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Temporal instability assessment of injury severities of motor vehicle drivers at give-way controlled unsignalized intersections: A random parameters approach with heterogeneity in means and variances

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ABSTRACT

Unsignalized intersections are highly susceptible to traffic crashes compared to signalized ones. By taking into account temporal stability and unobserved heterogeneity, this study investigates the determinants of the injury severity of drivers involved in crashes at unsignalized intersections controlled by give-way (yield) signs. Mixed logit models with three approaches were employed, namely random parameters, random parameters with heterogeneity in means, and random parameters with heterogeneity in means and variances. The investigation covered four years (2015–2018) of motor vehicle crashes in South Australia, and the injury severity was categorized into no injury, minor injury, and severe injury. Log-likelihood ratio tests revealed that there is a significant temporal instability in the four years of crashes. Thus, each year was considered separately to avoid any potential erroneous conclusions and unreliable countermeasures. The study found 28 indicator variables were temporally unstable over the four years of crashes, such as driver gender, time of the crash, rear-end involvement, sideswipes, right-angle crash type, vehicle movement at crash time, and crash time. Whereas several variables were stable over the same period, for example, crashes within metropolitan areas were temporally stable over four years, crashes in dry pavement condition were temporally stable over three consecutive years. Four factors have temporal stability over two consecutive years: alcohol involvement crashes, hitting fixed objects, hitting cyclists, and crashes during winter. Overall, mixed logit models with heterogeneity in means and with/without variance performed better than the standard one. It is recommended that temporal instability be considered in order to avoid any potential inconsistent countermeasures.

1. Introduction

Intersections have been considered the highest-risk urban traffic locations due to the complex traffic environment (Li et al., 2019; Tay, 2015). Crashes at intersections account for approximately 20 % of fatalities in Australia (NRSAP, 2018). Unsignalized intersections are highly prone to traffic crashes compared to signalized ones (Ramlan et al., 2020). The vast majority of intersections in Australia are unsignalized and give rise to many motor vehicles' conflicts and between motor vehicles and other road users (Steinmetz et al., 2017).

Many studies have been performed to enhance the safety at unsignalized intersections (Ahmed et al., 2016; Himes et al., 2016; Kaysi and Abbany, 2007; Li et al., 2019; Montella et al., 2020; Neham, 2020; Paul and Ghosh, 2018; Ramlan et al., 2020; Schorr and Hamdar, 2014; Shams et al., 2020; Zhang et al., 2019; Zheng et al., 2018). However, studies investigating the injury severity of crashes at unsignalized intersections are minimal. For example, Arhin and Gatiba (2020) employed support vector machines and naive Bayes classifiers to estimate the injury severity of crashes at unsignalized intersections. This model was capable of predicting the injury severity with an accuracy of approximately 83.2 %. Haleem et al. (2015) examined the pedestrian injury severity at unsignalized intersections. Pedestrians on the vehicle travel path, middle and elderly pedestrians, at-fault pedestrians, dark lighting conditions, vans, and high-posted speed limits were found to contribute to

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higher injures to pedestrians. Pei and Fu (2014) investigated the crash injury severity at unsignalized intersections in Heilongjiang Province, China, and the results showed the contributory factors that increase the probability of severe injuries are inclement weather conditions, side-swiping pedestrians on poor pavement condition, the interaction of rear-ends, and third-class highways (particular highway class in China), dark lighting during winter, and interaction between traffic signs or markings and third-class highways. Haleem and Abdel-Aty (2010) performed crash severity analysis at unsignalized intersections in Florida. The findings show several factors influencing crash injury types at unsignalized intersections, which were categorized under traffic, geometric, and driver factors.

Focusing on injury-severity-related crashes at controlled unsignalized intersections, Pai and Saleh (2008) and Pai (2009) identified the contributory factors associated with the motorcyclists failed to yield at T-junctions. The results showed that greater injuries were found when an approaching motorcycle collided with a turning-right vehicle, and such a scenario was found to increase the injury severity when stop, give-way signs, and markings controlled the junction. The literature review reveals that injury severity studies at controlled unsignalized intersections are limited. Moreover, the previous studies investigating the injury severities at unsignalized intersections did not consider the temporal stability and the heterogeneity in mean and variance to develop a comprehensive understanding of factors associated with injury severities.

Recent studies on crash severity analysis have emphasized taking into account unobserved heterogeneity associated with safety modeling (Heydari et al., 2017; Anastasopoulos, 2016; Behnood and Mannering, 2015; Russo et al., 2014). While random parameters models are now widely applied to take into account unobserved heterogeneity, the specifications for heterogeneity in means and variances have received less attention. Failure to consider heterogeneity in the means may lead to model specification error resulting in erroneous inferences (Hamed and Al-Eideh, 2020). Few of the latest studies showed that the random parameters logit model with heterogeneity in means and variances perform better than the standard random parameters logit model (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2019, 2017a; Seraneeprakarn et al., 2017; Waseem et al., 2019; Xin et al., 2017). Heterogeneity without considering means and variances may underestimate or overestimate the direct marginal effects, influencing the likelihood of injury-severity levels (Yu et al., 2020a).

Furthermore, overlooking the temporal stability may result in an inaccurate and unreliable decision (Mannering, 2018). Using work-zone-related data, Islam et al. (2020) examined temporal instability of the contributing factors determining the crash-injury severities. The model estimates generated significantly different parameters over different time periods. It was concluded that temporal instability does not solely result from the variations in driver behavior in work-zone-related crashes. Islam and Mannering (2020) examined the changes in crash-injury severities overtime when aggressive and non-aggressive driving behavior is observed. Results showed there is a statistically significant temporal instability. Yu et al. (2020b) identified strong temporal stability of significant factors influencing driver injury severity in run-off-road crashes. Yu et al. (2020a) analyzed work-zone-related rear-end crash data and found considerable temporal instability between time periods (2010 and 2011 and 2012–2013). Using a seven-year period of snow-related single-vehicle crash data, Yu et al. (2020c) found the heterogeneous factors for driver injury severity variations. Results showed there are temporal instabilities for more than three years of the dataset. Alnawmasi and Mannering (2019) statistically assessed the temporal instability in the determinants affecting motorcyclist injury severities. The findings showed there are temporal changes in gaining experience in addition to general temporal shifts. Behnood and Mannering (2019) conducted likelihood ratio tests to evaluate the transferability of model estimation results of large-truck crashes and found that the parameter estimates on crash severities vary by day of the week and from one year to another year.

Mannering (2018) suggested that temporal instability is expected in every statistical analysis of crash injury severity, and accounting for such instability is essential and can be applied in several safety practices. Accordingly, several studies found a significant temporal instability in contributing factors associated with crash injury severities (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2019, 2015; Islam et al., 2020; Islam and Mannering, 2020; Yu et al., 2020b). Therefore, it is also expected that such instability can be a concerning issue for injury severities resulting from crashes at unsignalized intersections controlled by give-way traffic signs. The evaluation of temporal instability for injury severity of crashes at unsignalized intersections is essential because such intersections are not controlled by traffic signals, so the traffic flow is not controlled in a timely manner and not stable over time. According to Federal Highway Administration (2009), around 72 percent of fatal crashes at unsignalized intersections are related to drivers failing to give the right of way. In addition, most maneuvers at these locations are fundamentally related to individual driver decisions that vary from one driver to another. This also may involve unobserved factors that potentially influence injury-severity outcomes.

The literature showed that several studies had been performed to enhance safety at unsignalized intersections. However, studies investigating the injury severity of crashes at unsignalized intersections are very limited. Moreover, the previous studies investigating the injury severities at unsignalized intersections controlled by give-way signage did not consider the temporal stability and the heterogeneity in mean and variance to develop a comprehensive understanding of factors associated with injury severities. Therefore, the objective of this study is to identify the determinant factors influencing the injury severity of motor vehicle drivers involved in crashes at unsignalized intersections controlled by give-way signage. In addition, this study aims to determine if there is any temporal instability between the variables and if there is a need to separate the years to get better insights into the contributing factors. Four years of South Australian crash data (2015–2018) were used. Three methodological approaches were applied in this study: mixed logit model, mixed logit model with heterogeneity in means, and mixed logit model with heterogeneity in means and variances. In addition, these determinants were assessed for any potential temporal instability over the investigated period.

This paper starts with the data description, followed by detailed information about the methodology. Final models are illustrated and discussed in addition to the statistical tests for temporal instability. Finally, the last section covers the summary, conclusions, and implications.

2. Methodology

This study has estimated a set of mixed (random parameter) logit models (MXL) to identify significant contributing factors and assess their influence on the injury severity of drivers involved in crashes at unsignalized intersections controlled by give-way signs. The MXL model is a generalized methodological approach to address the existing limitations of the multinomial logit structure. The application of MXL has several promising advantages in that it is flexible in the model definition, easy to interpret, allows for parameter randomness of an independent variable, and relaxes the independence of irrelevant alternatives. It has been shown that the MXL model may be specified to approximate any discrete outcome model (Behnood and Mannering, 2017b, 2017a; Haleem and Gan, 2013; Moore et al., 2011; Seraneeprakarn et al., 2017; Wu et al., 2014). Three injury severity levels are considered in this study: no injury or property damage only (PDO), minor injury (non-incapacitating injury), and severe injury (incapacitating or fatal injury). To begin constructing an MXL model, Eq. (1) is defined as

$$S_{kn}= \beta_k X_{kn} + \mathcal{E}_{kn} \tag{1}$$

where S_{kn} is the value of the function that defines the probability of driver injury-severity level k in crash n. Consider β_k a vector of estimable parameters, X_{kn} a vector of dependent variables that influence injury-severity level k, and ε_{kn} the error term, which is considered to be independent and identically distributed (Washington et al., 2011). Also, this study considers unobserved heterogeneity across observations by letting βk to be a vector of estimable parameters that vary across these observations, as defined in Eq. (2) (Mannering et al., 2016).

$$\beta_k = b + \Theta Z_k + \varphi_k \tag{2}$$

where b is the mean parameter estimate across all crashes, Zk is a vector of dependent variables from crash n, Θ is a vector of estimable parameters, and φ_k is a randomly distributed term that depicts unobserved heterogeneity across the observations. Unobserved heterogeneity in the means and variances of random parameters as characterized in Eq. 3 is accounted by β_{kn} be a vector of estimable parameters that shifts over the significant perceptions (Behnood and Mannering, 2019; Seraneeprakarn et al., 2017).

$$\beta_{kn} = \beta + \Theta_{kn} Z_{kn} + \sigma_{kn} exp(\omega_{kn} W_{kn})_{v_{kn}} \tag{3}$$

where β is the mean parameter estimate across all crashes, Z_{kn} is a vector of dependent variables that captures heterogeneity in the mean that influences driver injury-severity level k, Θ_{kn} is a corresponding vector of estimable parameters, W_{kn} is a vector of crash-specific explanatory variables that captures heterogeneity in the standard deviation σ_{kn} with comparing parameter vector ω_{kn}, and the disturbance term is (v_{kn})

The probability of injury severity k incurred by the driver in crash n, p_n (k), can be described by allowing the vector β_{kn} with a continuous density function so that:

Prob $(\beta_{kn} = \beta) = f(\beta\ |\varphi)$ (Behnood and Mannering, 2017b, 2017a; Seraneeprakarn et al., 2017):

$$p_n(\mathrm{k}) = \int exp|\varphi_k) d\beta_k \tag{4}$$

where p_n (k) is the likelihood of injury severity k in crash n, and all remaining factors are characterized prior to that.

Model estimation was embraced utilizing simulated maximum likelihood with 1000 Halton draws, which is a deterministic sequence of numbers that provides well-spaced 'draws' from an interval and provides a negative correlation between simulated probability for individuals (McFadden and Train, 2000). Many different distributions for the random parameter have been measured, and the normal distribution had the most excellent measurable fit in this study, similar to (Zubaidi et al., 2021, 2020). Marginal effects are moreover calculated to give more insight into the estimated results since that permits assessing the impacts of various parameter estimates on the model outcomes. The marginal effect shows the impact which a one-unit increment in an indicator variable has on the injury-severity result probabilities *I,* which deliver the impact of the informative variable going from zero to one (Washington et al., 2011).

$$\delta_{\Im}(kj) = \frac{\partial Prob[y_i = m]}{\partial x_i(kj)} = \left[1(j = m) - P_{ij}\right] P_{\Im}\beta_k \tag{5}$$

3. Temporal instability and transferability tests

This study conducted a sequence of likelihood ratio tests. The first log-likelihood ratio test for transferability is to statistically test the significance of temporal stability by using an all-years model instead of separate models by year (2015, 2016, 2017, and 2018) as follows:

$$\chi^2 = -2\left[\mathrm{LL}(\beta_{2015-2018}) - \mathrm{LL}(\beta_{2018}) - \mathrm{LL}(\beta_{2017}) - \mathrm{LL}(\beta_{2016}) - \mathrm{LL}(\beta_{2015})\right] \tag{6}$$

where $(\beta_{2015-2018})$ is the log-likelihood at the convergence of the model that used all of the available crash data from years 2015 to 2018, (β_{2018}) is the log-likelihood at the convergence of the model based on data only from the year 2018, (β_{2017}) is the log-likelihood at the convergence of a model based on data only from 2017. (β_{2016}) (β_{2015}) are the log-likelihoods at the convergence of the models based on data only from 2016 and 2015, respectively

To investigate the resemblance of parameter estimates between the different models, another transferability test was conducted. This test allows us to subgroups of data stability of the estimated parameters over time as follows (Washington et al., 2011):

$$x^2 = -2[(LL_{t1_{t2}}) - (LL_{t1})] \tag{7}$$

where $(LL_{t1_{t2}})$ is the log-likelihood at convergence for the converged parameters of the time of period t_1 using the data from the time period of t_2 and (LL_{t1}) is the log-likelihood at convergence for the converged parameters of the time of period t_1.

4. Data description

The road crashes data in South Australia were used (Data.Sa, 2018), which covered a period of four years (2015–2018). Data were filtered to include motor-vehicle crashes at unsignalized intersections under give-way traffic control. Then the data were filtered again to also include most at-fault driver from each multi-vehicle crash who engaged in the crash event. Thus, for a multi-vehicle crash, only the most at-fault driver from that crash was included in the analysis. The final dataset included detailed information about the driver, crash, roadway, temporal, and spatial characteristics, vehicle movements, and weather conditions. Overall, there were 8448 observations which are distributed as 2307, 2409, 1857, 1875 observations for 2015, 2016, 2017, 2018, respectively. The provided injury severities were divided into no injury, minor injury, severe injury, and fatal injury. However, with the minimal number of observations of fatal injuries, that group was merged with severe injury to produce three groups: no injury, minor injury, and severe injury. Fig. 1 shows the distribution of the severity types across the four years (2015–2018) with a percentage at the unsignalized intersection controlled by give-way signage. Overall, there was a drop in the number of crashes-injury severities for the last two years (2017–2018) compared to 2015 and 2016. This downward trend could be related to the local Australian initiative towards zero serious injuries by enhancing the overall traffic safety.

Table 1 provides the descriptive statistics of all the significant variables for 2018, 2017, 2016, and 2015 after excluded all the insignificant variables, based on the coefficients, from the final models no matter the effect of marginal effect was following Greene (2016) assessment. Factors are classified under the driver, crash, vehicle, temporal, spatial, and roadway characteristics, vehicle movement, and weather conditions.

5. Results and discussions

Regarding the transferability test, using Eq. (6) results in an associated critical chi-square (χ^2) value of 418.21 with 12 degrees of freedom that equal to the summation of the number of estimated random parameters in all separate models (2015 model,2016 model, 2017 model, and 2018 model) minus the number of estimated random parameters in the all-years-together model (2015–2018 model), results in rejecting the null hypothesis that the all- years model's and the separate models' parameters are equal with 99 % confidence. The temporal instability has been tested by applying Eq. (7), in this equation, t_1 refers to the 2015 model and t_2 refers to one of the other configuration models using 2016 data. Results from this process for each model are shown in Table 2. The x^2 statistic with degrees of freedom equal to the number of estimated parameters in $(\beta_{t1_{t2}})$ can provide 99 % confidence in the likelihood that the evaluated models have diverse parameters. So, the null hypotheses that the evaluated parameters are rising to between the two time period

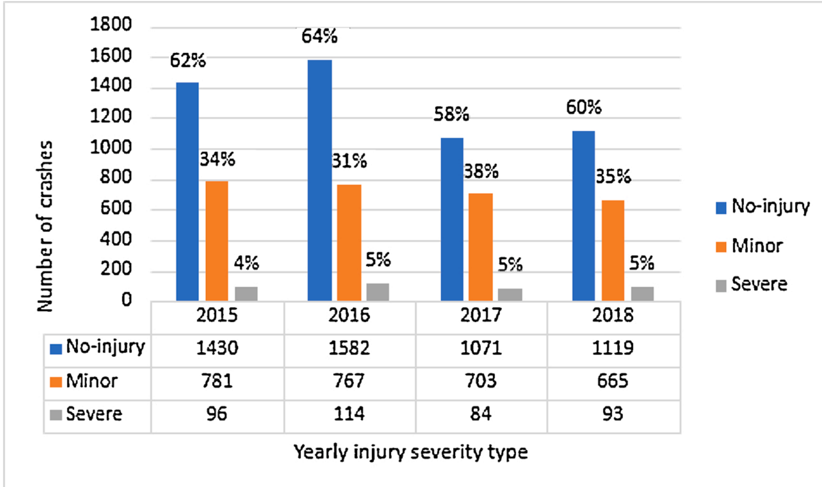

Fig. 1. Number of injury severities at unsignalized intersection controlled by give-way signage across four years of crashes.

datasets can be rejected.

The model estimates of mixed logit with random parameter (MXL), mixed logit with heterogeneity in means (MXL-M), and mixed logit with heterogeneity in means and variances (MXL-MV) of the random parameters are provided in Tables 3–6, while Tables 7–10 present the comparison of marginal effects for injury severities across different models. Finally, the temporal stability assessment can be found in Table 11. This study reported all the result outputs of the three approaches to have more clarification about the log-likelihood improvement at each model. In addition, discussing the three approaches make this work a comparable with other studies that may not consider heterogeneity in means and variances.

Overall, the results indicated that MXL-M performed better than MXL in the 2018, 2017, and 2015 databases. In addition, no heterogeneity in random parameter variances was found in these time periods, whereas in the 2016 database, MXL-MV performed better than MXL and MXL-M.

The discussion is divided into three subsections, random parameters, random parameters with heterogeneity in means, random parameters with heterogeneity in means and variances, and the explanatory variables discussion.

5.1. Random parameters

Several parameters were found to be random and normally distributed in each of the four estimated models, as shown in Tables 3–6. For 2018, 2017, and 2015 there are two estimated models, MXL and MXL-M, while no heterogeneity in mean and variance were found in these models except for the 2016 database, where the three models are significant. In the 2018 models (Table 3), the time of the crash (if at afternoon between 12 pm-6 pm, 0 otherwise) was found to be a statistically significant random parameter in the MXL (and MXL-M) with a mean of -0.55 (-2.83) and standard deviation of 1.55 (2.62), respectively. This indicates that the indicator variable using MXL (and MXL-M) increases the probability of minor injuries by 36.14 % (14 %) and decreases the probability of minor injuries by 63.66 % (86 %), respectively.

Moving to other parameters, horizontal alignment (1 if curved road, 0 otherwise) was found to be statistically significant and, also, a random and normally distributed parameter in 2018 models. A mean of -0.79 (-1.05) and a standard deviation of 3.39 (3.05) indicates that 59.21 % (63.47 %) (less than zero) of the crash have less likelihood of being involved in injury outcomes, whereas 40.79 % (36.53 %) of them have more likelihood of being involved in injury outcomes using MXL (and MXL-M), respectively. Looking at the effect of posted speed limit (1 if the speed limit is less than 50 km/hr., 0 otherwise), the estimated parameter using MXL-M was found to have a normally distributed random parameter with a mean of 5.41 and a standard deviation of 4.43 in the 2017 model (Table 4). The result suggests that about 11.1 % of drivers decrease the likelihood of being injured, while for 89.9 %, the opposite is true. Similar results were obtained while using MXL. In 2016 models (Table 5), posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) was found to be random and normally distributed, with a mean (standard deviation) of 1.29 (1.50), 1.07 (1.93), and 1.10 (2.70), in MXL, MXL-M, and MXL-MV, respectively. This suggests that about 19.49 %, 28.97 %, and 34.19 % of crashes with a speed limit less than 50 km/hr have a mean less than zero, while about 80.51 %, 81.03 %, and 65.81 % of them have a mean more than zero for MXL, MXL-M, and MXL-MV, respectively. In other words, a speed limit less than 50 km/hr increases the likelihood of severe injuries for 80.51 %, 81.03 %, and 65.81 of the observations, whereas 19.49 %, 28.97 %, and 34.19 % are less likely to do so.

In the same 2016 database, weather condition (1 if raining, 0 otherwise) was found to have a normally distributed random parameter with a mean (standard deviation) of -1.82 (4.13), -5.32 (6.46), and -5.97 (5.62) in MXL, MXL-M, and MXL-MV, respectively. The indicator variable increased the probability of minor injuries for 32.97 %, 20.51 %, and 14.41 % of the observations, respectively. In the 2015 models (Table 6), the distribution of crash type (1 if rear-end, 0 otherwise) variable implies that this variable decreases the probability of no injuries for 22.79 % and 43.12 % of the observations when MXL and MXL-M are used, respectively. Lastly, the time of the crash (1 if during evening between 6 pm-12 am, 0 otherwise) was found to be significant and random in the severe-injury 2015 models.

5.2. Heterogeneity in mean measures of the random parameters

All explanatory variables in each yearly model were tested for potential heterogeneity in mean measures of random parameters. The estimated results of 2018, 2017, 2016, and 2015 models showed significant heterogeneity in means of some of the random parameters, as shown in Tables 3–6.

In the 2018 model (Table 3), six variables are significantly associated with the mean of the random parameters in MXL-M. Indicator variables for alcohol indicator (1 if that participant had been drinking, 0 otherwise) was found to increase the mean of the horizontal curve alignment. This suggests more no-injury severity crashes when motorists are under the effect of alcohol who failed to give way at the unsignalized intersections with curved roads. With regards to the random parameter crash time (between 12 pm-6 pm), four indicator variables: alcohol indicator (1 if that participant had been drinking, 0 otherwise), crash type

Table 1
Descriptive statistics of the significant variables in the injury severity models.

Variable	2018		2017		2016		2015	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Driver Characteristics								
Alcohol indicator (1 if that participant had been drinking, 0 otherwise)	0.04	0.19	0.03	0.16	0.03	0.16	0.03	0.17
Gender of driver (1 if male, 0 otherwise)	0.51	0.49	0.53	0.49	–	–	–	–
Gender of driver (1 if female, 0 otherwise)	–	–	0.37	0.48	–	–	–	–
Driver age (1 if the age between 35−64, 0 otherwise)	–	–	–	–	–	–	0.36	0.48
Driver license type (1 if provisional LIC, 0 otherwise)	0.11	0.31	–	–	0.06	0.24	–	–
Driver license type (1 if full LIC, 0 otherwise)	–	–	–	–	0.71	0.46	–	–
Crash Characteristics								
Number of involved vehicles *(continues)*	2.18	0.66	2.13	0.44	2.16	0.51	2.16	0.52
Number of vehicle occupant *(continues)*	–	–	–	–	–	–	1.38	0.97
Crash type (1 if rear-end crash, 0 otherwise)	0.10	0.30	–	–	0.14	0.35	0.15	0.36
Crash type (1 if side-swap crash, 0 otherwise)	0.06	0.23	–	–	0.05	0.22	–	–
Crash type (1 if hit fixed object, 0 otherwise)	0.08	0.27	0.08	0.27	0.07	0.25	0.08	0.27
Crash type (1 if hit ped cyclist, 0 otherwise)	0.04	0.19	0.04	0.19	0.03	0.17	0.03	0.18
Crash type (1 if right angle crash, 0 otherwise)	–	–	–	–	0.59	0.49	–	–
Vehicle Movement								
Vehicle movement (1 if stopped on carriage way, 0 otherwise)	0.06	0.23	–	–	–	–	–	–
Vehicle movement (1 if turning right, 0 otherwise)	–	–	0.11	0.31	–			
Vehicle movement (1 if straight ahead, 0 otherwise)	–	–	–	–	0.59	0.49	–	–
Vehicle Characteristics								
Vehicle type (1 if passenger car, 0 otherwise) [NI]	–	–	–	–	0.79	0.41	–	–
Vehicle age (1 if vehicle age < 20 yrs., 0 otherwise) [MI]	–	–	–	–	0.65	0.48	–	–
Temporal Characteristics								
Time of the crash (if during nighttime between 12am–6am, 0 otherwise)	0.03	0.16	–	–	–	–	–	–
Time of the crash (if at afternoon between 12 pm–6 pm, 0 otherwise)	0.49	0.49	–	–		–	–	–
Time of the crash (if at morning between 6 am–12pm, 0 otherwise)	–	–	–	–	–	–	0.33	0.47
Time of the crash (if at evening between 6 pm–12am, 0 otherwise)	–	–	–	–	–	–	0.15	0.36
Time of the crash (if during a daylight, 0 otherwise)	–	–	–	–	0.82	0.38	0.84	0.37
Season of the crash (1 if in Winter (June–August), 0 otherwise)	0.24	0.43	–	–	0.22	0.42	0.24	0.43
Season of the crash (1 if in Spring (September–November), 0 otherwise)	–	–	0.25	0.43	–	–	–	–
Season of the crash (1 if in Summer (December–February), 0 otherwise)	–	–	–	–	0.25	0.43	–	–
Spatial Characteristics								
Stats area (1 if the crash occurred within metropolitan, 0 otherwise)	0.72	0.45	0.72	0.43	0.72	0.45	0.73	0.45
Stats area (1 if the crash occurred within country, 0 otherwise)	–	–	0.24	0.43	–	–	–	–
Stats area (1 if the crash occurred within city, 0 otherwise)	–	–	–	–	0.03	0.17	0.03	0.19
Roadway characteristics								
Pavement condition (1 if sealed, 0 otherwise)	0.99	0.09	–	–	–	–	–	–
Pavement condition (1 if dry, 0 otherwise)	–	–	0.88	0.32	0.87	0.33	0.87	0.33
Horizontal alignment (1 if curved road, 0 otherwise)	0.09	0.29	–	–	–	–	–	–
Vertical alignment (1 if road with slop, 0 otherwise)	0.10	0.30	–	–	–	–	–	–
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise)	0.38	0.49	0.39	0.49	0.39	0.49	0.38	0.49
Weather Condition								
Weather condition (1 if raining, 0 otherwise)	–	–	0.91	0.28	0.91	0.29	–	–

Table 2
Transferability test results (degrees of freedom numbers in the parentheses and confidence level in brackets).

t_1	t_2			
	2015 (model)	2016 (model)	2017 (model)	2018 (model)
2015 (Data)	0	154.44 (22) [>99.99 %]	146.32 (15) [>99.99 %]	133.73 (19) [>99.99 %]
2016 (Data)	126.56 (19) [>99.99 %]	0	144.48 (15) [>99.99 %]	153.23 (19) [>99.99 %]
2017 (Data)	113.83 (19) [>99.99 %]	199.03(22) [>99.99 %]	0	144.61(19) [>99.99 %]
2018 (Data)	118.17 (19) [>99.99 %]	187.25 (22) [>99.99 %]	131.53(15) [>99.99 %]	0

(1 if side-swap crash, 0 otherwise), crash type (1 if rear-end crash, 0 otherwise), and vertical alignment (1 if road with slop, 0 otherwise), were found to increase the mean of the random parameter to make the minor injuries more likely. However, the indicator variable season of the crash (1 if in winter (June-August), 0 otherwise) decreased the mean, which means fewer minor injuries during winter when the time of crashes is between 12 pm-6 pm.

In the 2017 model (Table 4), the number of involved vehicles (continues) was the only indicator variable that significantly influenced the random parameter posted speed limit that less than 50 km/hr by decreasing the no-injury mean in the MXL-M model. In the 2016 model (Table 5), the indicator number of involved vehicles (continues) increased the mean on the minor injury of the random parameter rainy weather, while the indicator variable crash type (1 if right-angle crash, 0 otherwise) decreased the means for the same random parameter in both MXL-M and MXL-MV. Moreover, the indicator variable vehicle type (1 if passenger car, 0 otherwise) was found to increase the mean of no injury for the random parameter posted speed limit in both MXL-M and MXL-MV. This indicates that no-injury severities are more likely when the vehicle type is a passenger car on roads with a speed limit of less than

Table 3
Estimation results of the mixed logit models for yield collisions severity at the unsignalized intersections – for 2018 time period (Note: [NI]: No injury; [MI] Minor injury; [SI]: Severe injury).

Variable	MXL		MXL-M	
	Parameter estimate	t-stat	Parameter estimate	t-stat
Constant [MI]	1.36	2.51	1.06	2.08
Constant [SI]	−0.72	−1.99	−1.07	−1.73
Driver Characteristics				
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [NI]	−3.54	−7.05	−3.68	−7.15
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	−0.75	−2.01	−1.12	−2.74
Gender of driver (1 if male, 0 otherwise) [NI]	0.27	2.24	0.32	2.50
Driver license type (1 if provisional LIC, 0 otherwise) [SI]	−.082	−1.68	−0.83	−1.65
Crash Characteristics				
Number of involved vehicles *(continues)* [NI]	−0.47	−4.01	−0.50	−4.20
Crash type (1 if rear-end crash, 0 otherwise) [NI]	−0.91	−4.25	−0.70	−2.91
Crash type (1 if side-swap crash, 0 otherwise) [NI]	0.78	2.47	1.49	3.47
Crash type (1 if hit fixed object, 0 otherwise) [NI]	1.49	4.33	1.53	4.11
Crash type (1 if hit ped cyclist, 0 otherwise) [MI]	1.72	5.17	1.89	5.27
Vehicle Movement				
Vehicle movement (1 if stopped on carriage way, 0 otherwise) [NI]	0.53	1.85	0.56	1.84
Temporal Characteristics				
Time of the crash (if during nighttime between 12am–6am, 0 otherwise) [NI]	2.38	3.18	2.04	2.91
Time of the crash (if at afternoon between 12 pm–6 pm, 0 otherwise) [MI]	−0.55	−2.45	−2.83	1.26
Standard Deviation of Parameter, Normally Distributed	1.55	2.60	2.62	3.01
Season of the crash (1 if in Winter (June–August), 0 otherwise) [MI]	−0.40	−2.68	−0.42	−2.59
Season of the crash (1 if in Winter (June–August), 0 otherwise) [SI]	−0.63	−2.02	−0.64	−2.02
Spatial Characteristics				
Stats Area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	−0.78	−3.29	−0.79	−3.28
Roadway characteristics				
Pavement condition (1 if sealed, 0 otherwise) [NI]	1.75	2.59	1.41	1.85
Vertical alignment (1 if road with slop, 0 otherwise) [MI]	0.65	3.23	0.41	1.75
Horizontal alignment (1 if curved road, 0 otherwise) [NI]	−0.79	−2.03	−1.05	−2.77
	3.39	2.09	3.05	1.88
Standard Deviation of Parameter, Normally Distributed				
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [SI]	−1.73	−4.93	−1.76	−4.90
Heterogeneity in the means of the random parameters				
Horizontal Alignment (curved) [NI]: Alcohol indicator (1 if that participant had been drinking, 0 otherwise)	–	–	2.86	1.87
Time of the crash (afternoon) [MI]: Alcohol indicator (1 if that participant had been drinking, 0 otherwise)	–	–	2.41	2.07
Time of the crash (afternoon) [MI]: Season of the crash (1 if in Winter (June-August), 0 otherwise)	–	–	−4.23	−1.75
Time of the crash (afternoon) [MI]: Crash type (1 if side-swap crash, 0 otherwise)	–	–	1.92	2.60
Time of the crash (afternoon) [MI]: Crash type (1 if rear-end crash, 0 otherwise)	–	–	1.17	1.93
Time of the crash (afternoon) [MI]: Vertical alignment (1 if road with slop, 0 otherwise)	–	–	1.18	1.80
Model statistics				
Log likelihood at convergence	−1394.50		−1379.23	
Log-likelihood with constants only	−2050.74		−2058.55	
McFadden Pseudo R-squared	0.32		0.33	
AIC	2835.0		2816.5	
No. of Observations	1875		1875	

50 km/hr.

As shown in Table 6, the 2015 model in MXL-M, only pavement condition (1 if dry, 0 otherwise) was the indicator variable significantly influencing the heterogeneity in the mean of random parameters time of the crash and crash type by decreasing the mean (severe injuries less likely) and increasing the mean (no injuries more likely) respectively.

5.3. *Heterogeneity in mean and variance measures of the random parameters*

Similar to the previous subsection, explanatory or dependent variables in all developed models were examined, but this time, for possible heterogeneity in variances of random parameters. Only the 2016 model showed significant heterogeneity in the variance of random parameters, as shown in Table 5. Two indicator variables were found to significantly affected the random parameter of rainy weather. The pavement condition (1 if dry, 0 otherwise) increased the variance of the random parameter, whereas the time of the crash (1 if during daylight, 0 otherwise) decreased the variance as shown in the MXL-MV section. The decrease in the variance of the weather condition makes their distribution narrower and decreases their randomness and vice versa. This approach showed dispersion of the weather condition across observations, which provided more flexibility to identify the underlying unobserved heterogeneity.

5.4. *Exploratory variables*

5.4.1. *Driver characteristics*

As shown in Tables 3–6, alcohol indicator (1 if that participant had

Table 4
Estimation results of the mixed logit models for yield collisions severity at the unsignalized intersections – for 2017 time period (Note: [NI]: No injury; [MI] Minor injury; [SI]: Severe injury).

Variable	MXL		MXL-M	
	Parameter estimate	t-stat	Parameter estimate	t-stat
Constant [MI]	−1.92	−5.54	−1.68	−4.73
Constant [SI]	−2.25	−4.63	−2.03	−4.11
Driver Characteristics				
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [NI]	−1.76	−3.14	−1.87	−3.25
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	−1.11	−2.27	−1.11	−2.26
Gender of driver (1 if female, 0 otherwise) [NI]	−0.34	−2.70	−0.36	−2.81
Gender of driver (1 if male, 0 otherwise) [SI]	0.53	2.18	0.54	2.19
Crash Characteristics				
Number of involved vehicles *(continues)* [NI]	−0.39	−3.09	−0.29	−2.25
Crash Type (1 if hit fixed object, 0 otherwise) [NI]	0.78	2.79	0.89	3.14
Crash Type (1 if hit ped cyclist, 0 otherwise) [MI]	1.37	4.07	1.39	4.00
Vehicle Movement				
Vehicle movement (1 if turning right, 0 otherwise) [MI]	0.38	2.17	0.42	2.35
Temporal Characteristics				
Season of the crash (1 if in Spring (September–November), 0 otherwise) [SI]	−1.05	−2.98	−1.06	−3.01
Spatial Characteristics				
Stats area (1 if the crash occurred within country, 0 otherwise) [NI]	−0.39	−2.68	−0.41	−2.75
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	−1.49	−5.97	−1.48	−5.94
Roadway Characteristics				
Pavement condition (1 if dry, 0 otherwise) [NI]	−0.51	−2.62	−0.47	−2.38
Posted Speed Limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [NI]	0.67	1.64	5.41	1.67
Standard Deviation of Parameter, Normally Distributed	2.91	1.91	4.43	1.82
Posted Speed Limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [SI]	−0.74	−2.64	−0.73	−2.62
Weather Condition				
Weather condition (1 if raining, 0 otherwise) [SI]	−0.95	−2.67	−0.93	−2.61
Heterogeneity in the means of the random parameters				
Posted speed limit <50 km/hr. [NI]: Number of involved vehicles *(continues)*	–	–	−2.07	−1.65
Model statistics				
Log likelihood at convergence	−1454.41		−1449.72	
Log-likelihood with constants only	−1888.31		−2041.86	
McFadden Pseudo R-squared	0.23		0.29	
AIC	2944.8		2937.4	
No. of Observation	1857		1857	

been drinking, 0 otherwise) was found to be a significant variable in all years (2015–2018). Using MXL (Tables 7 and 8), alcohol indicator was found to decrease the likelihood of no and minor injuries by −0.0103 and −0.018 in the 2018 database and by −0.018 and −0.015 in the 2017 database, respectively. However, the same indicator in 2016 and 2015 (Tables 9 and 10) was associated with an increased probability of minor and severe injuries. Similar marginal effects were obtained while using MXL-M and MXL-MV. This confirms the previous studies that found alcohol consumption has a complex impact on crash injury severity (Behnood et al., 2014; Behnood and Mannering, 2017c; Darban Khales et al., 2019; Russo et al., 2014; Sarwar et al., 2017; Zubaidi et al., 2020)

Looking at male drivers in 2018 using MXL-M (Table 7), that (gender) parameter was found to significantly increase the likelihood of no injury by 0.109 and decrease the likelihood of minor and severe injury by −0.075 and −0.034, respectively. The same variable in 2017 using MXL-M (Table 8) was found to increase the likelihood of severe injury by 0.067 and decrease the likelihood of no and minor injuries by −0.029 and −0.038, respectively. The male gender variable was not found to be significant in the 2016 and 2015 models. Similar marginal effects were noticed while using MXL. Several studies found male drivers increase the probability of severe-injury outcomes (Kim et al., 2013; Weiss et al., 2014), while some studies found male drivers decrease that probability (Chiou et al., 2013). Interestingly, the female driver's indicator was found to be significant in the 2017 model only, as listed in Table 4. This specific variable tends to lower the probability of a no-injury outcome and increase the probability of minor and severe injuries for both MXL and MXL-M models, as shown in Table 8.

Moving to the driver with provisional license type as shown in Table 7, the indicator was found to decrease the possibility of severe injury and increase the probability of a minor and no-injury outcome in the 2018 models for both MXL and MXL-M, while it was not significant in the 2017 and 2015 models. In the 2016 model (Table 9), driver license type (1 if provisional, 0 otherwise) showed a significant increase in the probability of minor and severe driver injury and a significant reduction in the no-injury crashes. Similar marginal effects were obtained while using MXL, MXL-M, and MXL-MV models. Furthermore, driver license type (1 if full, 0 otherwise) was found to be associated with driver injury severities in 2016 models (Table 5). Nevertheless, this driver's license type (1 if full, 0 otherwise) was statistically insignificant in 2018, 2017, and 2015. The marginal effects for MXL-MV (Table 9) show that the indicator variable is associated with the increment of the probability of severe injuries by 0.054 and is associated with lowering the probability of minor and no injuries by −0.032 and −0.022, respectively.

Driver age (1 if the age is between 35−64 yrs., 0 otherwise) was statistically insignificant except for 2015, as listed in Table 6. The marginal effects in Table 10 using MXL-M were found to increase the likelihood of severe injury by 0.066 and decrease the probability of minor and no injuries by −0.035 and −0.031, respectively.

5.4.2. Crash characteristics

As shown in Tables 7–10, the number of involved vehicles (continues) was found to result in decreases in no driver-injury probabilities and increases in severe and minor driver-injury probabilities in 2018, 2017, 2016, and 2015 using MXL, MXL-M, and MXL-MV models. The number of vehicle occupants (continues) was found to decrease the likelihood of no injury and increase the likelihood of minor and severe injuries in 2015 models only (Table 10). Similarly, Behnood and Mannering (2017a) found that the passengers have a significant effect on driver-injury severities.

Crash type (1 if rear-end crash, 0 otherwise) was found to reduce the likelihood of no injury outcome in 2018 and 2016 models (Tables 7 and 9), but to increase no and minor injuries in 2015 models (Table 10). This indicator was not found to be a substantial factor influencing the outcomes of the injury severity in 2017 models. Using MXL-M in 2018 (Table 7), crash type (1 if side-swap crash, 0 otherwise) indicator variable increased the no injury driver probability by 0.061 and reduced the

Table 5
Estimation results of the mixed logit models for yield collisions severity at the unsignalized intersections – for 2016 time period (Note: [NI]: No injury; [MI] Minor injury; [SI]: Severe injury).

Variable	MXL		MXL-M		MXL-MV	
	Parameter estimate	t-stat	Parameter estimate	t-stat	Parameter estimate	t-stat
Constant [NI]	0.05	0.09	−0.43	−0.64	−0.31	−0.40
Constant [SI]	−2.34	−4.46	−2.11	−3.64	−1.89	−3.24
Driver Characteristics						
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	2.46	3.26	3.19	3.10	3.96	2.95
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [SI]	2.04	3.99	2.03	3.78	2.13	4.14
Driver license type (1 if provisional LIC, 0 otherwise) [NI]	−1.33	−3.72	−1.42	−3.65	−1.44	−3.38
Driver license type (1 if full LIC, 0 otherwise) [SI]	0.98	3.16	1.03	3.17	1.05	3.05
Crash Characteristics						
Number of involved vehicles *(continues)* [NI]	−0.77	−4.58	−0.52	−2.48	−0.54	−2.16
Crash Type (1 if rear-end crash, 0 otherwise) [NI]	1.56	4.36	1.92	4.80	2.01	4.85
Crash Type (1 if right angle crash, 0 otherwise) [NI]	0.62	2.89	0.49	1.97	0.53	2.01
Crash Type (1 if sideswipe crash, 0 otherwise) [NI]	0.94	1.99	1.20	2.06	1.21	1.76
Crash Type (1 if hit fixed object, 0 otherwise) [MI]	−3.18	−4.28	−4.53	−4.11	−5.31	−3.60
Crash Type (1 if hit ped cyclist, 0 otherwise) [MI]	3.04	3.10	4.55	2.97	4.72	2.86
Crash Type (1 if hit ped cyclist, 0 otherwise) [SI]	2.19	3.46	2.12	3.16	2.16	3.16
Vehicle Characteristics						
Vehicle type (1 if passenger car, 0 otherwise) [NI]	0.55	2.71	0.38	1.52	0.36	1.39
Vehicle age (1 if vehicle age < 20 yrs., 0 otherwise) [MI]	0.74	2.79	0.98	3.04	1.12	3.20
Vehicle Movement						
Vehicle movement (1 if straight ahead, 0 otherwise) [SI]	0.48	1.88	0.39	1.46	0.40	1.40
Temporal Characteristics						
Time of the crash (1 if during a daylight, 0 otherwise) [NI]	0.51	2.48	0.53	2.34	0.39	1.66
Season of the crash (1 if in Sumer (December–February), 0 otherwise) [NI]	0.71	3.18	0.82	3.27	0.85	3.19
Season of the crash (1 if in Winter (June–August), 0 otherwise) [SI]	−0.96	−2.96	−1.02	−3.04	−1.06	−2.96
Spatial Characteristics						
Stats area (1 if the crash occurred within city, 0 otherwise) [MI]	−3.39	−2.62	−5.08	−2.47	−5.87	−2.52
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	−1.76	−7.27	−1.82	−7.21	−1.83	−7.21
Roadway Characteristics						
Pavement condition (1 if dry, 0 otherwise) [NI]	−0.93	−2.32	−0.86	−1.95	−0.75	−1.65
Posted Speed Limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [NI]	1.29	3.37	1.07	2.10	1.10	1.98
Standard Deviation of Parameter, Normally Distributed	1.50	2.58	1.93	3.51	2.70	2.94
Weather Condition						
Weather condition (1 if raining, 0 otherwise) [MI]	−1.82	−3.27	−5.32	−2. 87	−5.97	−2.82
Standard Deviation of Parameter, Normally Distributed	4.13	3.68	6.46	3.72	5.62	2.34
Heterogeneity in the means of the random parameters						
Weather condition (raining) [MI]: Number of involved vehicles *(continues)*	–	–	1.49	2.37	1.77	2.43
Weather condition (raining) [MI]: Crash type (1 if right angle crash, 0 otherwise)	–	–	−0.83	−1.75	−0.93	−1.74
Posted speed limit <50 km/hr. [NI]: Vehicle type (1 if passenger car, 0 otherwise)	–	–	0.88	1.71	0.88	1.73
Heterogeneity in the variances of the random parameters						
Weather condition (raining) [MI]: Pavement condition (1 if dry, 0 otherwise)	–	–	–	–	0.62	2.08
Weather condition (raining) [MI]: Time of the crash (1 if during a daylight, 0 otherwise)	–	–	–	–	−0.42	−2.03
Model statistics						
Log likelihood at convergence	−1754.69		−1745.74		−1740.93	
Log-likelihood with constants only	−2658.62		−2645.06		−2637.77	
McFadden Pseudo R-squared	0.34		0.34		0.34	
AIC	3563.4		3551.5		3547.9	
No. of Observation	2409		2409		2409	

possibilities of minor and severe injuries by -0.040 and -0.021, respectively. A comparable effect was noticed for the 2016 database (Table 9). Crash type (1 if hit fixed object, 0 otherwise) was found to be a significant indicator variable in all time periods, as shown in Tables 3 and 6. This indicator generated greater likelihoods of no injuries and lower likelihoods of minor and severe injuries in 2018 and 2017 models (Tables 7 and 8). While in the 2016 and 2015 models, the same indicator decreased the likelihood of minor injuries and increased the probability of no and severe injuries, as shown in Tables 9 and 10. Similar marginal effects were observed for MXL, MXL-M, and MXL-MV models.

Turning to crash type (1 if hit ped cyclist, 0 otherwise), hit cyclist and pedestrian has a greater likelihood of causing the driver a minor injury and a reduced the probability of no and severe injuries in the 2018 and 2017 databases. While in 2016 and 2015 models (Tables 9 and 10), the same indicator increased the likelihood of both minor and severe injuries for the driver. The reduction of the likelihood of severe injuries in

Table 6
Estimation results of the mixed logit models for yield collisions severity at the unsignalized intersections – for 2015 time period (Note: [NI]: No injury; [MI] Minor injury; [SI]: Severe injury).

Variable	MXL		MXL-M	
	Parameter estimate	t-stat	Parameter estimate	t-stat
Constant [NI]	3.61	5.40	4.80	6.77
Constant [MI]	0.67	1.62	0.61	1.53
Standard Deviation of Parameter, Normally Distributed	3.24	4.46	–	–
Driver Characteristics				
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	1.15	1.78	1.20	1.97
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [SI]	2.43	4.33	2.60	4.60
Driver age (1 if the age between 35–64, 0 otherwise) [SI]	0.58	2.13	0.56	2.06
Crash Characteristics				
Number of involved vehicles *(continues)* [NI]	−1.31	−6.14	−1.30	−5.87
Number of vehicle occupants *(continues)* [NI]	−0.19	−2.08	−0.18	−2.02
Crash Type (1 if rear end, 0 otherwise) [NI]	6.30	2.57	0.85	1.46
Standard Deviation of Parameter, Normally Distributed	8.44	1.70	4.92	1.73
Crash type (1 if hit fixed object, 0 otherwise) [MI]	−1.85	−3.58	−1.38	−2.99
Crash type (1 if hit ped cyclist, 0 otherwise) [MI]	1.75	2.75	1.68	2.80
Crash type (1 if rear end, 0 otherwise) [MI]	5.53	3.03	4.55	2.46
Crash type (1 if hit ped cyclist, 0 otherwise) [SI]	2.34	4.01	2.31	4.02
Temporal Characteristics				
Time of the crash (if during morning between 6am–12pm, 0 otherwise) [NI]	−0.56	−2.82	−0.51	−2.77
Time of the crash (1 if during a daylight, 0 otherwise) [MI]	−0.71	−2.19	−0.66	−2.18
Time of the crash (if during evening between 6pm–12am, 0 otherwise) [SI]	−3.91	−1.10	−2.49	−1.66
Standard Deviation of Parameter, Normally Distributed	5.05	2.00	5.36	1.97
Season of the crash (1 if in Winter (June–August), 0 otherwise) [SI]	−1.10	−2.65	−1.11	−2.66
Spatial Characteristics				
Stats area (1 if the crash occurred within city, 0 otherwise) [NI]	1.67	2.74	1.52	2.69
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	−2.09	−7.14	−2.09	−7.23
Roadway Characteristics				
Pavement condition (1 if dry, 0 otherwise) [NI]	−1.42	−3.92	−1.49	−4.05
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [NI]	1.98	5.03	2.02	5.11
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [MI]	1.93	4.39	1.95	4.49
Heterogeneity in the means of the random parameters				
Time of the crash (evening) [SI]: Pavement condition (1 if dry, 0 otherwise)	–	–	−2.59	−1.69
Crash type (rear end) [NI]: Pavement condition (1 if dry, 0 otherwise)	–	–	4.18	1.93
Model statistics				
Log likelihood at convergence	−1674.003		−1661.98	
Log-likelihood with constants only	−2536.37		−2556.89	
McFadden Pseudo R-squared	0.34		0.35	
AIC	3400		3322	
No. of Observation	2307		2307	

the latter years (2017–2018) could be attributed to the fact that pedestrians and cyclists have less impact on the motor vehicle during the accident. Table 9 showed crash type (1 if right-angle crash, 0 otherwise) indicator variable using MXL-MV increased the probability of a no-injury outcome by 0.069 and reduced the probability of minor and severe injuries outcome by −0.045 and −0.024, respectively. The indicator variable was found to be a statistically insignificant factor in influencing the injury severities in 2018, 2017, and 2015.

5.4.3. Vehicle movement

Each indicator variable under vehicle movement was found to be significant in only one single year of the database. For instance, in the 2018 models (Table 7), vehicle movement (1 if stopped on the carriageway, 0 otherwise) was associated with more no-injuries outcomes by increasing the likelihood by 0.021 and 0.023 and decreased the likelihood of minor and severe injury for MXL and MXL-M, respectively. In 2017 models (Table 8), vehicle movement (1 if turning right, 0 otherwise) in MXL and MXL-M increased the probability of minor injuries by 0.019 and 0.020 and decreased the likelihood of no and severe injuries by −0.017 and −0.018, and −0.002 and −0.002, respectively. The other indicator, variable vehicle movement (1 if straight ahead, 0 otherwise), was found to be statistically significant in 2016 models (Table 9). The indicator outcomes showed a higher likelihood of severe injuries and a low probability for both no and minor injuries.

5.4.4. Vehicle characteristics

It was found that two indicator variables were statistically significant within vehicle characteristics and for only 2016 models, as shown in Table 5. The marginal effect in Table 9 showed that vehicle type (1 if passenger car, 0 otherwise) using MXL-MV was found to increase the probability of no injury by 0.040 and decrease the probability of minor and severe injuries by −0.024 and −0.016, respectively. Similar marginal effects were obtained while using MXL and MXL-M. The other indicator variable vehicle age (1 if vehicle age < 20 yrs., 0 otherwise) increased the likelihood of minor injuries by 0.038 and reduced the likelihood of no and severe injuries by −0.018 and −0.020, respectively using MXL-MV. It was noticed that the marginal effect values were higher in MXL-MV compared to MXL and MXL-M.

5.4.5. Temporal characteristics

In 2018 models, as shown in Table 7, the positive marginal effects suggest that time of the crash (1 if during night-time between 12 am and 6 am, 0 otherwise) means a higher possibility of resulting in a no-injury

Table 7
Averaged marginal for yield sign of the unsignalized intersection collisions injury severity effects over all crash observations for year of 2018.

Variable	MXL			MXL-M		
	No inj.	Minor inj.	Severe inj.	No inj.	Minor inj.	Severe inj.
Driver Characteristics						
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [NI]	**−0.103**	0.055	0.048	**−0.104**	0.056	0.048
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	0.011	**−0.018**	0.077	0.012	**−0.026**	0.014
Gender of driver (1 if male, 0 otherwise) [NI]	**0.085**	−0.059	−0.026	**0.109**	−0.075	−0.034
Driver license type (1 if provisional LIC, 0 otherwise) [SI]	0.044	0.042	**−0.086**	0.044	0.042	**−0.086**
Crash Characteristics						
Number of involved vehicles *(continues)* [NI]	**−0.761**	0.482	0.279	**−0.762**	0.460	0.302
Crash type (1 if rear-end crash, 0 otherwise) [NI]	**−0.048**	0.024	0.024	**−0.039**	0.023	0.016
Crash type (1 if side-swap crash, 0 otherwise) [NI]	**0.033**	−0.014	−0.019	**0.061**	−0.040	−0.021
Crash type (1 if hit fixed object, 0 otherwise) [NI]	**0.091**	−0.073	−0.081	**0.092**	−0.069	−0.023
Crash type (1 if hit ped cyclist, 0 otherwise) [MI]	−0.021	**0.045**	−0.024	−0.021	**0.046**	−0.025
Vehicle Movement						
Vehicle movement (1 if stopped on carriage way, 0 otherwise) [NI]	**0.021**	−0.013	−0.008	**0.023**	−0.014	−0.009
Temporal Characteristics						
Time of the crash (if during nighttime between 12am-6am, 0 otherwise) [NI]	**0.05**	−0.029	−0.021	**0.047**	−0.023	−0.024
Time of the crash (if at afternoon between 12 pm-6 pm, 0 otherwise) [MI]	0.022	**−0.040**	0.018	0.011	**−0.022**	0.011
Season of the crash (1 if in Winter (June-August), 0 otherwise) [MI]	0.027	**−0.056**	0.029	0.023	**−0.052**	0.028
Season of the crash (1 if in Winter (June-August), 0 otherwise) [SI]	0.022	0.025	**−0.047**	0.024	0.024	**−0.048**
Spatial Characteristics						
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	0.004	0.007	**−0.011**	0.015	0.027	**−0.042**
Roadway characteristics						
Pavement condition (1 if sealed, 0 otherwise) [NI]	**0.084**	−0.053	−0.31	**0.042**	−0.018	−0.024
Horizontal alignment (1 if curved road, 0 otherwise) [NI]	**−0.030**	0.016	0.014	**−0.043**	0.026	0.017
Vertical alignment (1 if road with slop, 0 otherwise) [MI]	−0.012	**0.026**	−0.014	−0.004	**0.016**	−0.012
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [SI]	0.020	0.029	**−0.049**	0.031	0.028	**−0.059**

Table 8
Averaged marginal for yield sign of the unsignalized intersection collisions injury severity effects over all crash observations for year of 2017.

Variable	MXL			MXL-M		
	No inj.	Minor inj.	Severe inj.	No inj.	Minor inj.	Severe inj.
Driver Characteristics						
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [NI]	**−0.018**	0.006	0.012	**−0.018**	0.011	0.007
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	0.008	**−0.015**	0.007	0.007	**−0.014**	0.007
Gender of driver (1 if female, 0 otherwise) [NI]	**−0.045**	0.021	0.024	**−0.045**	0.023	0.022
Gender of driver (1 if male, 0 otherwise) [SI]	−0.029	−0.037	**0.066**	−0.029	−0.038	**0.067**
Crash Characteristics						
Number of involved vehicles *(continues)* [NI]	**−0.095**	0.065	0.030	**−0.033**	0.015	0.018
Crash type (1 if hit fixed object, 0 otherwise) [NI]	**0.044**	−0.025	−0.019	**0.044**	−0.027	−0.017
Crash type (1 if hit ped cyclist, 0 otherwise) [MI]	−0.025	**0.044**	−0.019	−0.024	**0.043**	−0.019
Vehicle Movement						
Vehicle movement (1 if turning right, 0 otherwise) [MI]	−0.017	**0.019**	−0.002	−0.018	**0.020**	−0.002
Temporal Characteristics						
Season of the crash (1 if in Spring (September–November), 0 otherwise) [SI]	0.017	0.037	**−0.054**	0.020	0.037	**−0.057**
Spatial Characteristics						
Stats area (1 if the crash occurred within country, 0 otherwise) [NI]	**−0.039**	0.027	0.012	**−0.038**	0.015	0.023
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	0.019	0.019	**−0.038**	0.019	0.013	**−0.032**
Roadway Characteristics						
Pavement condition (1 if dry, 0 otherwise) [NI]	**−0.057**	0.038	0.019	**−0.038**	0.022	0.016
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [NI]	**−0.009**	0.007	0.002	**−0.003**	0.002	0.001
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [SI]	0.031	0.044	**−0.075**	0.035	0.036	**−0.071**
Weather Condition						
Weather condition (1 if raining, 0 otherwise) [SI]	0.010	0.013	**−0.023**	0.002	0.003	**−0.005**

outcome and lower possibility of resulting in minor and severe-injury outcomes, although this variable was statistically insignificant in other models. The time of the crash (1 if at afternoon between 12 pm and 6 pm, 0 otherwise) was found significant for the same time period (2018). The indicator variable showed a different effect for MXL and MXL-M. For instance, the indicator variable was associated with a less possibility of

Table 9
Averaged marginal for yield sign of the unsignalized intersection collisions injury severity effects over all crash observations for year of 2016.

Variable	MXL			MXL-M			MXL-MV		
	No inj.	Minor inj.	Severe inj.	No inj.	Minor inj.	Severe inj.	No inj.	Minor inj.	Severe inj.
Driver Characteristics									
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	−0.011	**0.014**	−0.003	−0.009	**0.015**	−0.006	−0.011	**0.016**	−0.005
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [SI]	−0.021	−0.014	**0.035**	−0.019	−0.013	**0.032**	−0.020	−0.013	**0.033**
Driver license type (1 if provisional LIC, 0 otherwise) [NI]	**−0.025**	0.016	0.009	**−0.023**	0.013	0.010	**−0.025**	0.012	0.013
Driver license type (1 if full LIC, 0 otherwise) [SI]	−0.013	−0.015	**0.028**	−0.026	−0.012	**0.038**	−0.022	−0.032	**0.054**
Crash Characteristics									
Number of involved vehicles *(continues)* [NI]	**−0.331**	0.230	0.101	**−0.987**	0.334	0.653	**−0.984**	0.298	0.686
Crash type (1 if rear-end crash, 0 otherwise) [NI]	**0.089**	−0.059	−0.030	**0.088**	−0.054	−0.034	**0.097**	−0.063	−0.034
Crash type (1 if right angle crash, 0 otherwise) [NI]	**0.079**	−0.043	−0.036	**0.077**	−0.054	−0.023	**0.069**	−0.045	−0.024
Crash type (1 if sideswipe crash, 0 otherwise) [NI]	**0.088**	−0.042	−0.046	**0.068**	−0.041	−0.027	**0.067**	−0.030	−0.037
Crash type (1 if hit fixed object, 0 otherwise) [MI]	0.036	**−0.089**	0.053	0.055	**−0.103**	0.048	0.074	**−0.111**	0.037
Crash type (1 if hit ped cyclist, 0 otherwise) [MI]	−0.011	**0.020**	−0.009	−0.009	**0.022**	−0.013	−0.017	**0.025**	−0.008
Crash type (1 if hit ped cyclist, 0 otherwise) [SI]	−0.031	−0.022	**0.053**	−0.027	−0.021	**0.048**	−0.027	−0.022	**0.049**
Vehicle Characteristics									
Vehicle type (1 if passenger car, 0 otherwise) [NI]	**0.077**	−0.018	−0.059	**0.044**	−0.031	−0.013	**0.040**	−0.024	−0.016
Vehicle age (1 if vehicle age < 20 yrs., 0 otherwise) [MI]	−0.015	**0.032**	−0.0017	−0.014	**0.028**	−0.014	−0.018	**0.038**	−0.020
Vehicle Movement									
Vehicle movement (1 if straight ahead, 0 otherwise) [SI]	−0.020	−0.029	**0.049**	−0.030	−0.064	**0.094**	−0.018	−0.055	**0.073**
Temporal Characteristics									
Time of the crash (1 if during a daylight, 0 otherwise) [NI]	**−0.076**	0.031	0.045	**−0.052**	0.034	0.018	**−0.039**	0.017	0.022
Season of the crash (1 if in Sumer (December–February), 0 otherwise) [NI]	**0.066**	−0.049	−0.014	**0.064**	−0.040	−0.024	**0.083**	−0.039	−0.044
Season of the crash (1 if in Winter (June–August), 0 otherwise) [SI]	0.008	0.013	**−0.021**	0.008	0.010	**−0.018**	0.006	0.012	**−0.018**
Spatial Characteristics									
Stats area (1 if the crash occurred within city, 0 otherwise) [MI]	0.024	**−0.046**	0.022	0.023	**−0.054**	0.031	0.023	**−0.063**	0.040
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	0.033	0.064	**−0.097**	0.028	0.061	**−0.089**	0.029	0.064	**−0.093**
Roadway Characteristics									
Pavement condition (1 if dry, 0 otherwise) [NI]	**−0.149**	0.113	0.036	**−0.111**	0.076	0.053	**−0.093**	0.060	0.033
Posted Speed Limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [NI]	**0.096**	−0.069	−0.027	**0.041**	−0.026	−0.015	**0.039**	−0.021	−0.018
Weather Condition									
Weather condition (1 if raining, 0 otherwise) [MI]	−0.027	**0.045**	−0.018	−0.036	**0.061**	−0.025	−0.034	**0.066**	−0.032

minor injury for both MXL and MXL-M. In 2015 models (Table 10), the time of the crash (1 if during morning between 6 am and 12 pm, 0 otherwise) using MXL and MXL-M were statistically significant, resulting in a lower probability of no driver injury of −0.038 and −0.037, respectively. In addition, the same variable increased the possibility of minor and severe injuries. This indicator was statistically insignificant in other time periods. The other time of the crash indicator variable (1 if during evening between 6 pm and 12 am, 0 otherwise) in 2015 increased the possibility of severe injuries by 0.030 and decreased the likelihood of no and minor injuries by −0.010 and −0.019, respectively. The MXL-MV model showed almost similar marginal effects. Time of the crash (1 if during daylight, 0 otherwise) decreased the likelihood of no-injury driver injury in 2016 models but increased that probability in 2015 models.

Turning to the temporal seasonal characteristics, the season of the crash (1 if in winter (June-August), 0 otherwise) was found to be significant in all years except for 2017. The variable decreased the likelihood of minor and severe injuries in 2018 models only, while for 2016 and 2015 databases (Tables 9 and 10), the negative values of the season of the crash (1 if in winter (June–August), 0 otherwise) indicates that the indicator variable decreases the likelihood of severe injury outcome and the positive values increase the likelihood of no and minor injuries outcomes.

Furthermore, the positive values of the season of the crash (1 if in summer (December-February), 0 otherwise) indicates that this variable expands the probability of a no-injury outcome in 2016 models (Table 9). The marginal effects of MXL-MV in Table 9 show that the indicator variable increases the probability of no injury by 0.083 and lessens the probability of minor and severe injuries by −0.039 and −0.044, respectively. Interestingly, this variable was statistically insignificant in the 2018, 2017, and 2015 models compared to the winter variable. Season of the crash (1 if in spring (September-November), 0 otherwise) was found significant in 2017 models only (Table 4). Using MXL-M in Table 8, the indicator variable decreased the probability of severe injuries by −0.057 and increased the probability of no and minor injury outcomes by 0.020 and 0.037, respectively. Almost comparable marginal effects were recorded for MXL.

5.4.6. *Spatial characteristics*

As shown in Tables 7–10, the indicator variable for stats area (1 if the crash in the metropolitan zone, 0 otherwise) were associated with less severe driver injuries and higher no and minor driver injuries. This is

Table 10
Averaged marginal for yield sign of the unsignalized intersection collisions injury severity effects over all crash observations for year of 2015.

Variable	MXL			MXL-M		
	No inj.	Minor inj.	Severe inj.	No inj.	Minor inj.	Severe inj.
Driver Characteristics						
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [MI]	−0.007	**0.009**	−0.002	−0.008	**0.010**	−0.002
Alcohol indicator (1 if that participant had been drinking, 0 otherwise) [SI]	−0.017	−0.025	**0.042**	−0.019	−0.026	**0.045**
Driver age (1 if the age between 35−64, 0 otherwise) [SI]	−0.037	−0.034	**0.071**	−0.031	−0.035	**0.066**
Crash Characteristics						
Number of involved vehicles *(continues)* [NI]	**−0.047**	0.036	0.011	**−0.081**	0.069	0.012
Number of vehicle occupants *(continues)* [NI]	**−0.050**	0.036	0.015	**−0.049**	0.037	0.012
Crash type (1 if rear end, 0 otherwise) [NI]	**0.051**	−0.043	−0.008	**0.063**	−0.052	−0.011
Crash type (1 if rear end, 0 otherwise) [MI]	−0.060	**0.093**	−0.033	−0.076	**0.095**	−0.019
Crash type (1 if hit fixed object, 0 otherwise) [MI]	0.023	**−0.050**	0.027	0.023	**−0.043**	0.020
Crash type (1 if hit ped cyclist, 0 otherwise) [MI]	−0.011	**0.013**	−0.002	−0.012	**0.013**	−0.001
Crash type (1 if hit ped cyclist, 0 otherwise) [SI]	−0.035	−0.023	**0.058**	−0.034	−0.023	**0.057**
Temporal Characteristics						
Time of the crash (if during morning between 6am–12pm, 0 otherwise) [NI]	**−0.038**	0.015	0.023	**−0.037**	0.015	0.022
Time of the crash (1 if during a daylight, 0 otherwise) [MI]	0.049	**−0.063**	0.014	0.041	**−0.064**	0.023
Time of the crash (if during evening between 6pm–12am, 0 otherwise) [SI]	−0.018	−0.029	**0.047**	−0.010	−0.019	**0.030**
Season of the crash (1 if in Winter (June–August), 0 otherwise) [SI]	0.014	0.012	**−0.026**	0.016	0.012	**−0.028**
Spatial Characteristics						
Stats area (1 if the crash occurred within city, 0 otherwise) [NI]	**0.066**	−0.017	−0.049	**0.065**	−0.023	−0.042
Stats area (1 if the crash occurred within metropolitan, 0 otherwise) [SI]	0.013	0.016	**−0.029**	0.013	0.017	**−0.030**
Roadway Characteristics						
Pavement condition (1 if dry, 0 otherwise) [NI]	**−0.040**	0.025	0.015	**−0.070**	0.052	0.018
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [NI]	**0.018**	−0.010	−0.008	**0.029**	−0.014	−0.015
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise) [MI]	−0.102	**0.213**	−0.111	−0.098	**0.232**	−0.134

indicated by negative marginal effects values for severe injury and positive marginal effects values for no and minor injury-severity outcomes in all models.

As shown in Table 8, crashes at country stats area (sparsely populated and rural districts) decreased the probabilities of no injury and increased the probabilities of minor and severe driver injuries in 2017 models. Finally, stats area (1 if the crash occurred within city, 0 otherwise) was found significant in 2016 and 2015 databases. For instance, using MXL-M, the indicator variable in Table 9 showed a decrease associated with the probability of minor injury by 0.054 and an increase in the probability of no and severe injuries by 0.023 and 0.031, respectively, in the 2016 models. While in the 2015 model (Table 10), the marginal effects indicated a likelihood increase in no injury by 0.065 and a likelihood decrease in both minor and severe injuries by −0.023 and −0.042, respectively. Comparable values for marginal effects were obtained while using MXL.

5.4.7. Roadway characteristics

In 2018 models (Table 7), pavement condition (1 if sealed, 0 otherwise) was found to considerably raise the likelihood of no injury and decrease the likelihood of minor and severe injuries, While the same indicator variable had no effect on injury severities in 2017, 2016, and 2015 models. Pavement condition (1 if dry, 0 otherwise) indicator variable showed a similar influence on driver injury severities over three consecutive years (2017, 2016, and 2015). Pavement condition (1 if dry, 0 otherwise) was associated with lowering the likelihood of no injury and increasing the likelihood of both minor and severe injuries, as shown in Tables 8–10.

Turning to the geometric alignments, the marginal effect of the horizontal alignment indicator (1 if curved road, 0 otherwise) in 2018 MXL-M lowered the probability of no driver injury by −0.043 and increased that of minor and severe driver injuries by 0.026 and 0.017, respectively. This indicator variable was insignificant in the other years. Vertical alignment (1 if road with slope, 0 otherwise) was associated with higher chances of minor injury and lower chances of severe and no injury outcomes in 2018 models only (Table 7).

The indicator variable posted speed limit (1 if the speed limit less than 50 km/hr. or 31 mph, 0 otherwise) had a complex effect over the four years of the database. For example, the likelihood of severe driver injury was decreased by −0.059 in 2018 using MXL-M, while it increased the likelihood of no injury in all the 2016 models. Different effects were observed for the 2017 and 2015 models. Speeds lower than 50 km are not typically associated with higher injury severity. However, there is apparent severities variance between years. The estimated parameters of this indicator are found to be random in some of the developed models, which highlight a potential unobserved heterogeneity. In addition, heterogeneity in the means (and variances) is also associated with this factor. The study showed that there are other variables like the number of vehicles involved and vehicle type that affect the mean of the speed parameter (Tables 4 and 5, respectively).

5.4.8. Weather condition

There is no information regarding the weather except an indicator variable for rainy weather, which was found a significant variable in the model. In 2017 models using MXL-M (Table 8), weather condition (1 if raining, 0 otherwise) reduced the severe injury likelihood by -0.005 and increased the possibilities of the minor and no injury outcomes by 0.003 and 0.002, respectively, whereas, in 2016, this variable increased the probabilities for all injury severity types: none, minor and severe by 0.034, 0.066, and 0.032, respectively.

6. Temporal stability

After comprehensive experimental testing, the temporal stability evaluation of the exploratory indicator variables against the driver injury severities were presented in Table 11. The table shows some indicator variables that have stable influence over the four years. For instance, the number of involved vehicles (continues) indicator was temporally stable over 2018, 2017, 2016, and 2015 models, as well as the indicator variable stats area (1 if the crash occurred within the metropolitan zone, 0 otherwise). Another group demonstrated temporal stability over two consecutive years, including alcohol indicator (1 if

Table 11
Temporal stability assessment.

Variable	Temporally unstable	Temporally stable		
		4 consecutive years	3 consecutive years	2 consecutive years
Driver Characteristics				
Alcohol indicator (1 if that participant had been drinking, 0 otherwise)				X
Gender of driver (1 if male, 0 otherwise)	X			
Gender of driver (1 if female, 0 otherwise)	X			
Driver age (1 if the age between 35−64, 0 otherwise)	X			
Driver license type (1 if provisional LIC, 0 otherwise)	X			
Driver license type (1 if full LIC, 0 otherwise)	X			
Crash Characteristics				
Number of involved vehicles *(continues)*		X		
Number of vehicle occupant *(continues)*	X			
Crash type (1 if rear-end crash, 0 otherwise)	X			
Crash type (1 if side-swap crash, 0 otherwise)	X			
Crash type (1 if hit fixed object, 0 otherwise)				X
Crash type (1 if hit ped cyclist, 0 otherwise)				X
Crash type (1 if right angle crash, 0 otherwise)	X			
Vehicle Movement				
Vehicle movement (1 if stopped on carriage way, 0 otherwise)	X			
Vehicle movement (1 if turning right, 0 otherwise)	X			
Vehicle movement (1 if straight ahead, 0 otherwise)	X			
Vehicle Characteristics				
Vehicle type (1 if passenger car, 0 otherwise) [NI]	X			
Vehicle age (1 if vehicle age < 20 yrs., 0 otherwise) [MI]	X			
Temporal Characteristics				
Time of the crash (if during night-time between 12am–6am, 0 otherwise)	X			
Time of the crash (if at afternoon between 12 pm–6 pm, 0 otherwise)	X			
Time of the crash (if at morning between 6 am–12pm, 0 otherwise)	X			
Time of the crash (if at evening between 6 pm–12am, 0 otherwise)	X			
Time of the crash (if during a daylight, 0 otherwise)	X			
Season of the crash (1 if in Winter (June–August), 0 otherwise)				X
Season of the crash (1 if in Spring (September–November), 0 otherwise)	X			
Season of the crash (1 if in Summer (December–February), 0 otherwise)	X			
Spatial Characteristics				
Stats area (1 if the crash occurred within metropolitan, 0 otherwise)		X		
Stats area (1 if the crash occurred within country, 0 otherwise)	X			
Stats area (1 if the crash occurred within city, 0 otherwise)	X			
Roadway characteristics				
Pavement condition (1 if sealed, 0 otherwise)	X			
Pavement condition (1 if dry, 0 otherwise)			X	
Horizontal alignment (1 if curved road, 0 otherwise)	X			
Vertical alignment (1 if road with slop, 0 otherwise)	X			
Posted speed limit (1 if the speed limit less than 50 km/hr., 0 otherwise)	X			
Weather Condition				
Weather condition (1 if raining, 0 otherwise)	X			

that participant had been drinking, 0 otherwise), crash type (1 if hit fixed object, 0 otherwise), crash type (1 if hit cyclist, 0 otherwise), and season of the crash (1 if in winter (June-August), 0 otherwise). Moreover, pavement condition (1 if dry, 0 otherwise) showed temporal stability over three consecutive years.

However, most of the significant factors were found instable over the investigated four years (2018−2015). This means that either the parameter was insignificant, or it has a different effect on the injury severity in some years of the database. For instance, the model estimation results (Tables 3–6) revealed that the indicator variable of male drivers is temporally unstable over time. Likewise, the model estimates and marginal effects showed there is a temporal instability for license type over different time periods. Generally, the cause of the observed temporal instability is not entirely understood, as temporal changes may result from general temporal shifts in unobserved heterogeneity. It is expected that the temporal instability could be linked to different causes such as cognitive biases, macroeconomics, and risk-taking behavior (Mannering, 2018). However, in the current study, it can be noticed that the year 2016 has the highest number of crashes and could be a possible reason for the temporal instability in the vehicle's characteristics (vehicle type and age), which were found only significant in 2016 model. In addition to these factors, the police judgments while recording the data could vary from person to person and over time (Alnawmasi and Mannering, 2019). It has also been noticed, in some reports, that there is a missing in some of the information such as gender, age, or license type of the drivers that could affect the estimated results outcomes. Another possible reason might be the police enforcement measures for drink driving, distraction, and speeding. These enforcement measures may vary across the years, which have not been captured within our dataset. Besides, the same database does not include any information about the school, and public holidays, which might explain the instability in the temporal characteristics such as the time of the crash (night-time, afternoon, morning, and evening). The instability of the crash types (rear-end, side-swap, hit a fixed object, and tight angle) is expected, as such crashes are basically related to the position/location of the collided vehicles, which continuously vary.

Overall, the temporal instability at unsignalized intersections controlled by give-way traffic signs could be attributed to the unique nature of traffic nodes in the transportation network. Such intersections are not controlled by traffic signals, so traffic flow is not controlled in a timely manner and not stable over time. In addition, any maneuvers in these locations fundamentally depend on the individual driver's action, which varies from person to person. It can be concluded that overlooking the temporal stability in driver injury severities related crashes may result in erroneous outcomes and unreliable conclusions. This study highlights the recent call by Islam and Mannering (2020) to develop a new approach that could reveal the complexities of temporal instability in safety data.

7. Summary and conclusions

This research explored the temporal stability of several contributing factors that may affect injury severities at unsignalized intersection crashes under give-way traffic control. Three mixed logit approaches were employed: random parameters, random parameters with heterogeneity in means, random parameters with heterogeneity in means, and variances to encapsulate the determinants factors that may affect the injury severity type related crashes. The investigated data covered four years of motor vehicle crashes in South Australia, between 2018 and 2015. The injury severity is categorized into three groups (no injury, minor injury, and severe injury). The likelihood ratio tests revealed that there is a significant temporal instability in those four years. Therefore, the determinant factors that influence the injury-severity related crashes should be considered each year individually. However, a few indicator variables showed a stable influence over the four years, and another group demonstrated temporal stability over two or three consecutive years.

A wide spectrum of determinant factors was found to significantly influence the driver-injury outcomes. These factors were categorized into driver, crash, vehicle, temporal, spatial, and roadway characteristics, vehicle movement, and weather conditions. Although most of these determinants have been shared across the different models, the values of the estimates showed significant differences. Only the 2016 model showed substantial heterogeneity in the variances of random parameters, while all other models (2018−2015) showed significant heterogeneity in means of random parameters. In addition, the mixed logit model with heterogeneity in the means and variances of the random parameters has a better statistical fit compared to the other developed models. However, the differences among the three approaches were marginal (i.e., mixed logit model accounting for random parameters, random parameters with heterogeneity in means, random parameters with heterogeneity in means and variances). It is worth mentioning that the database does not include many spatial details about the crash locations, which might explain some of the apparent variances between years.

Findings from this study can help authorities and policymakers to develop an insight into the impact of the temporal instability of the determinant factors to avoid any potential inconsistent countermeasures.

Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: H. Zubaidi, I. Obaid and A. Alnedawi; data analysis: H. Zubaidi and I. Obaid; interpretation of results: H. Zubaidi, I. Obaid, and A. Alnedawi; draft manuscript preparation: H. Zubaidi, I. Obaid, A. Alnedawi, S. Das, and MD. Haque. All authors reviewed the results and approved the final version of the manuscript.

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Declaration of Competing Interest

The authors report no declarations of interest.

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