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Short-Duration Crash Modeling to Understand the Impact of Operating Speed on Freeway Crashes During COVID-19

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Abstract

Gaining an understanding of speed–crash relationships is a critical issue in highway safety research. Because of the ongoing pandemic (COVID-19) there has been a reduction in traffic volume, and some early studies explain that speeding in an environment with less traffic is associated with a high number of crashes, especially fatal and serious injury crashes. This study aims to quantify the impact of operating speed on traffic crash occurrences. The study conflated several databases (speed data, roadway inventory data, and crash data) that contain data from Dallas, Texas, spanning from 2018 to 2020, to examine the speed–crash association. Using the negative binomial Lindley regression model, this study showed that the trends of crash prediction models vary over the years (2018, 2019, and 2020) by different injury severity levels (i.e., fatal crashes, fatal and incapacitating injury crashes). The 2020 models show that operating speed measures (i.e., average operating speed) have a significant impact on crash frequencies. The magnitudes of the speed measures show variations across the models at different injury severity levels.

Keywords

data and data science, safety, planning and analysis, safety plan, safety, *Highway Safety Manual*

To address the ongoing COVID-19 pandemic and mitigate the spreading of the coronavirus, many policies have been implemented in the U.S.A., including "shelter-in-place" orders, halting non-essential business operations, limiting gathering sizes, and banning non-essential travel (*1*). Inevitably, these mitigation measures affected every aspect of people's lives, including travel behavior. Some studies examined the impact travel restrictions on safety issues during COVID-19. During March and April of 2020, the significant drop in traffic volumes across the U.S.A. was historical and unprecedented (*2*, *3*). Unfortunately, lower traffic volumes and fewer traffic crashes do not indicate a higher level of safety on these roadways. As the traffic volume dropped, higher travel speeds were encouraged (*4*). Many travel reports from various states in the U.S.A. reported statistics indicating increasing travel speed and increasing fatal crashes on their roadways (*5*). For example, in Connecticut, the traffic volume has been cut in half. Compared to the same time period of previous years, there was a 90% increase in cars speeding over 15 mph of the speed limit and a 40% increase in fatal crashes (*5*). The California Highway Patrol also reported an 87% increase in cars speeding over 100 mph from mid-March to mid-April of 2020 (*6*). High speed is considered a risk factor of being involved in a crash, particularly more severe crashes (*7*). However, crashes are affected by many factors other than speed, including complicated psychosocial reasons. Rella Riccardi et al. (*8*) analyzed the relationship between crash involvement and driver psychological state. The results showed that drivers with a high level of stress, sleep deprivation, or both, had a higher risk of crash involvement. Rella Riccardi et al. (*9*) investigated the relationship between driver stress and crash risk. The

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results showed that drivers who reported high levels of stress had a higher risk of crash involvement. The increased stress and anxiety, more idle time, greater opportunities for speeding and stunt driving, and increased use of drugs and alcohol because of the pandemic could have the opposite effect on road safety.

A few studies explored the severity injury patterns during COVID-19. Gao et al. (*4*) analyzed crash data from New York City and found that the number of fatalities has increased during the pandemic, even though the number of crashes has decreased. A study in Japan also indicated similar findings by showing that the number of collisions decreased, while the number of fatalities increased during the pandemic. Stiles et al. (*10*) investigated the changes to crash type, timing, and severity on urban roads as a result of COVID-19 stay-at-home policies, which resulted in lower volumes and higher speeds. The results showed that while the overall number of crashes decreased, the severity of crashes increased, and there was a shift in crash timing and type. The authors concluded that the changes in crash characteristics were likely caused by the combination of lower volumes and higher speeds on urban roads during the COVID-19 pandemic. These results indicate that the drivers who continued driving during the pandemic were more likely to be involved in speed-related collisions, especially on uncongested roadways, which could encourage or trigger speeding behavior (*11*). By the same token, the French Road Safety Observatory (*12*) recently reported a 75.6% reduction in fatal and injury crashes in April 2020, but only a 55.8% reduction in fatal crashes, compared to April 2019. Similar results were observed in the Netherlands as well (*13*). Results showed that even though a 50% decrease was observed in crash frequency per year, the number of road victims per accident increased by 14% during the pandemic. Qureshi et al. (*14*) determined that the number of property damage only (PDO) and minor injury crashes decreased during the pandemic. However, the difference in the frequency of fatal and severe crashes compared with the previous year's data was not statistically significant (*14*). The study period could have potentially affected the study results. Some published studies used only March and April data and reached different conclusions. For example, a study conducted by Katrakazas et al. (*15*) concluded by only using March 2020 crash data that the total number of crashes and the number of fatal crashes both decreased. In addition to the study period, the study results varied over different states as well. Based on the National Safety Council (NSC) recent reports, 11 states observed an increase in roadway deaths (6%–42%) within the first three months of 2020; however, eight states showed fewer fatal collisions (4%–32%) (*16*). Shilling and Waetjen (*17*) used California Highway Incident Processing System (CHIPS) and California Highway Patrol incident reports to estimate the impact of the Governor's "shelter-in-place" order on the reduction of traffic crashes on rural roads and state highways. The authors estimated that total and fatal/injury crashes decreased by approximately 50% per day since the order was put in place. This is presumably because of the reduction of traffic volumes (60% lower on certain highways). Owen et al. (*18*) investigated the relationship between traffic flow and vehicle speeds during the COVID-19 pandemic (specifically March and April 2020) using data from automated traffic counters (ATCs) collected from 91 permanent survey sites in England with a variety of speed limits. The operating speed changes observed showed variation based on the speed limit, with larger decreases on rural single carriageway roads that had a 60-mph limit. Changes in average speeds of between + 0.85 and + 2.23 mph were indicated by the results when the model was transformed for flow. An analysis of the highest-speed offenders showed a greater proportional increase in people traveling 15 mph above the speed limit, with higher-speed roads showing larger shifts.

Understanding the association between exposures and traffic crashes is an important topic. Some studies used innovative data sources to examine this association. Vingilis et al. (*19*) used an interactionist model to identify research questions to consider potential factors that could affect road safety during the pandemic. Pishue (*20*) analyzed INRIX incident data from major U.S. metropolitan areas before and during the COVID-19 pandemic. The information included was travel speed, vehicle miles traveled (VMT), and collisions for the top 25 metropolitan statistical areas (MSAs). VMT decreased significantly throughout the country with the onset of COVID-19, with major metropolitan areas still yet to recover, which led to higher traffic speeds and decreased congestion. These findings are in line with the Stavrinos et al. (*21*) study where driving behavior before and during the restriction was analyzed. This study indicated that there is a 37% decrease of driving days per week as well as a 35% reduction in VMT among adolescents, who appeared to be less likely to change their driving behavior. Wagner et al. (*22*) reviewed changes in roadway travel and in drivers' behavior since the start of COVID-19 (focusing on the second quarter of 2020) and studied the subsequent impacts on motor vehicle crashes and fatalities. This report worked to provide an understanding of traffic safety environments and to address changes in traffic safety needs. Although there are some similarities with previous economic downturns (such as the financial crisis of 2008), there are also differences, such as the impact on speeding and other dangerous driving behaviors. Doucette et al. (*23*) examined the impact on daily VMT and motor vehicle collisions (MVCs) of

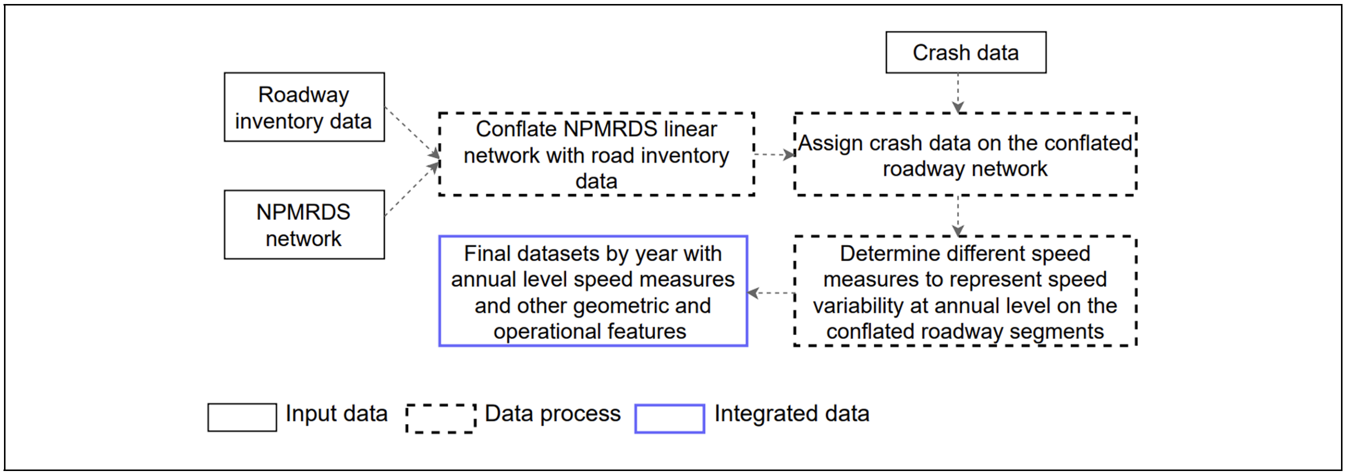

Figure 1. Flowchart of the data preparation.
Note: NPMRDS = National Performance Management Research Dataset.

Connecticut's COVID-19 stay-at-home order. They compared the daily MVCs and VMT using an interrupted time series design both before and during the order. Despite that there was a decrease in daily VMT and multiple-vehicle crashes after the stay-at-home period, there was a rise in the rates of single-vehicle crashes and fatal crashes. Vanlaar et al. (*24*) examined the travel behavior of Canadian drivers in relation to COVID-19 using data based on the Traffic Injury Research Foundation's (TIRF's) Road Safety Monitor. With respect to driving behavior, 5.5% of respondents said they were more likely to speed excessively, 16.9% were less likely to speed excessively, and 77.5% reported no change.

The literature search found that many of the studies are exploratory in nature. Given the variability of results across various study periods as well as study locations, there is a need for advanced statistical models to explore the speed–crash association during COVID-19. The originality of this study lies in its focus on understanding the impact of the COVID-19 pandemic on driving behavior and the subsequent impact on the different severity levels of crashes. This study aims to explore the associations between the traffic characteristics and crashes by examining crash data on freeways in the Dallas, Texas, metro area before and during the pandemic. This research could further contribute to the transportation safety study community. Understanding the fatal and severe injury crash patterns during the pandemic could help transportation agencies to mitigate the ongoing and future impacts of the pandemic on roadway safety. Finally, the most significant and unique contribution of this study is a comprehensive safety assessment framework that provides aspects of short-duration safety modeling using granular operational data.

Methodology

For this study, the research team used three datasets for the freeways of Dallas District: (1) 2018–2020 crash data from 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 following section describes the overall methods for data conflation, traffic volume estimation for 2020, descriptive statistics of the key variables, variable selection, and modeling concepts.

Data Preparation

The data conflation procedure has four steps: Step 1: conflate roadway inventory data and the NPMRDS; Step 2: develop speed measures for conflated segments; Step 3: assign crashes to the conflated segments; and Step 4: develop final merged data.

- Step 1: Conflate the roadway inventory data and NPMRDS. The roadway inventory data for the freeways in the Dallas area were collected from the RHiNO by using appropriate filters (see Figure 1).
- Step 2: Develop speed measures for conflated segments. The research team extracted all freeway NPMRDS segments in the Dallas District. Three years (2018–2020) of speed data were downloaded from the NPMRDS website (https://npmrds.ritis.org/analytics/) for all freeway segments. Only the speed data from April 1 to September 30 were collected for each year. The data collection was

Table 1. Total Crashes and Total Crashes per 100 Million Vehicle Miles Traveled (VMT) by Crash Severity and Year

Year	K	KA	KAB	KABC	KABCO
Total crashes					
2018 (Apr–Sep)	69	282	1249	3030	8660
2019 (Apr–Sep)	56	285	1261	3267	9459
2020 (Apr–Sep)	67	238	1040	2345	7310
Total crashes per 100 million VMT					
2018 (Apr–Sep)	0.911	3.725	16.499	40.025	114.396
2019 (Apr–Sep)	0.737	3.748	16.584	42.967	124.403
2020 (Apr–Sep)	1.321	4.694	20.513	46.252	144.179

Note: KABCO means total crashes with all severity levels (K = fatal; A = incapacitating injury; B = non-incapacitating injury; C = minor injury; O = no injury or property damage only [PDO]).

limited to April–September as traffic exposures were disrupted during these months in 2020 because of COVID-19. After September 2020, the overall VMT has almost reached to the pre-COVID era. To compare the yearly results, data from April–September were used for the years considered. Several speed measures were calculated based on different temporal clusters (e.g., daytime, nighttime, weekday, and weekend) of the speed data. Based on the correlation analysis results (which is not presented here to avoid describing a long list of speed measures that will be redundant for the next steps of this process), two speed measures have been selected for the final analysis:

- ○ SpdAve: Average operating speed by year by considering all 5-min interval operating speed data on the same segment during a particular year;
- ○ SpdStd: Standard deviation of operating speed by year by considering all 5-min interval operating speed data on the same segment during a particular year.

- Step 3: Assign crashes to the conflated segments. Crash data from a three-year period (2018–2020) were collected from the CRIS. The research team only kept crashes from April 1 to September 30 for each year. Crash events were assigned to the RHiNO roadway segment by using the near function in ArcMap. Each crash event is assigned with a RHiNO segment within 10 ft from the crash event. The 10 ft threshold has been determined after several iterations. The researchers developed datasets for several distance thresholds: 50, 25, 20, 15, and 10 ft. The cross-checking of these assignments was meticulously done to see the most optimum threshold. Finally, 10 ft has been considered as the optimum threshold. For each unique RHiNO segment, the research team 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 all three years separately.
- Step 4: Develop the final merged data. The near function in ArcMap was used to assign each RHiNO roadway segment a unique NPMRDS segment. Each RHiNO segment might have multiple segments aligned with it as the NPMRDS contains both directions in the spatial database. The closest RHiNO segment was assigned with one NPMRDS segment. Thus, the near function's input feature is the RHiNO segment, and the near feature is the traffic message channel (TMC) segment. After all RHiNO segments were assigned with TMC segments, three years of speed measure data can be added to the data frame based on the TMC name of each RHiNO. Finally, crash summary data for three years were added to the conflated RHiNO segments.

Descriptive Statistics

Table 1 lists the total crashes and crash rates, or total crashes per 100 million VMT on Dallas freeways. Although the total crash frequencies are lower as compared to the earlier years, the crash rates show that 2020 had a higher crash rate than previous years (for all severity groups) because traffic exposure, or VMT, decreased during COVID-19. This study explored modeling for the different severity groups.

This study used a wide range of geometric variables, traffic volumes, and speed measures to perform the analysis. Table 2 lists the descriptive statistics for the selected variables by year. The descriptive statistics of the geometric variables are the same for all years because the 2019 roadway inventory network was used for all three years. The general finding of Table 2 is that the mean traffic volume in 2020 is smaller than that for other years.

Table 2. Statistics of the Selected Variables (by Year)

Code	Description	Mean	SD	Min.	Max.
2020 Data					
K	Count of K crashes	0.05	0.23	0	2
KA	Count of KA crashes	0.19	0.54	0	7
KAB	Count of KAB crashes	0.81	1.92	0	19
KABC	Count of KABC crashes	1.83	4.1	0	46
KABCO	Count of KABCO crashes	5.7	12.26	0	152
LEN_SEC	Segment length (mi)	0.32	0.43	0	3.67
ADT	Annual daily traffic (vpd)	68,662	38,457	17,672	180,313
NUM_LANES	Number of lanes	5.88	1.83	4	11
SUR_W	Surface width	71.8	22.77	48	144
S_WID_I	Shoulder width inside (ft)	14.6	6.94	0	24
SpdAve	Average operating speed (mi/h)	60.68	13.5	10.45	74.6
SpdStd	Standard deviation of operating speed	6.57	2.77	3.05	21.97
2019 Data					
K	Count of K crashes	0.04	0.2	0	2
KA	Count of KA crashes	0.22	0.6	0	4
KAB	Count of KAB crashes	0.97	2.2	0	21
KABC	Count of KABC crashes	2.51	5.66	0	78
KABCO	Count of KABCO crashes	7.25	15.62	0	203
LEN_SEC	Segment length (mi)	0.32	0.43	0	3.67
ADT	Annual daily traffic (vpd)	102,746	56,966	24,904	263,936
NUM_LANES	Number of lanes	5.88	1.83	4	11
SUR_W	Surface width	71.8	22.77	48	144
S_WID_I	Shoulder width inside (ft)	14.6	6.94	0	24
SpdAve	Average operating speed (mi/h)	58.79	13.6	9.69	71.02
SpdStd	Standard deviation of operating speed	8.3	3.62	3.17	23.18
2018 Data					
K	Count of K crashes	0.05	0.24	0	2
KA	Count of KA crashes	0.22	0.61	0	7
KAB	Count of KAB crashes	0.97	2.21	0	26
KABC	Count of KABC crashes	2.36	5.44	0	77
KABCO	Count of KABCO crashes	6.75	14.05	0	194
LEN_SEC	Segment length (mi)	0.32	0.43	0	3.67
ADT	Annual average daily traffic (vpd)	102,421	57,550	26,180	267,131
NUM_LANES	Number of lanes	5.88	1.83	4	11
SUR_W	Surface width	71.8	22.77	48	144
S_WID_I	Shoulder width inside (ft)	14.6	6.94	0	24
SpdAve	Average operating speed (mi/h)	58.01	13.46	11.23	69.31
SpdStd	Standard deviation of operating speed	8.02	3.75	2.57	23.02

Note: SE = standard deviation; vpd = vehicles per day; Min. = minimum; Max. = maximum; K = fatal; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; and O = not injured and unknown.

Most of the average speed measures in 2020 are higher than 2018 and 2019. Note that this study applied correlation tests to identify the most significant variables. As the annual average daily traffic (AADT) value ranges differ significantly from other variables, the "log of AADT" is considered for the model developed, which is also a common practice in many traffic safety studies, including the Highway Safety Manual (HSM).

Safety Performance Functions by Year

The underlying assumption in the Poisson regression model is that the mean value is equal to the variance, also known as equal dispersion. However, the variance of crash data is usually greater than its mean, also known as over-dispersion. Applying the Poisson model to intersection crash data in such situations would underestimate the standard error of the regression variables, which could ultimately lead to a bias in the selection of covariates. In some situations, there are many zeros in the crash data, which can be considered as over-dispersion. The Poisson model cannot be applied for these cases, and because of the zeros, it cannot accommodate the over-dispersion.

The negative binomial (NB) model can be alternatively used to address this challenge; however, the number of sites with zero crashes could be so large that even traditional NB models cannot provide a good fit. To overcome this problem, extensions of the NB models, such as negative binomial Lindley (NB-L), have been proposed and proven to be capable of analyzing such a problematic dataset (*25–28*). The Lindley parameter (γ) embedded in the NB-L distribution can provide the model with a more flexible structure while preserving the NB distribution characteristics. The hierarchical representation of the NB-L model could be written as follows:

$$P(Y = y_i; \lambda_i, \alpha \mid \gamma) = NB(y_i; \alpha, \gamma\lambda_i) \\ \gamma \sim Lindley\ (\theta) \quad (1)$$

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

where λ_i is the estimated number of crashes per year at intersection i, x_q is a set of the independent variables (AADT, road geometric design, etc.) at intersection i, β_q is the regression coefficients estimated from the set of data, and ε_i is a gamma distributed error term with mean 1 and over-dispersion parameter α.

The mean and variance of the NB-L model are shown in Equations 3 and 4:

$$E(y_i) = \lambda_i E(\gamma) = \lambda_i \frac{\theta + 2}{\theta(\theta + 1)} \quad (3)$$

$$Var(y_i) = \lambda_i \frac{\theta + 2}{\theta(\theta + 1)} + \lambda_i^2 \left(\frac{2(\theta + 3)}{\theta^2(\theta + 1)}\right)(\alpha + 1) - \left(\lambda_i \frac{\theta + 2}{\theta(\theta + 1)}\right)^2 \quad (4)$$

The crash dataset used in this study also suffered from the excess zero and long tails problem. The problem was more critical when developing a crash prediction model for higher crash severity levels, as 95%, 85%, and 65% of the sites never experience any crashes at the K, A, and B severity levels, respectively.

As there is no closed-form solution for the NB-L model, a full Bayesian approach was conducted to compute the posterior inference and regression coefficients. A more tractable formulation of the NB-L model proposed by Doucette et al. (*23*) was used to specify the model hierarchy. Using Markov chain Monte Carlo (MCMC) analysis, three Markov chains, each including 30,000 draws from the joint posterior distribution, were run. The first 6000 draws were considered as burn-in samples, and only one draw out of each three draws was used to estimate the coefficient to ensure the independence of the draws. The validation was performed using 20% of randomly selected data.

Note that this study used “log of AADT” instead of “AADT” in the modeling framework because of its magnitude compared to other variables. AADT changes by roadway segments are not on a small scale (e.g., AADT changes usually occur in hundreds or thousands, not like a 5–10 mph change in operating speed) and thus comparisons between these coefficients require engineering judgment and a perspective of the overall transportation network system.

Results and Discussion

As mentioned earlier, the models were based on geometric variables, traffic volumes, and speed measures for different temporal clusters. This study explored the following models:

1. K (individual year models for 2018, 2019, and 2020);
2. KA (individual year models for 2018, 2019, and 2020);
3. KAB (individual year models for 2018, 2019, and 2020);
4. KABC (individual year models for 2018, 2019, and 2020);
5. KABCO (individual year models for 2018, 2019, and 2020).

K Models

As nearly 95% of the sites did not experience any crashes during each year, the excess zero problem was critical in these models. The NB-L modeling results in Table 3 show that, except for AADT and segment length, almost all the other variables turned out to be non-significant at the 90% confidence level, meaning that the variation in fatal crashes cannot be significantly explained by the proposed covariates. The speed measures also showed no significance. Even though the operating speed (SpdAve) and speed standard deviation (SpdStd) were found to be not significant for the fatal crash models, this does not necessarily mean that operating speed has no impact on crash severity. There could be other factors that are confounding the relationship between operating speed and crash severity. Furthermore, the lack of significance for SpdAve and SpdStd in the K and KA models does not necessarily mean that they are not associated with KAB and KABCO models. In fact, the KAB and KABCO models showed significant associations. However, ignoring the *p*-values, the sign of the average speed coefficient in 2020 was similar to other recent studies. This could be a clue that the speed measures recorded in 2020 affect crash frequencies differently.

KA Models

Including the incapacitating crashes in the response variable, more covariates showed significance. In particular,

Table 3. Crash Modeling Results for Severity Levels K and KA

Variables	K-2020		K-2019		K-2018		KA-2020		KA-2019		KA-2018	
	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value
(Intercept)	−14.79 (4.28)	**0.000**	−12.08 (5.08)	**0.017**	−10.9 (4.47)	**0.014**	−13.22 (2.46)	**0.000**	−7.47 (2.42)	**0.000**	−10.28 (2.54)	**0.000**
LnAADT	0.86 (0.42)	**0.040**	0.68 (0.48)	0.156	0.75 (0.42)	**0.074**	0.86 (0.24)	**0.000**	0.39 (0.22)	**0.076**	0.67 (0.24)	**0.005**
SUR_W	0.001 (0.013)	0.930	−0.006 (0.015)	0.680	0.011 (0.012)	0.360	0.003 (0.007)	0.660	0.013 (0.007)	**0.063**	0.008 (0.008)	0.310
S_WID_I	−0.02 (0.025)	0.420	−0.013 (0.027)	0.630	0.022 (0.024)	0.360	−0.018 (0.014)	0.190	−0.02 (0.013)	0.123	−0.002 (0.013)	0.870
NUM_LANES	0.13 (0.18)	0.470	0.086 (0.22)	0.690	−0.24 (0.17)	0.158	0.05 (0.11)	0.640	−0.029 (0.1)	0.770	−0.1 (0.1)	0.310
SpdAve	0.011 (0.01)	0.360	−0.005 (0.009)	0.570	−0.014 (0.008)	**0.080**	0.002 (0.005)	0.680	−0.01 (0.004)	0.800	−0.004 (0.005)	0.420
SpdStd	−0.019 (0.064)	0.760	0.06 (0.047)	0.200	0.023 (0.043)	0.590	0.069 (0.032)	**0.031**	0.044 (0.023)	**0.055**	0.06 (0.02)	**0.002**
Length	1.53 (0.21)	**0.000**	1.51 (0.21)	**0.000**	1.04 (0.22)	**0.000**	1.52 (0.14)	**0.000**	1.6 (0.13)	**0.000**	1.46 (0.13)	**0.000**
DIC	508		437		546		1181		1360		1381	
WAIC	473		410		508		1084		1214		1242	
LOO	479		415		514		1112		1244		1275	
Log-likelihood	−214		−185		−230		−483		−539		−553	

Note: Std = standard deviation; DIC = deviance information criterion; WAIC = Watanabe–Akaike information criterion; LOO = leave-one-out cross-validation; K = fatal; A = incapacitating injury. Bolded are significance levels equal or lower than 0.10.

the speed standard deviation showed a positive association with the KA crash frequencies. These results are in line with the previous findings that the speed variation is positively associated with crash frequency. For the 2020 model, this coefficient is high. This indicates a more powerful association between the speed measures and crash frequencies during the pandemic.

KAB Models

Almost all the variables, including the operating speed average and standard deviation, were significant in the KAB models (see Table 4). The speed average showed significance for the first time, and as expected, it was negatively associated with the crash frequency. The sign of the speed standard deviation and average speed were the same over the KAB models. However, the magnitudes were slightly different. Besides, the coefficient of the speed standard deviation in 2020 is high. The results make sense because slower speeds and less consistent speeds can lead to driver confusion and unpredictability, making it more difficult for other drivers to anticipate and respond to road conditions. In addition, slower speeds can result in longer reaction times and braking distances, which can also contribute to increased crash risk. Also, based on the literature, lower average speed and higher speed variation increase the crash probability. Tanishita and Van Wee (*29*) found that low speeds and high speed variability were associated with increased crash risk. Quddus (*30*) also found that more variable speeds were associated with a higher likelihood of crashes. Given all these findings, it could be implied that the speed standard deviation in 2020 increases the KAB crashes more effectively, whereas the average speed decreases the KAB crashes to a lesser extent, comparing with those of 2018 and 2019. In other words, both the speed measure coefficients during the pandemic are relatively different from the coefficients of 2018 and 2019, in a way that triggers a relative increase in crash frequencies.

KABC and KABCO Models

The same pattern as seen in the KAB models was also observed in the KABC and KABCO models (see Tables 4 and 5). The lower speed average coefficient and higher speed standard deviation coefficient indicate the more influential and critical roles of the speed measures in 2020. Also, this study observed that the magnitude of the speed average coefficient increases as the lower crash severity levels are included in the response variable. This could be attributed to two possible reasons. Firstly, the sparser datasets (i.e., K and KA models) are much harder to fit because of less variability and many zeros in the

Table 4. Crash Modeling Results for Severity Levels KAB And KABC

	KAB-2020		KAB-2019		KAB-2018		KABC-2020		KABC-2019		KABC-2018	
Variables	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value
(Intercept)	−13.58	**0.000**	−11.48	**0.000**	−13.47	**0.000**	−11.6	**0.000**	−13.29	**0.000**	−12.91	**0.000**
	(1.55)		(1.53)		(1.59)		(1.27)		(1.33)		(1.34)	
LnAADT	1.08	**0.000**	0.97	**0.000**	1.07	**0.000**	0.96	**0.000**	1.14	**0.000**	1.13	**0.000**
	(0.15)		(0.14)		(0.15)		(0.12)		(0.12)		(0.12)	
SUR_W	0.002	0.680	0.013	**0.001**	0.011	**0.027**	0.002	0.610	0.011	**0.006**	0.009	**0.024**
	(0.005)		(0.004)		(0.005)		(0.004)		(0.004)		(0.004)	
S_WID_I	−0.02	**0.026**	−0.014	**0.080**	−0.001	0.910	−0.018	**0.010**	−0.012	**0.086**	−0.001	0.880
	(0.009)		(0.008)		(0.009)		(0.007)		(0.007)		(0.007)	
NUM_LANES	0.025	0.710	−0.066	0.324	−0.13	**0.030**	0.074	0.210	−0.086	0.120	−0.11	**0.066**
	(0.069)		(0.067)		(0.06)		(0.06)		(0.056)		(0.06)	
SpdAve	−0.007	**0.019**	−0.012	**0.000**	−0.008	**0.007**	−0.01	**0.000**	−0.015	**0.000**	−0.013	**0.000**
	(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.003)	
SpdStd	0.076	**0.000**	0.053	**0.000**	0.046	**0.002**	0.081	**0.000**	0.06	**0.000**	0.053	**0.000**
	(0.021)		(0.014)		(0.015)		(0.018)		(0.013)		(0.013)	
Length	1.74	**0.000**	1.78	**0.000**	1.8	**0.000**	1.82	**0.000**	1.88	**0.000**	1.95	**0.000**
	(0.11)		(0.1)		(0.1)		(0.1)		(0.1)		(0.1)	
DIC	2883		3219		3094		4781		6146		5961	
WAIC	2334		2570		2561		2247		3849		3690	
LOO	2430		2684		2681		3513		4031		3885	
Log-likelihood	−1025		−1128		−1120		−1467		−1704		−1620	

Note: Std = standard deviation; DIC = deviance information criterion; WAIC = Watanabe–Akaike information criterion; LOO = leave-one-out cross-validation; K = fatal; A = incapacitating injury; B = non-incapacitating injury; C = possible injury. Bolded are significance levels equal or lower than 0.10.

Table 5. Crash Modeling Results for Severity Level KABCO

	KABCO-2020		KABCO-2019		KABCO-2018	
Variables	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value	Estimate (Std)	*p*-value
(Intercept)	−9.54 (1.1)	**0.000**	−9.86 (1.16)	**0.000**	−11.09 (1.14)	**0.000**
LnAADT	0.89 (0.1)	**0.000**	0.94 (0.1)	**0.000**	1.07 (0.1)	**0.000**
SUR_W	0.007 (0.004)	**0.008**	0.015 (0.003)	**0.000**	0.008 (0.004)	**0.045**
S_WID_I	−0.02 (0.006)	**0.000**	−0.016 (0.007)	**0.022**	−0.015 (0.006)	**0.012**
NUM_LANES	0.017 (0.054)	0.750	−0.098 (0.054)	**0.069**	−0.005 (0.056)	0.370
SpdAve	−0.014 (0.003)	**0.000**	−0.019 (0.002)	**0.000**	−0.017 (0.002)	**0.000**
SpdStd	0.074 (0.018)	**0.000**	0.05 (0.012)	**0.000**	0.039 (0.012)	**0.001**
Length	2.04 (0.1)	**0.000**	2.14 (0.1)	**0.000**	2.09 (0.1)	**0.000**
DIC	9039		10214		10623	
WAIC	5345		5794		5636	
LOO	5573		6047		5922	
Log-likelihood	−2393		−2600		−2513	

Note: Std = standard deviation; DIC = deviance information criterion; WAIC = Watanabe–Akaike information criterion; LOO = leave-one-out cross-validation; K = fatal; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = not injured and unknown. Bolded are significance level equal or lower than 0.10.

dataset. As a result, the majority of the covariates (e.g., the speed average) in the mean function fail to explain the response variable. Secondly, the underlying variables used to predict the crash frequency are more associated with less severe crashes (e.g., B, C, and O); therefore, their coefficient estimates would be higher in the models with the less severe crashes included. The speed standard deviation of the KABC models displayed a similar pattern as the speed average coefficient. The coefficient of the speed standard deviation slightly decreased in the models with property damage crashes included (i.e., KABCO). This could indicate that the speed standard deviation affects the property damage crashes at a lower magnitude than the more severe crashes.

Conclusions

The COVID-19 pandemic has affected life from every imaginable perspective, and it has also provided an opportunity for researchers to explore the possible impacts of the pandemic from different viewpoints. Understanding the impacts of the pandemic could help mitigate the negative effects of the ongoing pandemic and help prepare for the future. Researchers and leaders of public and private sectors will need to work together to gather data and develop road safety strategies in relation to COVID-19. There is a need to explore how low traffic volumes affect drivers' visual information, appropriateness of driving behavior, and perceptions of speed and safety.

This study aims to understand how driving behavior changed during the pandemic and how the changing driving behavior affected the frequency of fatal and severe crashes. This research quantifies the driving behavior from the operating speed perspective. Three disparate databases, speed data from the NPMRDS, roadway inventory data, and crash data, were conflated into one database to perform the analysis. The analysis used data for six months (April–September) for the years of 2018–2020. The statistics indicate that the increase in average speed in 2020 is obvious, comparing with 2018 and 2019. However, with a considerable amount of decrease in traffic volume in 2020, the decrease in fatal and severe crashes is not on the same scale.

The results of the NB-L models showed that the behavior of crash prediction models varies over the years (2018–2020) and the severity levels (K, KA, KAB, KABC, and KABCO). In the 2020 models, speed measures, average speed, and speed standard deviation had a more critical impact on the crash frequencies. In addition, the magnitude of the speed measures varies across the models with different crash severity levels indicating that the speed measures affect various crash severities differently. There is a need for mitigation strategies such as public communications and outreach and traffic enforcement to encourage people to drive safely and avoid risky driving behavior, such as speeding. In recent years, several traffic safety studies (*31–40*) have focused on research on the impact of traffic crash occurrences caused by operational change, traffic volume, and speeding-related issues. The unique contribution of this study is the application of NB-L models in the impact of traffic safety caused by operational change (i.e., operational speed change), which has been less explored in prior studies. This study can mitigate the current knowledge gap.

The current study has some limitations. Firstly, the overall impact of operating speed on crashes is performed at an aggregate level. Models with more granular temporal clusters can provide new insights. Secondly, the study period is short; only six months of data from each year were considered for analysis. The inclusion of additional months can enrich the analysis. Thirdly, the impact of the first two months (April and May) of 2020 might be more influential than the rest of the months of 2020 because of the trend returning to normality. Short-duration models are required to understand the impact of speed–crash associations during the COVID-19 pandemic. Future studies can address this research gap.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Das; data collection: S. Das; analysis and interpretation of results: S. Das, A. Khodadadi; draft manuscript preparation: S. Das, A. Khodadadi, J. Liu. All authors reviewed the results and approved the final version of the manuscript.

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