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Research Article

# Assessing distracted driving crash severities at New York City urban roads: A temporal analysis using random parameters logit model

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ABSTRACT

Distracted driving poses one of the most significant risks to road safety. The current study aims to provide a deeper understanding of the factors affecting the severity of distracted driving crashes in New York City and to explore the temporal stability in the effects of different variables on crash outcomes in 2016 to 2019 period by adopting a post-crash perspective. The police-reported data of single-vehicle distraction-related crashes of private cars on urban roads of New York City was used for this study. Three injury categories were considered: no injury, minor injury, and severe injury. To investigate crash severities and identify unobserved heterogeneities, a random parameters logit model was conducted. The results revealed that a wide variety of variables including driver traits, vehicle and temporal characteristics, and crash attributes were found to be significant in explaining distracted-related crash severities. Furthermore, a series of likelihood ratio tests were conducted to identify the temporal shifts of estimated variables during the period. The results of the temporal analysis showed that the estimated variables of the random parameters model were unstable during the 4-year period, which may be the result of shifting trends such as the development of in-vehicle technologies, and new sources of distraction. However, the complex nature of distracted-related crashes and changes in driver behavior should be considered for further interpretation. This research provides a set of policy implications for planners and policymakers, aiming at facing factors contributing to a higher level of injury severity in distracted driving crashes. This includes providing targeted information on distracted driving to high-risk groups, such as younger drivers, and also combining education, awareness programs, higher penalties, and intense patrolling. Engineering measures such as enhanced roadside illumination and audible edge lines can be effective, especially in reducing late-night distracted driving crashes.

## 1. Introduction

Distracted driving is a major safety concern worldwide, with recent research trends confirming that it is one of the causes of fatalities and injuries on the roads. According to the National Highway Traffic Safety Administration (NHTSA), “Anything that takes the driver's attention away from the task of safe driving is distracted driving” [1]. The distracted driver diverts his focus from the primary task of driving to perform another interventionist task which can come from different sources, including inside of the vehicle (in-vehicle distraction), outside of the vehicle (external distraction), or from one's mind (internal distraction). Distraction can emerge in different types including cognitive, visual, or physical [2]. These different types as well as various and complex factors in explaining distraction (driver, vehicle, road, and temporal characteristics, psychological factors, etc.) have led researchers to conduct extensive studies to reduce the negative effects of distraction on aspects of driving behavior. Also, knowing the consequences and costs of distracted driving crashes, policymakers have established policies to mitigate these consequences.

Research has shown that distracted driving is a leading cause of road collisions and can have serious consequences such as injuries or fatalities. Statistics reported by National Highway Traffic Safety Administration [3] showed that in the 2012 to 2018 period, approximately 9% of fatal crashes in the United States were due to distracted driving, which

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included 23,000 fatalities. In 2017, 2935 of the total 34,247 fatal accidents were related to distracted driving. In 2018, there were 2888 fatalities and 398,560 injuries due to distracted driving. This number reached 3142 casualties and 424,000 casualties in 2019. The share of distracted driving crashes compared to the total number of crashes showed that the risky situation has not experienced a significant improvement in recent years. Similar patterns have been found in other countries. For instance, distracted driving has been identified as the primary cause in nearly 16% of severe casualty crashes resulting in hospitalization in Australia [4].

### *1.1. Objectives and scope of the study*

The current study aims to improve the understanding of factors affecting the frequency and severity of single vehicle distracted driving crashes in New York City and to explore the temporal shifts in the effects of different variables on crash outcomes in the 2016 to 2019 period by adopting a post-crash perspective. In summary, the contributions of the article are as follows:

The existence of various forms and the many sources have caused the investigation of factors affecting distracted driving to have many aspects. To address these complexities and indicate unobserved heterogeneities in factors affecting distracted-related crashes, this study aims to characterize these crashes and resulting injury severities by presenting a random parameters logit model that can account for unobserved heterogeneity. Further, with the rapid development of technology, the sources of distraction are increasing at an unprecedented pace. In-vehicle technologies, wearable and portable devices, etc. have caused the need to continuously investigate distracted-related crashes and related factors. To explore the temporal shifts in the effects of different variables on distracted-related crash outcomes, this study aims to determine whether the proposed parameters were stable in the 2016 to 2019 period in New York City. Finally, Single-vehicle crashes make up a large proportion of fatal accidents in the United States. From 2011 to 2014, about 60% of deaths were related to single-vehicles accidents. Due to the importance these crashes, this study aimed to identify significant factors affecting single-vehicle distracted-related crashes and the resulting severities.

## 2. Research background

The study of distracted driving and its negative safety outcomes has always been of interest to researchers. The literature on distracted driving has started with the purpose of identifying conventional sources of in-vehicle distractions such as drinking, eating, distractions by pets, and interaction with children [5,6]. After the prevalence of using mobile phones, researchers focused on investigating the distraction caused by them while driving [4,7,8]. Since mobile phone distraction and resulting crashes were affected by various factors, different methods were used to investigate their role. Survey and questionnaire-based studies were conducted [4,9]. The self-reported data allowed researchers to evaluate different factors affecting distracted driving, however, the survey method had many limitations in investigating distracted driving crashes and their contributing factors. On the one hand, many variables that could affect these crashes were not evaluated in questionnaires, and on the other hand, the bias created by the survey respondents negatively affected the outcome of such studies. To overcome these concerns, subsequent studies proposed to adopt other methods such as simulators [10]. Even though the simulators depicted the real conditions for the participant, acceptably, due to the existence of the laboratory environment and pre-accident perspective, these methods could not provide results like the real-world conditions. These issues encouraged researchers to use naturalistic data for more accurate results [11]. The study of the naturalistic data led researchers to present new insights about distracted driving crashes such as the effect of distraction duration on the probability of a crash [12], the effect of the presence of speed limits on distraction [13], and the effect of off-road glances on distraction [14].

Although the pre-crash perspective provided a good understanding of different road users' crashes and resulting severities, using post-accident data to investigate the contributing factors and their impact on injury severities has been taken into consideration by researchers [15,16]. Post-accident perspective is not free of limitations and the data reported by Police can be biased, however, recent studies using this method have brought the study of distracted driving to a new stage to investigate distraction, its factors, and consequences [15,17,18]. Most of these studies used discrete outcome modeling including a latent class multinomial logit approach [19], random parameters binary logit model [20], ordered probability models [21], ordered logit models [17], logistic regression approach [22], and random parameters with heterogeneity in means/variances [15]. In a more recent study, Alnawmasi and Mannering [15], using unobserved-heterogeneity modeling approaches, assessed temporal changes in the factors affecting distracted driving crashes. The model results were able to determine many factors related to driver characteristics, vehicle characteristics, roadway, and environmental conditions, roadway characteristics, and temporal characteristics that affect the severity of accidents.

Distracted driving-related studies mostly focused on investigating crashes and resulting injury severities. Using the mentioned methodologies, these studies evaluated the effect of various factors including the characteristics of the driver, vehicle, road, weather and lighting conditions, driver's behavior, etc. on crash severities. Regarding the characteristics of the driver, previous literature showed conflicting results regarding its role in the severity of distracted-related accidents. While Liu, et al. [22] and Donmez and Liu [23] confirmed that young drivers had a higher probability of severe injuries in distracted-related crashes, Fatmi and Habib [19] and Razi-Ardakani, et al. [21] stated that the chance of severe injury in distracted-related accidents was considered higher for older drivers. This is also true for the effect of gender. While Liu, et al. [22] reported that the probability of severe injury was higher for men, Liu and Donmez [24] and Razi-Ardakani, et al. [21] presented conflicting results and found that the probability of women being severely injured in distracted-related accidents was higher. Studies have also confirmed that fatigue and alcohol can increase the chance of serious injury in distracted-related crashes [20,21]. Regarding vehicle characteristics, Razi-Ardakani, et al. [21] confirmed that sport utility vehicles (SUVs) reduced the chance of severe injury in distracted-related crashes. Previous literature also presented significant results regarding the impact of road characteristics on the severity of distraction-related crashes. For example, roundabouts, intersections, and the presence of speed limits can reduce the chance of serious injury in these crashes [17,21,24]. However, a higher speed limit increases the possibility of severe injury in such crashes [18]. Also, the chance of severe injury in distraction-related crashes is less on urban roads and more on rural or interstate highways [17,20]. Other variables such as dark conditions, not wearing seat belts, and driving late at night can increase the chance of injury in distracted-related crashes [19,20].

## 3. Data description and empirical setting

The police-reported data of the single-vehicle distracted-related crashes of private cars on urban roads of New York City was used for this study [25]. This dataset contains 15,536 observations of single-vehicle distracted-related crashes for a period of 4 years from January 1, 2016 to December 31, 2019. Single vehicle distracted-related accidents in this dataset are those in which only one vehicle is involved, usually in the form of hitting a fixed object, going off the road, or overturning, and the reported contributing factors include driver inattention, driver distraction, or cell phone or electronic device usage. The data contains various and detailed information about crash severities in five categories no injury, possible, minor injury, severe injury, and fatal. In this study, two categories of possible injury and minor injury were merged and presented as minor injury. Also, two categories of severe injury and fatal injury were merged and presented as severe injury. Table 1 and Fig. 1 present the yearly distribution of injury severities of distraction-related single vehicle crashes.

The independent variables used in this study are categorized in four major groups as follows:

- Driver traits include age, gender, driver license, and driver under alcohol influence.
- Vehicle traits include vehicle age and sport utility vehicle (SUV) indicator.
- Temporal traits include season, day of week (weekend or weekday), and daily peaks or off-peaks.
- Crash attributes and other variables include daylight, passenger presence, safety belt usage, overturning, ejection, frontal point of impact, turning before crash, public property damage, and going straight before crash.

Table 2 shows the summary statistics of the parameters estimated in this study that can affect injury levels.

## 4. Model selection

This study utilized a Random parameters logit model to investigate crash outcomes. The mixed logit model, with the ability to allow the effect of the parameters to vary among observations, can identify unobserved heterogeneities. Unlike other models, mixed logit is not affected by the independence of irrelevant alternatives (IIA) problem. The random parameters logit model uses the following severity function, which can explain distracted-related crash severity outcomes [26,27]:

$$U_{ij} = \beta_j X_{ij} + \varepsilon_{ij} \tag{1}$$

In this equation, $U_{ij}$ is the injury-severity function that determines the probability of crash severity j in accident i. $X_{ij}$ is a vector related to the suggested variables and these variables can affect the severity of distracted-related accidents. Also, $\beta_j$ is the vector specifies the effect of each parameter, and $\varepsilon_{ij}$ specifies the error term. Considering the generalized extreme value distribution of the error term, the probability function of the multinomial logit model is as follows:

$$P_i(j) = \frac{EXP(\beta_j X_{ij})}{\sum_{\forall J} EXP(\beta_j X_{ij})} \tag{2}$$

where $P_i(j)$ is the crash i probability function that causes the j crash severity. Since $\beta_j$ can vary across crash dataset parameters, the mixed logit model can address the unobserved heterogeneity issue. The model outcomes include constants and $\beta_j$ can be fixed or randomly distributed with fixed means across all parameters. As a result, the probability function $P_i(j)$ converts to $P_i(j|\varphi)$ and is determined as follows:

$$P_i(j|\varphi) = \int \frac{EXP(\beta_j X_{ij})}{\sum_{\forall i} EXP(\beta_j X_{ij})} f(\beta_j|\varphi) d\beta_j \tag{3}$$

In this function $P_i(j|\varphi)$ is the probability of injury severity j and$f(\beta_j|\varphi)$, is the density function of $\beta_j$ and $\varphi$ is a known vector of parameters (mean and variance) that defines the density function. If the parameters are random, the density function $f(\beta_j|\varphi)$ generates the random parameters' logit weights. For the distribution of random parameters, normal, lognormal, triangular, and uniform distributions are considered, however, the superiority of one distribution over another one is not determined. The empirical analysis revealed that the normal distribution can provide the best fit for crash injury severity data [28]. For the estimation of the model, the maximum likelihood method with 1000 Halton draws was conducted [29]. Marginal effects were also used to determine the impact of the estimated parameters on crash severities. The marginal effects are the differences in estimated probability when indicator variables are changed from zero to one. To calculate marginal effects, the following equation was used:

$$E_{X_{ik}}^{P_i(j)} = P_i(j|X_{ik} = 1) - P_i(j|X_{ik} = 0) \tag{4}$$

To test the model fit, log-likelihood at convergence (See Eq. (5)), Akaike information criterion (AIC), and Bayesian information criterion (BIC) were calculated.

$$LL = \sum_{i=1}^{I} \sum_{j=1}^{J} \delta_{ij} ln[P_i(j)] \tag{5}$$

In this equation, J is equal to the total number of crash severity outcomes, I is equal to the total number of observations, and $\delta_{ij}$ is equal to 1 if the crash severity outcome in the observation i is equal to j.

## 5. Temporal stability test

Among different methods to investigate temporal instability, dividing data based on different time periods has been the most accepted among researchers in investigating distracted-related crashes [30]. In this method, a series of likelihood ratio tests will be performed for different years. The purpose of performing these tests is to determine the stability of the parameters at different times. Likelihood ratio tests are conducted using the following equation:

$$X^2 = -2[LL(\beta_{t2t1}) - LL(\beta_{t1})] \tag{8}$$

In this equation, $LL(\beta_{t2t1})$ represents the log-likelihood of a converged model including parameters from $t_2$ using year $t_1$ data. Also, $LL(\beta_{t1})$ represents the log-likelihood of a converged model using $t_1$'s data. Also, the number of degrees of freedom is equal to the number of estimated parameters in$\beta_{t2t1}$. Also, in this equation, the values obtained from $X^2$ have a $\chi^2$ distribution, which shows that the null hypothesis (variables do not change in time intervals) is rejected or supported.

Table 3 presents the results of temporal stability tests for each year. Twelve likelihood ratio tests were conducted in total, and the null hypothesis was rejected at the confidence level of 99% in 10 out of 12 tests, showing that the injury severity models (estimated parameters and model characteristics) were not stable over time. While The results revealed that the impact of explanatory variables on the severity of distracted driver injuries has changed temporally throughout the period, determining the cause of the temporal shifts is challenging, as it is unclear whether they arise from an underlying evolution of factors influencing injuries, changes in human behavior such as technology usage among drivers, variations in socioeconomic conditions, or a combination of these factors [15]. However, Mannering [31] stated that temporal instability is likely to exist due to fundamental behavioral reasons, including structural shifts prompted by evolving behaviors or behavioral changes induced by technological innovations. The results of the temporal stability test highlight the importance of analyzing the temporal instability of factors affecting distracted-related crashes and resulting severities beyond the evaluation of the likelihood ratio tests, therefore, the effect of each estimated variable on severity outcomes and its variation over time was assessed by comparing marginal effects during the period (See Section 6 Model estimation results).

**Table 1**
Crash injury frequency and percentage for each year.

| Year | No injury | Minor injury | Severe injury |
|---|---|---|---|
| 2016 | 1458 (49.27%) | 1365 (46.14%) | 136 (4.59%) |
| 2017 | 2071 (50.97%) | 1859 (45.75%) | 133 (3.28%) |
| 2018 | 2125 (49.69%) | 2100 (49.10%) | 52 (1.21%) |
| 2019 | 2122 (50.08%) | 1972 (46.55%) | 143 (3.37%) |
| 2016–2019 | 7776 (50.05%) | 7296 (46.97%) | 464 (2.98%) |

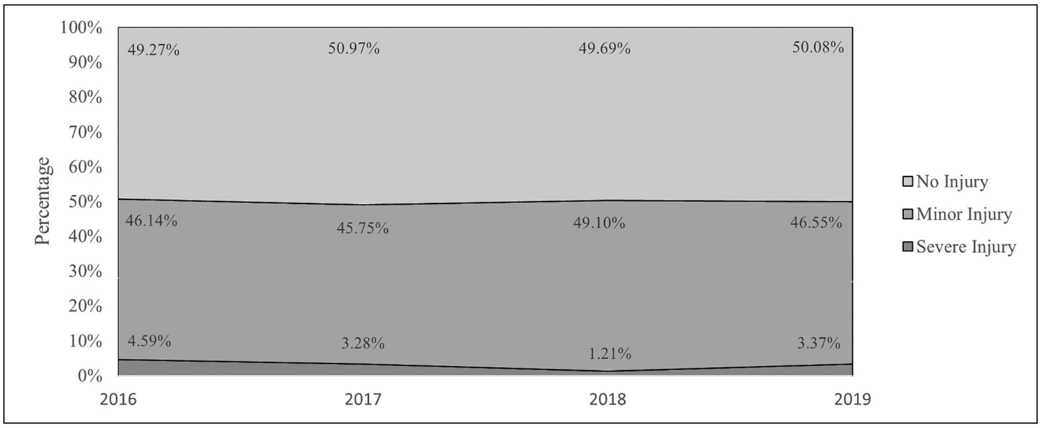


**Fig. 1.** The distribution of injury severities by year.

## 6. Model estimation results

The results of the random parameters logit model for 2016 to 2019 are presented in Tables 4 to 7. The results of models' fit revealed that all random parameters logit models showed appropriate statistically fit (2016 time period: log-likelihood = −2254.93, AIC=4625.86, BIC = 4973.43; 2017 time period: likelihood = −1591.49, AIC = 3306.99, BIC = 3698.19; 2018 time period: log-likelihood = −1392.92, AIC = 2913.84, BIC = 3220.94; 2019 time period: log-likelihood = −1735.29, AIC = 3594.58, BIC = 3988.38). The model results showed that all models had at least two random parameters (normally distributed). For 2016 period, the model had significant random parameters in the effects of passenger presence, weekends, and frontal point of impact on injury severities. The 2017 model had significant random parameters in the effects of frontal point of impact, spring, and daylight indicators on distracted-related crash severities. For the 2018 model, weekends, turning before the crash, and passenger presence were found to be random parameters. It is in line with the 2019 model that showed a significant random parameter in the effects of passenger presence and daylight indicators on crash outcomes. Due to the differences among estimated variables affecting severity levels (temporal instability) (See Section 5 Temporal stability test), Table 8 presents the marginal effects of severity outcomes on a yearly basis to facilitate the interpretation.

### 6.1. Driver characteristics

The results of the model estimation showed that driver characteristics were found to have a significant effect on injury severities. Regarding the effect of gender, the marginal effects confirmed that female drivers significantly had a lower probability of no injury and a higher probability of minor and severe injury than male drivers in 2016, 2018, and 2019 models. Additionally, females were more likely to involve in severe distracted-related crashes in 2016 and 2017 models. According to the past literature, a strong body of research on distracted driving crash severity supported this notion, stating that females had a higher likelihood to be severely injured in a distracted-related crashes [21,23,24]. This discrepancy in injury severities of males and females in distracted driving crashes was explained in two ways. First, Fofanova and Vollrath [32] stated that male drivers are more likely to engage in distracted driving than females, resulting in a higher chance of severe injuries. Second, Razi-Ardakani, et al. [21] justified this difference as significant physical differences between female and male groups. However, a deeper investigation in crash severity literature of all crashes revealed that males showed a significantly higher proportion of fatal or severe injuries compared to females, possibly due to the higher likelihood of aggressive driving behavior for males [33]. This contrast in the literature between distraction and non-distraction crashes highlights the different nature of distracted driving crashes and raises the need for further investigation into this matter.

Regarding the effect of age on crash severities, the results of model estimation revealed that only in 2016 model, young drivers (under 24 years) had a lower probability of minor injury. The results for middle-aged drivers (25–39 years) in 2018 showed that these drivers were more likely to be severely injured in distracted-related crashes. The model results showed that for 2016, 2017, and 2019, older drivers (>60 years) significantly had a higher likelihood of being involved in minor injury distracted-related crashes. Previous studies in this field, however, stated that aging can increase the severity of distracted driving crashes [15,19,23,24]. A recent study by Xing, et al. [34] noted that cognitive impairment of older drivers can result in more severe injuries.

The influence of alcohol and drug usage on injury severities showed that this variable significantly increased the probability of severe injury crashes in 2016, 2018, and 2019 with marginal effects of 0.2417, 0.1819, and 0.0952 respectively. The general research trend also suggested that consuming drugs and alcohol can increase the chance of severe distraction-related crashes [19,21]. According to Scott-Parker and Oviedo-Trespalacios [35], drink driving and distracted driving may have an interdependent relationship, stating that those reported not using a handheld mobile phone while driving also reported a lower incidence of driving under the influence of alcohol. Additionally, according to Ahlström, et al. [36], alcohol can inhibit self-regulation among drivers. This lack of self-regulation can increase the chance of risky behavior, resulting in higher crash severities. For the no driving license group, the estimation models showed that in two years of 2016 and 2018, this variable considerably and significantly increased the probability of minor injury crash with marginal effects of 0.1715 and 0.0517.

### 6.2. Vehicle characteristics

The results revealed that vehicle features played a key role in explaining crash outcomes. The older vehicle (>10 years) indicator was found to have a significant positive association with minor injury crashes in 2016, however, there was a slight negative association between older vehicles and minor injury in 2018. In short, this study could not confirm that higher vehicle age can increase the likelihood of severe injury in crashes. A possible explanation for this result suggested by Alnawmasi and Mannering [15] was that older vehicle use lower in-vehicle technologies than newer models. These lower sources of distraction may decrease the level of distraction experienced by the driver by reducing the engagement of the driver in non-driving tasks and leading to lower severity outcomes in crashes [37]. However, this might not be attributed to all vehicles with new advanced technologies as a recent study by Masello, et al. [38] confirmed that warning-based

**Table 2**
Descriptive analysis of distracted drivers crash data in New York City.

| Variable | 2016 | | | | 2017 | | | | 2018 | | | | 2019 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Frequency (percentage) | | | | Frequency (percentage) | | | | Frequency (percentage) | | | | Frequency (percentage) | | | |
| | NI | MI | SI | Total | NI | MI | SI | Total | NI | MI | SI | Total | NI | MI | SI | Total |
| Driver traits | | | | | | | | | | | | | | | | |
| Gender | | | | | | | | | | | | | | | | |
| *Male* | 990 (47.71) | 992 (47.8) | 93 (4.48) | 2075 (70.12) | 1445 (50.03) | 1348 (46.68) | 95 (3.29) | 2888 (71.08) | 1431 (47.81) | 1519 (50.75) | 43 (1.43) | 2993 (69.97) | 1460 (49.24) | 1403 (47.31) | 102 (3.44) | 2965 (69.97) |
| *Female* | 468 (52.94) | 373 (42.19) | 43 (4.84) | 884 (29.87) | 626 (53.28) | 511 (43.49) | 38 (3.23) | 1175 (28.92) | 694 (54.04) | 581 (45.24) | 9 (0.7) | 1284 (30.02) | 662 (52.04) | 569 (44.73) | 41 (3.22) | 1272 (30.02) |
| Age | | | | | | | | | | | | | | | | |
| *18–24 years* | 219 (57.78) | 146 (38.52) | 14 (3.69) | 379 (12.8) | 293 (56.24) | 218 (41.84) | 10 (1.91) | 521 (12.82) | 260 (54.62) | 213 (44.74) | 3 (0.63) | 476 (11.12) | 297 (55.51) | 225 (42.05) | 13 (2.42) | 535 (12.62) |
| *25–39 years* | 550 (54.02) | 426 (41.84) | 42 (4.12) | 1018 (34.4) | 825 (56.12) | 602 (40.95) | 43 (2.92) | 1470 (36.18) | 849 (56.59) | 634 (42.26) | 17 (1.13) | 1500 (35.07) | 816 (54) | 635 (42.02) | 60 (3.97) | 1511 (35.66) |
| *40–60 years* | 511 (46.79) | 523 (47.89) | 58 (5.31) | 1092 (36.9) | 683 (47.43) | 700 (48.61) | 57 (3.95) | 1440 (35.44) | 765 (48.14) | 802 (50.67) | 22 (1.38) | 1589 (37.15) | 766 (50.46) | 698 (45.98) | 54 (3.55) | 1518 (35.82) |
| *>60* | 178 (37.87) | 270 (57.44) | 22 (4.68) | 470 (15.88) | 270 (42.72) | 339 (53.63) | 23 (3.63) | 632 (15.55) | 251 (35.25) | 451 (53.34) | 10 (1.4) | 712 (16.64) | 243 (36.1) | 414 (61.51) | 16 (2.37) | 673 (15.88) |
| Under Alcohol or drug influence | | | | | | | | | | | | | | | | |
| *Yes* | 170 (58.02) | 113 (38.56) | 10 (3.41) | 293 (9.9) | 239 (64.07) | 117 (31.36) | 17 (4.55) | 373 (9.18) | 245 (68.05) | 112 (31.11) | 3 (0.83) | 360 (8.41) | 195 (63.1) | 102 (33) | 12 (3.88) | 309 (7.29) |
| *No* | 1288 (48.31) | 1252 (46.96) | 126 (4.72) | 2666 (90.09) | 1832 (49.64) | 1742 (47.2) | 116 (3.14) | 3690 (90.81) | 1880 (47.99) | 1988 (50.75) | 49 (1.25) | 3917 (91.58) | 1927 (49.05) | 1870 (47.6) | 131 (3.33) | 3928 (92.7) |
| Driver license | | | | | | | | | | | | | | | | |
| *Yes* | 1428 (49.56) | 1320 (45.81) | 133 (4.61) | 2881 (97.36) | 2016 (51.21) | 1793 (45.55) | 127 (3.22) | 3936 (96.87) | 2069 (49.84) | 2032 (48.95) | 50 (1.2) | 4151 (97.05) | 2077 (50.24) | 1919 (46.42) | 138 (3.33) | 4134 (97.56) |
| *No* | 30 (38.46) | 45 (57.69) | 3 (3.84) | 78 (2.64) | 55 (43.3) | 66 (51.96) | 6 (4.72) | 127 (3.12) | 56 (44.44) | 68 (53.96) | 2 (1.58) | 126 (2.94) | 45 (43.68) | 53 (51.45) | 5 (4.85) | 103 (2.43) |
| Vehicle traits | | | | | | | | | | | | | | | | |
| Vehicle age | | | | | | | | | | | | | | | | |
| *>10 years* | 320 (44.5) | 358 (49.79) | 41 (5.7) | 719 (24.29) | 475 (48.56) | 462 (47.23) | 41 (4.19) | 978 (24.07) | 462 (44.29) | 571 (54.74) | 10 (0.95) | 1043 (24.38) | 435 (44.66) | 506 (51.95) | 33 (3.38) | 974 (22.98) |
| *<10 years* | 1138 (50.8) | 1007 (44.95) | 95 (4.24) | 2240 (75.7) | 1596 (51.73) | 1397 (45.28) | 92 (2.98) | 3085 (75.92) | 1663 (51.42) | 1529 (47.27) | 42 (1.29) | 3234 (75.61) | 1687 (51.7) | 1466 (44.92) | 110 (3.37) | 3263 (77.01) |
| Sport Utility Vehicle | | | | | | | | | | | | | | | | |
| *Yes* | 496 (46.61) | 509 (47.83) | 59 (5.54) | 1064 (35.95) | 780 (47.38) | 808 (49.08) | 58 (3.52) | 1646 (40.51) | 890 (47.31) | 967 (51.4) | 24 (1.27) | 1881 (43.97) | 927 (48.61) | 909 (47.66) | 71 (3.72) | 1907 (45) |
| *No* | 962 (50.76) | 856 (45.17) | 77 (4.06) | 1895 (64.04) | 1291 (53.41) | 1051 (43.48) | 75 (3.1) | 2417 (59.48) | 1235 (51.54) | 1133 (47.28) | 28 (1.16) | 2396 (56.02) | 1195 (51.28) | 1063 (45.62) | 72 (3.09) | 2330 (54.99) |
| Temporal traits | | | | | | | | | | | | | | | | |
| Season | | | | | | | | | | | | | | | | |
| *Spring* | 348 (50.14) | 315 (45.38) | 31 (4.46) | 696 (23.45) | 517 (51.34) | 455 (45.18) | 35 (3.47) | 1007 (24.78) | 497 (50.97) | 452 (46.36) | 26 (2.66) | 975 (22.79) | 572 (53.65) | 448 (42.02) | 46 (4.31) | 1066 (25.15) |
| *Summer* | 403 (48.26) | 396 (47.42) | 36 (4.31) | 835 (28.23) | 506 (54.11) | 399 (42.67) | 30 (3.2) | 935 (23.01) | 559 (58.35) | 392 (40.91) | 7 (0.73) | 958 (22.39) | 486 (52.88) | 395 (42.98) | 38 (4.13) | 919 (21.68) |
| *Fall* | 523 (49.85) | 480 (45.57) | 46 (4.38) | 1049 (35.45) | 529 (51.6) | 473 (46.14) | 23 (2.24) | 1025 (25.22) | 557 (48.18) | 588 (50.86) | 11 (0.95) | 1156 (27.02) | 508 (48.56) | 514 (49.13) | 24 (2.29) | 1046 (24.68) |
| *Winter* | 184 (48.29) | 174 (45.66) | 23 (6.03) | 381 (12.87) | 519 (47.35) | 532 (48.54) | 45 (4.1) | 1096 (26.97) | 512 (43.09) | 668 (56.22) | 8 (0.67) | 1188 (27.77) | 556 (46.1) | 615 (50.99) | 35 (2.9) | 1206 (28.46) |
| Day of Week | | | | | | | | | | | | | | | | |
| *Weekends* | 449 (56.05) | 320 (39.95) | 32 (3.99) | 801 (27.06) | 646 (56.07) | 473 (41.05) | 33 (2.86) | 1152 (28.35) | 596 (52.41) | 525 (46.17) | 16 (1.4) | 1137 (26.58) | 652 (55.39) | 488 (41.46) | 37 (3.14) | 1137 (27.77) |

(*continued on next page*)

**Table 2** (*continued*)

| Variable | 2016 | | | | 2017 | | | | 2018 | | | | 2019 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Frequency (percentage) | | | | Frequency (percentage) | | | | Frequency (percentage) | | | | Frequency (percentage) | | | |
| | NI | MI | SI | Total | NI | MI | SI | Total | NI | MI | SI | Total | NI | MI | SI | Total |
| *Weekdays* | 1009 (46.75) | 1045 (48.42) | 104 (4.81) | 2158 (72.93) | 1425 (48.95) | 1386 (47.61) | 100 (3.43) | 2911 (71.64) | 1529 (48.69) | 1575 (50.15) | 36 (1.14) | 3140 (73.41) | 1470 (48.69) | 1484 (50.15) | 106 (1.14) | 3060 (72.22) |
| Hours of day | | | | | | | | | | | | | | | | |
| *7 AM–9 AM (Morning peak)* | 103 (40.71) | 134 (52.96) | 16 (6.32) | 253 (8.55) | 163 (46.43) | 183 (52.13) | 5 (1.42) | 351 (8.63) | 149 (42.57) | 196 (56) | 5 (1.42) | 350 (8.18) | 190 (47.73) | 191 (47.98) | 17 (4.27) | 398 (9.39) |
| *9 AM-3 PM (Morning off-peak)* | 410 (49.1) | 392 (46.94) | 33 (3.95) | 835 (28.21) | 580 (50) | 536 (46.2) | 44 (3.79) | 1160 (28.55) | 621 (51.92) | 559 (46.73) | 16 (1.33) | 1196 (27.96) | 570 (50.62) | 524 (46.53) | 32 (2.84) | 1126 (26.57) |
| *3 PM–7 PM (Evening peak)* | 324 (45.44) | 350 (49.08) | 39 (5.46) | 713 (24.09) | 450 (46.68) | 480 (49.79) | 34 (3.52) | 964 (23.72) | 502 (45.34) | 594 (53.65) | 11 (0.99) | 1107 (25.88) | 451 (43.28) | 556 (53.35) | 35 (3.35) | 1042 (24.59) |
| *7 PM-12 AM (Evening off-peak)* | 343 (53.51) | 272 (42.43) | 26 (4.05) | 641 (21.66) | 460 (52.81) | 386 (44.31) | 25 (2.87) | 871 (21.43) | 417 (48.43) | 434 (50.4) | 10 (1.16) | 861 (20.13) | 486 (52.25) | 413 (44.4) | 31 (3.33) | 930 (21.94) |
| *12 AM–7 AM (Midnight)* | 278 (53.77) | 217 (41.97) | 22 (4.25) | 517 (17.47) | 418 (58.29) | 274 (38.21) | 25 (3.48) | 717 (17.64) | 436 (57.14) | 317 (41.54) | 10 (1.31) | 763 (17.83) | 425 (57.35) | 288 (38.86) | 28 (3.77) | 741 (21.94) |
| Crash attributes and other variables | | | | | | | | | | | | | | | | |
| Lighting | | | | | | | | | | | | | | | | |
| *Daylight* | 815 (48.08) | 804 (47.43) | 76 (4.48) | 1695 (57.29) | 1143 (49.89) | 1076 (46.96) | 72 (3.14) | 2291 (56.38) | 1202 (51.06) | 1118 (47.49) | 34 (1.44) | 2354 (55.03) | 1141 (49.93) | 1061 (46.43) | 83 (3.63) | 2285 (53.92) |
| *Darkness* | 643 (50.87) | 561 (44.38) | 60 (4.74) | 1264 (42.71) | 928 (52.37) | 783 (44.18) | 61 (3.44) | 1772 (43.61) | 923 (47.99) | 982 (51.06) | 18 (0.93) | 1923 (44.96) | 981 (50.25) | 911 (46.67) | 60 (3.07) | 1952 (46.07) |
| Cell phone Usage | | | | | | | | | | | | | | | | |
| *Yes* | 11 (73.33) | 4 (26.66) | 0 (0) | 15 (0.5) | 11 (68.75) | 5 (31.25) | 0 (0) | 16 (0.39) | 10 (71.42) | 4 (28.57) | 0 (0) | 14 (0.32) | 6 (66.66) | 3 (33.33) | 0 (0) | 9 (0.21) |
| *No* | 1447 (49.15) | 1361 (46.22) | 136 (4.61) | 2944 (99.49) | 2060 (49.15) | 1854 (46.22) | 133 (4.6) | 4047 (99.6) | 2115 (49.61) | 2096 (49.16) | 52 (1.21) | 4047 (99.67) | 2116 (50.04) | 1969 (46.57) | 143 (3.38) | 4228 (99.78) |
| Passenger presence | | | | | | | | | ( | | | | | | | |
| *Yes* | 343 (49.35) | 324 (46.61) | 28 (4.02) | 695 (23.49) | 422 (46.99) | 438 (48.77) | 38 (4.21) | 898 (22.1) | 451 (52.56) | 393 (45.8) | 14 (1.63) | 858 (20.06) | 426 (48.51) | 415 (47.26) | 37 (4.27) | 878 (20.72) |
| *No* | 1115 (49.24) | 1041 (45.98) | 108 (4.77) | 2264 (76.51) | 1649 (52.1) | 1421 (44.89) | 95 (3) | 3165 (77.89) | 1674 (48.96) | 1707 (49.92) | 38 (1.11) | 3419 (79.93) | 1696 (50.49) | 1557 (46.35) | 106 (3.15) | 3359 (79.27) |
| Safety belt usage | | | | | | | | | | | | | | | | |
| *Yes* | 1358 (49.14) | 1275 (46.14) | 130 (4.7) | 2763 (93.37) | 1930 (50.33) | 1776 (46.32) | 128 (3.33) | 3834 (94.36) | 1987 (48.94) | 2015 (49.85) | 48 (1.18) | 4041 (94.48) | 1980 (49.5) | 1885 (47.12) | 135 (3.37) | 4000 (94.4) |
| *No* | 100 (51.02) | 90 (45.91) | 6 (3.06) | 196 (6.62) | 141 (61.57) | 83 (36.24) | 5 (2.18) | 229 (5.63) | 147 (62.28) | 85 (36.01) | 4 (1.69) | 236 (5.51) | 142 (59.91) | 87 (36.7) | 8 (3.37) | 237 (5.59) |
| Overturning | | | | | | | | | | | | | | | | |
| *Yes* | 4 (44.44) | 5 (55.55) | 0 (0) | 9 (0.3) | 8 (47.05) | 9 (52.94) | 0 (0) | 17 (0.41) | 4 (30.76) | 9 (69.23) | 0 (0) | 13 (0.3) | 3 (25.76) | 8 (66.66) | 1 (8.33) | 12 (0.28) |
| *No* | 1454 (49.28) | 1360 (46.1) | 136 (4.61) | 2950 (99.69) | 2063 (50.98) | 1850 (45.72) | 133 (3.28) | 4046 (99.58) | 2121 (50.98) | 2091 (45.72) | 52 (3.28) | 4246 ((99.69) | 2119 (50.15) | 1964 (46.48) | 142 (3.36) | 4225 (99.71) |
| Ejection | | | | | | | | | | | | | | | | |
| *Ejected* | 2 (50) | 2 (50) | 0 (0) | 4 (0.13) | 3 (33.33) | 6 (66.66) | 0 (0) | 9 (0.22) | 2 (50) | 2 (50) | 0 (0) | 4 (0.09) | 1 (20) | 4 (80) | 0 (0) | 5 (0.11) |
| *Partially ejected* | 2 (33.33) | 4 (66.66) | 0 (0) | 6 (0.2) | 7 (63.53) | 3 (27.27) | 1 (9.09) | 11 (0.27) | 3 (50) | 3 (50) | 0 (0) | 6 (0.14) | 6 (66.66) | 3 (33.33) | 0 (0) | 9 (0.21) |
| *Not ejected* | 1454 (49.3) | 1359 (46.08) | 136 (4.61) | 2949 (99.66) | 2061 (50.97) | 1850 (45.75) | 132 (3.26) | 4043 (99.5) | 2120 (49.68) | 2095 (49.09) | 52 (1.21) | 4267 (99.76) | 2115 (50.08) | 1965 (46.53) | 143 (3.38) | 4223 (99.66) |
| Frontal point of impact | | | | | | | | | | | | | | | | |
| Yes | 425 (39.09) | 595 (54.73) | 67 (6.16) | 1087 (36.73) | 619 (39.12) | 891 (56.32) | 72 (4.55) | 1582 (38.93) | 683 (40.12) | 993 (58.34) | 26 (1.52) | 1702 (39.79) | 602 (37.48) | 934 (58.15) | 70 (4.35) | 1606 (37.9) |
| No | 1033 | 770 | 69 | 1872 | 1452 | 968 | 61 | 2481 | 1442 | 1107 | 26 | 2481 | 1520 | 1038 | 73 | 2631 |

(*continued on next page*)

**Table 2** (*continued*)

| Variable | 2016 | | | | 2017 | | | | 2018 | | | | 2019 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Frequency (percentage) | | | | Frequency (percentage) | | | | Frequency (percentage) | | | | Frequency (percentage) | | | |
| | NI | MI | SI | Total | NI | MI | SI | Total | NI | MI | SI | Total | NI | MI | SI | Total |
| | (55.18) | (41.13) | (3.68) | (63.26) | (58.52) | (39.01) | (2.45) | (61.06) | (56) | (42.99) | (1) | (60.2) | (57.77) | (39.45) | (2.77) | (62.09) |
| Turning before accident | | | | | | | | | | | | | | | | |
| *Yes* | 251 (26.87) | 615 (65.84) | 68 (7.28) | 934 (31.56) | 308 (23.85) | 925 (71.64) | 58 (4.49) | 1291 (31.77) | 316 (22.78) | 1044 (75.27) | 27 (1.94) | 1387 (32.42) | 319 (23.16) | 999 (72.54) | 59 (4.28) | 1377 (32.49) |
| *No* | 1207 (59.6) | 750 (37.03) | 68 (3.35) | 2025 (68.43) | 1763 (63.6) | 934 (33.69) | 75 (2.7) | 2772 (68.22) | 1809 (62.59) | 1056 (36.53) | 25 (0.85) | 2890 (67.57) | 1803 (23.16) | 973 (34.02) | 84 (2.93) | 2860 (67.5) |
| Public property damage | | | | | | | | | | | | | | | | |
| *Yes* | 125 (74.7) | 39 (23.21) | 4 (2.38) | 168 (5.67) | 154 (66.95) | 68 (29.56) | 8 (3.47) | 230 (5.66) | 148 (68.51) | 66 (30.55) | 2 (0.92) | 216 (5.05) | 114 (65.89) | 52 (30.05) | 7 (4.04) | 173 (4.08) |
| *No* | 1333 (47.76) | 1326 (47.5) | 132 (4.72) | 2791 (94.32) | 1917 (50.01) | 1791 (46.72) | 125 (3.26) | 3833 (94.33) | 1977 (48.68) | 2034 (50.08) | 50 (1.23) | 4061 (94.94) | 2008 (49.4) | 1920 (47.24) | 136 (3.34) | 4046 (95.91) |
| Going straight before accident | | | | | | | | | | | | | | | | |
| *Yes* | 799 (57.39) | 541 (38.86) | 52 (3.73) | 1392 (47.04) | 1129 (59.38) | 712 (37.45) | 60 (3.15) | 1901 (46.78) | 1149 (57.82) | 817 (41.11) | 21 (1.05) | 1987 (46.45) | 1114 (57.87) | 746 (38.75) | 65 (3.37) | 1925 (45.43) |
| *No* | 659 (42.05) | 824 (52.58) | 84 (5.36) | 1567 (52.95) | 942 (43.57) | 1147 (53.05) | 73 (3.37) | 2162 (53.21) | 976 (42.62) | 1283 (56.02) | 31 (1.35) | 2290 (53.54) | 1008 (43.59) | 1226 (53.02) | 78 (3.37) | 2312 (54.56) |

Note: NI = No Injury, MI = Minor Injury, SI = Severe Injury.

**Table 3**
Likelihood ratio tests, 2016–2019.

| $t_1$ | $t_2$ | | | |
|---|---|---|---|---|
| | 2016 | 2017 | 2018 | 2019 |
| 2016 | – | 20.66(14) [85.19%] | 671.39(18) [>99.99%] | 1200.46(16) [>99.99%] |
| 2017 | 570.37(19) [>99.99%] | – | 21.90(18) [76.35%] | 430.83(16) [>99.99%] |
| 2018 | 62.61(19) [>99.99%] | 721.91(14) [>99.99%] | – | 1005.94(16) [>99.99%] |
| 2019 | 837.55(19) [>99.99%] | 167.18(14) [>99.99%] | 482.22(18) [>99.99%] | – |

Note: $\chi 2$ values with degrees of freedom are presented in parentheses and confidence level in brackets.

advanced driving systems can decrease the level of distraction while driving.

For sport utility vehicles, the model suggested temporal shifting over the years. While SUV decreased the likelihood of no injury and increased the probability of minor injury in 2016, it was found to have a negative association with SUV and minor injury in 2018 and 2019 with −0.0330 and − 0.0358 marginal effects. In a recent study, Alnawmasi and Mannering [15] reported that SUVs can significantly increase the probability of severe injury. Oviedo-Trespalacios and Scott-Parker [39] noted on this matter that this type of car is frequently driven by riskier groups (such as males or younger drivers) and considering the higher likelihood of these groups engaging in distracted driving, the resulting risks are higher and more severe.

### 6.3. Temporal characteristics

The results of model estimation regarding the temporal characteristics showed that seasons can significantly affect the resulting severities of distracted-related crashes in different periods, however, the effect of this variable was not consistent during the 4-year period. The results showed that the summer indicator (marginal effect: 0.2755) significantly increased the probability of severe injury crashes in 2019. Regarding the fall indicator, the results showed that this variable could significantly decrease the chance of severe injury crashes in 2017 (marginal effect: −0.0879). Finally, the winter indicator increased the probability of no injury outcome in 2016 model (marginal effect: 0.0361). A probable interpretation for the results in 2016, supported by the past literature, is that drivers may be more conservative with their driving behavior during winter weather. For instance, a driver behavior analysis by Fu, et al. [40] showed that the average speed of drivers decreased significantly during snow conditions compared to good weather conditions. However, it remains challenging to identify whether the observed shifts in different years stem from an underlying influence of factors, changes in drivers' behavior, the nature of the data, or a combination of these elements [15]. Therefore, it is important to acknowledge the potential influence of behavioral and external factors that might contribute to the variability in crash injury severities across different years when analyzing the instability in temporal characteristics observed in this study. Similar to the seasons, hours of the day impacted the outcome of crashes in specific years, however, this variable was not found to be significant steadily. Morning peak negatively affected the minor injury level in 2017. Also, the evening peak increased the chance of no injury crashes in 2019. Alnawmasi and Mannering [15] also confirmed that the late afternoon indicator was positively associated with no injury crashes. The results also showed that the midnight indicator positively impacted severe injury in 2018 (marginal effect: 0.1286). As reported by Fatmi and Habib [19], driving at late-night hours increases the likelihood of fatality and incapacitating injury in distracted driving related crashes.

**Table 4**
Random parameters logit model results of distracted drivers injury severity-2016 time period.

| Variable | Estimated parameter | Z value | Marginal effects | | |
|---|---|---|---|---|---|
| | | | No injury | Minor injury | Severe injury |
| No injury level [NI] | | | | | |
| Passenger presence | 0.893 | 6.50 | 0.0777 | −0.0151 | −0.0626 |
| *Standard deviation for "Passenger presence" (Normally distributed)* | 2.368 | 3.00 | | | |
| Female | −0.474 | −3.31 | -0.0891 | 0.0360 | 0.0531 |
| Winter | 0.352 | 2.09 | 0.0361 | −0.0045 | −0.0316 |
| Minor injury level [MI] | | | | | |
| Constant | −1.971 | −4.94 | | | |
| No driving license | 0.951 | 2.57 | −0.0656 | 0.1715 | −0.1059 |
| Weekends | −0.506 | −2.69 | 0.0471 | −0.0737 | 0.0266 |
| *Standard deviation for "Weekends" (Normally distributed)* | 1.460 | 2.32 | | | |
| Older driver (>60 years) | 0.547 | 2.95 | −0.0398 | 0.1035 | −0.0637 |
| Young driver (under 24 years) | −0.624 | −2.87 | 0.0544 | −0.0773 | 0.0229 |
| Older vehicle (>10 years) | 0.411 | 2.78 | −0.0040 | 0.0515 | −0.0475 |
| Going straight before crash | 1.229 | 5.71 | −0.0981 | 0.2159 | −0.1178 |
| Severe injury level [SI] | | | | | |
| Constant | −3.552 | −7.49 | | | |
| Public property damage | −1.301 | −2.28 | 0.0307 | 0.2236 | −0.2543 |
| Frontal impact | 0.858 | 3.34 | −0.0540 | −0.0369 | 0.0909 |
| *Standard deviation for "Frontal impact" (Normally distributed)* | −1.358 | −2.48 | | | |
| Turning before crash | 1.754 | 4.27 | −0.0129 | −0.1703 | 0.1832 |
| No safety belt | 0.537 | 4.96 | −0.0417 | −0.0409 | 0.0826 |
| Under alcohol/ drug influence | 0.963 | 11.87 | −0.0539 | −0.1878 | 0.2417 |
| Model statistics | | | | | |
| Number of observations | 2959 | | | | |
| Log-likelihood at convergence | −2254.93 | | | | |
| AIC | 4625.86 | | | | |
| BIC | 4973.43 | | | | |

### 6.4. Crash attributes and other variables

The results of mixed logit models showed that daylight indicators' impact on severity levels experienced a shift over the period. While in 2017, daylight negatively impacted the minor injury outcome (marginal effects: −0.0741), in 2019, this indicator was found to have a negative effect on no injury (marginal effects: −0.2206) and a positive effect on minor injury level (marginal effects: 0.0116). Regarding passenger presence, it was found that in all four years, passenger presence could significantly impact outcomes, however, its effect was not steady over the period and experienced significant shifts. The no safety belt usage indicator was only significant in 2016 mode. The results showed that no safety belt usage increased the likelihood of severe injury crashes. This is a well-accepted finding by past literature that safety belt usage can decrease the chance of incapacitating and fatal injuries in distracted-related crashes [15,20,21,23]. The results regarding the role of the frontal point of impact indicator showed that frontal impact increased the likelihood of minor and severe injury crashes during the period. The 2016 and 2017 models also produced random parameters effects of frontal impact positively on severe injury and negatively on no injury level, respectively 2016 and 2017. The 2018 and 2019 models reported conflicting results on the role of public property damage indicator on crash outcomes. While this variable increased the likelihood of minor injury in 2018, it was positively associated with severe injury crashes in 2019.

**Table 5**
Random parameters logit model results of distracted drivers injury severity-2017 time period.

| Variable | Estimated parameter | Z value | Marginal effects | | |
|---|---|---|---|---|---|
| | | | No injury | Minor injury | Severe injury |
| No injury level [NI] | | | | | |
| Sport utility vehicle (SUV) | −0771 | −2.65 | −0.1276 | 0.1176 | 0.0100 |
| Frontal impact | −0.584 | −1.28 | −0.1829 | 0.1821 | 0.0008 |
| *Standard deviation for "frontal impact" (Normally distributed)* | −1.859 | −2.53 | | | |
| Minor injury level [MI] | | | | | |
| Constant | −3.262 | −9.19 | | | |
| Morning peak (7 AM – 9 AM) | −1.140 | −2.05 | 0.1332 | −0.2358 | 0.1026 |
| Spring | −0.706 | −1.60 | 0.0030 | -0.2341 | 0.2311 |
| *Standard deviation for "Spring" (Normally distributed)* | 1.624 | 2.36 | | | |
| Daylight | −0.471 | −1.53 | 0.0732 | −0.0741 | 0.0009 |
| *Standard deviation for "daylight" (Normally distributed)* | 1.211 | 2.53 | | | |
| Going straight before crash | 1.088 | 4.85 | −0.1253 | 0.2242 | −0.0988 |
| Severe injury level [SI] | | | | | |
| Constant | −6.483 | −7.06 | | | |
| Fall | −0.910 | −2.17 | 0.0828 | 0.0051 | −0.0879 |
| Passenger presence | 1.728 | 2.39 | −0.1083 | −0.1550 | 0.2633 |
| Under alcohol/ drug influence | 1.624 | 2.80 | −0.1346 | −0.0473 | 0.1819 |
| Model statistics | | | | | |
| Number of observations | 4063 | | | | |
| Log-likelihood at convergence | −1591.49 | | | | |
| AIC | 3306.99 | | | | |
| BIC | 3698.19 | | | | |

## 7. Policy implications

This research provides a set of policy and practical implications for planners and policymakers, aiming at facing factors contributing to a higher level of injury severities in distracted driving crashes. These implications are in three major areas including legislation and enforcement, education, and engineering.

**Table 6**
Random parameters logit model results of distracted drivers injury severity-2018 time period.

| Variable | Estimated parameter | Z value | Marginal effects | | |
|---|---|---|---|---|---|
| | | | No injury | Minor injury | Severe injury |
| No injury level [NI] | | | | | |
| Older vehicle (>10 years) | 0.447 | 2.60 | 0.0851 | −0.0083 | −0.0768 |
| Going straight before crash | 0.883 | 4.44 | 0.1639 | −0.0341 | −0.1298 |
| Female | −0.214 | −2.87 | −0.1391 | 0.0759 | 0.0632 |
| Minor injury level [MI] | | | | | |
| Constant | −3.173 | −9.95 | | | |
| Public property damage | 0.658 | 2.61 | −0.0395 | 0.0552 | −0.0157 |
| Sport utility vehicle (SUV) | −0.378 | −2.37 | 0.0131 | −0.0330 | 0.0199 |
| Older driver (>60 years) | 0.934 | 4.11 | −0.0469 | 0.1114 | −0.0645 |
| Frontal impact | 0.364 | 2.22 | −0.0368 | 0.0374 | −0.0006 |
| Weekends | −0.617 | −1.35 | 0.0360 | −0.0471 | 0.0111 |
| *Standard deviation for "Weekends" (Normally distributed)* | 2.169 | 2.88 | | | |
| Turning before crash | −1.444 | −1.39 | 0.0219 | −0.2248 | 0.2029 |
| *Standard deviation for "Turning before crash" (Normally distributed)* | −2.558 | −2.07 | | | |
| No driving license | 0.612 | 2.96 | −0.0056 | 0.0517 | −0.0461 |
| Severe injury level [SI] | | | | | |
| Constant | −7.863 | −2.79 | | | |
| Passenger presence | 1.304 | 1.82 | −0.0461 | −0.0429 | 0.0890 |
| *Standard deviation for "Passenger presence" (Normally distributed)* | 2.423 | 2.63 | | | |
| Middle-aged driver (25–39 years) | 0.504 | 4.93 | −0.0040 | −0.0462 | 0.0502 |
| Midnight (12 AM – 7 AM) | 1.863 | 6.10 | −0.0636 | −0.0650 | 0.1286 |
| Model statistics | | | | | |
| Number of observations | 4277 | | | | |
| Log-likelihood at convergence | −1392.92 | | | | |
| AIC | 2913.84 | | | | |
| BIC | 3220.94 | | | | |

Considering that driving characteristics were found to be a significant variable in explaining the resulting severities of distraction-related crashes, presenting targeted information for risky groups such as younger drivers can enhance the current understanding of the topic and reduce the resulting risky outcomes. It is worth noting that reducing the associated risks of riskier groups may be more effective than preventive practices for specific distracted driving behaviors. Further, given that driving under alcohol influence can significantly increase the chance of severe injuries in distraction-related crashes, a multi-approach of education and enforcement may be effective to face the problem. Awareness programs can discourage drivers from drink driving, with higher level penalties and intense patrolling as complementary tools.

Passengers can be in-vehicle sources of distraction by diverting the driver's mind off the driving task and eyes off the roadway. Both education and legislation can reduce the resulting risky outcomes of the presence of passengers. The educational content on this regard can enhance driver's knowledge toward the passengers' risk while driving. Restricting the presence of passengers for learners and new drivers can be an effective way to minimize related risks. Further, engineering measures can be considered an effective way to help drivers stay attentive on the road or sustain lower levels of injuries after a potential crash. For instance, enhanced roadside illumination and audible edge lines can possibly reduce late-night distracted driving crashes, which were found to be more severe in this study.

**Table 7**
Random parameters logit model results of distracted drivers injury severity-2019 time period.

| Variable | Estimated parameter | Z value | Marginal effects | | |
|---|---|---|---|---|---|
| | | | No injury | Minor injury | Severe injury |
| No injury level [NI] | | | | | |
| Going straight before crash | 1.949 | 3.34 | 0.1499 | −0.0764 | −0.7362 |
| Evening peak (3 PM – 7 PM) | 0.669 | 2.84 | 0.0331 | −0.0096 | −0.0235 |
| Daylight | −1.401 | −1.82 | −0.2206 | 0.0116 | 0.2090 |
| *Standard deviation for "Daylight" (Normally distributed)* | 0.643 | 1.93 | | | |
| Minor injury level [MI] | | | | | |
| Constant | −3.132 | −11.94 | | | |
| Female | 0.326 | 2.43 | −0.0132 | 0.0206 | −0.0074 |
| Sport utility vehicle (SUV) | −0.432 | −3.26 | 0.0155 | −0.0358 | 0.0203 |
| Older driver (>60 years) | 0.549 | 2.77 | −0.0077 | 0.0906 | −0.0829 |
| Frontal impact | 0.352 | 2.66 | −0.0215 | 0.0240 | −0.0025 |
| Passenger presence | 1.602 | 1.93 | −0.0869 | 0.3860 | −0.2991 |
| *Standard deviation for "Passenger presence" (Normally distributed)* | 2.313 | 2.68 | | | |
| Severe injury level [SI] | | | | | |
| Constant | −6.334 | −9.26 | | | |
| Public property damage | 1.277 | 2.12 | −0.0399 | −0.0796 | 0.1195 |
| Summer | 0.942 | 2.28 | −0.0367 | −0.0388 | 0.0755 |
| Turning before crash | 1.390 | 7.73 | −0.0545 | −0.0902 | 0.1447 |
| Under alcohol/drug influence | 0.926 | 1.67 | −0.0313 | −0.0639 | 0.0952 |
| Model statistics | | | | | |
| Number of observations | 4237 | | | | |
| Log-likelihood at convergence | −1735.29 | | | | |
| AIC | 3594.58 | | | | |
| BIC | 3988.38 | | | | |

## 8. Conclusions

### 8.1. Summary

This study aimed to investigate the factors influencing the frequency

**Table 8**
Comparison of marginal effects based on the results of the mixed logit model, 2016–2019.

| Variable | 2016 | | | 2017 | | | 2018 | | | 2019 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | NI | MI | SI | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| Female | −0.0891 | 0.0360 | 0.0531 | – | – | – | −0.1391 | 0.0759 | 0.0632 | −0.0132 | 0.0206 | −0.0074 |
| Young driver (under 24 years) | 0.0544 | −0.0773 | 0.0229 | – | – | – | – | – | – | – | – | – |
| Middle-aged driver (25–39 years) | – | – | – | – | – | – | −0.0040 | −0.0462 | 0.0502 | – | – | – |
| Older driver (>60 years) | −0.0398 | 0.1035 | −0.0637 | – | – | – | −0.0469 | 0.1114 | −0.0645 | −0.0077 | 0.0906 | −0.0829 |
| Under alcohol/drug influence | −0.0539 | −0.1878 | 0.2417 | −0.1346 | −0.0473 | 0.1819 | – | – | – | −0.0313 | −0.0639 | 0.0952 |
| No driving license | −0.0656 | 0.1715 | −0.1059 | – | – | – | −0.0056 | 0.0517 | −0.0461 | – | – | – |
| Older vehicle (>10 years) | −0.0040 | 0.0515 | −0.0475 | – | – | – | 0.0851 | −0.0083 | −0.0768 | – | – | – |
| Sport utility vehicle (SUV) | – | – | – | −0.1276 | 0.1176 | 0.0100 | 0.0131 | −0.0330 | 0.0199 | 0.0155 | −0.0358 | 0.0203 |
| Summer | – | – | – | – | – | – | – | – | – | −0.0367 | −0.0388 | 0.0755 |
| Fall | – | – | – | 0.0828 | 0.0051 | −0.0879 | – | – | – | – | – | – |
| Winter | 0.0361 | −0.0045 | −0.0316 | – | – | – | – | – | – | – | – | – |
| Weekends | 0.0471 | −0.0737 | 0.0266 | – | – | – | 0.0360 | −0.0471 | 0.0111 | – | – | – |
| Morning peak (7 AM- 9 AM) | – | – | – | 0.1332 | −0.2358 | 0.1026 | – | – | – | – | – | – |
| Evening peak (3 PM – 7 PM) | – | – | – | – | – | – | – | – | – | 0.0331 | −0.0096 | −0.0235 |
| Midnight (12 AM – 7 AM) | – | – | – | – | – | – | −0.0636 | −0.0650 | 0.1286 | – | – | – |
| Daylight | – | – | – | 0.0732 | −0.0741 | 0.0009 | – | – | – | −0.2206 | 0.0116 | 0.2090 |
| Passenger presence | 0.0777 | −0.0151 | −0.0626 | −0.1083 | −0.1550 | 0.2633 | −0.0461 | −0.0429 | 0.0890 | −0.0869 | 0.3860 | −0.2991 |
| Safety belt usage | −0.0417 | −0.0409 | 0.0826 | – | – | – | – | – | – | – | – | – |
| Frontal point of impact | −0.0540 | −0.0369 | 0.0909 | −0.1829 | 0.1821 | 0.0008 | −0.0368 | 0.0374 | −0.0006 | −0.0215 | 0.0240 | −0.0025 |
| Turning before accident | −0.0129 | −0.1703 | 0.1832 | – | – | – | 0.0219 | −0.2248 | 0.2029 | −0.0545 | −0.0902 | 0.1447 |
| Public property damage | 0.0307 | 0.2236 | −0.2543 | – | – | – | −0.0395 | 0.0552 | −0.0157 | −0.0399 | −0.0796 | 0.1195 |
| Going straight before accident | −0.0981 | 0.2159 | −0.1178 | −0.1253 | 0.2242 | −0.0988 | 0.1639 | −0.0341 | −0.1298 | 0.1499 | −0.0764 | −0.7362 |

Note: blank cells show that the variable was not statistically significant, bold cells indicate the significant variable in each year; NI: No injury, MI: minor injury, SI: severe injury.

and severity of single vehicle distracted driving crashes in New York City, and to analyze the temporal shifts in the effects of these factors on crash outcomes between 2016 and 2019. Police-reported data on single-vehicle distracted-related crashes involving private cars on urban roads in New York City was analyzed, with crash severities classified into five categories ranging from no injury to fatal. The study used a Random Parameters Logit model to investigate the contributing factors and severity of the crashes. Results revealed that various driver, vehicle, temporal, and crash attributes were significant in explaining the severity of distracted-related crashes. However, the effects of some variables on crash outcomes were found to experience temporal instability during the study period. It is necessary to interpret the results carefully and consider the combination of marginal effects and overall trends to avoid misleading interpretations. The results of this study showed that the nature of distracted-related crashes and the rapid development of in-vehicle technologies and sources of distraction may increase the complexities of investigation and interpretation of these crashes, and earlier model results should be considered with more caution due to changes in estimated parameter effects over time.

### 8.2. Limitations

Similar to previous studies in the field of distracted-related crash severity analysis, this study also encountered some limitations. First, although the post-crash perspective can depict a more accurate estimation of the real situation, using the data reported by the police can be biased. Since the conventional data collection method for distraction crashes called the National Automotive Sampling System (NASS) was discontinued in 2016 and replaced with a new system called the Crash Report Sampling System (CRSS) [41], there is a possibility that some crashes related to distraction might not be accurately reported in this year, as the data suggests that in 2016, the frequency of crash injuries was roughly 25% lower compared to other years. This discrepancy could arise from varying interpretations of such crashes during the initial year of the system introduction and resulted in a decrease in the report of distracted behaviors, such as the use of mobile phones, within the dataset. Second, the collected dataset had some limitations in the number of variables such as weather conditions or geometric characteristics, therefore, the current study could not consider these variables in the model compared to the past literature [42]. Third, this study only considered single vehicle crashes in urban areas of New York City, however, investigating rural crashes or multi vehicle crashes might provide a different understanding of the topic.

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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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