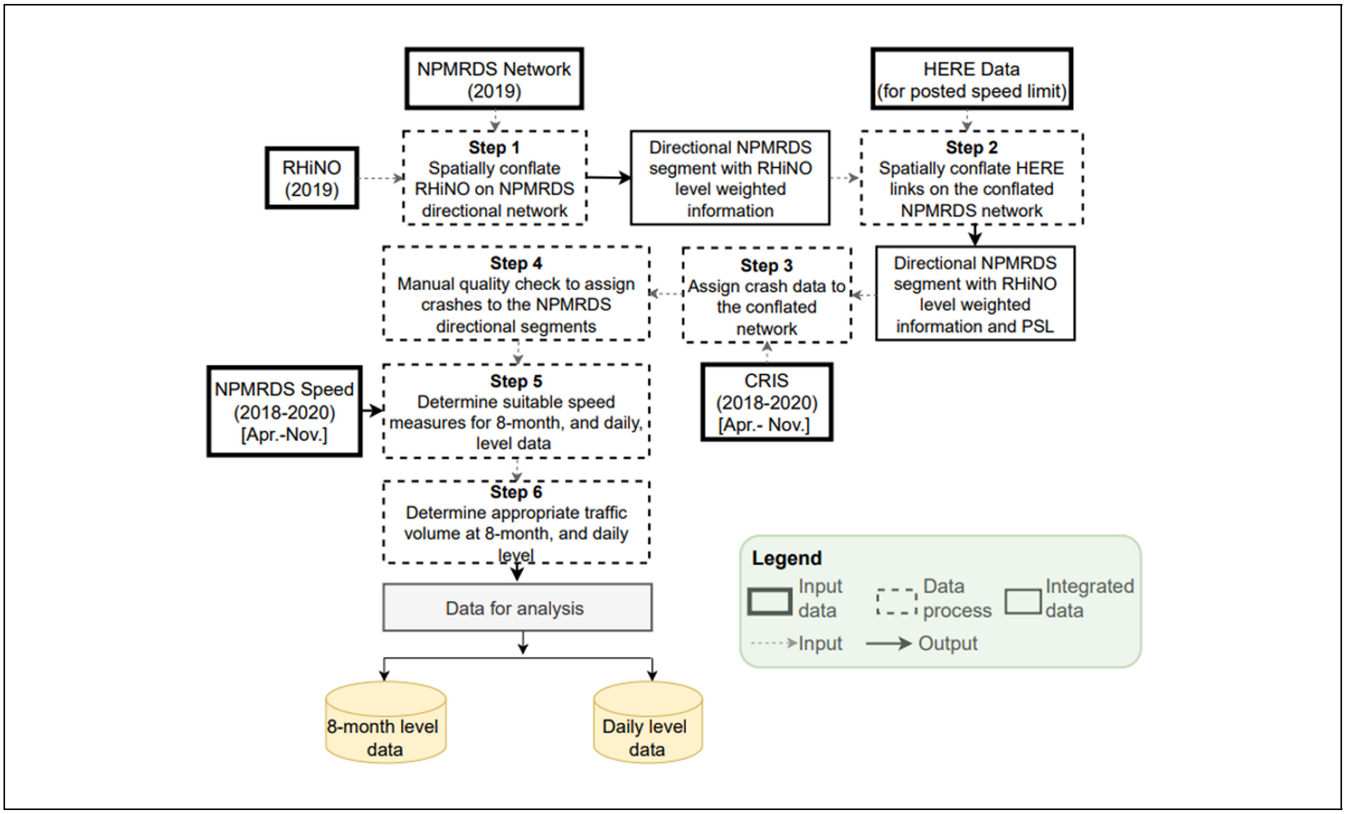

Figure 2. Flow chart of the data preparation.
Note: NPMRDS = National Performance Management Research Dataset; RHiNO = Road-Highway Inventory Network Offload; CRIS = Crash Records Information System; PSL = posted speed limit.

Table 3. Speed Measures for 8-month-level Data

Speed measure	Definition
SpdAve	Average operating speed using all data by each year's 8-month period (April–November)
SpdStd	Standard deviation of operating speed using all data by each year's 8-month period
Spd85	85th percentile operating speed using all data by each year's 8-month period
SpdAveDay	Average operating speed ($6 \leqslant$ hour $\leqslant 18$) using all data by each year's 8-month period representing typical average operating speed for daytime conditions
SpdStdDay	Standard deviation of operating speed ($6 \leqslant$ hour $\leqslant 18$) using all data by each year's 8-month period representing typical standard deviation for daytime conditions
SpdStdNight	Standard deviation of operating speed ($19 \leqslant$ hour $\leqslant 23$ and $0 \leqslant$ hour $\leqslant 5$) using all data by each year's 8-month period representing typical nighttime conditions
SpdAveMTWT	Average operating speed (Mon, Tues, Wed, Thurs) using all data by each year's 8-month period representing typical average operating speed for a weekday
SpdAveFSS	Average operating speed (Fri, Sat, Sun) using all data by each year's 8-month period representing typical average operating speed for a weekend
SpdFFAve	Average operating speed ($1 \leqslant$ hour $\leqslant 4$) using all data by each year's 8-month period representing typical average speed for late nighttime conditions, which is also assumed to represent free-flow (FF) conditions
SpdFF85	85th percentile operating speed ($1 \leqslant$ hour $\leqslant 4$) using all data by each year's 8-month period representing typical 85th percentile speed for late nighttime conditions, which is also assumed to represent free-flow conditions

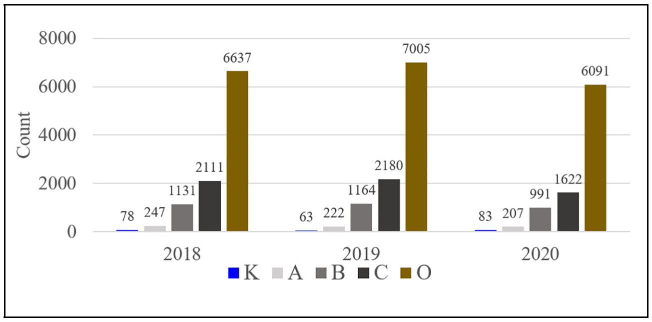

Figure 3. Crash injury counts by 8 months of each year.
Note: K = fatal; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = not injured and unknown.

SpdStdDaily, Spd85Daily, SpdAveDayDaily, SpdAveNightDaily, and SpdFFAveDaily. The speed measures calculated for the daily level were limited to the daily level. For example, SpdAveDaily indicates the average operating speed for a day determined by all the data in that year.

Step 6: Determine Traffic Volume for 8-month- and Daily-level Data. In the 8-month-level data, the traffic volume variable is determined by the annual average daily traffic (AADT) variables in the RHiNO roadway inventory database. This study used the 2019 RHiNO database, which has both 2018 and 2019 AADT values. TxDOT operates traffic management centers in several urban areas, such as Dallas. Each TMC manages and operates TxDOT freeways within its region. This study collected traffic data at several sites being used by the Dallas District as part of the COVID-19 monitoring. The data collected on those sites were assigned to the nearest conflated segment to acquire 2020 traffic volumes on those segments.

Descriptive Statistics

The 8-month-period data contains 4192 freeway segments with the total length of these segments representing 796 mi. Figure 3 shows the frequencies of crash injury types for April–November of each year (2018–2020). Five injury types are shown in the graphic. B, C, and O crashes increased from 2018 to 2019 and decreased from 2018 or 2019 to 2020. This outcome is probably because of the low traffic volume from the travel restrictions and WFH culture in 2020. Both K and A crashes decreased from 2018 to 2019. Incapacitating injury crashes (A) also decreased in 2020. However, fatal crashes (K) increased in 2020 when compared with 2018 or 2019. By considering VMT in the analysis, it is found that KA crashes per million VMT have increased by 25% and 26% in 2020 when compared with 2018 and 2019, respectively.

Table 4 lists the descriptive statistics of the key variables by year. The descriptive statistics of the geometric variables (e.g., length, shoulder width) remain the same for each year. The speed measures and traffic volume measures differ by year. The results show that traffic volume (AADT) decreased in 2020. The speed measure values show that 2020 experiences higher speed values compared to 2018 and 2019.

Table 4. Descriptive Statistics of the Key Variables

	2018 (April–November)				2019 (April–November)				2020 (April–November)			
Attribute	Mean	Min.	Median	Max.	Mean	Min.	Median	Max.	Mean	Min.	Median	Max.
KABC[a]	0.851	0.00	0.001	20.000	0.866	0.00	0.001	18.00	0.693	0.00	0.001	25
SpdAve	61.62	41.05	62.61	68.97	62.31	39.85	63.18	71.04	64.45	47.82	65.14	74.85
SpdStd	8.16	2.57	7.15	22.05	8.54	3.36	7.62	22.95	6.40	3.01	5.83	16.12
Spd85	67.45	52.00	68.00	74.00	68.48	52.00	69.00	78.00	69.09	58.00	69.00	83.00
SpdAveDay	60.43	33.40	62.04	68.94	61.04	30.64	62.46	70.97	64.03	43.93	65.01	75.09
SpdAveNight	63.00	43.08	63.54	69.03	63.80	44.68	64.28	71.51	64.96	48.53	65.55	74.33
SpdAveMTWT	61.04	39.65	62.24	68.81	61.58	38.71	62.70	70.76	64.05	47.33	64.78	73.42
SpdAveFSS	62.48	42.98	63.25	69.28	63.37	41.42	64.08	71.80	65.04	48.65	65.69	76.55
AADT_Tr1[b]	11.64	2.89	11.59	28.20	11.61	2.45	11.89	29.30	11.61	2.45	11.89	29.30
AADT1[c]	107.82	26.18	95.98	267.13	108.28	24.90	95.70	263.94	63.97	6.07	75.86	106.61
MWid[d]	28.05	1.00	28.00	248.00	28.05	1.00	28.00	248.00	28.05	1.00	28.00	248.00
LWid[e]	11.90	10.00	12.00	12.00	11.90	10.00	12.00	12.00	11.90	10.00	12.00	12.00
N_Lanes[f]	5.94	4	6	11	5.94	4	6	11	5.94	4	6	11
SWidI[g]	14.39	0.00	14.00	24.00	14.39	0.00	14.00	24.00	14.39	0.00	14.00	24.00
SWidO[h]	20.67	4.00	20.00	30.00	20.67	4.00	20.00	30.00	20.67	4.00	20.00	30.00
Seg_Len[i]	0.19	0.01	0.13	2.28	0.19	0.01	0.13	2.28	0.19	0.01	0.13	2.28

Note: Min. = minimum; Max. = maximum.
[a]KABC = fatal and injury crashes; [b]AADT_Tr1 = Truck AADT/1000 (vehicles per day [vpd]); [c]AADT1 = AADT/1000 (vpd); [d]MWid = median width (ft),[e]LWid = lane width (ft), [f]N_Lanes = number of lanes, [g]SWidI = shoulder width—inside (ft); [h]SWidO = shoulder width—outside (ft); [i]Seg_Len = segment length (mi).

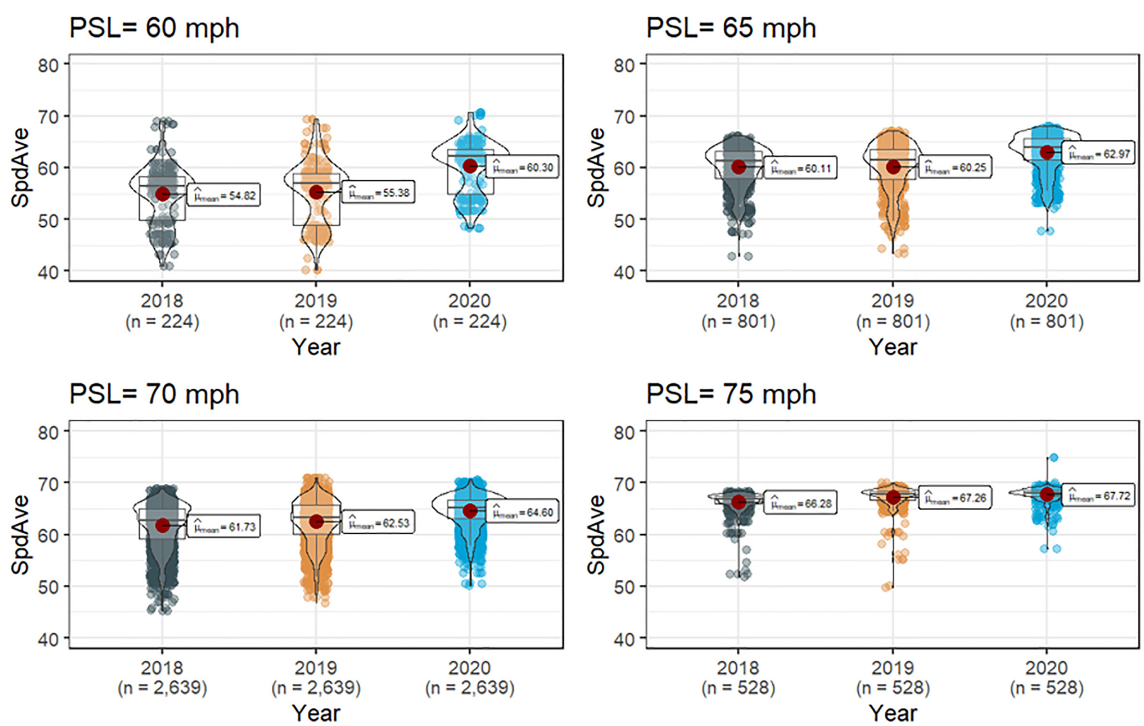

Figure 4. Violin plots showing distribution of operating speeds (average speed) by year and posted speed limit.
Note: PSL = posted speed limit.

Results

R software (https://www.r-project.org) was used for all statistical analyses. The library "ggstatsplot" was used for comparing average operating speed and standard deviation of operating speed measures by year for different posted speed roadways (*27*).

Operating Speed Comparisons by Year Within Posted Speed Limit Groups

Figure 4 shows the distribution of average speeds (in violin and boxplot format) by year for different PSLs. The display of *p*-measures (only statistically significant *p*-measures are shown on the top of each plot) indicates that operating speed varies by year for most of the combinations. From Table 5, it is seen that the in-between yearly differences are not significant for all combinations (for example, 2018 versus 2019, 2019 versus 2020, and 2018 versus 2020). For example, the differences between the speed distributions of 2018 and 2020 and between 2019 and 2020 are statistically significant (for 60 mph roadways). However, this difference is not statistically significant between 2018 and 2019 (for 60 mph roadways). It is also seen that the differences between the speed distributions of 2018 and 2020 and between 2019 and 2020 are statistically significant for all PSLs (except 75 mph roadways). For 70 mph roadways, the differences between speed distributions for all combinations (i.e., 2018 versus 2019, 2019 versus 2020, and 2018 versus 2020) are statistically significant. Note that the 2020 mean operating speed for all PSLs is higher compared to 2018 and 2019. For example, for 75 mph roadways, 2020 has a significantly higher mean operating speed (μ = 64.60 mph) in comparison to the 2018 (μ = 61.73 mph) and 2019 (μ = 62.53 mph) mean operating speed values. Another observation is that the difference between the range of mean operating speed for 2020 versus 2018 or 2019 for 75 mph roadways is narrower when compared with other PSLs.

Figure 5 shows the distribution of the standard deviation of operating speed by year for different PSL roadways. The Table 5 results indicate that the standard deviation of operating speed varies by year for most combinations. The in-between differences are not significant for all combinations. For example, the differences between the standard deviation of speed distributions of 2018 and 2020 and 2019 and 2020 are statistically significant (for 60 mph roadways). However, this difference is not statistically significant between 2018 and 2019 (for 60 mph roadways). It is interesting that the differences between the speed distributions of 2018 and 2020 and

Table 5. Comparison of Speed Measures by Posted Speed Limit

Posted speed limit (mph)	Mean operating speed (mph)			Difference in mean operating speed between years (mph)		
	2018	2019	2020	2019–2018	2020–2019	2020–2018
60	54.82	55.38	60.30	0.56	**4.92**	**5.48**
65	60.11	60.25	62.97	0.14	**2.72**	**2.86**
70	61.73	62.53	64.60	**0.80**	**2.07**	**2.87**
75	66.28	67.26	67.72	**0.98**	0.46	**1.44**
Posted speed limit (mph)	**Standard deviation of operating speed (mph)**			**Difference in standard deviation of operating speed between years (mph)**		
	2018	2019	2020	2019–2018	2020–2019	2020–2018
60	11.87	11.68	7.68	−0.19	**−4.00**	**−4.19**
65	8.90	9.17	6.94	0.27	**−2.23**	**−1.96**
70	8.23	8.69	6.49	**0.46**	−2.20	−1.74
75	5.16	5.49	4.62	0.33	**−0.87**	**−0.54**

Note: Bold numbers/shaded cells are statistically significant.

2019 and 2020 are statistically significant for 60, 65, and 75 mph roadways. For 70 mph roadways, the difference between the standard deviation of operating speed distribution is significant for only 2018 versus 2019. Note that the 2020 standard deviation of operating speed for all PSL roadways is lower compared to 2018 and 2019. For example, for 75 mph roadways, 2020 has a significantly lower standard deviation of operating speed (μ = 7.68 mph) in comparison to the 2018 (μ = 11.87 mph) and 2019 (μ = 11.68 mph) mean operating speed values. Another observation is that the difference between the standard deviation of operating speed decreases in values with the higher PSL roadways.

Figure 6 shows cumulative distribution plots of operating speeds by the PSL. Three S-curves in each of the PSL subgroups represents the cumulative distribution of the operating speeds for each of the study years. The graph clearly shows that operating speeds in 2020 are higher than in 2018 or 2019, especially for 60, 65, and 70 mph PSL roads. For 75 mph PSL roads, this difference is not discernible.

The results of the statistical analysis performed in this section answers the first research question (RQ1), "are operating speeds higher on freeways during 2020 as compared to previous years?". The results show that average operating speeds in 2020 are higher on freeways as compared to previous years. One important contribution of this study is that this research question is answered by considering data from four different PSLs on freeways.

Variable Selection for Modeling of KABC Crashes

Figure 7 (variable codes can be found in Tables 3 and 4) displays the correlation plot of the selected variables. It provides a visual display to identify correlated variables to aid in selecting variables for the modeling process. The plot clearly shows that segment length (Seg_Len), traffic volumes (AADT1, and AADT_Tr1), number of lanes (N_Lanes), lane width (LWid), inside shoulder width (SWidI), and standard deviation of operating speed are positively correlated with KABC crashes. The first row of the correlation plot clearly shows that operating speed measures for different temporal clusters (i.e., daytime, nighttime) have similar correlation patterns (for example, average operating speed [SpdAve] is negatively associated with the KABC crashes). Variables with the highest correlation measures have been considered for final analysis.

Safety Performance Functions

A common issue of safety data modeling is the presence of many zero crash frequencies. The negative binomial (NB) model can somewhat address this challenge, and can be shown as follows:

$$\ln(\lambda_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_q x_{qi} + \varepsilon_I \quad (1)$$

where λ_i is the estimated number of crashes per year at segment i, x_q is a set of the independent variables at segment i, β_q is the regression coefficients estimated from the dataset, and ε_i is a gamma distributed error term with mean 1 and overdispersion parameter α.

The NB distribution of the number of crashes can be written as follows:

$$P(y_i|\lambda_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})}\left(\frac{1}{1+\alpha\lambda_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right)^{y_i} \quad (2)$$

where $P(y_i|\lambda_i)$ is the probability of y_i crashes at segment i.

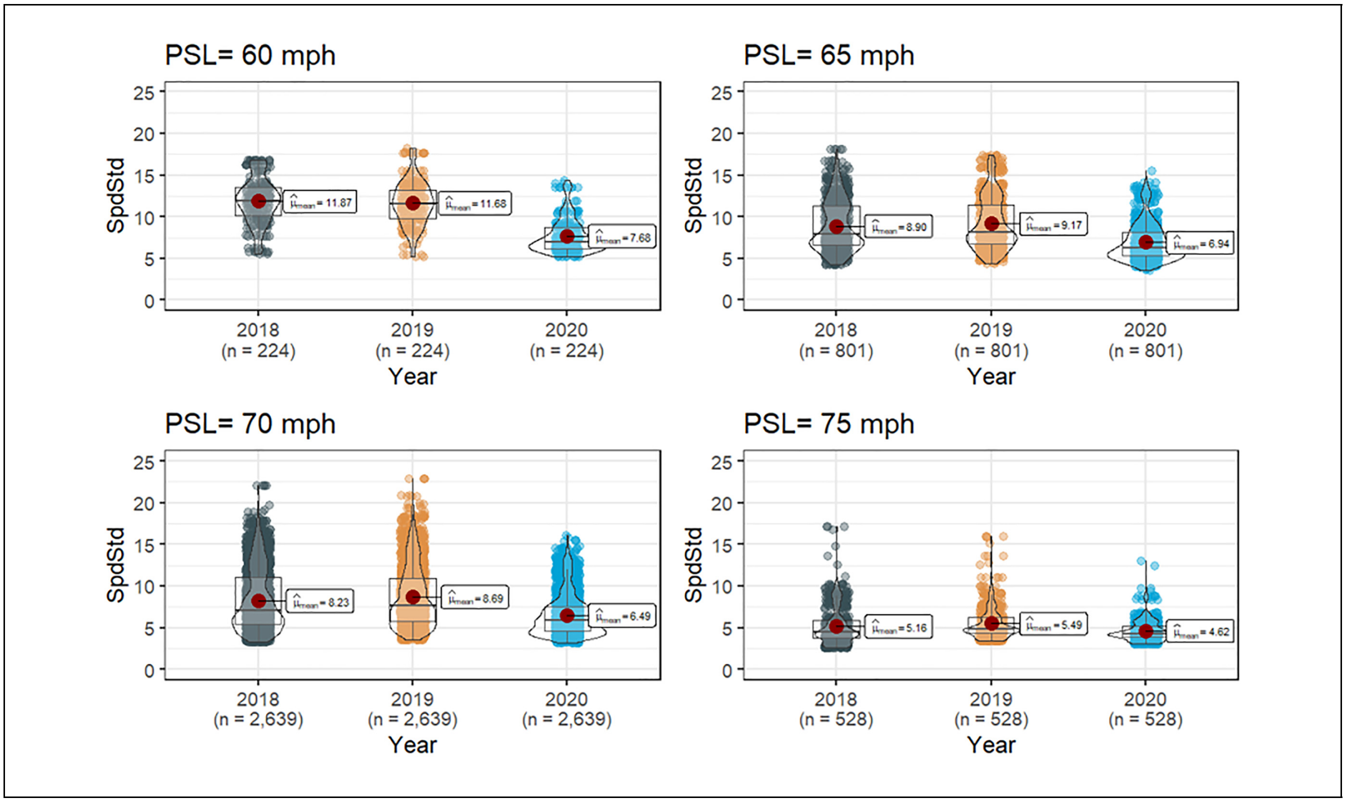

Figure 5. Violin plots showing distribution of operating speeds (standard deviation) by year and posted speed limit (PSL).

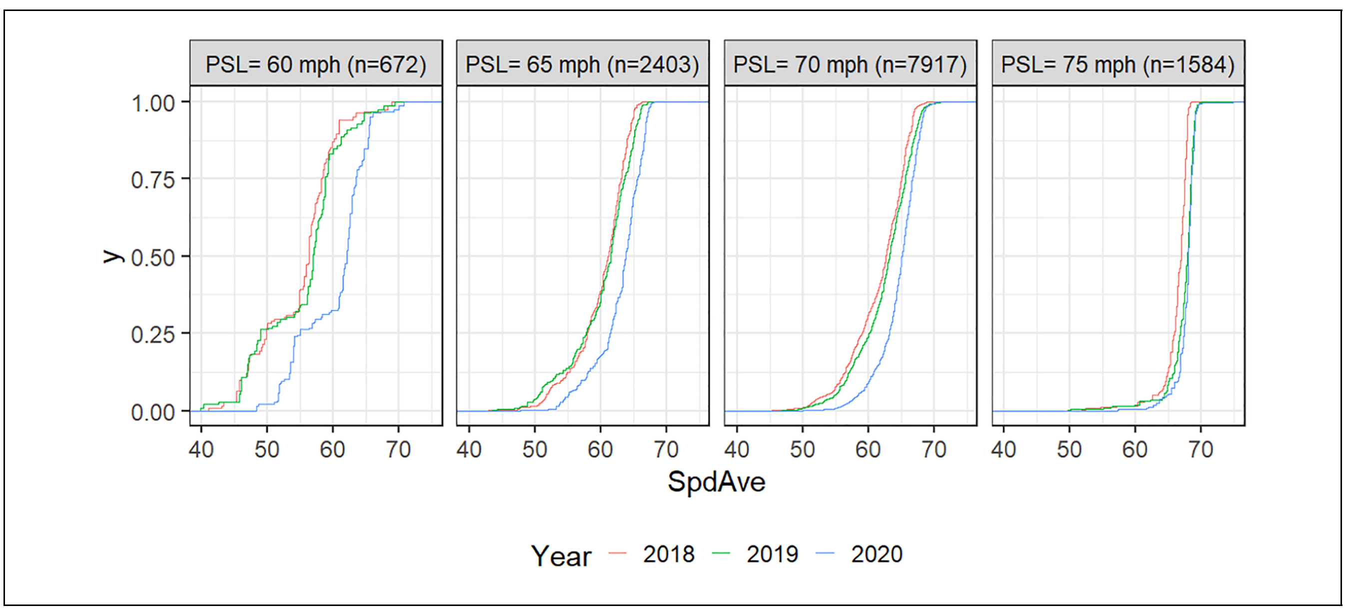

Figure 6. Cumulative speed plots by posted speed limit (PSL).

Mixed-effect Modeling

This study applied generalized linear mixed-effects models (GLMMs) to develop the safety performance functions for the 8-month dataset and daily dataset. GLMMs can incorporate both fixed and random effects. GLMMs are an extended version of linear mixed models to allow response variables from different distributions. GLMMs are chosen in this study as these models can provide the best combination of independent variables for estimating

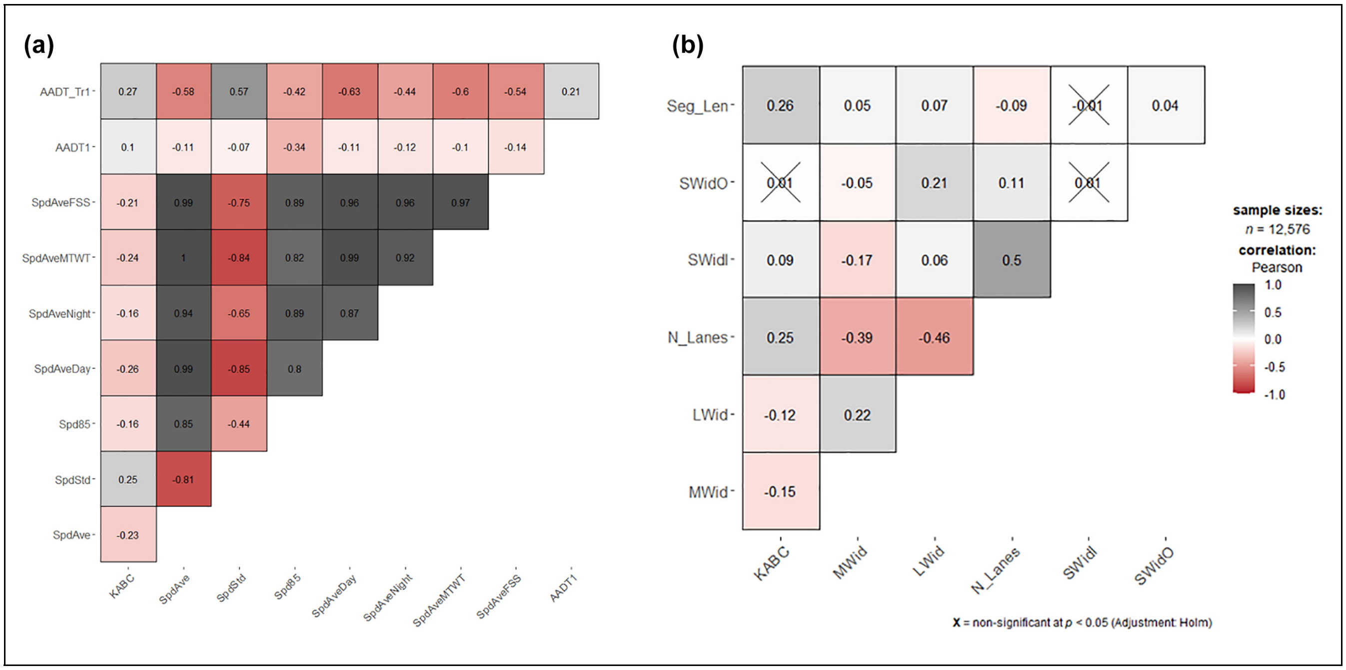

Figure 7. Correlation plots: (a) correlation plot and (b) correlation plot with Pearson value.
Note: KABC = fatal and injury.

the expected crash frequencies. The coefficients for the major variables (for example, geometric variables and speed measures) are considered as fixed effects. These variables are designed as the long-term underlying parameter. On the other hand, random effect variables contain observed realizations of these variables. The variability explained by the random effect variables is suitable for quantifying the variability explained by the independent variable of interest. Mixed effects can also handle the analysis of repeated measures. For example, the TMC segments were re-segmented because of the conflation procedure, and clustering the TMC IDs as the random effect variable can provide the significance of clustering by TMC ID. The modeling framework is $N \sim f$(geometric variables, exposure, operating speed measures, year), where N indicates KABC crash frequencies at the 8-month or daily level. The number of crashes is considered to follow a NB model. The independent variables include geometric variables (e.g., number of lanes, median width), exposure (e.g., annual traffic volume and annual truck volume), operating speed measures (e.g., average operating speed, the standard deviation of operating speed), and year (e.g., 2019, 2020).

Models Developed for 8-month Data

The 8-month data models were based on geometric variables, traffic volume, and speed measures for different temporal clusters. This study explored the following models (see Table 6):

1. Model 1: all PSL (2018–2020) model;
2. Model 2: 65 mph (2018–2020) model;
3. Model 3: 70 mph (2018–2020) model;
4. Model 4: 75 mph (2018–2020) model;
5. Model 5: all PSL (2020 only) model.

The results from the generalized linear mixed model are shown in Table 6. The estimations in Table 6 were obtained by restricted maximum likelihood. Segment ID (TMC) has been considered as the random effect variable. AADT1 and AADT_Tr1 variables are scaled by dividing the original AADT and AADT_Tr values by 1000 as an effort of normalization.

Geometric Variables. For 8-month models, several geometric variables, such as segment length, number of lanes, and lane width, were included. Segment length was the only geometric variable that was statistically significant for all models. The coefficient of segment length is positive for all models. The number of lanes is statistically significant for two models (Models 1 and 3). Lane width is negatively associated with KABC crash frequencies. This variable is statistically significant for Models 1, 3, and 4. For the 2020 model, only one geometric variable is statistically significant, which is segment length.

Table 6. Model Coefficient for 8-month Models

Variables	Model 1: All PSL (2018–2020) Estimate	Std.	*p*-Value	Model 2: 65 mph (2018–2020) Estimate	Std.	*p*-Value	Model 3: 70 mph (2018–2020) Estimate	Std.	*p*-Value	Model 4: 75 mph (2018–2020) Estimate	Std.	*p*-Value	Model 5: All PSL (2020 only) Estimate	Std.	*p*-Value
Fixed effects															
(Intercept)	5.530	1.460	**0.000**	10.12	6.02	**0.093**	5.969	1.824	**0.001**	19.570	6.090	**0.002**	−4.464	0.878	**0.000**
Seg_Len	2.317	0.072	**0.000**	3.26	0.19	**0.000**	2.689	0.099	**0.000**	0.665	0.068	**0.000**	2.767	0.112	**0.000**
AADT1	0.002	0.000	**0.000**	0.00	0.00	0.966	0.003	0.000	**0.000**	0.003	0.001	**0.001**	0.010	0.001	**0.000**
N_Lanes	0.164	0.021	**0.000**	0.01	0.05	0.879	0.218	0.028	**0.000**	0.019	0.083	0.815	NA	NA	**NA**
LWid	−0.314	0.101	**0.002**	−0.67	0.48	0.167	−0.248	0.112	**0.027**	−1.260	0.553	**0.024**	NA	NA	**NA**
SpdAve	−0.041	0.010	**0.000**	−0.05	0.02	**0.013**	−0.043	0.014	**0.003**	−0.064	0.038	**0.090**	0.044	0.012	**0.000**
SpdStd	0.032	0.012	**0.009**	0.02	0.03	0.440	0.030	0.016	**0.064**	0.065	0.022	**0.004**	0.125	0.015	**0.000**
PSL65	0.629	0.176	**0.000**	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PSL70	0.643	0.163	**0.000**	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PSL75	0.255	0.199	0.201	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
AADT_Tr1	0.028	0.008	**0.000**	0.06	0.02	**0.001**	0.018	0.009	**0.050**	−0.026	0.031	0.401	NA	NA	NA
Year2019	0.030	0.032	0.347	0.02	0.07	0.798	0.028	0.043	0.515	0.002	0.060	0.972	NA	NA	NA
Year2020	0.088	0.037	**0.017**	0.12	0.09	0.170	0.085	0.048	**0.078**	−0.024	0.066	0.712	NA	NA	NA
	Variance	Std.	NA	Variance	Std.	NA	Variance	Std.	NA	Variance	Std.	NA	Variance	Std.	NA
Random effects															
TMC (Intercept)	1.434	1.197	NA	1.384	1.176	NA	1.531	1.237	NA	0.7563	0.8697	NA	0.550	0.7416	NA
Residual	1.927	1.388	NA	1.893	1.376	NA	1.973	1.405	NA	0.4844	0.6960	NA	1.918	1.3850	NA
No. of obs	12574	NA	NA	2403	NA	NA	7915	NA	NA	1584	NA	NA	4192	NA	NA
TMC	1509	NA	NA	345	NA	NA	941	NA	NA	154	NA	NA	1509	NA	NA
REML	46694.6	NA	NA	8958.2	NA	NA	29618.2	NA	NA	3789.3	NA	NA	15467.2	NA	NA
Median residuals	−0.0946	NA	NA	−0.1227	NA	NA	−0.0793	NA	NA	−0.0789	NA	NA	−0.0927	NA	NA

Note: TMC = traffic message channel (segment); REML = restricted (residual) maximum likelihood estimation; PSL = posted speed limit.
Bolded number of p-values are significance level equal or lower than 0.10. '-' means not available.

Traffic Volume. Two traffic volume measures were used in the model development: AADT1 and AADT_Tr1. AADT1 is statistically significant for all models except Model 2. Note that Model 2 relies on three major variables (segment length, truck volume (AADT_Tr1), and SpdAve). The coefficient of length and AADT_Tr1 are higher compared to the other models. Based on the data properties of Model 2, the impact of AADT is captured by length or AADT_Tr1. AADT_Tr1 is statistically significant for three models: Models 1–3. The coefficients are positive for both of these measures, which is in line with the majority of safety analysis studies.

Speed Measures. Out of several operating speed measures, two influential speed measures (average and standard deviation of operating speed) were selected for final analysis. Except Model 5 (the 2020 only model), average operating speed (SpdAve) is negatively associated with KABC crashes, indicating that higher operating speeds on urban freeways are associated with fewer KABC crashes when including data for 2018–2020 (i.e., both pre-COVID and COVID periods). Operating speed increase is usually not associated with a higher number of crashes because urban freeways have high design standards. Few studies (for example [*10, 13*]) show similar findings.

Model 5 focused only on the COVID period and found that the association between average operating speed and KABC crashes was positive, indicating that higher operating speeds and comparatively low traffic volume (caused by pandemic-related travel restrictions and the WFH culture) are associated with more KABC crashes on freeways. The standard deviation of operating speed is positively associated with KABC crashes, indicating more KABC crashes are associated with greater variability in operating speed (e.g., larger standard deviations).

For all models, greater variability in operating speed (e.g., larger standard deviations) are associated with more KABC crashes. This variable is not statistically significant for Model 2, perhaps because of the smaller sample size.

The PSL is considered as a variable for Model 1. Considering 60 mph roadways as the base, it shows that higher PSL roadways are associated with more KABC crashes.

In addition, the year was considered as a variable for Models 1–4. The year 2020 is statistically significant for Models 1 and 3. The sign of the coefficient is positive, which indicates that 2020 is associated with more KABC crashes when compared with 2018.

The second research (RQ2) question asked, "Are higher operating speed measures associated with more KABC crashes during 2020 after consideration of other influential factors?," which is answered in this section. It demonstrated that more KABC crashes are associated with higher average operating speeds and larger standard deviations for speed during 2020 (the COVID period).

Models Developed for Daily-level Data

This study also developed daily-level models to answer research question 3 (RQ3), "Are 5-minute operational speed measures more useful for assessing the speed–crash relationship when analyzed at a 24-hour (daily) interval rather than annually?". The 8-month-level dataset contains speed measures as an aggregate for the 8-month period. Such aggregation is often not sufficient to examine the impact of operational factors such as speed. To mitigate this issue, this study also developed a daily-level database that includes operating speeds and KABC crashes at the daily level. The daily-level dataset includes geometric variables similar to the 8-month-level dataset.

Because of the data structure, this process generated a dataset with extreme zero-inflation problems. No conventional statistical model can handle count data regression with over 99.5% zero counts as the response variable. To resolve this issue, this study designed a matched pair dataset. Segments experiencing KABC crashes were temporally matched with the same segment with the same day of the week and with no KABC crash occurrences. A range of four weeks before or after was considered to determine the matched pair entries. The daily-level modeling framework is logistic in nature. The daily-level analysis explored four different models (see Table 7):

1. Model 1: all PSL (2018–2020) model;
2. Model 2: 65 mph (2018–2020) model;
3. Model 3: 70 mph (2018–2020) model;
4. Model 4: 75 mph (2018–2020) model.

Daily-level models used several variables, such as VMT, geometric variables (median width, shoulder width, and the number of lanes), speed measures (daily average operating speed or SpdAveDaily, and standard deviation of daily operating speed or SpdStdDaily), and temporal variables (i.e., 2018). The traffic exposure measure VMT is not statistically significant. A more precise and disaggregate traffic volume, such as traffic volume on the day considered for analysis, can provide more insights on traffic volume and KABC crash association at the daily level; however, such a level of data was not readily available. The median width and number of lanes are statistically significant for two of the models (Models 1 and 3). Shoulder width is not statistically significant in any of the models. The year 2020 shows a positive association with KABC crash occurrences for three models,

Table 7. Model Coefficient for Daily-level Models

Variables	Model 1: All PSL (2018–2020) Est.	LL	UL	Model 2: 65 mph (2018–2020) Est.	LL	UL	Model 3: 70 mph (2018–2020) Est.	LL	UL	Model 4: 75 mph (2018–2020) Est.	LL	UL
Fixed effects												
(Intercept)	−2.937	**−3.516**	**−2.359**	−2.725	**−4.219**	**−1.232**	−3.009	**−3.832**	**−2.185**	−8.624	**−13.135**	**−4.112**
VMT	−0.003	−0.007	0.000	−0.003	−0.013	0.007	−0.003	−0.007	0.001	−0.004	−0.024	0.017
SpdAveDaily	0.031	**0.023**	**0.039**	0.023	**0.003**	**0.042**	0.033	**0.022**	**0.044**	0.104	**0.045**	**0.162**
SpdStdDaily	0.124	**0.114**	**0.134**	0.123	**0.100**	**0.147**	0.124	**0.111**	**0.137**	0.249	**0.192**	**0.306**
MedW	0.002	**0.001**	**0.003**	0.002	−0.001	0.005	0.003	**0.001**	**0.004**	−0.006	−0.015	0.002
N_Lanes	−0.029	**−0.052**	**−0.006**	−0.020	−0.082	0.042	−0.041	**−0.071**	**−0.012**	−0.104	−0.282	0.073
SWidI	0.004	−0.001	0.009	0.005	−0.007	0.017	0.004	−0.001	0.010	−0.013	−0.074	0.048
SWidO	0.000	−0.011	0.011	0.011	−0.012	0.034	−0.003	−0.017	0.011	0.050	−0.072	0.172
Year2019	−0.041	−0.108	0.026	−0.022	−0.178	0.135	−0.060	−0.143	0.023	−0.051	−0.367	0.264
Year2020	0.256	**0.182**	**0.331**	0.248	**0.081**	**0.416**	0.258	**0.165**	**0.351**	0.205	−0.156	0.566
	Var.	NA	NA	Var.	NA	NA	Var.	NA	NA	Var.	NA	NA
Mixed effects												
UniqID (intercept)	0.000	NA	NA	0.000	NA	NA	0.000	NA	NA;	0.000	NA	NA
PSL (intercept)	0.053	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
No. of obs	20387	NA	NA	3870	NA	NA	13316	NA	NA	985	NA	NA
UniqID	2352	NA	NA	483	NA	NA	1452	NA	NA	198	NA	NA
PSL	4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
AIC	27411	NA		5219	NA		17891	NA		1261	NA	
BIC	27506	NA	NA	5288	NA	NA	17973	NA	NA	1315	NA	NA
LogLik	−13693	NA	NA	−2598	NA	NA	−8934	NA	NA	−619	NA	NA

Note: PSL = posted speed limit; VMT = vehicle miles traveled; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; UL= upper limit; LL = lower limit; NA = not available. Bolded number of p-values are significance level equal or lower than 0.10.

excluding Model 4. Both speed measures (daily average operating speed or SpdAveDaily, and standard deviation of daily operating speed or SpdStdDaily) showed positive and statistically significant association with KABC crash occurrences. The findings are in line with the Das and Geedipally (*11*) study. This observation is found when compared with the 8-month-level data. The literature review section shows that many studies were not able to determine a conclusive association between crash and speed because of the study design, data aggregation, and data availability. The daily-level analysis shows that daily-level KABC crash occurrence is associated with higher operating speed measures at the daily level. These findings answer RQ3 by providing evidence that additional granular-level data analysis can provide more insights on speed–crash association.

Conclusions

In recent years, several studies explored the association between operating speed and traffic crashes (*28–32*). However, in-depth investigation on this issue during COVID-19 is still limited. This study explored how operating speeds on freeways changed during the pandemic and how this change affected the frequencies of KABC crashes. Two datasets were developed, an 8-month dataset and a daily dataset (April–November). The data were obtained from several sources for the years 2018–2020. Three research questions were explored, namely, (1) were operating speeds higher on freeways during 2020, (2) were those higher operating speed measures associated with more KABC crashes, and (3) were 5-min operational speed measures more useful for assessing the speed–crash relationship when analyzed at a 24-h (daily) interval rather than annually?

The key results are listed below.

- The results show that operating speed in 2020 is statistically significantly higher than the other two years; however, these differences vary by the PSL.
- The results of mixed-effect modeling confirmed that the uptick of operating speed measures in 2020 is associated with a higher number of KABC crashes. The 8-month model with consideration of all PSLs for Dallas freeways (60, 65, 70, and 75 mph) and consideration of the 3-year period (2018–2020) shows that the coefficient of average operating speed is small and negative in value.
- As freeways are of high design standards, an increase in operating speed may not be associated with higher crash frequencies. Interestingly, during this pandemic (2020 only model), the finding changes in those higher average operating speeds are associated with a statistically significant increase in KABC crash frequencies.
- The daily-level analysis also shows that daily-level operating speed measures were positively associated with KABC crash occurrences, indicating that higher operating speeds are associated with more crashes. The changing impact of this operating speed variable on the fatal and severe crash occurrences during COVID provides transportation researchers and practitioners new perspectives of the relationship of driving behavior (operating speed) and crashes.

Information from other sources have shown that in addition to higher operating speeds, drivers during the pandemic were associated with more risky behaviors, including lower seat belt use (resulting in more ejections from vehicles) and driving while impaired. The National Highway Traffic Safety Administration (NHTSA) reported that driving patterns and behaviors in the U.S.A. changed significantly during COVID-19, and of the drivers who remained on the roads, some engaged in riskier behavior (*33*). These behaviors include speeding (where average speeds increased during Quarters 2 and 3 in 2020), failure to wear seat belts based on an increase in the ejection rate in most of 2020 after week 10 of the COVID-19 public health emergency, and almost two-thirds of seriously or fatally injured drivers tested positive to be impaired between mid-March and mid-July of 2020, whereas the opioid-related positivity rate nearly doubled after mid-March when compared with the prior six months.

These riskier behaviors were exasperated, in part, by the likelihood of decreased traffic enforcement, as law enforcement agencies changed their response protocols and shifted priorities during the pandemic because of the increase in 911 calls and challenges in resource management of finance, personnel, and personal protection equipment (PPE) (*34*). The Vera Institute of Justice (*35*) provided seven key guidance points on preemptive and approachable measures for enforcement officers, including “limit police response to low-risk incidents to focus on critical incidents and community health needs (such as traffic stops, noise complaints, etc.).” This guidance was in line with the initial sentiment where officers grew more uncomfortable/hesitant being around, or close to, persons who break social distancing protocols because of concern for their own health.

While this research provided more detailed understanding of the relationship between speed and crashes, the current study has some limitations. The current analysis is limited to KABC crashes only. Future studies are needed for examining other severity groups, such as K crashes, KA crashes, KAB crashes, and KABCO crashes. The current data collection is limited to 8 months. This study used only 8 months of data because of the availability of crash data until November of 2020 (when the study was conducted). Consideration of additional months and years could make the study findings more insightful. The result of this analysis is not transferable unless the freeway and traffic characteristics are similar to those included in this study.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Das, and M. Le; data collection: M. Le, S. Das, and D. Wu; analysis and interpretation of results: S. Das, K. Fitzpatrick, and M. Le; draft manuscript preparation: S. Das, M. Le, K. Fitzpatrick, and D. Wu. All authors reviewed the results and approved the final version of the manuscript.

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