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How did the COVID-19 pandemic affect road crashes and crash outcomes in Alabama?

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ABSTRACT

With the rising number of cases and deaths from the COVID-19 pandemic, nations and local governments, including many across the U.S., imposed travel restrictions on their citizens. This travel restriction order led to a significant reduction in traffic volumes and a generally lower exposure to crashes. However, recent preliminary statistics in the US suggest an increase in fatal crashes over the period of lockdown in comparison to the same period in previous years. This study sought to investigate how the pandemic affected road crashes and crash outcomes in Alabama. Daily vehicle miles traveled and crashes were obtained and explored. To understand the factors associated with crash outcomes, four crash-severity models were developed: (1) Single-vehicle (SV) crashes prior to lockdown order (Normal times SV); (2) multi-vehicle (MV) crashes prior to lockdown order (Normal times MV); (3) Single-vehicle crashes after lockdown order (COVID times SV); and (4) Multi-vehicle crashes after lockdown order (COVID times MV). The models were developed using the first 28 weeks of crashes recorded in 2020. The findings of the study reveal that although traffic volumes and vehicle miles traveled had significantly dropped during the lockdown, there was an increase in the total number of crashes and major injury crashes compared to the period prior to the lockdown order, with speeding, DUI, and weekends accounting for a significant proportion of these crashes. These observations provide useful lessons for road safety improvements during extreme events that may require statewide lockdown, as has been done with the COVID-19 pandemic. Traffic management around shopping areas and other areas that may experience increased traffic volumes provide opportunities for road safety stakeholders to reduce the occurrence of crashes in the weeks leading to an announcement of any future statewide or local lockdowns. Additionally, increased law enforcement efforts can help to reduce risky driving activities as traffic volumes decrease.

1. Introduction

The outbreak of the coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was declared a public health emergency in January 2020 and upgraded to a pandemic in March 2020. Response to the COVID-19 pandemic has had tremendous effects on the global economy and social life, and it has significantly disrupted transportation systems across the world. With the rising number of cases and deaths from the pandemic, nations and local governments, including many across the U.S., imposed travel restrictions on their citizens. These measures have reduced travel and lowered the risk of collisions. However, recent preliminary statistics in the US suggest an increase in fatal crashes over the period of the lockdown in comparison to the same period in previous years. This was established by Brown (2020), who looked not only at fatal crashes but several other crash types.

Indeed, reports point to similar increases in other countries during the COVID-19 pandemic (Australian Road Safety Foundation, 2020; BBC, 2020; City News, 2020). In the US, Carter (2020) and Lockwood et al (2020) observed that the proportion of speeding-related crashes and fatalities had increased during the pandemic lockdown in North Carolina and Virginia, respectively. Vingilis et al (2020) identified personal factors, such as: (1) the propensity for risky behaviors, (2) situational and structural factors such as gas price changes, and (3) reduced law enforcement, as potential factors that affected road safety performance during the pandemic. The pandemic has also been characterized by increased alcohol sale and use (Benzie, 2020; Sharpe, 2020), potentially as a result of reported increase in stress, anxiety, and depression among

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certain population groups (e.g., Liu et al., 2020). With these factors known to be risk factors in road crashes (Wickens et al., 2014), the impacts of the pandemic on road safety appear to be multifactorial requiring an interdisciplinary approach to unravel.

In this study, we investigated the pattern of crashes that occurred in the state of Alabama for the first 28 weeks of 2020. The state announced a stay-at-home (or lockdown) order on March 11, 2020 (week 11) and so, the crash data has been segmented into crashes that occurred prior to March 11, as Normal times and those that occurred after March 11 as COVID times. This order strongly recommended that travel be restricted to only essential trips and this generally impacted traffic volumes and likelihood of crash occurrence. To understand the effect of the stay-at-home order on the trend and primary contributing factors of crashes in the state, the preliminary analysis included historical crash data for the same period in 2018 and 2019. Additionally, we performed injury-severity analyses to understand the association between various crash factors and crash outcomes before and after the lockdown order in the state. This was done to assess whether the factors that influenced crash outcomes differed before and after the lockdown order. As such, only the crash data for the first 28 weeks of 2020 were used for the injury-severity analysis. The 2020 data was further segmented into single-vehicle and multi-vehicle crashes for the period before and after the lockdown order went into effect. Subsets of the crash data were considered to unravel the complex relationships within the injury-severity analysis with regards to the effects of the manner of collision and the lockdown order. Latent Class Multinomial Logit (LC-MNL) and random parameters logit with heterogeneity in means and variances modeling approaches were adopted to address the limitations in the crash data that have the potential to bias the results and the resulting decisions. Segmentation of the crash data for modeling purposes helped to better understand how the crash factors influenced crash outcomes under different scenarios and this provides an opportunity for state officials to target specific countermeasure efforts in a more efficient manner.

2. Review of previous studies

Human factors have previously been shown to be the leading contributing factor in crash occurrence (Tillmann and Hobbs, 1949; Treat, 1977; Hendricks et al., 2001). The National Highway Traffic Safety Administration (NHTSA) has identified DUI (drunk and drug-impaired driving), speeding, failure to seat belts, and drowsy and distracted driving to be the major risky driver behaviors that contribute to crashes. While factors, such as DUI, contribute to crash occurrence, speeding increases the severity of the crash. Similarly, although failure to use seatbelt does not in itself cause crashes, it increases the probability of being injured in a crash (Evans, 1996; Abdel-Aty, 2003; Wang and Jiang, 2003; Kim et al., 2013; Adanu and Jones, 2017). Nonetheless, many studies have found a strong correlation between serious injury crash outcomes and risky behaviors such as DUI (e.g., Tavris et al., 2001; Abdel-Aty, 2003; Dabbour, 2017), aggressive driving (Paleti et al., 2010; Dahlen et al., 2012; Islam and Mannering, 2020), and driving without a valid license (Blows et al., 2005; Adanu et al., 2018). The propensity of certain road user groups to engage in risky driving behaviors have been linked to many factors such as age (e.g., Elander et al., 1993; Chliaoutakis et al., 2000; Adanu et al., 2017), gender (e.g., Miller et al., 1998; Turner and McClure, 2003; Adanu et al., 2018), socioeconomic status (e.g., Abdalla et al., 1997; Liu et al., 1998), personality (e.g., Yu and Williford, 1993; Nicholson et al., 2005), type of vehicle being driven (e.g., Ulfarsson and Mannering, 2004), and even regional culture and systems (e.g., Lund and Rundmo, 2009; Atchley et al., 2014; Adanu et al., 2017; Adanu et al., 2019). It has also been observed that risky drivers often engage in multiple traffic violations (Kweon and Kockelman, 2010; Briggs et al., 2008; Phillips and Brewer, 2011; Pulido et al., 2011; Stübig et al., 2012); NHTSA, 2012). For instance, Bogstrand et al (2015) observed that a higher proportion of alcohol impaired drivers were less likely to use seatbelt and more likely to speed. They also found that a large proportion of drivers who engage in drunk or drugged driving are repeat offenders. Methodologically, a wide range of discrete-outcome models have been used to analyze crash severity due to the classification of the severities into discrete outcomes (see Savolainen et al., 2011; Mannering and Bhat, 2014 for injury-severity methodology reviews). To account for unobserved heterogeneity (Mannering et al., 2016), recent crash studies have used random parameters (mixed) logit models (e.g. Milton et al., 2008; Kim et al., 2013; Anastasopoulos and Mannering, 2011; Morgan and Mannering, 2011; Cerwick et al., 2014; Islam et al., 2014; Behnood and Mannering, 2016; Seraneeprakarn et al., 2017; Waseem et al., 2019), latent class models (Eluru et al., 2012; Xiong and Mannering, 2013; Cerwick et al., 2014; Shaheed and Gkritza, 2014; Yasmin et al., 2014; Adanu et al., 2018; Fountas et al., 2018a; Fountas et al., 2018b; Lidbe et al., 2020), Markov switching models (Malyshkina and Mannering, 2009), Markov switching with random parameters (Xiong et al., 2014), bivariate/multivariate models with random parameters (Abay et al., 2013; Russo et al., 2014), random parameters generalized ordered probability with heterogeneity in means and variances (Xin et al., 2017), random thresholds random parameters hierarchical ordered probit (Fountas and Anastasopoulos, 2017), and correlated random parameters ordered probit (Fountas et al., 2018a; Fountas et al., 2018b). Anastasopoulos and Mannering (2011) observed that while injury severity models that do not use detailed crash-specific data underperform compared to those that do, random parameter models using less detailed data can provide a reasonable level of accuracy. Recent studies have also explored the temporal stability of factors that affect crash injury severities (e.g., Behnood and Mannering, 2015; Mannering, 2018; Islam and Mannering, 2020).

3. Data

The study was based on crash data obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety (CAPS) at the University of Alabama. The CARE database serves as the primary source of historical crash data for research and policy decision-making in the State of Alabama. For ease of comparison of crash factors across the years in order to understand the impact of the COVID-19 pandemic on crash trends, the database was queried to select crashes that occurred in the first 28 weeks for 2018, 2019, and 2020, as crash data for 2020 was only available for the first 28 weeks at the time of this study. Daily county vehicle miles travelled (VMT) was also obtained as a measure of exposure to crashes. To explore the differences in factors that influenced crash injury severity before and after the lockdown order, the crash data for 2020 was segmented into crashes that occurred before March 11 as Normal times and those that occurred after March 11 as COVID times. The data was further divided by crash mechanism as: (1) Single-vehicle (SV) crashes before the lockdown order (Normal times SV); (2) multi-vehicle (MV) crashes before the lockdown order (Normal times MV); (3) Single-vehicle crashes after the lockdown order (COVID times SV); and (4) Multi-vehicle crashes after the lockdown order (COVID times MV).

Figs. 1 and 2 present the distribution of crashes per daily county VMT before and after the lockdown order, respectively. Fig. 3 shows that the highest number of crashes occurred in week 11, which coincides with the week when the lockdown order was announced. After week 11, both VMT and number of crashes decreased significantly. This reduction lasted until week 15 when crashes began to increase again but not reaching the numbers recorded prior to the lockdown order, although VMT was approaching those prior to week 11. Figs. 4–12 show the comparative historical trend of crashes for the first 28 weeks of 2018, 2019, and 2020, by injury severity and contributing factors.

It can be observed from Fig. 4 that the total number of crashes prior to week 11 in 2020 followed the same pattern as 2018 and 2019. However, the crash fatalities (see Fig. 5) did not follow any particular pattern. For example, it can be observed that the fatality numbers for

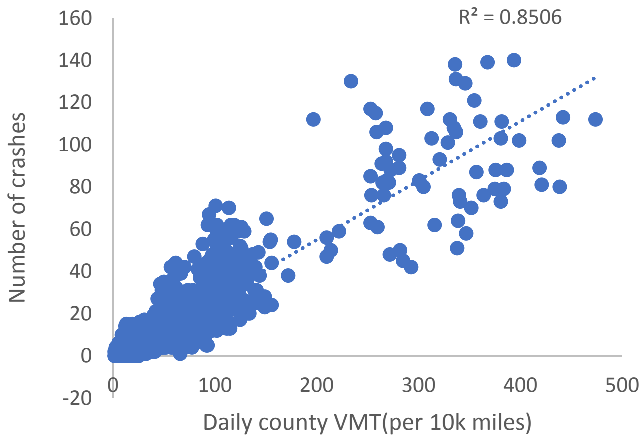

Fig. 1. Pattern of road crashes and daily county VMT in Normal times.

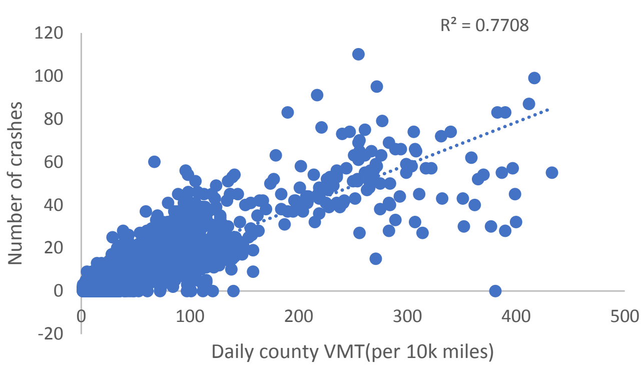

Fig. 2. Pattern of road crashes and daily county VMT in COVID times.

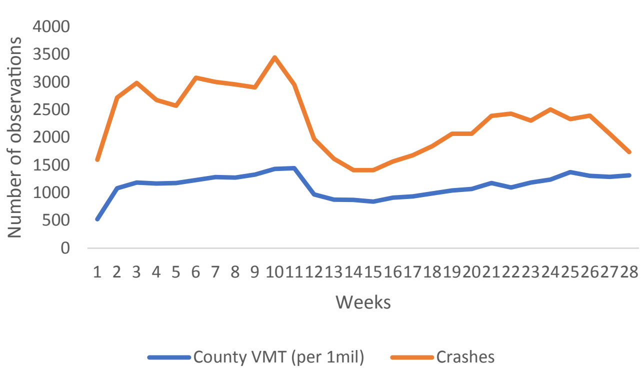

Fig. 3. Weekly variation in VMT and crashes.

weeks 6 and 10 in 2020 were higher compared to those in 2018 and 2019, and the lowest number of fatalities in 2020 occurred in week 14 (three weeks after the lockdown order). By the 20th week of 2020, crash fatalities had increased to a level higher than those recorded around the same period in 2018 and 2019.

The number of people who sustained severe or incapacitating injury crashes in the first 28 weeks of 2020 had a trend similar to that of 2019 until week 11, and by week 19 the number of severe injuries returned to the levels recorded in 2019. With regard to the contributing factors (see Figs. 7–11), crashes involving DUI, aggressive driving, distracted driving, and drowsy driving were lower after week 11 in 2020 compared to 2018 and 2019, but this trend lasted for only a few weeks. However, there has not been any significant difference in speeding-related crashes across the three years. Similarly, failure to use safety equipment (predominantly seatbelt) has not seen any major change due to the lockdown

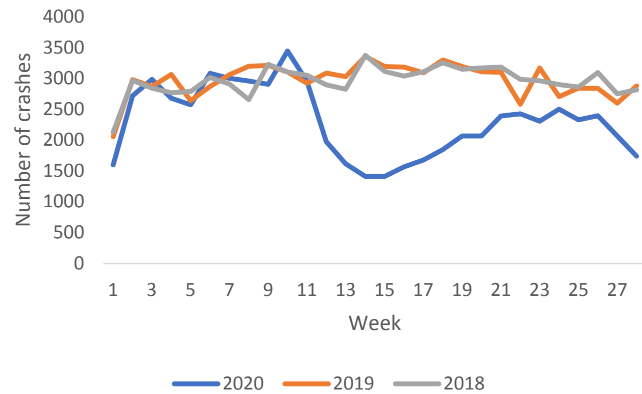

Fig. 4. Comparison of total crash patterns in 2018, 2019, and 2020.

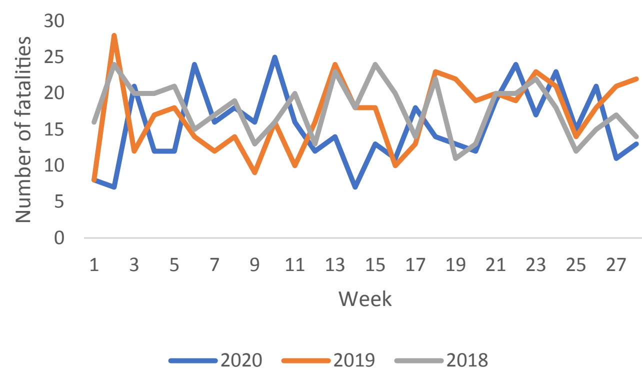

Fig. 5. Comparison of road fatality patterns in 2018, 2019, and 2020.

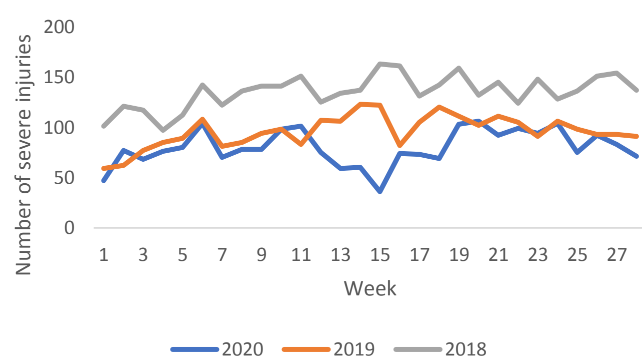

Fig. 6. Comparison of major injury patterns in 2018, 2019, and 2020.

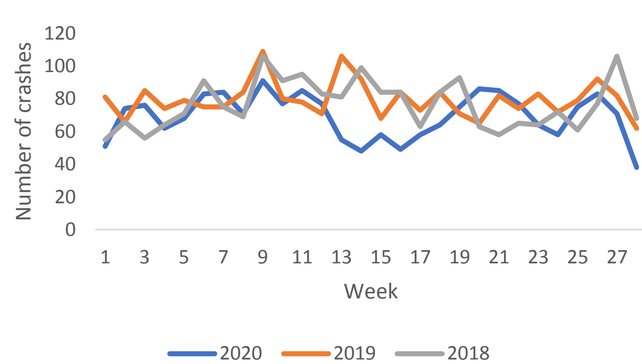

Fig. 7. Comparison of DUI crash patterns in 2018, 2019, and 2020.

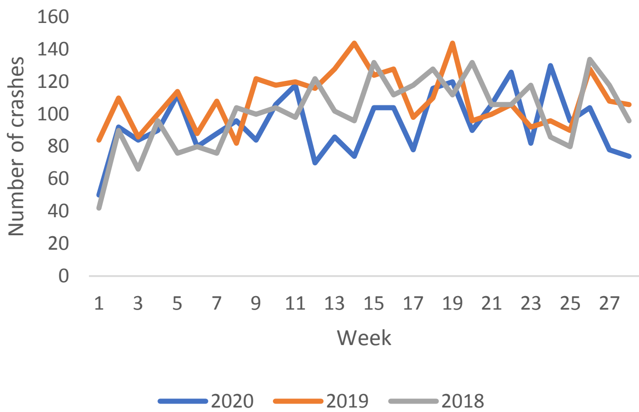

Fig. 8. Comparison of aggressive driving patterns in 2018, 2019, and 2020.

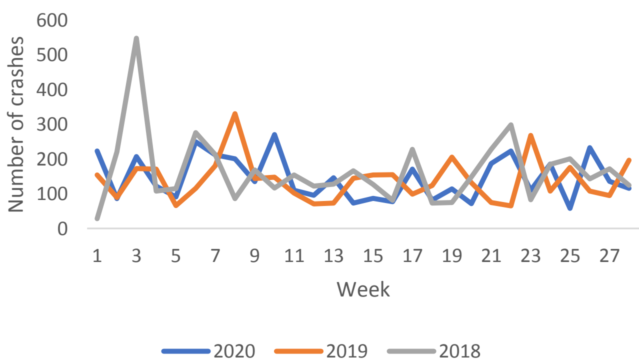

Fig. 9. Comparison of speeding-related crash patterns in 2018, 2019, and 2020.

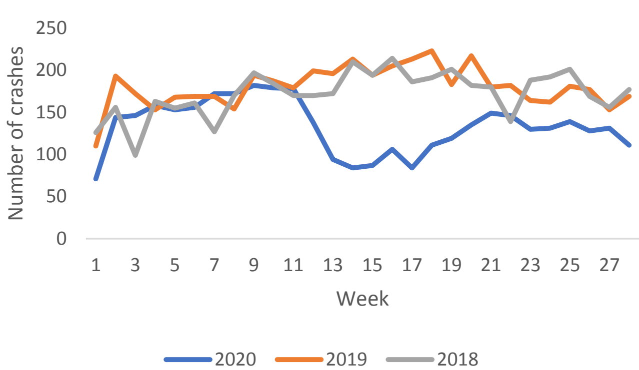

Fig. 10. Comparison of distracted driving crash patterns in 2018, 2019, and 2020.

order in 2020 according to Fig. 12.

Table 1 shows the distribution of the crash severities by crash mechanism and period of crash occurrence. From this table, it can be observed that the highest number of major injury (both SV and MV) crashes occurred during the lockdown period when traffic volumes were low.

Table 2 presents the descriptive statistics of the variables found to be statistically significant during model estimation. From Table 2, it can be observed that the proportions of SV crashes that occurred on interstate highways and those that occurred in rural areas in the first 28 weeks of 2020 are about 10 percentage points and 40 percentage points, respectively higher than MV crashes. This means that a higher proportion of SV crashes occurred on interstates and in rural areas of the state compared to MV crashes.

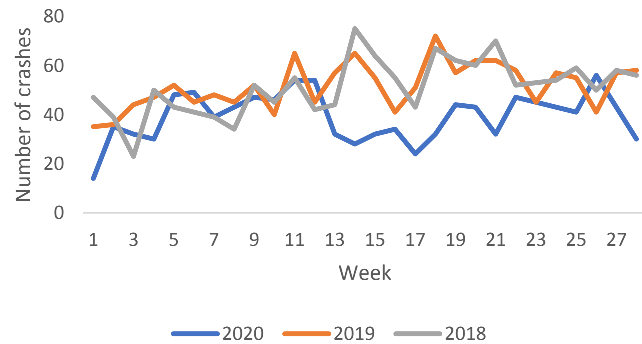

Fig. 11. Comparison of drowsy driving crash patterns in 2018, 2019, and 2020.

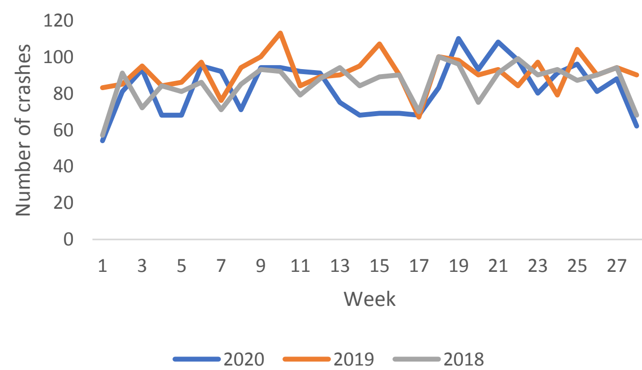

Fig. 12. Comparison of crashes involving no seatbelt use in 2018, 2019, and 2020.

Analysis of the data as shown in Table 2 also revealed that more than half of the MV crashes occurred at shopping areas and intersection-related crashes make up about 65% of all MV crashes. About 20% of SV crashes involved speeding while less than 3% of MV crashes involved speeding. Similarly, nearly 8% of SV crashes involved DUI and less than 2% of MV crashes involved DUI. However, in absolute terms, more speeding and DUI crashes occurred after the lockdown order. Also, more aggressive driving crashes occurred during the stay at home order. More drivers involved in SV crashes failed to wear seatbelt compared to MV crashes, with the highest proportions happening during the lockdown period. Additionally, more than 10% of the drivers involved in crashes prior to the lockdown order did not have a valid license while 16.8% and 13.8% of drivers involved in SV and MV crashes, respectively during the lockdown did not have a valid license. Drivers aged more than 65 years were involved in more MV crashes than in SV crashes.

4. Method

Road crash occurrence is complex in nature and may involve a variety of factors; many of which may be unknown and not recorded by the reporting police officer. It is therefore not possible to include all probable crash factors in the standard crash report form. This limitation can affect the accuracy of results from traditional statistical analyses of crash data, hence leading to biased parameter estimates which may affect the accuracy of decisions made from such crash models. Various statistical methods (see Savolainen et al., 2011; Mannering and Bhat, 2014 for injury-severity methodology reviews) can be used to overcome this inherent problem typically referred to as unobserved heterogeneity in crash data and analysis (Mannering et al., 2016). For instance, recent studies have used random parameters (mixed logit) models (Milton et al., 2008; Morgan and Mannering, 2011; Anastasopoulos and Mannering, 2011; Kim et al., 2013) and latent class (finite mixture) models (Yasmin et al., 2014; Shaheed and Gkritza, 2014; Lidbe et al., 2020) to

Table 1
Trend of crash outcomes by crash type and period.

Crash severity	Normal SV		COVID SV		Normal MV		COVID MV	
Major injury	301	5.5%	667	8.8%	358	1.8%	543	2.4%
Minor injury	1166	21.2%	1735	22.8%	3316	17.0%	3996	17.8%
No injury	4042	73.4%	5220	68.5%	15,785	81.1%	17,952	79.8%
Total	5509	100.0%	7622	100.0%	19,459	100.0%	22,491	100.0%

Table 2
Descriptive statistics of variables used in model estimation.

Variables	Normal SV		COVID SV		Normal MV		COVID MV	
Crash location								
Interstate highway	1030	18.7%	1380	18.1%	1810	9.3%	1822	8.1%
Rural area	3096	56.2%	4444	58.3%	3133	16.1%	3913	17.4%
Intersection	2054	37.3%	2621	34.4%	12,843	66.0%	14,799	65.8%
Shopping area	753	13.7%	1008	13.2%	10,761	55.3%	11,830	52.6%
Residential area	1323	24.0%	1894	24.8%	3717	19.1%	4993	22.2%
Contributing circumstances								
Speeding	1135	20.6%	1486	19.5%	564	2.9%	562	2.5%
DUI	413	7.5%	671	8.8%	311	1.6%	450	2.0%
Aggressive driving	121	2.2%	282	3.7%	195	1.0%	315	1.4%
Drowsy driving	288	5.2%	511	6.7%	116	0.6%	157	0.7%
Distracted driving	534	9.7%	487	6.4%	1342	6.9%	1668	7.4%
Temporal factors								
Between midnight and 6AM	992	18.0%	1311	17.2%	584	3.0%	630	2.8%
Between midday and 6PM	1565	28.4%	2401	31.5%	9574	49.2%	12,393	55.1%
Between 6PM and midnight	1476	26.8%	2256	29.6%	3425	17.6%	3846	17.1%
Weekend	1543	28.0%	2271	29.8%	5585	28.7%	7040	31.3%
Six weeks after lockdown			2248	29.5%			9779	43.5%
Three weeks before lockdown	1223	22.2%			8529	43.8%		
Manner of crash								
Rear-end collision					8893	45.7%	9424	41.9%
Side impact					4573	23.5%	5488	24.4%
Sideswipe					2335	12.0%	2744	12.2%
Driver demographics and behavioral factors								
Female driver	2115	38.4%	2599	34.1%	8795	45.2%	9446	42.0%
Driver less than 25 years	1559	28.3%	2271	29.8%	5487	28.2%	6118	27.2%
Driver age between 25 and 45 years	2231	40.5%	3186	41.8%	7064	36.3%	8322	37.0%
Driver between 45 and 65 years	1339	24.3%	1684	22.1%	4378	22.5%	5285	23.5%
Driver aged 65 years or more	380	6.9%	434	5.7%	2355	12.1%	2586	11.5%
Employed	3041	55.2%	3910	51.3%	10,469	53.8%	11,538	51.3%
Unemployed	970	17.6%	1616	21.2%	2160	11.1%	2969	13.2%
Self employed	220	4.0%	366	4.8%	720	3.7%	900	4.0%
No seatbelt	446	8.1%	808	10.6%	331	1.7%	517	2.3%
Invalid license	600	10.9%	1280	16.8%	2004	10.3%	3104	13.8%
Vehicle type								
SUV	1140	20.7%	1502	19.7%	4690	24.1%	5038	22.4%
Pickup truck	959	17.4%	1479	19.4%	3405	17.5%	4498	20.0%

capture unobserved heterogeneity (defined as the existence of variations in the effect of variables across the sample population that maybe unknown to the analyst) in crash data (Mannering et al., 2016). Whereas the random parameters approach uses continuous mixing distributions (for example, normal, lognormal, uniform, triangular, etc.) to capture heterogeneity, the latent class approach identifies unobserved classes by replacing the continuous distribution assumption of random parameter model with a discrete distribution in which unobserved heterogeneity is captured by the membership of distinct classes (Mannering and Bhat, 2014).

This study used both latent class multinomial logit (LC-MNL) (e.g., Shaheed and Gkritza, 2014; Adanu et al., 2018; Lidbe et al., 2020) and random parameters with heterogeneity in means and variances models (e.g. Venkataraman et al. 2014; Behnood and Mannering, 2017; Adanu et al., 2021; Damsere-Derry et al., 2021) to account for unobserved heterogeneity across the crash observations, as these methods have been shown to perform better than the traditional multinomial logit and random parameters logit models (Shaheed and Gkritza, 2014; Adanu and Jones, 2017). The models were developed using the first 28 weeks of crashes recorded in 2020. Single-vehicle (SV) models were developed to eliminate the influence of other vehicles/drivers on the crash occurrence and outcome. Also, separate crash severity models were developed based on the period of the crash in order to understand whether the lockdown order issued in the state on March 11, 2020 had any effects on the crash mechanisms and outcomes. The study used three crash injury-severity categories: severe injury (fatal or incapacitating injury), minor injury (non-incapacitating injury or possible injury), and no injury (property damage only).

To obtain an estimable model, a crash severity function S_{in} that determines the probability that crash n will result in injury severity i is defined as (McFadden, 1981):

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

where $\beta_i$is a vector of estimable parameter for crash outcome i (major injury, minor injury, or no injury), X_{in} is a vector of explanatory variables that affect the likelihood of damage outcome i in crash n and ε_{in} is the stochastic error term. If ε_{in} is assumed to follow an independent and identically distributed extreme value Type I distribution (McFadden, 1981), and we allow for parameter variations across observations by introducing a mixing distribution (McFadden and Train, 2000) the resulting mixed logit model is:

$$P_n(i) = \int \frac{exp(\beta_i X_{in})}{\Sigma exp(\beta_i X_{in})} f(\beta|\varphi) d\beta \tag{2}$$

where $f(\beta|\varphi)$is the density of β and φcorresponding to a vector of parameters of the density function (mean and variance), $P_n(i)$ is the probability of crash severity i in crash $n$conditional on$f(\beta|\varphi)$. With this formulation, βcan now account for observation-specific variations in the effect of X on crash outcome probabilities, with $f(\beta|\varphi)$ used to determineβ. Mixed-logit probabilities are then a weighted average for different values of β across observations where some elements of β can be fixed across observations and some may vary across observations (known as random parameters). This model is estimated by simulated maximum likelihood estimation with the logit probabilities shown in Eq. (3) approximated by drawing values of β from $f(\beta|\varphi)$ for given values of φ, using Halton draws (Halton. 1960; Bhat, 2003; Train, 1999). Heterogeneity in means and variances of random parameters is accounted for by allowing β_i to vary across crashes as (Seraneeprakarn et al., 2017):

$$\beta_i = \beta + \Theta_i Z_i + \sigma_i exp(\omega_i W_i) \upsilon_i \tag{3}$$

where β is the mean parameter estimate across all crashes, Z_i is a vector of attributes that capture heterogeneity in the mean, Θ_i is a corresponding vector of estimable parameters, W_i is a vector of attributes that capture heterogeneity in standard deviation σ_i with corresponding parameter vector ω_i and a disturbance term υi, andZ_i and W_i may contain crash attributes or other sources of heterogeneity which may not be captured by variables recorded in the crash database.

In contrast, the LC-MNL model allows the crash severity, based on Eq. (1), to have C different classes so that each of the classes will have its own parameters, with the probability given by (Behnood et al., 2014):

$$P_n(c) = \frac{exp(\alpha_c Z_n)}{\sum_{\forall C} exp(\alpha_c Z_n)} \tag{4}$$

where Z_n represents a vector that shows the probabilities of c for crash$n$, C is the possible classes c, and α_c represents the estimable parameters (class specific parameters). The unconditional probability that a crash will result in severity i is given by:

$$P_n(i) = \sum_{\forall C} P_n(c)^* P_n(i/c) \tag{5}$$

where $P_n(i/c)$ is the probability of crash n to result in severity i in class c. Based on Eqs. (4) and (5), the LC-MNL model for class c will be:

$$P_n(i/c) = \frac{exp(\beta_{ic} X_{in})}{\sum_{\forall I} exp(\beta_{ic} X_{in})} \tag{6}$$

where I represents the possible number of crash severity levels andβ_{ic} is a class-specific parameter vector that takes a finite set of values.

Marginal effects were computed to assess the effect of the crash-contributing factors on the likelihood of crash-severity outcomes (Washington et al 2011). In this study, all the explanatory variables are coded as indicator variables. As such, the marginal effects are calculated as:

$$ME_{X_{ijk}}^{P_{ij}} = P_{ij}(X_{ijk} = 1) - P_{ij}(X_{ijk} = 0) \tag{7}$$

The probabilities specific to each severity level i for crash j, are calculated when the k^{th} indicator variable, X_{ijk} equals to 1 or 0, respectively. Specifically, a marginal effect for X_{ijk} is the difference in probabilities when X_{ijk} changes from 0 to 1 while all other variables remain constant. For variables with random parameter across all observations, only the estimated mean value of the coefficients is used in the utility function to calculate the marginal effects. The marginal effect for each parameter is calculated by averaging the marginal effects over all crash observations.

5. Results

Four crash-severity models (single-vehicle crashes prior to lockdown order (Normal times SV), multi-vehicle crashes prior to lockdown order (Normal times MV), single-vehicle crashes after lockdown order (COVID times SV) and multi-vehicle crashes after lockdown order (COVID times MV)) were developed using LC-MNL and random parameters with heterogeneity in means and variances approaches. A comparison of the model fit statistics revealed that the LC-MNL model was superior to the random parameters with heterogeneity in means and variances model in three out of the four scenarios (COVID times SV, Normal times MV, and COVID times MV). The Normal times SV random parameters with heterogeneity in means and variances model performed better than the LC-MNL model. The random parameters multinomial logit with heterogeneity in means and variances model was estimated by simulated maximum likelihood with 500 Halton draws (McFadden and Train, 2000). The normal probability density function was used for random parameters (e.g. Milton et al. 2008; Behnood and Mannering, 2016). With respect to the LC-MNL models, two distinct classes with homogeneous attributes were found significant; Latent Class 1 with probability 0.62 and Latent Class 2 with probability 0.38, for the Normal times MV model, Latent Class 1 with probability 0.54 and Latent Class 2 with probability 0.46, for the COVID times MV model, and Latent Class 1 with probability 0.63 and Latent Class 2 with probability 0.37, for the COVID times SV model. Estimation results with more than two latent classes did not statistically improve the models in terms of data fit.

The class-specific probabilities are a set of fixed constants since segmentation based on crash-specific characteristics did not produce a superior model. Tables 3–6 present the best model estimation results for all the four scenarios considered and Table 7 presents a comparative summary of how the variables influence the likelihood of major injury outcome. The model estimation results for each latent class crash severity model show that each variable has two sets of parameters associated with it. However, it can be observed that some of the parameters have the same sign between the two latent classes (e.g., rural area, shopping area, residential area in the COVID MV model; rural area, aggressive driving, no seatbelt in the COVID SV model, rural area; and DUI, sideswipe in the Normal times MV model). Others were found to have opposite signs (e.g., intersection, DUI in the COVID MV model, crash time between midday and 6PM in the COVID SV model, self-employed driver in the Normal times MV model) or are not significant in both classes (e.g., interstate highway and DUI in the COVID MV model, driver less than 25 years, unemployed driver in the COVID SV model, no seatbelt in the Normal times MV model). This indicates that there is heterogeneity between the two classes. For this reason, it would be inaccurate to base the interpretation of the model on the magnitude and sign of the parameters. Rather, model interpretation and comparison of variable effects on crash outcomes across all models are more appropriately based on examining the marginal effects.

The marginal effects shown in Table 3 reveal that the probability of major injury increased by 0.0007 for crashes involving aggressive driving while the "no seatbelt" indicator variable increased the probability of major injury by 0.023. The results further show that the likelihood of major injury increased by 0.007 for crashes that occurred within three weeks of when the statewide lockdown order was announced. The variable associated with crashes that occurred within this period was found to be random with mean of −2.16 and standard deviation of 2.11. These numbers plotted on the normal distribution curve indicate that the probability of minor injury was lower in 15.3% of the crashes recorded within three weeks of the lockdown order (this implies increased likelihood of major injury or no injury) and the

Table 3
Model estimation results for Normal SV crashes.

Variable	In severity function of	Parameter estimate	t-statistics	Marginal effects		
				Major injury	Minor injury	No injury
Constant	Minor injury	−1.06	−17.47			
Random parameter (normally distributed)						
Three weeks before lockdown	Major injury	−2.16	−3.12	0.007	−0.0016	−0.0054
Standard deviation of "Three weeks before lockdown"		2.11	3.21			
Heterogeneity in means						
Three weeks before lockdown: Dark roadway condition	Major injury	0.86	1.87			
Heterogeneity in variance						
Three weeks before lockdown: Open country		0.40	2.10			
Three weeks before lockdown: Car		−0.26	−1.81			
Crash location						
Interstate highway	Major injury	−1.14	−5.27	−0.0054	0.0013	0.0041
Rural area	Major injury	−0.45	−3.26	−0.0116	0.0027	0.0089
Contributing circumstances						
Speeding	Minor injury	0.26	3.26	−0.0007	0.0098	−0.0091
DUI	Minor injury	0.39	3.16	−0.061	0.0762	−0.0152
Aggressive driving	No injury	−0.41	−2.12	0.0007	0.0013	−0.002
Distracted driving	Major injury	−0.40	−1.87	−0.0017	0.0003	0.0013
Temporal factors						
Between midnight and 6AM	No injury	0.32	3.64	−0.0027	−0.0076	0.0103
Between midday and 6PM	No injury	0.12	1.64	−0.0016	−0.0049	0.0065
Between 6PM and midnight	Major injury	−0.89	−6.08	−0.0101	0.0025	0.0076
Weekend	Major injury	−0.72	−5.15	−0.0088	0.0021	0.0067
Driver demographics and behavioral factors						
Female driver	Major injury	−0.93	−6.64	−0.0124	0.0029	0.0095
Driver less than 25 years	No injury	0.30	4.03	−0.0033	−0.0123	0.0156
Driver between 45 and 65 years	No injury	0.23	2.90	−0.0024	−0.0077	0.0102
Driver aged 65 years or more	Major injury	−0.80	−3.60	−0.0031	0.0007	0.0024
Employed	Major injury	−1.76	−12.27	−0.0322	0.0075	0.0248
Unemployed	Major injury	−1.23	−6.65	−0.0114	0.0028	0.0086
Self-employed	No injury	0.84	4.74	−0.0024	−0.0028	0.0052
No seatbelt	Major injury	1.95	13.70	0.023	−0.0057	−0.0173
Invalid license	Minor injury	0.28	2.76	−0.0007	0.0057	−0.005
Vehicle type						
SUV	Major injury	−0.80	−4.48	−0.0058	0.0014	0.0044
Pickup truck	No injury	0.21	2.45	−0.002	−0.0047	0.0067
Model fit statistics						
Number of observations		5509				
Log likelihood function		−3909.3871				
Log likelihood at zero		−6052.2551				
McFadden pseudo R-sq		0.35				

probability of minor injury was higher in 84.7% of the crashes.

One variable (indicator variable for dark and unlit roadway condition) and two variables (indicator variable for car and indicator variable for open country) were found to produce random parameters with means and variances, respectively. For the "three weeks to lockdown" crash indicator, crashes that occurred under dark and unlit roadway conditions had an increase in their mean making minor injury more likely (relative to crashes that occurred under daylight or lit roadway conditions). Regarding the heterogeneity in variance of random parameter, a crash that involves a car was found to decrease the variance of three weeks to lockdown indicator variable, and a crash that occurred at open country was found to increase the variance. The results further show that SV crashes that occurred prior to the lockdown period on interstate highways and in rural areas were less likely to result in major injury. Similarly, SV crashes involving speeding, distracted driving, DUI and those that occurred on weekends were more likely to record minor injury but not major injury. The employed driver and unemployed driver indicator variables decrease the likelihood of major injury, but they increase the likelihood of minor injury by 0.0075 and 0.0028, respectively.

During the lockdown period, Table 4 shows that SV crashes that occurred on interstate highways were less likely to record major injury, whereas the probability of major injury increased by 0.0457 for crashes that occurred in rural areas. Speeding, aggressive driving, and drowsy driving indicator variables increased the likelihood of major injury by 0.0087, 0.004, and 0.0011, respectively. DUI was less likely to be primary contributing factor in major injury SV crashes after the lockdown order. The weekend crash indicator increased the probability of major injury by 0.006 and minor injury was more likely to be recorded between 6PM and midnight. By the sixth week after the lockdown order, the chance of injury was reduced by 0.0027 for major injury and 0.0012 for minor injury. SV crashes that occurred during the lockdown involving drivers aged 25–45 and 45–65 years were more likely to record major injury. Also, the no seatbelt indicator variable was found to increase the probability of major injury by 0.0378. The employed driver variable decreased the likelihood of major injury but increased the likelihood of minor injury by 0.0019, while the unemployed driver variable decreased the probability of injury in general.

With respect to Normal times MV crashes, Table 5 revealed that injury outcome was less likely for crashes that occurred on Interstate highways. The probability of major injury in MV crashes that occurred in rural areas increased by 0.0125 before the lockdown order. The intersection indicator and shopping area indicator variables also increased the probability of major injury by 0.0291 and 0.0008, respectively. MV crashes that involved speeding, DUI, and aggressive driving were more likely to result in major injury prior to the lockdown order than after it.

Table 4
Model estimation results for Normal MV crashes.

Variable	In severity function of	Latent Class 1		Latent Class 2		Marginal effects		
		Parameter estimate	t-statistics	Parameter estimate	t-statistics	Major injury	Minor injury	No injury
Constant	Major injury	−12.72	−0.95	−1.73	−8.14			
Crash location								
Interstate highway	No injury	−0.06	−0.22	0.12	2.77	−0.0001	−0.0005	0.0007
Rural area	Major injury	0.95	0.55	1.80	13.57	0.0125	−0.0050	−0.0076
Intersection	Minor injury	−0.65	−2.88	0.04	0.37	0.0291	−0.0691	0.0399
Shopping area	Minor injury	−0.19	−0.88	−0.32	−3.16	0.0008	−0.0159	0.0151
Residential area	No injury	0.30	1.09	0.23	1.90	−0.0004	−0.0045	0.0049
Contributing circumstances								
Speeding	Minor injury	1.99	4.75	−0.63	−1.16	0.0001	0.0046	−0.0047
DUI	Major injury	5.24	2.60	0.63	1.64	0.0016	−0.0002	−0.0014
Aggressive driving	Minor injury	2.76	5.23	−3.84	−0.65	0.0002	0.0026	−0.0028
Temporal factors								
Between midnight and 6AM	Major injury	−6.11	−0.05	0.75	2.95	0.0008	−0.0003	−0.0005
Between midday and 6PM	No injury	0.19	1.96	0.02	0.2	−0.0001	−0.0028	0.0029
Between 6PM and midnight	Major injury	1.48	0.96	0.29	1.86	0.0014	−0.0004	−0.001
Weekend	Major injury	2.63	1.45	0.21	1.84	0.0018	−0.0005	−0.0013
Manner of crash								
Rear-end collision	Major injury	−2.31	−1.28	−1.50	−9.73	−0.0058	0.002	0.0038
Side impact crash	Minor injury	−0.87	−2.18	1.08	6.67	−0.0029	0.019	−0.0161
Sideswipe	No injury	0.69	2.41	1.72	9.40	−0.0021	−0.0079	0.0101
Driver demographics and behavioral factors								
Female driver	Major injury	−1.34	−0.75	−0.52	−3.91	−0.0028	0.0012	0.0016
Driver less than 25 years	No injury	1.95	6.17	0.59	4.46	−0.0012	−0.0297	0.0309
Driver age between 25 and 45 years	Minor injury	−2.15	−6.37	−0.47	−3.66	0.0012	−0.0343	0.0331
Driver between 45 and 65 years	Minor injury	−2.71	−5.94	−0.10	−0.71	0.0002	−0.0113	0.0111
Driver aged 65 years or more	No injury	1.88	4.36	0.32	1.79	−0.0004	−0.0083	0.0086
Employed	Major injury	4.45	0.35	−0.55	−4.06	−0.0021	0.0014	0.0008
Unemployed	Minor injury	−0.24	−0.74	0.36	2.59	−0.0004	0.0025	−0.0021
Self-employed	No injury	−0.85	−2.06	0.64	2.41	−0.0003	−0.0001	0.0004
No seatbelt	Minor injury	4.33	6.32	−4.63	−0.43	0.0002	0.0059	−0.0061
Invalid license	Minor injury	−0.01	−0.02	0.46	3.15	−0.0003	0.0037	−0.0033
Vehicle type								
SUV	Minor injury	21.19	−3.3	0.13	1.12	−0.0002	−0.0011	0.0013
Pickup truck	No injury	0.64	2.2	0.07	2.62	−0.0002	−0.0033	0.0035
Model fit statistics								
Class member probability		0.62	17.76	0.38	10.72			
Number of observations		19,459						
Log likelihood function		−10050.594						
Log likelihood at zero		−21377.897						
McFadden pseudo R-sq		0.53						

Major injury was more likely to be recorded between 6PM and 6AM and on weekends. The indicator variables for driver aged 25–45 years and 45–65 years increased the probability of major injury by 0.0012 and 0.0002, respectively. Failure to wear seatbelt was also found to increase the likelihood of major injury in MV crashes that occurred before the lockdown.

The marginal effects in Table 6 show that the interstate highway indicator variable increased the likelihood of major injury by 0.0047 in MV crashes during lockdown, while the rural area indicator increased the likelihood of major injury by 0.0104. During the lockdown, the chance of major injury was lower at intersections, shopping areas and residential areas. However, the probability of injury increased for crashes involving speeding, DUI, aggressive driving and drowsy driving. The likelihood of major injury increased by 0.0014, 0.0012, 0.001, and 0.0002, for crashes involving speeding, DUI, aggressive driving, and drowsy driving, respectively. The likelihood of minor injury decreased by 0.0001 for speeding, but it increased by 0.0002, 0.0009, and 0.001 for DUI, aggressive driving, and drowsy driving, respectively. It was also found that MV crashes that occurred during the lockdown order were more likely to record major injury between 6PM and 6AM and during weekends. The side-impact indicator variable also increased the probability of major injury by 0.0005 and minor injury by 0.03 while rear-end crashes and sideswipes were more likely to result in minor injury.

A comparison of variables across all four models show some consistency and variations in how variables influence crash severity based on the period and manner of crash. For instance, the female driver and younger driver indicators decreased the probability of major injury, with the female driver indicator increasing the likelihood of minor injury across all four models. Older drivers were found to less likely to be involved in injury crashes except for SV crashes that occurred before lockdown. Also, it was found that in exception of MV crashes during the lockdown, drivers with no valid license were less likely to be involved in major injury crashes. Drivers of SUVs were found to have higher chances of sustaining minor injury in SV crashes prior to and during the lockdown period but were generally less likely to be injured in MV crashes. MV crashes that occurred in residential areas were less likely to record any form of injury.

Table 7 was further developed to isolate and better understand how the variables compare in terms of their contribution to major injury outcome. It can be observed that the probability of major injury on interstate highways was only high for MV crashes that occurred after the lockdown order, and rural area MV crashes were generally more likely to record major injury outcome compared to SV crashes. Intersection crashes and shopping area crashes involving two or more vehicles had

Table 5
Model estimation results for COVID SV crashes.

Variable	In severity function of	Latent Class 1		Latent Class 2		Marginal effects		
		Parameter estimate	t-statistics	Parameter estimate	t-statistics	Major injury	Minor injury	No injury
Constant	Major injury	−1.90	−8.20	−2.21	−5.90			
Crash location								
Interstate highway	Major injury	−1.05	−3.51	0.07	0.23	−0.0035	0.0001	0.0034
Rural area	Major injury	0.97	4.90	1.04	3.67	0.0457	−0.0137	−0.032
Contributing circumstances								
Speeding	Major injury	0.99	4.41	−0.36	−0.92	0.0087	0.0002	−0.0088
DUI	No injury	0.61	2.43	−0.27	−1.05	−0.0021	0.0011	0.001
Aggressive	Major injury	0.99	2.89	0.81	1.65	0.004	−0.0011	−0.0029
Drowsy driving	Major injury	0.62	1.85	−0.44	−0.86	0.0011	0.0003	−0.0014
Temporal factors								
Between midnight and 6AM	Minor injury	−3.94	−1.47	0.43	1.86	−0.0472	−0.3379	0.3851
Between midday and 6PM	No injury	0.74	3.56	−0.50	−2.22	−0.0037	0.0044	−0.0007
Between 6PM and midnight	Major injury	4.40	2.25	−0.53	−1.52	0.0567	0.0017	−0.0584
Between 6PM and midnight	No injury	4.38	1.25	−0.33	−1.94	−0.0586	0.0061	0.0525
Weekend	Major injury	0.25	1.84	0.31	1.27	0.006	−0.0019	−0.0041
Six weeks after lockdown	No injury	0.28	1.75	−0.01	−0.04	−0.0027	−0.0012	0.0038
Driver demographics and behavioral factors								
Female driver	Major injury	0.16	0.8	−1.23	−3.11	−0.0034	0.0031	0.0003
Driver less than 25 years	No injury	1.15	6.24	0.16	0.68	−0.0076	−0.0146	0.0221
Driver age between 25 and 45 years	Minor injury	−2.64	−5.38	−0.15	−0.74	0.0029	−0.0168	0.0139
Driver between 45 and 65 years	Minor injury	−2.16	−4.36	−0.22	−0.99	0.0019	−0.0118	0.0098
Driver aged 65 years or more	No injury	1.79	3.99	−0.60	−1.18	−0.0015	−0.0008	0.0024
Employed	Major injury	−1.90	−7.15	−0.07	−0.22	−0.026	0.0019	0.0241
Unemployed	Major injury	−1.47	−5.03	0.40	1.08	−0.0089	−0.0011	0.01
Self employed	No injury	1.39	3.85	0.23	0.84	−0.003	−0.0012	0.0042
No seatbelt	Major injury	2.76	10.06	1.08	2.52	0.0378	−0.0077	−0.0301
Invalid license	Minor injury	−1.93	−2.04	0.62	2.99	−0.0014	0.0072	−0.0058
Vehicle type								
SUV	Minor injury	−4.81	−0.47	0.18	2.08	−0.0005	0.0028	−0.0023
Pickup truck	No injury	0.35	1.77	0.38	2.26	−0.0033	−0.0067	0.01
Model fit statistics								
Class membership probability		0.63	12.76	0.37	7.64			
Number of observations		7622						
Log likelihood function		−5731.08						
Log likelihood at zero		−8373.6229						
McFadden pseudo R-sq		0.32						

higher chances of recording major injury prior to the lockdown. With regard to primary crash contributing factor, aggressive driving was more associated with major injury outcomes across all four models, while speeding and DUI were linked with major injury in only three (SV during lockdown, MV prior to lockdown and MV during lockdown) and two models (MV prior to lockdown and MV during lockdown), respectively. Furthermore, drowsy driving was more likely to result in major injury in both SV and MV crashes during the lockdown. The chances of major injury were low for crashes that occurred between midday and 6PM, across all models. However, MV crashes that occurred between 6PM and 6AM were more likely to record major injury prior to and after the stay at home order. Weekends were found to have higher chances of recording major injury during the lockdown order and in MV crashes prior to the lockdown order. Female drivers and younger drivers were less likely to be at fault in major injury crashes in all four models. On the other hand, drivers aged between 25 and 65 years were observed to be more likely at fault in major injury crashes during the lockdown and in MV crashes prior to the lockdown. The effect of failure to use seatbelt on major injury outcome has also been observed to be consistent across all four models. The variable increased the likelihood of major injury in all the models.

6. Discussion and recommendations for traffic safety management during pandemics

The rate of road crashes is predominantly influenced by traffic characteristics such as traffic volume and VMT. Generally, as traffic volume and VMT increase, the likelihood and frequency of crashes are expected to increase (as examples, refer to Figs. 1 and 2 where the correlation coefficients for daily county VMT and number of crashes in Alabama are 0.771 and 0.851 for COVID times and normal times respectively). The lockdown order that has been placed on states across the US during the COVID-19 global pandemic has caused a decline in travel activities. In Alabama, Fig. 3 shows a significant drop in VMT and total crashes after the week when the stay-at-home order was issued (March 11 i.e., week 11). This observation affirms the relationship between exposure (measured as VMT) and crashes.

A comparative analysis of the pattern of crashes that occurred within the first 28 weeks in the last three years revealed that crashes attributed to DUI, aggressive driving, distraction, and drowsy driving appeared to follow a similar pattern in 2018, 2019, and the first 11 weeks of 2020. After the stay-at-home order was issued in week 11, there was a general drop in the number of crashes until about week 17 where the number of crashes began to increase. A remarkable departure from this trend was observed for speeding crashes and crashes in which the driver failed to use seatbelt. These crashes appeared not to have been significantly impacted by the stay-at-home order. In fact, these risky behaviors contributed to a higher proportion of crashes that occurred after the lockdown than prior to the lockdown order. This observation may perhaps be due to the reduced traffic volumes and reduced law enforcement. Indeed, this finding is consistent with previous studies. For instance, according to Adanu et al. (2019), risky driver behaviors and

Table 6
Model estimation results for COVID MV crashes.

Variable	In severity function of	Latent Class 1		Latent Class 2		Marginal effects		
		Parameter estimate	t-statistics	Parameter estimate	t-statistics	Major injury	Minor injury	No injury
Constant	Major injury	−8.19	−2.06	−2.23	−14.07			
Crash location								
Interstate highway	Major injury	5.16	1.29	−1.21	−2.53	0.0047	−0.0016	−0.0031
Rural area	Major injury	1.14	2.15	1.45	12.3	0.0104	−0.0005	−0.0099
Intersection	Minor injury	0.13	2.07	−2.77	−2.11	−0.0019	0.0083	−0.0063
Shopping area	Minor injury	−0.10	−1.69	−2.46	−2.31	−0.0005	−0.0072	0.0077
Residential area	No injury	0.20	2.87	0.37	2.93	−0.0013	−0.0053	0.0067
Contributing circumstances								
Speeding	Major injury	0.25	0.28	1.45	5.28	0.0014	−0.0001	−0.0013
DUI	Major injury	−4.83	−0.23	1.50	5.58	0.0012	0.0002	−0.0014
Aggressive	Major injury	0.88	0.66	1.41	4.64	0.001	0.0009	−0.0019
Drowsy driving	Minor injury	1.46	4.11	−0.29	−0.17	0.0002	0.001	−0.0012
Temporal factors								
Between midnight and 6AM	Minor injury	0.06	0.44	−2.69	−1.68	0.0003	0.0001	−0.0004
Between midday and 6PM	No injury	0.19	4.05	0.41	3.59	−0.0031	−0.0124	0.0155
Between 6PM and midnight	Major injury	1.40	2.67	0.35	2.44	0.0023	−0.0002	−0.0021
Weekend	Minor injury	0.01	0.09	−2.81	−1.96	0.0002	−0.0004	0.0002
Manner of crash								
Rear-end collision	Major injury	0.34	0.44	−1.46	−10.22	−0.0048	0.0008	0.004
Side impact	Minor injury	0.94	11.29	−2.79	−1.25	0.0005	0.03	−0.0305
Sideswipe	Major injury	−0.31	−0.33	−2.19	−7.55	−0.0016	0.0001	0.0015
Driver demographics and behavioral factors								
Female driver	Major injury	0.20	0.38	−0.19	−1.67	−0.0012	0.0002	0.001
Driver less than 25 years	No injury	0.96	7.69	0.45	3.61	−0.0018	−0.0303	0.0321
Driver age between 25 and 45 years	Minor injury	−0.90	−6.93	−2.10	−3.56	0.0003	−0.04	0.0398
Driver between 45 and 65 years	Minor injury	−0.97	−7.51	−2.50	−3.08	0.0002	−0.0263	0.0262
Driver aged 65 years or more	No injury	1.03	7.68	0.41	2.43	−0.0008	−0.0134	0.0142
Employed	Major injury	−1.63	−3.02	−0.51	−4.09	−0.0046	0.0003	0.0043
Unemployed	Major injury	−6.31	−0.64	−0.14	−1.83	−0.0004	0.0002	0.0002
Self employed	No injury	0.11	1.89	0.24	0.92	−0.0002	−0.0005	0.0007
No seatbelt	Major injury	1.29	1.31	2.79	10.79	0.0044	−0.0002	−0.0042
Invalid license	Minor injury	0.39	5.41	−3.52	−1.32	0.0001	0.0064	−0.0065
Vehicle type								
SUV	Minor injury	−0.02	−0.32	−0.92	−1.82	0.0001	−0.0012	0.0011
Pickup truck	No injury	0.11	1.84	0.32	2.43	−0.0011	−0.0027	0.0038
Model fit statistics								
Class membership probability		0.54	10.77	0.46	9.08			
Number of observations		22,491						
Log likelihood function		−12349.644						
Log likelihood at zero		−24708.889						
McFadden pseudo R-sq		0.50						

the crashes they contribute to may be influenced by situational and regional factors/systems such as traffic laws and rigor of traffic law enforcement. Further analysis of the 2020 crash data revealed that more than half of all multi-vehicle crashes occurred at intersections and at shopping areas compared to open country and more crashes occurred in residential areas during the stay-at-home order than the period prior to the order. These findings reflect the events leading to the lockdown where panic-buying was at a peak, with increased traffic activities at shopping areas and residential areas.

The crash severity analyses performed in this study further revealed the factors that contributed to the crashes, but more importantly, how these factors influenced the outcome of the crashes. For instance, while drowsy driving was found to be account for only 0.7% of multi-vehicle crashes and 6.7% of single-vehicle crashes during the lockdown period, the model estimation results show that these crashes had significantly higher probability to be associated with major injury outcome. Similarly, speeding and weekends were observed to be significantly associated with major injury crash outcome in crashes that occurred during the lockdown period and in multi-vehicle crashes prior to the lockdown order. These major injury outcome crashes were more likely to involve drivers aged between 25 and 65 years and there was also higher probability that these crashes occurred in the rural areas of the state and between 6PM and 6AM. Female drivers and younger drivers were less likely to be involved in major injury crashes. For single-vehicle crashes that occurred within three weeks to the lockdown order, the chances of recording major injury were high, whereas crashes that occurred six weeks into the lockdown period, the likelihood of major injury was low. Multi-vehicle crashes in which SUV was at fault during the lockdown were more likely to result in major injury.

Aggressive driving was found to be associated with major injury crash outcome irrespective of when the crash occurred. Similarly, crashes involving drivers who failed to use seatbelt were more likely to record major injury irrespective of the time of the crash. While these findings are generally consistent with previous studies, it is important to recognize the influence of the lockdown order on crashes and crash outcomes. Although traffic volumes and VMT had significantly dropped during the lockdown, there have been an increase in the total number of crashes and major injury crashes compared to the period prior to the lockdown order, with speeding, DUI, and weekends accounting for a significant proportion of these crashes.

These findings provide useful lessons for road safety improvements during extreme events that may require statewide lockdown, as has been

Table 7
Comparison of the effect of crash factors on major injury crash outcome.

Variables	Normal SV	COVID SV	Normal MV	COVID MV
Crash location				
Interstate highway	Low	Low	Low	High
Rural area	Low	High	High	High
Intersection	–	–	High	Low
Shopping area	–	–	High	Low
Residential area	–	–	Low	Low
Contributing circumstances				
Speeding	Low	High	High	High
DUI	Low	Low	High	High
Aggressive	High	High	High	High
Drowsy driving	–	High	–	High
Distracted driving	Low	–	–	–
Temporal factors				
Between midnight and 6AM	Low	Low	High	High
Between midday and 6PM	Low	Low	Low	Low
Between 6PM and midnight	Low	Low	High	High
Weekend	Low	High	High	High
Six weeks after lockdown	–	Low	–	–
Three weeks before lockdown	High	–	–	–
Manner of crash				
Rear-end collision	–	–	Low	Low
Side impact	–	–	Low	High
Sideswipe	–	–	Low	Low
Driver demographics and behavioral factors				
Female driver	Low	Low	Low	Low
Driver less than 25 years	Low	Low	Low	Low
Driver age between 25 and 45 years	–	High	High	High
Driver between 45 and 65 years	Low	High	High	High
Driver aged 65 years or more	Low	Low	Low	Low
Employed	Low	Low	Low	Low
Unemployed	Low	Low	Low	Low
Self employed	Low	Low	Low	Low
No seatbelt	High	High	High	High
Invalid license	Low	Low	Low	High
Vehicle type				
SUV	Low	Low	Low	High
Pickup truck	Low	Low	Low	Low

done with the COVID-19 pandemic. Traffic management around shopping areas and other areas that may experience increased traffic provide opportunities for road safety stakeholders to reduce the occurrence of crashes in the weeks leading to an announcement of any future statewide or local lockdowns. Lessons learned from the COVID-19 pandemic could also help in managing anxiety among citizens that may prompt panic shopping and rushed travel decisions which may have indirect consequences for road safety. Beyond the wholesale traditional road safety and public awareness campaigns, it would be necessary to identify and target messages to road users that have been shown to exhibit risky behaviors. This process should include strategies and appropriate media through which the majority of these road users could be reached in an efficient and effective manner. Also, traffic enforcement could be intensified during weekends and between 6PM and 6AM to reduce risky driving behaviors. Additionally, the use of technology in traffic law enforcement efforts across the state such as red light running and automated speed enforcement cameras, particularly at high risk locations, would ensure continuous enforcement in times when it becomes difficult to deploy law enforcement personnel into the field.

7. Conclusion

The road safety implications of the COVID-19 pandemic are beginning to be understood across various jurisdictions. Despite a significant decrease in traffic volumes and VMT, many regions of the world have reported increases in the number and severity of crashes during the pandemic. This observation offers the opportunity for traffic safety professionals to plan for appropriate countermeasures for a third wave or even future pandemics. However, in order to develop and prioritize the implementation of countermeasures, it is imperative to understand the trends and factors that influence the occurrence and outcome of crashes. Consequently, this study was carried out in the state of Alabama to inform policy and decision makers on the best strategies on how to improve road safety in the midst of a pandemic. The first 28 weeks of crash data in 2020 was obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety at the University of Alabama and for the purposes of comparing the crash trends, data for the two previous years were also obtained. However, only the crash data for 2020 was analyzed to understand how the pandemic affected the factors that influenced crash outcomes. The data were segmented into manner of collision and period of the crash. Latent class multinomial logit and random parameters with heterogeneity in means and variances modeling techniques were used to address the challenge of unobserved heterogeneity in the crash data.

The model estimation results generally show that aggressive driving, DUI, drowsy driving, speeding and failure to use seatbelt were more associated with major injury crash outcome. Rural areas and weekends were also found to have higher chances of recording major injury crashes. Multi-vehicle crashes that occurred prior to the lockdown order recorded the highest number of major injury outcomes. Perhaps, this was due to the increased traffic activities that occurred around shopping areas in the days prior to the lockdown order. Younger drivers and senior drivers were less likely to sustain major injury, whereas drivers aged between 25 and 65 years had higher probability of being involved in major injury crashes, particularly during the lockdown. Multi-vehicle crashes that occurred between 6PM and 6AM were also found to be more likely to result in major injury before and during the lockdown.

Segmentation of the data by manner of collision and period of crash provided detailed insight into how various crash factors influenced crash outcomes. The findings of the study further reveal how the COVID-19 pandemic has affected crash trends and outcomes across the state of Alabama. For instance, it was found that while the total number of crashes decreased in the weeks after the lockdown order in comparison to the crashes that occurred during the same period in previous years, the number of fatalities during the lockdown period was similar to those in previous years. With respect to contributing factors, speeding and failure to use seatbelt were observed to play significant roles in the high fatalities recorded over the lockdown period. These observations are expected to provide a data-driven foundation to prioritize road safety strategies in order to minimize the effects of the pandemic on road safety.

CRediT authorship contribution statement

Emmanuel Kofi Adanu: Conceptualization, Methodology, Writing – original draft. **David Brown:** Data curation, Writing – original draft, Writing – review & editing. **Steven Jones:** Writing – review & editing. **Allen Parrish:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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