# How did COVID-19 impact driving behaviors and crash Severity? A multigroup structural equation modeling

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## ARTICLE INFO

## ABSTRACT

Risky driving behaviors such as speeding and failing to signal have been witnessed more frequently during the COVID-19 pandemic, resulting in higher rates of severe crashes. This study aims to investigate how the COVID-19 pandemic impacts the likelihood of severe crashes via changing driving behaviors. Multigroup structural equation modeling (SEM) is used to capture the complex interrelationships between crash injury severity, the context of COVID-19, driving behaviors, and other risk factors for two different groups, i.e., highways and non-highways. The SEM constructs two latent variables, namely aggressiveness and inattentiveness, which are indicated by risk driving behaviors such as speeding, drunk driving, and distraction. One great advantage of SEM is that the measurement of latent variables and interrelationship modeling can be achieved simultaneously in one statistical estimation procedure. Group differences between highways and non-highways are tested using different equality constraints and multigroup SEM with equal regressions can deliver the augmented performance. The smaller severity threshold for the highway group indicates that it is more likely that a crash could involve severe injuries on highways as compared to those on non-highways. Results suggest that aggressiveness and inattentiveness of drivers increased significantly after the outbreak of COVID-19, leading to a higher likelihood of severe crashes. Failing to account for the indirect effect of COVID-19 via changing driving behaviors, the conventional probit model suggests an insignificant impact of COVID-19 on crash severity. Findings of this study provide insights into the effect of changing driving behaviors on safety during disruptive events like COVID-19.

## 1. Introduction

Traffic conditions have been changing widely since the lockdown of the COVID-19 pandemic in 2020. Studies have shown that there is a dramatic drop in traffic demand during the pandemic. For instance, Parr et al. (2020) analyzed same-day traffic volume for 2019 and 2020 across Florida to identify spatial and temporal changes and found that compared to similar days in 2019, overall statewide traffic volume dropped by 47.5%. Zuo et al. (2020) investigated the impact of COVID-19 on mobility in New York City since the pandemic outbroke. Their dashboard illustrated that both transit ridership and vehicular traffic declined steeply in March and April 2020. The reduction in traffic demand caused by the pandemic leads to lower crash frequencies (Zuo et al. 2020), but it is unclear how the COVID-19 has impacted the crash severity. According to crash data we collected in Virginia, risky driving

behaviors such as speeding, driving under the influence of alcohol, and unbelted driving are observed more frequently after the outbreak of COVID-19, raising the proportion of severe crashes (including serious injuries and fatal injuries) to 7.63% from 6.09% in comparison with the same period of last year. New York City has also witnessed changes in driving behaviors and the increase in the proportion of fatal crashes after the outbreak of COVID-19. Zuo et al. (2020) found that the mean traffic speed on the Midtown Avenue increased by 108% from 8AM to 6PM (Apr vs. Feb 2020), and school zone speeding tickets increased by 72% (March 13 to Apr 19 vs. Jan 1 to Mar 12, 2020). They also found that the crash fatality rate increased from 1.4 to 1.9 per thousand crashes in the first three weeks for April 2020 compared to the same period of February 2020. Doucette et al. (2021) analyzed daily vehicle miles travelled (VMT) and motor vehicle collision (MVC), and they found despite a decrease in the number of VMT and MVCs, the single vehicle fatal crash

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rates increased by 410% than the pre-lockdown period in Connecticut. The Police have seen an increase in drivers speeding during the pandemic, suggesting more risky driving has been occurring (Doucette et al. 2021).

Previous studies have reported increases in risky driving behaviors and proportions of severe crashes due to the lockdown of the COVID-19 pandemic. However, there is limited research that systematically models the effects of the pandemic on the crash severity. This study aims to investigate how the COVID-19 pandemic impacts the likelihood of severe crashes via changing driving behaviors. We propose to use multi-group structural equation modeling (SEM) to capture the complex interrelationships between crash injury severity, COVID-19, driving behaviors, and other risk factors for different road groups. Virginia is selected as a case study.

## 2. Literature review

Driving is a dynamic process which is comprised of three key components including driver, vehicle and the driving environment (Khan & Lee, 2019). Human drivers have differently abnormal driving behaviors which could be acquired from causes of crash data recorded by the Police in Virginia. There are intensive studies that have classified driving behaviors to types. It is efficient and vital to discuss and classify drivers' risky driving behaviors for the future study of automated transportation safety. Shahverdy et al. (2020) have defined driving behaviors as different habits, manners, and actions of the drivers, and have gathered vehicle data to divide the driver behaviors into five classes: safe or normal, aggressive, distracted, drowsy, and drunk driving. The impatient activities of a driver are aggressive when he tries to minimize travel time, and transient inattention of a driver to the task of driving might make a distracted driving pattern (Shahverdy et al. 2020). Alkinani et al. (2020) classified and discussed the abnormal human driving behaviors into two types: Human Aggressive Driving Behavior (HADB), and Human Inattentive Driving Behaviors (HIDB) that led to road crashes. The aggressiveness refers to an intentional risk-taking behavior for instance, making frequent or unsafe lane changes, excessive speeding, tailgating etc. The inattentiveness refers to distractions of a human driver from driving by another activity or object, and drowsiness of a human driver when he is too tired to remain alert (Hendricks et al., 2001). It is the driver who is responsible to make appropriate decision and take actions accordingly by staying aware and attentive to the environment and the current situation (Alkinani et al., 2020).

There are numerous studies investigating the impacts of risky driving behaviors on crash injury severity. For instance, Cooper (1997) followed three years of speeding conviction records, and found that both excessive speed and exceeding speed limit were significant predictors of subsequent crash severity. Abegaz et al. (2014) also found that the probability of serious injury and death exceptionally increased with increasing speed. In addition, Compton et al. (2002) found that traffic crashes were more likely to result in deaths or injuries if alcohol was involved. They collected the data on 4,919 drivers involved in crashes of all severities, and the study results showed that the crash risk increased as the blood alcohol concentration (BAC) increased with an accelerated rise at BACs in excess of 0.10 BAC. Peck et al. (2008) found BACs in drivers under the age of 21 were associated with higher relative crash risks than would be predicted from the addictive effect of BAC and age. Hingson et al. (2002) found that 4% of all alcohol-related crashes resulted in deaths and 42% leaded to injuries; in contrast, of the crashes that did not involve alcohol, the proportions of death and injury occurrence were merely 0.6% and 31%. Furthermore, there are a number of studies found that the use of seatbelts could limit the severity of injuries. Høye (2016) performed a *meta*-analysis that was based on 24 studies from 2000 or later and estimated that the unbelted drivers have 8.3 times the fatal crash risk and 5.2 times the serious injury crash risk of the belted drivers. Ichikawa et al. (2002) compared risk of death and severe injury of front-seat occupants in car crashes with belted or

unbelted rear-seat passengers and found that the risk of death of belted front-seat occupants with unbelted rea-seat passengers was raised nearly five-fold. These previous studies were explaining the impact of separate risky driving behaviors on traffic safety by case-control study, logistic regressions, or statics summaries. The complex analysis of several risky driving behaviors can be further explored.

Several studies have investigated the impact of COVID-19 lockdown-related policies on road safety. Most of these studies analyzed traffic crash data using descriptive analysis approach. As some examples, Christey et al. (2020) analyzed patients who were admitted to hospitals and had suffered injuries from traffic crashes immediately after the start of the pandemic in New Zealand. A reduction in traffic crashes has been found by comparing with patients injured in traffic crashes during the same period in the previous year and different crash reductions were found for different injury severity levels. The finding of different crash reductions for different severity levels has also been observed by Katrakazas et al. (2020) in Greece and Kingdom of Saudi Arabia, Saladié et al. (2020) in Tarragona, Spain, and Muley et al. (2021) in the State of Qatar. Beside using the descriptive analysis approach, Oguzoglu (2020) and Brodeur et al. (2021) applied difference-in-difference approach and developed Poisson regression model respectively to investigate the safety effect of COVID-19 lockdown in Turkey and the US. Findings from these two studies are similar to that obtained from applying descriptive analysis approach as discussed above. In addition to analyzing crash data, Katrakazas et al. (2020) also analyzed driving behaviors after the implementation of lockdown using data collected from smartphone applications in Greece and Kingdom of Saudi Arabia. Increases in speeding violations and harsh braking events during the first two months of the lockdown were reported.

The SEM is gaining increasing attention in modeling crash severity (Tazul Islam et al., 2017). Najaf et al. (2017) stated that SEMs were able to account for complex relationships between multiple dependent and multiple independent variables, their interrelationships, and also indirect relationships between dependent and independent variables through latent variables. Xu et al. (2018) used SEMs to transform several correlated traffic variables into four independent latent traffic factors and established the interrelationships among traffic variables and crash risks. They found that the measurement equations in SEM could both capture the direct and indirect effects of traffic variables on crash risks. Xie et al. (2018) proposed SEMs to jointly model the presence of secondary collisions and crash severity levels and found that the SEM with no constraint did better performance in investigating the contributing factors to secondary collisions. They found that thirteen variables were contributing to the presence of secondary collisions, including alcohol, drugs, inattention, inexperience, sleep, control disregarded, speeding, etc. Barman and Bandyopadhyaya (2020) used SEMs to assess the direct and latent influence of driver, vehicle, crash along with environmental factors. They found that the SEM model showed a better overall model fit compared to the ordered probit model.

How the COVID-19 affects the driving behaviors and crash severity have not been fully explored in the literature. One great advantage of SEM is that the measurement of latent variables and structure modeling can occur simultaneously in one statistical estimation procedure. This study proposes to use the SEM to construct latent variables indicated by risky driving behaviors and to model how the COVID-19 affect crash severity via impacting those latent variables.

## 3. Crash data and descriptive analysis

Virginia issued the stay-at-home order on March 30, 2020, in response to the COVID-19 pandemic. To study the impact of the COVID-19 on crash severity, we acquired crash data in the periods of April 1st - April 30th, 2020 and April 1st - April 30th, 2019 from the Virginia
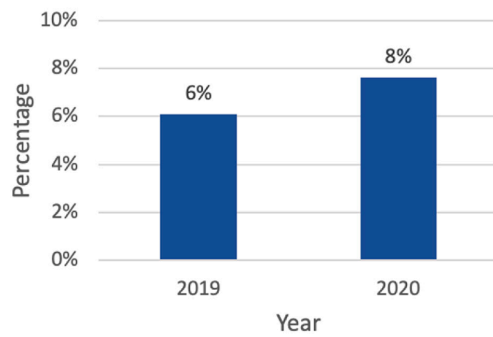
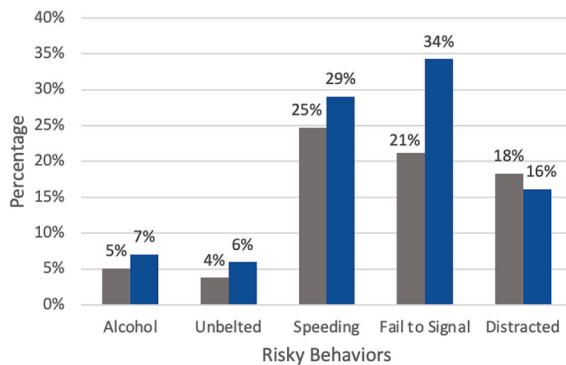**Fig. 1.** Compared proportions of severe crashes in April 2019 and April 2020.



**Fig. 2.** Proportions of severe crashes by risky driving behaviors in April 2019 and April 2020.

Department of Transportation (VDOT)[1]. There were 10,138 crashes in April 2019, while the crash count decreased dramatically to 5,259 in April 2020 since there were far less traffic.

There are five injury severity levels in the VDOT crash record: property damage only (PDO), nonvisible injury (C), visible injury (B), severe injury (A), and fatal injury (K). We reclassified crashes into two crash types, i.e., severe crashes including fatal injury and severe injury, and non-severe crashes including proper damage only, nonvisible injury and visible injury. The proportion of severe crashes in April 2019 was 6.09%, while this proportion increased to 7.63% in April 2020. Empirically, COVID-19 pandemic raised the likelihood of severe crashes. Fig. 1 presents the comparison of crash severity between April 2019 and April 2020 in Virginia.

Driver, collision type, road, and environmental features with the potential to affect the occurrence of injury severity were extracted from the crash records. Driver features mostly described the risky driving behaviors such as speeding, following closely, driving under the influence of alcohol, and unbelted seat. From Fig. 2, the proportions of different risky behaviors are compared between April 2019 and April 2020. The crashes involved risky driving behaviors of drinking alcohol have increased from 5.10% to 7.05%, and the crashes involved risky driving behaviors of speeding have increased from 24.73% to 29.09%. The proportion of failing to signal has increased the most from 21.19% to 34.30%. For severe crashes, they were further classified into rear-end, head-on, sideswipe, and pedestrian, etc. Road types were divided into two types: highways (including interstate highways, US highways, state highways, and county highways in the National Highway System of U. S.), of which speed limit is 55 or more miles per hour, and local ways, of which the speed limit was below 35 miles per hour. Road surface conditions (e.g., dry, wet, and snowy) and environmental features (e.g.,

**Table 1**
Descriptions and Descriptive Statistics of Key Variables (N = 7,432 Crashes).

| Variable | Description | Mean | S.D. |
|---|---|---|---|
| Crash severity | 1 for severe injury; 0 for non-severe injury | 0.07 | 0.25 |
| COVID-19 | 1 for post-COVID-19; 0 for pre-COVID-19 | 0.33 | 0.47 |
| **Driver** | | | |
| Alcohol | 1 for crashes with drivers involving alcohol; 0 for others | 0.05 | 0.23 |
| Distraction | 1 for crashes with distracted drivers; 0 for others | 0.17 | 0.38 |
| Unbelted | 1 for crashes with unbelted drivers; 0 for others | 0.04 | 0.21 |
| Speeding | 1 for crashes caused by speeding; 0 for others | 0.17 | 0.38 |
| Follow closely | 1 for crashes caused by following too closely; 0 for others | 0.26 | 0.44 |
| Turn improperly | 1 for crashes caused by turning improperly; 0 for others | 0.02 | 0.12 |
| Disregard | 1 for crashes caused by driver's disregard; 0 for others | 0.04 | 0.20 |
| Avoid other objects | 1 for crashes caused by avoiding other objects; 0 for others | 0.03 | 0.18 |
| Improper lane change | 1 for crashes caused by improper lane change; 0 for others | 0.08 | 0.28 |
| Wrong side of road | 1 for crashes caused by wrong side of road; 0 for others | 0.12 | 0.33 |
| Fail to signal | 1 for crashes caused by failure of signaling; 0 for others | 0.25 | 0.43 |
| Fail to stop | 1 for crashes caused by failure of stopping; 0 for others | 0.00 | 0.03 |
| Pass improperly | 1 for crashes caused by improper passing; 0 for others | 0.01 | 0.10 |
| **Collision Type** | | | |
| Rear-end | 1 for rear-end crashes; 0 for others | 0.33 | 0.47 |
| Head-on | 1 for head-on crashes; 0 for others | 0.01 | 0.11 |
| Fixed objects | 1 for crashes on fixed objects; 0 for others | 0.26 | 0.44 |
| Angle | 1 for crashes with angle; 0 for others | 0.20 | 0.40 |
| Side swipe | 1 for crashes with side swipe; 0 for others | 0.10 | 0.29 |
| Pedestrian | 1 for crashes involving pedestrians; 0 for others | 0.01 | 0.08 |
| **Road** | | | |
| Highway | 1 for crashes occurring on highways; 0 for others | 0.52 | 0.50 |
| Local | 1 for crashes occurring on local ways; 0 for others | 0.14 | 0.35 |
| Dry | 1 for crashes occurring at roads with dry surface; 0 for others | 0.78 | 0.42 |
| Wet | 1 for crashes occurring at roads with wet surface; 0 for others | 0.22 | 0.41 |
| Snowy | 1 for crashes occurring at roads with snowy surface; 0 for others | 0.00 | 0.03 |
| Truck percentage | Sum of percentages of different types of trucks on the road (%) | 5.44 | 5.89 |
| Log (AADT) | Log value of AADT on the specific road where the crash happened | 9.98 | 1.47 |
| Number of the lane | Number of the lane at the crash location | 3.17 | 1.27 |
| **Environment** | | | |
| Area type | 1 for crashes occurring at urban areas; 0 for others | 0.71 | 0.45 |
| Adverse conditions | 1 for crashes occurring during adverse conditions; 0 for others | 0.20 | 0.40 |
| Daylight | 1 for crashes occurring during the daylight; 0 for others | 0.73 | 0.44 |
| Darkness | 1 for crashes occurring during the darkness; 0 for others | 0.22 | 0.41 |
| Dawn | 1 for crashes occurring during the dawn; 0 for others | 0.05 | 0.22 |

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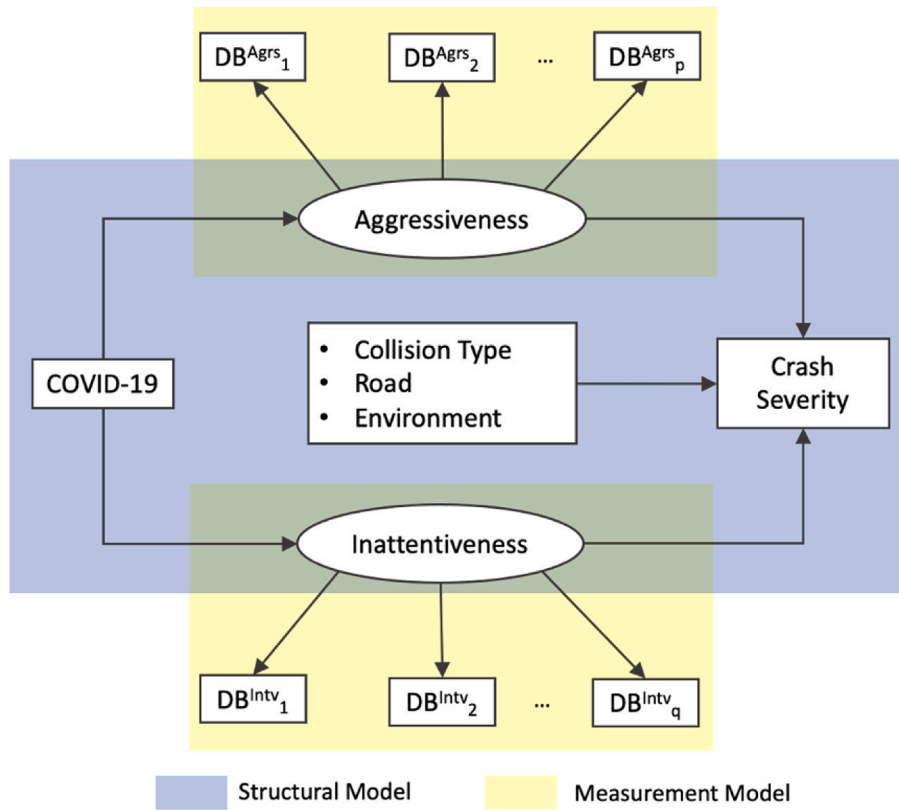[1] Source: https://www.virginiaroads.org/.

**Fig. 3.** Conceptual path diagram of the proposed SEM.

adverse condition, daylight) were also collected.

There were 7,432 crash records with complete information, and they were used for multigroup SEM modeling in this study. The description and descriptive statistics of the data are listed in Table 1.

## 4. Structural equation modeling (SEM)

### 4.1. Model specification

The SEM framework is used to transform several driving behavior indicators into latent variables and explore interrelations between crash severity, latent variables, COVID-19, and other contributing factors. The conceptual framework of the proposed SEM is shown in Fig. 3. With the pandemic of COVID-19 and issued stay-home orders, it is hypothesized that drivers' driving behaviors had been influenced. Hypothetically, drivers might drive more aggressively and inattentively than they previously did in Virginia, which might result in higher likelihood of severe crashes. We construct two latent variables, i.e., aggressiveness and inattentiveness, which are indicated by risky driving behaviors (e.g., speeding, drunk driving) and influenced by the outbreak of COVID-19. Crash severity is jointly affected by observed features of road and environment, as well as the latent variables aggressiveness and inattentiveness. The model parameters including coefficients and p-values of explanatory variables, which aims to define the significance of variable COVID-19 in relation with the crash severity.

The structural model of the SEM is expressed as:

$$y_i^* = \boldsymbol{x}_i\boldsymbol{\beta} + \gamma_1 Agrs_i + \gamma_2 Intv_i + \varepsilon_i^y$$

$$y_i = 1, if y_i^* > \varphi, y_i = 0, otherwise$$

$$Agrs_i = \alpha_1 COVID_i + \varepsilon_i^{Agrs}$$

$$Intv_i = \alpha_2 COVID_i + \varepsilon_i^{Intv}$$

(1)

where $i(i = 1, 2, \cdots, N)$ is the index for crashes; $y_i^*$ is propensity of crash severity (the lager the more likely to be involved with severe crashes); $y_i$ is the observed injury severity (0 for non-severe injury, 1 for severe injury) for crash $i$; $\boldsymbol{x}_i$ is a vector of observed variables that indicate collision type, road and environment features for crash $i$; $\boldsymbol{\beta}$ is a vector of coefficients corresponding to $\boldsymbol{x}_i$; $Agrs_i$ is a latent variable indicated by aggressive driving behaviors in crash $i$; $Intv_i$ is a latent variable indicated by inattentive driving behaviors in crash $i$; $COVID_i$ is an observed variables that indicates the crash $i$ is during the presence of COVID-19 pandemic; $\gamma_1$ and $\gamma_2$ are the coefficients of the two latent variables; $\alpha_1$ and $\alpha_2$ are the coefficients of $COVID_i$; $\varepsilon_i^y$, $\varepsilon_i^{Agrs}$, and $\varepsilon_i^{Intv}$ are normally distributed error terms; and $\varphi$ is a threshold to determine crash severity outcome. In multigroup SEM with equal thresholds, $\varphi$ is held the same across highway and non-highway groups, while other parameters are not contained. Similarly, in multigroup SEM with equal regressions, $\boldsymbol{\beta}$, $\alpha_1$, $\alpha_2$, $\gamma_1$, and $\gamma_2$ are held the same across groups, while other parameters are not constrained. For multigroup SEM with no constraint, all parameters are freely estimated across groups.

The measurement model of the SEM is formulated as:

$$\boldsymbol{DB}^{Agrs} = \boldsymbol{Agrs}\boldsymbol{\Lambda}^{Agrs} + \boldsymbol{\delta}^{Agrs}$$
$$\boldsymbol{DB}^{Intv} = \boldsymbol{Intv}\boldsymbol{\Lambda}^{Intv} + \boldsymbol{\delta}^{Intv}$$

(2)

where $\boldsymbol{DB}^{Args}$ is a $(N \times p)$ matrix of the observed driving behaviors associated with aggressiveness, and $\boldsymbol{DB}^{Intv}$ is a $(N \times q)$ matrix of the observed driving behaviors associated with inattentiveness; $\boldsymbol{Agrs}$ is a $(N \times 1)$ vector of the latent variable aggressiveness, while $\boldsymbol{Intv}$ is a $(N \times 1)$ vector of the latent variable inattentiveness; $\boldsymbol{\Lambda}^{Args}$ is a $(1 \times p)$ vector of factor loading for aggressiveness, and $\boldsymbol{\Lambda}^{Intv}$ is a $(1 \times q)$ vector of factor loading for inattentiveness; $\boldsymbol{\delta}^{Agrs}$ and $\boldsymbol{\delta}^{Intv}$ are $(N \times p)$ matrices of gaussian errors.

Mean- and variance- adjusted weighted least squares (WLSMV) estimator is robust for the estimation of models with ordered-categorical

**Table 2**

Statistical Indices of Multigroup Structural Equation Models (SEMs) with Equal Thresholds, Equal Regressions and No Constraint.

| | Multigroup Structural Equation Models (SEMs) | | |
|---|---|---|---|
| | Equal Thresholds | Equal Regressions | No Constraint |
| **Chi-square statistics** | | | |
| Chi-square | 1582.32 | 1564.23 | 1431.24 |
| Degrees of freedom | 124 | 131 | 60 |
| P-value | 0.000 | 0.000 | 0.000 |
| **RMSEA** | 0.056 | 0.054 | 0.055 |
| **TLI** | 0.385 | 0.428 | 0.370 |

response variables (Markus, 2012). Therefore, we used the WLSMV estimator to estimate the parameters of the proposed SEMs.

### 4.2. Model assessment

A set of statistical indices can be used to assess the performance of the SEMs. Chi-square ($\chi^2$) tests are widely used to indicate the model goodness of fit. The null hypothesis of a chi-square test is that the proposed model can fit the data, so insignificant results are desired. However, the chi-square tests always tend to be statistically significant for models with large sample size (Markus, 2012). Another widely used measure of model fit is the root mean square error of approximation (RMSEA). The RMSEA is computed based on the chi-square statistic, but it considers the model complexity by including degrees of freedom. The RMSEA is given by:

$$RMSEA = \sqrt{\frac{\chi_M^2 - df_M}{df_M(N-1)}} \quad (3)$$

where $\chi_M^2$ is the chi-square statistic for the proposed model $M$ $df_M$ is the chi-square statistic for the proposed model $M$ and it indicates the degrees of freedom; and $N$ is the number of samples. The RMSEA ranges from 0 to 1, with smaller value indicating a better fit. Generally, a model with RMSEA less than 0.05 is favored (Markus, 2012).

Relative fit indices measure the relative improvement in the fit of the proposed model over that of a baseline model (null model with no explanatory variables) (Markus, 2012). Widely used relative fit indices for SEM include comparative fit index (CFI) and Tucker Lewis index (TLI). The CFI and TLI penalize model complexity using $\chi_M^2 - df_M$ and $\chi_M^2/df_M$, respectively. Compared with CFI, TLI is less affected by sample size (Bollen, 1990) and is used for model assessment given the large sample size in this study. The TLI is given by:

$$TLI = \frac{\chi_B^2/df_B - \chi_M^2/df_M}{\chi_B^2/df_B - 1}$$

where $\chi_B^2$ and $df_B$ are the chi-square statistics and degrees of freedom for the baseline model, respectively. A larger TLI indicates a better fit to the data (Hu and Bentler 1995).

## 5. Model results

The SEM framework in Fig. 3 was used to model the interrelationships between crash injury severity, COVID-19, driving behaviors, and other risk factors using data collected in VA. To test group differences between highways and non-highways, three multigroup SEMs are proposed to with equal thresholds (the thresholds are constrained to be the same for the groups of crashes on highway and non-highway), equal regressions (the regression coefficients are constrained to be the same for the groups of crashes on highways and non-highways) and no constraint (the thresholds and regression coefficients for groups of crashes on highway and non-highway are set to be different). Only the explanatory variables with statistically significance are used in the final models. Each SEM has the same selection of explanatory variables so effective comparison can be performed. Statistic indices are reported in Table 2.

Considering the great number of samples (N = 7,432) used for model development, the significant results of chi-square tests can be ignored. There is little difference of the chi-square among three SEMs. The SEM with no constraint can result in a slightly smaller chi-square at the expense of lower degrees of freedom. All the multigroup SEMs have
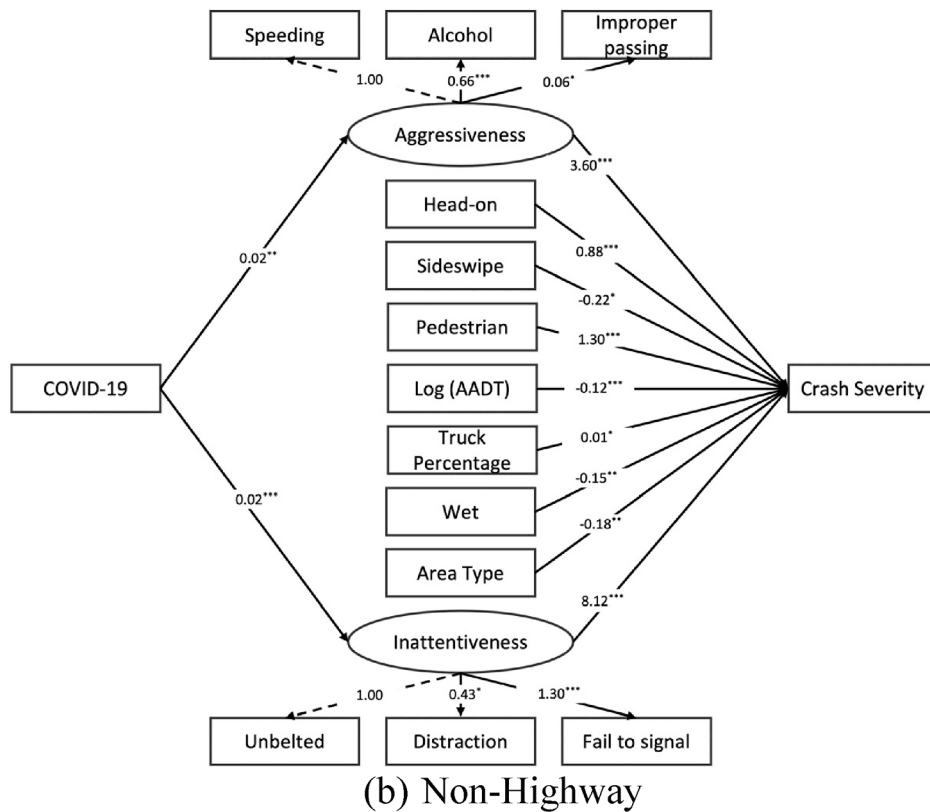
**Table 3**

Estimates of parameters in the multigroup SEM with equal regressions.

| | Highway | | | Non-Highway | | |
|---|---|---|---|---|---|---|
| | Estimate | Std. Err | P-value | Estimate | Std. Err | P-value |
| **Measurement Model** | | | | | | |
| **Aggressiveness =~** | | | | | | |
| Speeding | 1.000 | – | – | 1.000 | – | – |
| Alcohol | 0.361 | 0.112 | 0.001[**a] | 0.655 | 0.149 | 0.000[***] |
| Improper passing | 0.051 | 0.019 | 0.008[**] | 0.063 | 0.025 | 0.012* |
| **Inattentiveness =~** | | | | | | |
| Belt | 1.000 | – | – | 1.000 | – | – |
| Distraction | 0.400 | 0.143 | 0.005[**] | 0.431 | 0.218 | 0.048* |
| Fail to signal | 1.279 | 0.245 | 0.000[***] | 1.302 | 0.254 | 0.000[***] |
| | | | | | | |
| **Structural Model** | | | | | | |
| **Aggressiveness ~** | | | | | | |
| COVID_19 | 0.023 | 0.008 | 0.002[**] | 0.023 | 0.008 | 0.001[**] |
| **Inattentiveness ~** | | | | | | |
| COVID_19 | 0.015 | 0.004 | 0.000[***] | 0.015 | 0.004 | 0.000[***] |
| **Crash-Severity ~** | | | | | | |
| Aggressiveness | 3.598 | 0.670 | 0.000[***] | 3.598 | 0.678 | 0.000[***] |
| Inattentiveness | 8.123 | 1.132 | 0.000[***] | 8.123 | 1.176 | 0.000[***] |
| Head-on | 0.883 | 0.152 | 0.000[***] | 0.883 | 0.134 | 0.000[***] |
| Sideswipe | −0.224 | 0.096 | 0.000[***] | −0.224 | 0.096 | 0.018* |
| Pedestrian | 1.298 | 0.184 | 0.000[***] | 1.298 | 0.184 | 0.000[***] |
| Log (AADT) | −0.121 | 0.022 | 0.000[***] | −0.121 | 0.022 | 0.000[***] |
| Truck percentage | 0.009 | 0.005 | 0.045* | 0.009 | 0.005 | 0.045* |
| Wet | −0.148 | 0.061 | 0.015[**] | −0.148 | 0.061 | 0.015[**] |
| Area type | −0.184 | 0.064 | 0.004[**] | −0.184 | 0.064 | 0.004[**] |
| Threshold ($\varphi$) | 0.222 | 0.041 | 0.399 | 0.387 | 0.269 | 0.150 |

Significance levels: * for $0.01 \leq$ p-value $< 0.05$; ** for $0.001 \leq$ p-value $< 0.01$; *** for p-value $< 0.001$.
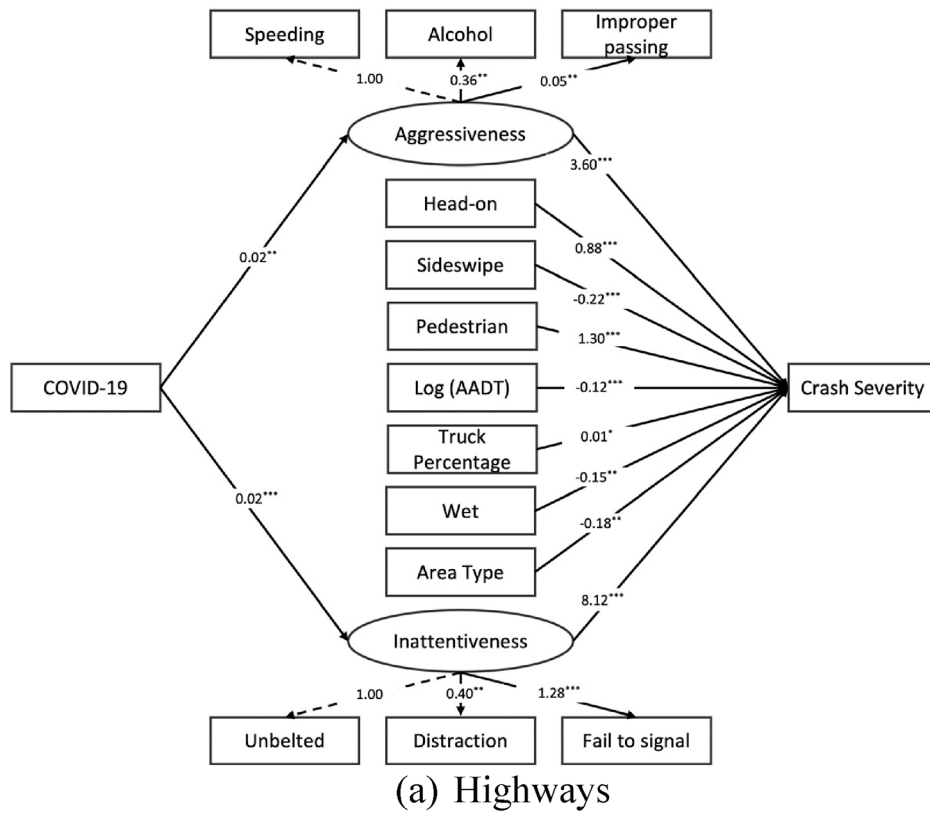
**Fig. 4.** Path diagrams of the proposed multigroup SEM with equal regressions (a) for highways and (b) for non-highways. (Numbers near each arrow indicate standardized path coefficients in the original metrics. Asterisks indicate values significantly different from 0: * for $0.01 \leq$ p-value $< 0.05$; ** for $0.001 \leq$ p-value $< 0.01$; *** for p-value $< 0.001$).

**Table 4**
Estimates of the Probit Models.

| | Crash Severity | | |
|---|---|---|---|
| | Estimate | Std. Err | P-value |
| **COVID-19** | 0.009 | 0.053 | 0.857 |
| **Driver** | | | |
| Speeding | 0.215 | 0.054 | 0.000*** a |
| Alcohol | 0.418 | 0.082 | 0.000*** |
| Improper passing | 0.275 | 0.213 | 0.197 |
| Belt | 1.192 | 0.076 | 0.000*** |
| Distraction | 0.020 | 0.063 | 0.750 |
| Fail to signal | 0.205 | 0.054 | 0.000*** |
| | | | |
| **Collision type** | | | |
| Head-on | 0.847 | 0.155 | 0.000*** |
| Sideswipe | −0.190 | 0.102 | 0.062 |
| Pedestrian | 1.413 | 0.197 | 0.000*** |
| | | | |
| **Road** | | | |
| Log (AADT) | −0.088 | 0.023 | 0.000*** |
| Truck percentage | 0.010 | 0.005 | 0.035* |
| Highway | 0.210 | 0.063 | 0.001*** |
| Wet | −0.221 | 0.065 | 0.001*** |
| | | | |
| **Environment** | | | |
| Area type | −0.161 | 0.067 | 0.017* |
| **Threshold ($\varphi$)** | 0.995 | 0.190 | 0.000*** |

a Significance levels: * for $0.01 \le$ p-value $< 0.05$; ** for $0.001 \le$ p-value $< 0.01$; *** for p-value $< 0.001$.

RMSEAs close to 0.05, suggesting a good fit to the data. Overall, the multigroup SEM with equal regressions outperforms the others by delivering the lowest RMSEA and the highest TLI.

With its better performance, the SEM with equal regressions is used for variable interpretation and its estimates of parameters are presented in Table 3. The path diagram of the SEM is illustrated in Fig. 4. The smaller threshold (φ) for the highway group indicates that it is more likely that a crash could involve severe injuries in highways compared with non-highways. Statistic indicator p-value was used to test the significance of explanatory variables. All the explanatory variables were regarded as statistically significant at 95% level (p-values < 0.05) in the proposed SEM.

For comparison purpose, the probit model was also developed with the same explanatory variables. Unlike the SEM assumption that COVID-19 affected crash severity via changing driving behaviors, the probit model assumes COVID-19 imposed a direct effect on crash severity. Estimation results of the probit model are reported in Table 4. All the explanatory variables were regarded as statistically significant at 95% level (p-values < 0.05) in the proposed SEM, whereas the variables COVID-19 and distraction were found to be insignificant in the probit model for the crash severity.

## 6. Discussion

### 6.1. Effects of contributing factors

The contributing factors to severe injuries have been fully explored in the literature, but limited studies are available by constructing latent variables of aggressive and inattentive driving behaviors. Furthermore, limited studies investigated the impacts of the lockdown during COVID-19 pandemic on the crash severity via changing the driving behaviors. Based on the modeling results in Table 3, the effect of risky driving behaviors, the COVID-19 pandemic, collision types, roads, and environment features on severe crashes are discussed in the following paragraphs.

Results show that speeding and drunk driving are positively associated with the latent variable aggressiveness we constructed, while the presence of drivers who are unbelted, distracted or fail to signal is positively associated with the latent variable inattentiveness. According to parameter estimates of Table 3, one unit increase in aggressiveness would lead to an increase in crash severity propensity ($y_i^*$) by 3.598 units. Similarly, one unit increase in inattentiveness would cause an increase in crash severity propensity by 8.123 units. After the outbreak of COVID-19, aggressiveness is estimated to increase by 0.023 and inattentiveness is estimated to increase by 0.015, resulting in a total indirect effect of 0.205 (3.598 × 0.023 + 8.123 × 0.015) on severity propensity. However, according to the probit model in Table 4, COVID-19 is not found to affect crash severity significantly, likely because risky driving behaviors (e.g., speeding, distraction) that COVID-19 is associated with are used to model crash severity directly.

The head-on collisions contribute to a higher likelihood of severe crashes. According to parameter estimated of Table 3, one unit increase in head-on collision would lead to a 0.883 unit increase in crash severity propensity. The impact of head-on collision could hurt the driver's body directly in several ways, which would lead to severe injured even fatal crashes. Liu and Fan (2019) reported that head-on crashes were the most severe crash types and always resulted in injuries and fatalities. Wegman (2004) reported that head-on crashes were responsible for nearly 25% of fatal crashes occurring on rural roads in OECD member countries. Sideswipe collisions are associated with a lower likelihood of severe crashes. In Table 3, one unit increase in sideswipe collisions would cause a decrease of 0.224 unit in crash severity propensity. Compared with the head-on collisions, sideswipe collisions cause less directly hurt on the driver or passengers. Zhang et al. (2018) utilized multinomial logit model to estimate the effect of variables and got the same decreased effect of sideswipe on the fatal injuries. Collisions involving pedestrians are mostly likely to involve severe injuries. One unit increase in pedestrians would lead to an increase in crash severity propensity by 1.298 units. Unfortunately, pedestrians on the road are the most vulnerable roles compared with bikes and vehicle. Toran Pour et al. (2017) reported that an average 34 pedestrians were killed every year between 2004 and 2013 in traffic crashes, and vehicle–pedestrian crashes accounted for 24% of all fatal crashes.

Roads with lower AADT and higher truck percentage are associated with a higher likelihood of severe crashes. According to Table 3, one unit increase in log value of traffic volume would lead to a decrease of 0.121 unit in crash severity propensity. One unit increase in the truck percentage would cause an increase of 0.009 unit in severe crash propensity. Dong et al. (2015) also found that lower traffic volume with higher truck percentage was associated with more serious traffic crash with fatal/incapacitating injury. The wet surface of road is found to be negatively associated with the severity propensity in this study. In Table 3, one unit increase in wet weather would lead to a decrease of 0.148 unit in crash severity propensity. Our conjectures is that drivers would drive more cautiously and keep a safer distance from the leading vehicle under the wet weather. Morgan and Mannering (2011) found that for male drivers under 45 years of age, the probability of severe injuries decreased on wet and snow/ice surface. Wang and Zhang (2017) also found that crashes occurred on wet road condition had lower odds of being fatal or severe injuries. Regarding the thresholds with equal regressions between crashes on highways and on non-highways, severities are more likely to occur on highways than non-highways. The threshold of crash severity propensity on highways is 0.165 lower on non-highways, which means that it is more possible for severe crashes happen on highways. A likely reason is that the speed of vehicles on highway are much higher that of vehicles on local roads. Khattak et al. (2012) also found that truck crashes found on local roads were less severe compared to those reported on other highways. Crashes in urban areas tended to be less severe than those in other areas. In Table 3, one unit of urban increase leads to a decrease of 0.184 unit in crash severe propensity. Zwerling et al. (2005) explored the factors associated with increased fatal crash rates and found the fatal crash incidence density

**Table 5**
Percentage differences of coefficient estimates of Exogenous variables of the probit model when compared to the multigroup SEM with equal regressions.

| | Crash Severity | | |
|---|---|---|---|
| | SEM Estimates | Probit Model Estimates | % Difference |
| **Collision type** | | | |
| Head-on | 0.883 | 0.847 | −4.25% |
| Sideswipe | −0.224 | −0.190 | −17.89% |
| Pedestrian | 1.298 | 1.413 | 8.14% |
| | | | |
| **Road** | | | |
| Log (AADT) | −0.121 | −0.088 | −37.50% |
| Truck percentage | 0.009 | 0.010 | 10.00% |
| Wet | −0.148 | −0.221 | 33.03% |
| | | | |
| **Environment** | | | |
| Area type | −0.184 | −0.161 | −14.29% |

was more than two times higher in rural areas than in urban areas.

The coefficient estimates of exogenous variables (i.e., collision type, road and environment features) of the SEM (presented in Table 3) are further compared with those of the probit models (presented in Table 5). The most coefficient estimates of contributing factors in the proposed SEM are quite different with those in the probit models, except the head-on collision type. For instance, the effects of sideswipe and the effects of traffic volume in the probit model are underestimated by 17.89% and 37.50% when compared with those in the SEM with equal regressions. According to SEM with equal regression estimates in Table 3, the marginal effects of side swipe on severity propensity is −0.224; while according to Table 4, the marginal effects of those variables is −0.190. Meanwhile, the effects of pedestrian and wet road are overestimated by 8.14%, and 33.03% in the probit model.

### 6.2. Analysis of driving behaviors

Two latent variables indicating driving behaviors, i.e., aggressiveness and inattentiveness were estimated using the multigroup SEM with equal regressions. The mean aggressiveness and inattentiveness for each district before and during the COVID-19 pandemic were computed as shown in Fig. 5. Cities/counties with a darker color are associated with a higher likelihood of risky driving behaviors. As indicated by subplots (a) of Fig. 5, most cities/counties were in the lightest shade associated with the least mean aggressiveness value before the COVID-19 pandemic (April 2019), and as indicated by subplots(b) of Fig. 5 most cities/counties turned to much darker colors during the COVID-19 pandemic (April 2020). A *t*-test was conducted to compare the aggressiveness before and during the pandemic, and results showed that the mean aggressiveness increased by 0.020 with a p-value less than 0.0001, which means that people drove in significantly more aggressive manners during the pandemic. Bath County, Richmond County, Williamsburg City, Charlotte County, and Patrick County are among the top areas of mean aggressiveness during the pandemic. Similarly, as shown by subplots (c) and (d) of Fig. 5, we can observe distinctive increases in mean inattentiveness values in most cities/counties. A *t*-test indicated an increase of 0.015 unit in mean inattentiveness during the pandemic with a p-value less than 0.0001. Bath County, Harrisonburg City, Lee County, Charlotte County and Nottoway County are among the top areas of mean inattentiveness during the pandemic. Bath County presents the highest mean values of both the aggressiveness and inattentiveness during the pandemic, while it belongs to the category with the least risky driving behaviors before the pandemic. Fig. 5 can provide policy makers insights into the statewide changing driving behaviors caused by the pandemic.

### 7. Summary and conclusions

This study reveals the impacts of COVID-19 pandemic on driving behaviors and crash severity in Virginia. Multigroup structural equation modeling (SEM) is used to jointly model the complex interrelationships
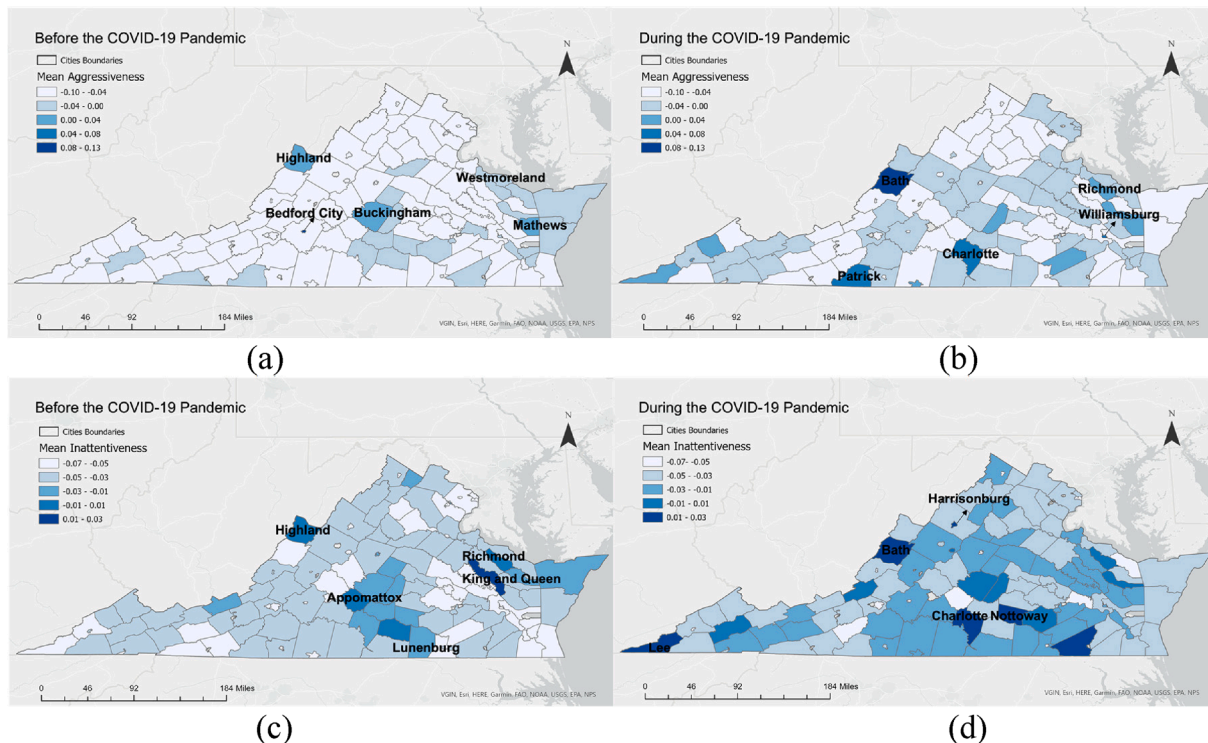


**Fig. 5.** Comparisons of aggressiveness (a) (b) and inattentiveness (c) (d) before and during the COVID-19 Pandemic. (Cities/countries with the highest aggressiveness and inattentiveness are labeled).

between driving behaviors, COVID-19, risky factors and crash severity for highways and non-highways. The SEM enables the measurement of driving behaviors using latent variables, which cannot be observed directly. Two latent variables aggressiveness and inattentiveness are constructed: the aggressiveness is used to measure risk-taking behaviors such as speeding and drunk driving, and the inattentiveness reflects distractions of a human driver from driving such as failing to yield. The SEM has the advantage of simultaneously measuring latent variables and modeling interrelationships of variables in one statistical estimation procedure.

The multigroup SEM with equal regressions (and different thresholds) outperforms the other tested models. The smaller severity threshold for the highway group indicates that severe crashes are more likely to occur on highways when compared to non-highways. It is found that speeding and drunk driving are positively associated with the aggressiveness we constructed, while the presence of drivers who are unbelted, distracted or fail to signal is positively contributes to the inattentiveness. According to the developed SEM with equal regressions, one unit increase in aggressiveness and inattentiveness would lead to an increase of 3.598 and 8.123 units in crash severity propensity, respectively. Results show that aggressiveness and inattentiveness of drivers increase significantly after the outbreak of COVID-19, and the total indirect effect of COVID-19 on severity propensity via changing driving behaviors is estimated to be 0.205. In contrast, the conventional probit model suggests an insignificant impact of COVID-19 on crash severity by treating COVID-19 equally as other contributing factors. In addition, exogenous variables including head-on, side swipe, pedestrian, wet, highway, and local are found to significantly affect crash severity in the SEM with equal regressions. The coefficients of those exogenous variables are estimated to be very different between the SEM with equal regressions and the probit model. Differences in coefficient estimates of those variables between the multigroup SEM with equal regressions and the probit model are considerably large. Paired t-tests suggest that there were significant increases in aggressiveness and inattentiveness across Virginia during the COVID-19 pandemic. Bath County, Richmond County, Williamsburg City, Charlotte County, and Patrick County are among the top areas of mean aggressiveness after the outbreak of COVID-19, while Bath County, Harrisonburg City, Lee County, Charlotte County and Nottoway County are among the top areas of inattentiveness.

This study contributes to the literature by offering a new perspective to explore how the COVID-19 pandemic impacts the likelihood of severe crashes via changing driving behaviors. Findings of this study can provide insights into effect of changing driving behaviors on safety during disruptive events like COVID-19. For future study, the generalizability of findings will benefit from validation using additional data from other regions.

*CRediT authorship contribution statement*

**Xiaomeng Dong:** Data curation, Methodology, Validation, Software. **Kun Xie:** Conceptualization, Methodology, Software, Writing – review & editing. **Hong Yang:** Methodology, 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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