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The role of gender and temporal instability in driver-injury severities in crashes caused by speeds too fast for conditions

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ABSTRACT

The effect of inappropriate speed adjustment to adverse conditions on crash-injury severities, and how this effect might vary across male and female drivers, and over time, is not well understood. To study this, single-vehicle crashes occurring in rainy weather, where speed too fast for conditions is a driver action identified as a contributing factor to the crash, were considered. The differences between the resulting crash-injury severities of male and female drivers (and how these differences change over time) is then studied utilizing three years of Florida crash data and estimating random parameters multinomial logit models of driver injury severity while considering potential heterogeneity in the means and variances of parameter estimates. Model estimation results show that there were significant differences in the driver-injury severities of male and female drivers, and that the effect of factors that determine injury severities varied significantly over time (statistically significant temporal instability). This suggests that male and female drivers generally perceive and react to rainy weather conditions in fundamentally different ways, and that their responses, as reflected by the effect that explanatory variables have on injury severity probabilities, change over time. However, there were two explanatory variables that had relatively stable effects on injury-severity probabilities over time and across genders: an indicator variable for crashes involving non-collision factors (including overturn/rollover crashes) and an indicator variable for restraint usage. Policies that target these two variables could produce long-term reductions in crash-injury severities under adverse conditions.

1. Introduction

Speeding has long been identified as a key factor in determining crash likelihoods and resulting injury severities. In the United States, speeding (defined by the National Highway Traffic Safety Administration (NHTSA) as crashes involving drivers who were charged with a variety of speeding-related offenses including exceeding the speed limit or driving too fast for prevailing conditions) has been found to be a key contributing factor in about one-fourth of fatalities in the United States (NHTSA, 2020). Globally, speeding has been identified as a contributing factor in about half of all crashes in middle- and low-income countries (World Health Organization (WHO, 2020).

Over the years, using a variety of methodological approaches such as ordered probability models, multinomial logit models, and mixed logit models, research has sought to quantify the effect of speed on the frequency and severity of crashes. For example, Finch et al. (1994) estimated that a 1% increase of average speed results in a 4% higher risk of crash involving fatalities and a 3% higher risk of crash involving injuries. In other work, Islam and Mannering (2020) found that drivers that exceeding the speed limit by more than 10 mi/hr was a consistent temporally stable predictor of driver injuries where aggressive driving was identified. Other studies have looked at the effect of speeding on injury severities and in rainy conditions (Fitzpatrrick et al., 2017; Li et al., 2019), and some work has found injury severity to be relatively lower under rainy conditions across all crash types because of drivers' adjustment of speed on wet surfaces (Lee et al., 2015). In general terms, excessive or inappropriate speed choice has been shown to be influenced by many factors such as age, gender, attitudes and safety perception, alcohol level, number of occupants in the vehicle, roadway geometry, road-surface conditions, type of vehicle, vehicle power, and ambient weather conditions (Finch et al., 1994; Mannering, 2009; Neuman et al., 2009; Anastasopoulos and Mannering, 2016; WHO, 2018).

Table 1 provides a summary of factors that past research has shown to be associated with speeding and driving too fast for conditions. This

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Table 1
Variables found to be statistically significant indicators of driving too fast for conditions in past studies.

Variables	Findings
Driver characteristics	
Age	Young drivers (less than 25 years) were found to be more likely to be involved in speeding-related crashes (Ulleberg, 2001; Bolderdijk et al., 2011; Li et al., 2019)
Gender	Male drivers are more likely to be involved in speeding-related crashes (Morgan and Mannering, 2011; Staff et al., 2014; Yasmin et al., 2014;)
Behavior	Seat belt non usage is related to speeding resulting in fatalities (NHTSA, 2020)
Experience	Speeding was more prevalent in older drivers (Greaves and Ellison, 2011; Stigson et al., 2014; Chevalier et al., 2016;)
Driver actions	
Traffic violations	Speeding violations and breaking other traffic rules are highly correlated with driving too fast for conditions (Reason et al., 1991; Alonso et al., 2013). Moving violations are also linked with the crash involvement (Zhang et al., 2013; Bener, 2013; Maycock et al., 1991)
Traffic characteristics	
Traffic volume	Lower traffic volume roads (0–2,000 AADT per lane) are associated with a higher likelihood of driving too fast for conditions (Council et al., 2010)
Temporal characteristics	
Time of day	Younger drivers drive too fast for the conditions at night, whereas older drivers in the afternoon (Summala and Mikkola, 1994)
Vehicle characteristics	
Vehicle type	Motorcycles are more likely to be in crashes too-fast-for-conditions crashes than other vehicle types (Council et al., 2010).
Roadway attributes	
Speed limits	Roadways with speed limit of 50-mph experienced more speeding related crashes relative above or below that limit (Dhungana and Qu, 2005)
Alignment	Curved roadway segments experienced more crashes with driving too fast for conditions relative to straight segments (Council, et al., 2010)
Crash characteristics	
Fixed object crash	Colliding with fixed objects is highly correlated with driving too fast for conditions (Council et al., 2010)

table indicates that a wide variety of variables relating to driver characteristics and actions, and vehicle, roadway and crash characteristics have been found to be associated with speeding. Among the various findings of past research, it is notable that male and female drivers have been found to respond differently to adverse weather (rainy weather, etc.). For example, studies by Ulfarsson and Mannering (2004); Islam and Mannering (2006) and Morgan and Mannering (2011) all found statistically significant differences in crash-injury severities due to gender. However, even though there has been abundance of recent research relating to temporal instability and unobserved heterogeneity in injury-severity models (Mannering and Bhat, 2014; Behnood and Mannering, 2015, 2016; Mannering et al., 2016; Mannering, 2018; Islam and Mannering, 2020; Islam et al., 2020), the effect of gender in speed-too-fast-for-conditions crashes has not yet been studied in the context of possible temporal instability and unobserved heterogeneity.

The intent of the current paper is to consider how the effects of possible temporal instability, unobserved heterogeneity, and gender influence on resulting crash-injury severities in crashes where the inappropriate choice of speed during adverse weather conditions is identified as a contributing factor to the crash. To achieve the objective, Florida crash data from 2015–17 are used to study the differences between male and female drivers in rainy weather, single-vehicle crashes where speed too fast for conditions was identified as a contributing factor to the crash.

The paper begins with a discussion of drivers' speed-choice decisions followed by a description of the available crash data. This data description is followed by a presentation of the methodological approach and estimation results, which include statistical tests for differences in male and female driver-injury outcomes, and tests for possible temporal instability of injury-severity probabilities in crashes involving drivers driving too fast for conditions in rainy weather. Model estimation results are then presented and discussed, with a comparison and discussion of marginal effects, and the paper concludes with a summary of findings and their implications.

2. Speed adjustment under adverse conditions

In the choice of driving speed, individual drivers make an inherent tradeoff between safety and speed. Generally, slower speeds will improve safety (down to speed zero, which is no travel) and higher

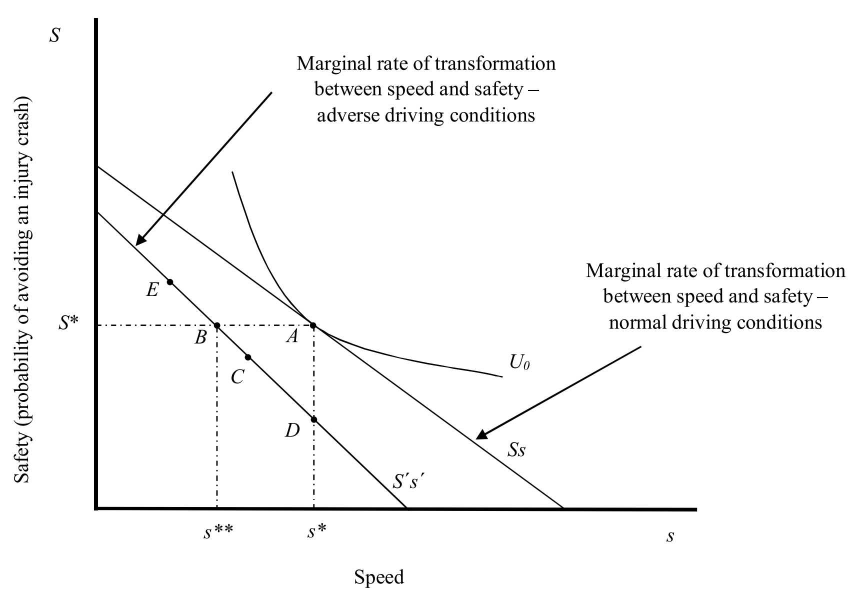

Fig. 1. The effect of speed selection on safety in normal and adverse driving conditions (adapted from Winston et al., 2006; Anastasopoulos and Mannering, 2016).

speeds will decrease safety. To visualize the speed selection process, consider Fig. 1, which shows the trade-off and marginal rate of transformation between safety (the probability of avoiding a crash resulting in injury) and speed (Winston et al., 2006; Anastasopoulos and Mannering, 2016). Under normal conditions (no adverse weather), the marginal rate of transformation between safety S and driving speed s is shown by the slope Ss (a simple linear relationship is shown here to demonstrate the concept). Given this marginal rate of transformation, individual drivers maximize their utility by trading off safety and speed at an equilibrium point A (reflecting the tangency of an indifference curve U_0), with S^* and s^* being an individual driver's optimal level of safety and speed. Under adverse weather conditions (such as the rainy weather conditions considered in this paper), the marginal rates of transformation will shift from Ss to $S's'$ reflecting reduced friction, reduced visibility, and other factors potentially making the roadway more dangerous. If a driver does not react to these adverse conditions and continues at the same speed s^* that was chosen during normal conditions, safety (the probability of avoiding a crash resulting in injury) would decrease from point A to point D. Should the driver seek to retain the same level of safety as that under normal conditions, a new speed s^{**} would be chosen and the new equilibrium point would be B. However, there is understandably much uncertainty regarding how the marginal rate of transformation will change under adverse weather conditions, and a driver's choice of speed could end up anywhere between points B and D (for example, point C), or possibly even at point E where drivers overcompensate for adverse conditions and actually drive more safely than they did under normal conditions.

In applying the concepts in Fig. 1 to driving too fast for conditions, the focus would be on drivers that end up somewhere between points B and D. That is, drivers that do not adequately adjust their speeds for adverse conditions and thus face a lower probability of avoiding an injury crash than would be the case under normal conditions.

It should be noted that crash-mitigation policies have not really addressed this speed adaptation problem directly. The underlying assumption is that driver experience will improve the effectiveness of speed adaptation under adverse conditions and individuals who successfully adapt will not appear in crash databases (since they will avoid crash involvement in adverse conditions). In addition, safety-conscious drivers may be more likely to buy vehicles with advanced safety features that reduces their crash likelihoods in adverse conditions making driver speed adaptation less critical. These two points should be kept in mind since observed crash data will be used herein to study speed adaptation, and that these data constitute a portion of the driving population that is more likely to adapt their speed inappropriately to adverse conditions.[1] Please see Mannering et al. (2020) for a discussion of issues such as this and the modelling consequences that may result when using observed crash data.

3. Data description

Data available for this study were crashes reported in the Florida Crash Analysis Reporting system (these are all police-reported crashes). For the purposes of this study, crash data were gathered over the three-year period from January 1, 2015 to December 31, 2017. Crash data filtered from the Florida Crash Analysis Reporting system, were linked with a vehicle and person dataset based on crash identification numbers. A police officer defined variable in the crash data indicating the driver's actions at the time of crash being "driving too fast for the conditions" and "rain" noted by the officer under weather condition were used to identify crash records for analysis.[2] The resulting combined dataset provided detailed information about the crash, including roadway characteristics, as well as the vehicle and person characteristics. The combined dataset was filtered for single-vehicle male drivers involved crashes, which resulted in 3981 observations over the studied three-year period. While the single-vehicle female driver involved crashes resulted in 2092 observations in the same analysis period.

Information available in the data includes the resulting injury severity of the driver (no injury, possible injury, non-incapacitating injury, incapacitating injury and fatality), type of vehicle (motorcycle, passenger car, pickup truck, sport-utility-vehicle, light truck), driver actions (evasive maneuvers, etc.), driver information (age, gender, usage of safety equipment, influence of alcohol, drug use, physical/emotional impairment, distraction, driving over/below the speed limit, ejection), information relating to the time of day, day of week, months of year, and location of the crash (jurisdiction of the district level defined by Florida Department of Transportation), roadway class, alignment of roadways, road surface condition, weather and light conditions, type of vehicles, lane and shoulder widths, median width, location of harmful events, traffic volume, percent of trucks, other factors (non-roadway geometrics, non-collision related) and so on.

4. Methodology

Savolainen et al. (2011), Mannering and Bhat (2014), and Mannering et al. (2016) provide a review of the statistical approaches used to study crash-injury severities. In recent years, various random parameters approaches have been used to account for possible unobserved heterogeneity in the statistical analysis of injury-severity data (Mannering et al., 2016). Among these random parameters methods, a random parameters logit model that accounts for possible heterogeneity in the means and variances of the random parameters is among the most flexible. This approach defines a function that determines injury-severity,

$$S_{kn} = \boldsymbol{\beta}_k \mathbf{X}_{kn} + \varepsilon_{kn} \tag{1}$$

where, S_{kn} is an injury-severity function determining the probability of injury-severity outcome k, which includes no injury, minor injury (possible injury and non-incapacitating injury) and severe injury (incapacitating injury and fatality) in crash n, $\mathbf{X}_{kn}$ is a vector of explanatory variables that affect drivers' injury-severity level k, $\boldsymbol{\beta}_k$ is a vector of estimable parameters, and ε_{kn} is an error term assumed to be generalized extreme value distributed. With the generalized extreme value distribution of the error term, McFadden (1981) has shown that the standard multinomial logit can be derived as,

$$P_n(k) = \frac{EXP[\boldsymbol{\beta}_k \mathbf{X}_{kn}]}{\sum_{\forall K} EXP[\boldsymbol{\beta}_k \mathbf{X}_{kn}]} \tag{2}$$

where, $P_n(k)$ is the probability that male and female drivers related crash n that will result in driver-injury severity outcome k and K is the set of the three possible injury-severity outcomes. Unobserved heterogeneity is then accounted for in the data by allowing one or more parameter estimates in the vector $\boldsymbol{\beta}_k$ to vary across crash observations by be

[1] There is also the possibility that a portion of the driving population (safety conscious drivers) will avoid driving during adverse conditions due to the increased risks, making the sample of people observed in adverse-condition crashes a sub-sample of riskier drivers. For mild adverse conditions such as rain, this is not likely to be a serious concern, since few car and truck drivers would consider this a driving condition that would necessitate the cancellation of a trip. However, it has been argued that even mild adverse conditions such as rain could affect the decision to travel for modes such as motorcycling where the crash risks resulting from such conditions could increase significantly (Mannering, 2018; Mannering et al., 2020).

[2] The determination of whether the vehicle is being operated in driving too fast for the conditions is made by police officers, all of whom are trained to identify such behavior. The authors acknowledge that other conditions of weather may also be appropriate to consider for driving too fast for the conditions, depending on available data.

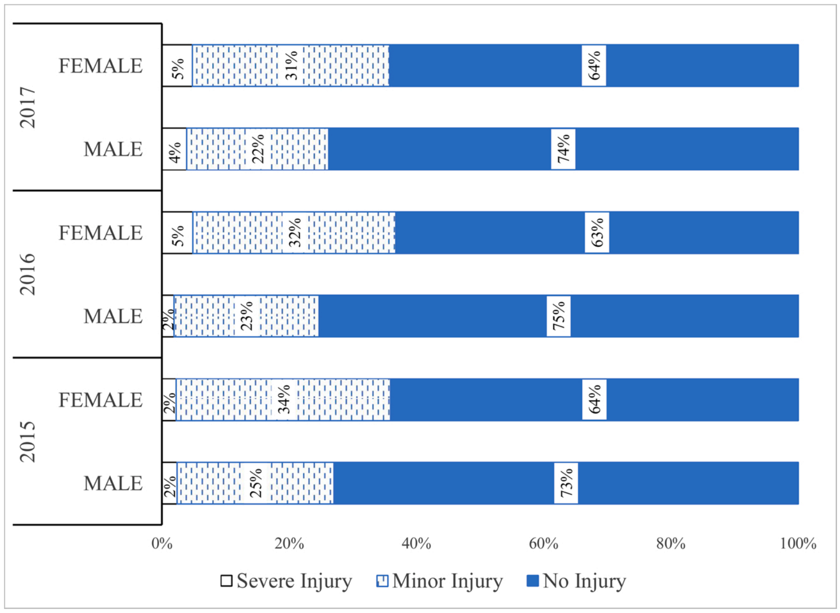

Fig. 2. Male and Female Driver Injury Severity for Driving Too Fast in Rainy Weather in Florida over the Years: 2015 – 17.

rewriting Equation 2 as (Train, 2009; Washington et al., 2020)

$$P^{n}(k) = \int \frac{EXP(\boldsymbol{\beta}_k \mathbf{X}_{kn})}{\sum_{\forall K} EXP(\boldsymbol{\beta}_k \mathbf{X}_{kn})} f(\boldsymbol{\beta}_k|\boldsymbol{\varphi}_k)d\boldsymbol{\beta}_k \quad (3)$$

where, $f(\boldsymbol{\beta}_k|\boldsymbol{\varphi}_k)$ is the density function of $\boldsymbol{\beta}_k$ and $\boldsymbol{\varphi}_k$ is a vector of parameters describing the density function (mean and variance), and all other terms are as previously defined. Following other recent work, possible heterogeneity in the means and variances of the random parameters is introduced by letting $\boldsymbol{\beta}_{kn}$ be a vector of estimable parameters that varies across crash observations as (Mannering et al., 2016; Seraneeprakarn et al., 2017; Behnood and Mannering, 2017a, 2017b; Waseem et al., 2019; Alnawmasi and Mannering, 2019; Behnood and Mannering, 2019; Islam and Mannering, 2020; Washington et al., 2020)

$$\boldsymbol{\beta}_{kn} = \boldsymbol{\beta}_k + \Theta_{kn}\mathbf{Z}_{kn} + \sigma_{kn}\mathrm{EXP}(\boldsymbol{\Psi}_{kn}\mathbf{W}_{kn})\,\nu_{kn} \quad (4)$$

where, $\boldsymbol{\beta}_k$ is the mean parameter estimate across all crashes, $\mathbf{Z}_{kn}$ is a vector of crash-specific explanatory variables that captures heterogeneity in the mean that affects male and female drivers' injury-severity level k, $\boldsymbol{\Theta}_{kn}$ is a corresponding vector of estimable parameters, $\mathbf{W}_{kn}$ is a vector of crash-specific explanatory variables that captures heterogeneity in the standard deviation σ_{kn} with corresponding parameter vector $\boldsymbol{\Psi}_{kn}$, and v_{kn} is a disturbance term.

For random parameters estimation, numerous density functions were empirically evaluated (see Eq.3) and none were found to be statistically superior to the normal distribution (this finding is consistent with past work including Milton et al., 2008; Alnawmasi and Mannering, 2019; Islam and Mannering, 2020; Islam et al., 2020, and others). All model estimations used simulated maximum likelihood with 1000 Halton draws (McFadden and Train, 2000; Bhat, 2001; Train, 2009).

To assess the influence of the explanatory variables on injury severity outcome probabilities, marginal effects (which provide the effect that a one-unit increase in an explanatory variable on the injury-outcome probability) were computed for each individual crash observation and the average marginal effect over all crash observations will be reported later in this paper.

5. Likelihood ratio tests

There is an extensive body of literature that suggests that the effect of factors determining injury severity may change over time (Behnood and Mannering, 2015, 2016, 2019; Mannering, 2018; Alnawmasi and Mannering, 2019; Islam et al., 2020), and that the factors determining injury severities may vary across genders (Ulfarsson and Mannering, 2004; Islam and Mannering, 2006; and Morgan and Mannering, 2011). Given this, tests are not only conducted for differences between injury outcomes in crashes involving male and female drivers, but also for temporal instability. This is done by running a series of likelihood ratio tests. To begin, for each year in the data (2015, 2016, and 2017) tests were conducted comparing male and female driver injury-severity outcomes. The test statistic is,

$$X_t^2 = -2\left[LL\left(\boldsymbol{\beta}_{FullModel,t}\right) - LL\left(\boldsymbol{\beta}_{Male,t}\right) - LL\left(\boldsymbol{\beta}_{Female,t}\right)\right] \quad (5)$$

where, $LL(\boldsymbol{\beta}_{combined,t})$ is the log-likelihood at the convergence of the model that used all of the available male and female driver crash data in year t (either years 2015, 2016 or 2017), $LL(\boldsymbol{\beta}_{female,t})$ is the log-likelihood at convergence of the model based on female driver crash data only in year t, and $LL(\boldsymbol{\beta}_{male,t})$ is the log-likelihood at the convergence of a model based on male driver crash data only in year t. For the years 2015, 2016 and 2017 the model estimates gave X^2values of 64.702, 33.128, and 59.944, respectively. These values are all χ^2 distributed with 18, 12, and 16 degrees of freedom respectively giving 99.99% confidence that the null hypothesis that the male and female driving parameters are equal in each of the three years, can be rejected.

Next, the temporal stability of male and female driver injury-severity outcomes is tested with the likelihood ratio test in this case,

$$X_g^2 = -2\left[LL(\boldsymbol{\beta}_{2015-17,g}) - LL(\boldsymbol{\beta}_{2015,g}) - LL(\boldsymbol{\beta}_{2016,g}) - LL(\boldsymbol{\beta}_{2017,g})\right] \quad (6)$$

where, $LL(\boldsymbol{\beta}_{2015-17,g})$ is the log-likelihood at the convergence of the driver injury-severity model that used all data 201517 for driver group g (either male or female driving data), $LL(\boldsymbol{\beta}_{2015,g})$ is the log-likelihood at convergence of the model using only 2015 data for driver group g, $LL(\boldsymbol{\beta}_{2016,g})$ is the log-likelihood at the convergence of the model using only 2016 data for driver group g, and $LL(\boldsymbol{\beta}_{2017,g})$ is the log-likelihood at the convergence of the model using only 2017 data for driver group g. For crashes involving male drivers, model estimates gave an X^2 of 229.048 which is χ^2 distributed with 30 degrees of freedom (the number of parameters found to be statistically significant in the model using all data years, 2015–17). This χ^2 value gives 99.99% confidence that the null hypothesis that the parameters are equal parameters over these three years (2015, 2016, and 2017), can be rejected. For crashes involving female drivers, model estimates gave an X^2 of 61.666 which is χ^2 distributed with 27 degrees of freedom (the number of parameters found to be statistically significant in the model using all data years, 2015−17). This χ^2 value gives 99.99% confidence that the null hypothesis that the parameters are equal over these three years (2015, 2016, and 2017), can be rejected. These tests suggest that temporal instability is clearly present in speeding crashes (driving too fast for the conditions) in rainy conditions for both male and female drivers.[3]

6. Model estimation results

Fig. 2 shows the percent distribution of severe, minor, and no injury crashes for male and female drivers involved in crashed for driving too fast in the rainy conditions over the three-year analysis period (2015−17). This figure shows that, while there is not much variation in the aggregate injury-severity totals over time for male and female drivers, there is a noticeable difference between male and female driver injuries with female drivers being much more involved in crashes resulting in injury, particularly severe injury in 2017 relative to prior years.

Table 2 provides the summary statistics of all explanatory variables found to be statistically significant (at the 90% confidence level or above using a two-tailed *t*-test) in one or more of the six models estimated (male and female models for each of the three years analyzed). Interestingly, male drivers were involved in a higher proportion of the reported driving-too-fast-for-conditions crashes in rainy weather (an average of about 65% for male and 35% for female drivers over all years). This does not create an issue for the injury-severity analysis undertaken in this paper since the models are split by gender, but this could be a concern if a crash-frequency analysis were to be conducted.

Model estimation results for male and female drivers are presented in Tables 3, 4 and 5 for the years 2015, 2016, and 2017, respectively. The male models have good overall statistical fit with ρ^2 values of 0.465 (Table 3), 0.479 (Table 4) and 0.457 (Table 6) for 2015, 2016 and 2017, respectively (see Washington et al., 2020 for a discussion and interpretation of ρ^2 values). Note that for the 2015, 2016 and 2017 models, the constant term specific to minor injury was found to be the only statistically significant random parameter, and in all cases, this parameter had statistically significant heterogeneity in the mean and variance. For two years (2015 and 2016), it was found that the mean varied by whether the driver was ejected from the vehicle. In those two years, driver not being ejected decreased the mean of the random parameter making minor injury less likely and other injury levels more likely. In 2015 (Table 3) the variance of the constant for minor injury was a function of suspected alcohol use, decreasing the minor-injury constant variance. In 2016 (Table 4) the variance was a function of non-geometry factor, with crash occurrence not related to roadway geometry decreasing the variance of the minor-injury constant. Finally, in 2017 (Table 5) the minor-injury constant variance was a function of young aged drivers (below 30 years), with greater variance in the minor-injury constant for crashes that involved male drivers below 30 years.

Model estimation results for female drivers are presented in Tables 6,7, and 8 for the years 2015, 2016, and 2017, respectively. The models have reasonably good fit with ρ^2 values of 0.398 (Table 6), 0.351 (Table 7), and 0.347 (Table 8) for 2015, 2016, and 2017, respectively. As was the case for the female drivers, for the 2015, 2016 and 2017 models, the constant term specific to minor injury was again found to be the only statistically significant random parameter and this parameter again had statistically significant heterogeneity in the mean and variance. For three years (2015−17), it was found that the mean varied by crash occurrence on an urban interstate (2015), due to suspected alcohol use (2016), and under normal driving conditions, driving without any physical/emotional impairment, (2017). The crashes occurring on urban interstates increased the minor-injury constant mean and thus likelihood of minor injury (and subsequently decreasing the likelihood of no injury and severe injury), whereas suspected alcohol use and the identification of normal driving conditions (a driving condition without any physical/emotional impairment) decreased the minor-injury constant mean. In contrast to the male drivers results, the variance of the minor-injury constant was influenced by medium traffic volume (40,000–80,000 vehicles/day) in 2015, involvement of middle-aged female drivers (30–49 years) in 2016, and crash occurrence on Saturday in 2017, having a higher minor-injury constant variance for female drivers.

All six models shown in Tables 3,4,5,6,7, and 8 show a wide variety of spatial, temporal, traffic, environmental, vehicle, roadway, crash, and driver characteristics influencing resulting driver injury severities. To compare the findings of all six models, Table 9 presents the marginal effects of all statistically significant variables for male and female driving crashes by year and injury levels. For the spatial variables, the Florida Department of Transportation District 1 indicator (Sarasota, Fort Myers, and Naples) shows that District 1 had a higher probability of severe injuries for male and female drivers in 2017, lower probability of minor injury in 2016. The District 2 indicator (Jacksonville and surrounding area) shows that District 2 had a higher probability of severe injury for the male drivers' model in 2015 but was insignificant in all other models. The District 4 indicator (Boca Raton, Fort Lauderdale, and West Palm Beach) was found to be significant in 2015 and 2016 for male drivers with lower probability of sever injury but insignificant in 2017 for male drivers and all years for female drivers. In 2015 and 2016 when this indicator variable was significant, the probability of a minor injury was lower in 2015 but higher in 2016 and the probability of no injury was higher in 2015 but lower in 2016. Finally, District 7 (Tampa Bay area) was only statistically insignificant for male drivers in all those years but statistically significant in only 2016 for female drivers. In 2016, female drivers were more likely to be severely injured in District 7 relative to other districts.[4] In addition, of spatial characteristics, temporal characteristics also played important role in driver injury severities.

Turning to temporal characteristics, during the time between midnight to 5:59 AM, was found statistically significant in 2015, when male drivers were found more likely to be severely injured, but this variable was insignificant in 2016 and 2017 and for all years in the female-driver models. The late night indicator (from 9 PM to 11:59 PM) was found statistically significant in 2017 with male drivers found to be likely to be severely injured, but this indicator was statistically insignificant in 2015 and 2016 and all years for female drivers. In contrast, female drivers were found to have higher probability of severe injury in 2016 but lower probability in minor injury during the afternoon peak time between 4 PM to 5:59 PM, where this afternoon peak time was found statistically insignificant in 2015 and 2017 and all years for male drivers. Moreover, male drivers were found to have higher probability of severe injury in 2017 during the second quarter of the year (April to June). However, the second quarter of year (April to June) was not found statistically significant in 2015 and 2016 and all the years for female drivers.

Traffic volume was found to contribute to driver injury severity in many instances. Female drivers had higher probability of severe injury

[3] Multiple combinations of years were also tested as part of the temporal instability tests, and likelihood ratio tests all indicate that the separate-year models were statistically justified.

[4] Regarding Florida's Department of Transportation districts, it should be noted that aggregate registered drivers and their socio-demographics obtained from the Florida Department of Highway Safety and Motor Vehicles indicates some variation in the proportion of male and female drivers, and their respective age groups, by district. This should be kept in mind when interpreting district indicators in the models.

Table 2
Male-driver descriptive statistics (female driver statistics in parentheses) of variables found to significantly influence severity-outcome probabilities.

Variables	2015 Mean	2015 Std. Dev.	2016 Mean	2016 Std. Dev.	2017 Mean	2017 Std. Dev.
Spatial characteristics						
District 1 indicator (1 if crash occurred in District 1, 0 otherwise)	0.145 (0.147)	0.352 (0.354)	0.172 (0.143)	0.377 (0.351)	0.141 (0.125)	0.348 (0.331)
District 2 indicator (1 if crash occurred in District 2, 0 otherwise)	0.160 (0.179)	0.367 (0.383)	0.142 (0.130)	0.349 (0.337)	0.147 (0.204)	0.354 (0.403)
District 4 indicator (1 if crash occurred in District 4, 0 otherwise)	0.225 (0.191)	0.417 (0.393)	0.199 (0.184)	0.399 (0.388)	0.194 (0.197)	0.395 (0.397)
District 7 indicator (1 if crash occurred in District 7, 0 otherwise)	0.144 (0.136)	0.351 (0.343)	0.148 (0.152)	0.355 (0.359)	0.127 (0.104)	0.333 (0.305)
Temporal characteristics						
Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	0.127 (0.080)	0.333 (0.271)	0.155 (0.095)	0.362 (0.294)	0.152 (0.107)	0.359 (0.309)
Late night indicator (1 if time of day is between 9 PM to 11:59 PM, 0 otherwise)	0.101 (0.104)	0.301 (0.305)	0.119 (0.091)	0.324 (0.288)	0.114 (0.085)	0.318 (0.279)
Afternoon peak indicator (1 if time of day is between 4 to 5:59 PM, 0 otherwise)	0.152 (0.168)	0.359 (0.374)	0.131 (0.177)	0.337 (0.382)	0.126 (0.132)	0.332 (0.339)
Second quarter indicator (1 if month of year is between April to June, 0 otherwise)	0.221 (0.179)	0.415 (0.383)	0.230 (0.245)	0.421 (0.431)	0.329 (0.304)	0.470 (0.460)
Saturday indicator (1 if the crash occurred on Saturday, 0 otherwise)	0.152 (0.147)	0.359 (0.354)	0.145 (0.138)	0.353 (0.345)	0.152 (0.138)	0.359 (0.345)
Traffic characteristics						
Low traffic condition indicator (1 if AADT is below 40,000 vehicles/day, 0 otherwise)	0.327 (0.360)	0.469 (0.480)	0.311 (0.331)	0.463 (0.471)	0.181 (0.189)	0.385 (0.392)
Medium traffic volume indicator (1 if AADT between 40,000–80,0000 vehicles/day, 0 otherwise)	0.201 (0.212)	0.4001 (0.409)	0.195 (0.235)	0.396 (0.424)	0.127 (0.137)	0.334 (0.344)
Environmental characteristics						
Dark indicator (1 if crash occurred at the time of darkness, 0 otherwise)	0.330 (0.281)	0.470 (0.449)	0.369 (0.263)	0.482 (0.440)	0.348 (0.264)	0.476 (0.441)
Vehicle characteristics						
Pickup truck indicator (1 if pickup, 0 otherwise)	0.196 (0.074)	0.397 (0.263)	0.201 (0.072)	0.401 (0.259)	0.194 (0.070)	0.396 (0.255)
Roadway characteristics						
Urban interstate indicator (1 if crash occurred on urban principal arterials/interstate, 0 otherwise)	0.240 (0.194)	0.427 (0.395)	0.185 (0.207)	0.388 (0.405)	0.169 (0.150)	0.375 (0.357)
Urban freeway indicator (1 if crash occurred on urban freeway, 0 otherwise)	0.090 (0.084)	0.287 (0.277)	0.108 (0.100)	0.311 (0.300)	0.056 (0.073)	0.230 (0.260)
Road surface indicator (1 if road surface condition was identified as contributing factor, 0 otherwise)	0.500 (0.496)	0.500 (0.500)	0.507 (0.546)	0.500 (0.497)	0.504 (0.483)	0.500 (0.499)
Curved segment indicator (1 if roadway curves to the right or left of travel direction, 0 otherwise)	0.317 (0.380)	0.465 (0.485)	0.325 (0.360)	0.468 (0.480)	0.264 (0.326)	0.441 (0.469)
Narrow shoulder width indicator (1 if shoulder width is below 4 feet, 0 otherwise)	0.184 (0.212)	0.387 (0.409)	0.200 (0.190)	0.400 (0.392)	0.104 (0.095)	0.306 (0.294)
Wide shoulder width indicator (1 if shoulder width is between 4–8 feet, 0 otherwise)	0.127 (0.147)	0.333 (0.354)	0.142 (0.135)	0.349 (0.341)	0.095 (0.104)	0.294 (0.305)
Right curved segment indicator (1 if roadway curves to the right of travel direction, 0 otherwise)	0.168 (0.207)	0.374 (0.405)	0.156 (0.175)	0.363 (0.380)	0.126 (0.152)	0.332 (0.359)
Left curved segment in the dark indicator (1 if crash occurred on roadway curves to the left of travel direction in the dark, 0 otherwise)	0.149 (0.172)	0.356 (0.378)	0.169 (0.184)	0.375 (0.388)	0.138 (0.174)	0.345 (0.379)
Most harmful median indicator (1 if most harmful event occurs in the median, 0 otherwise)	0.118 (0.096)	0.322 (0.295)	0.096 (0.088)	0.295 (0.284)	0.115 (0.080)	0.319 (0.272)
Straight segment in the dark indicator (1 if crash occurred on straight roadway segment in the dark, 0 otherwise)	0.222 (0.161)	0.416 (0.368)	0.257 (0.156)	0.437 (0.363)	0.258 (0.173)	0.438 (0.378)
Roadway surface with pickup truck indicator (1 if road surface contributed to crashes involving pickup truck, 0 otherwise)	0.094 (0.044)	0.292 (0.205)	0.111 (0.039)	0.314 (0.194)	0.091 (0.037)	0.287 (0.189)
Crash characteristics						
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise)	0.148 (0.112)	0.355 (0.315)	0.137 (0.119)	0.344 (0.324)	0.115 (0.092)	0.319 (0.289)
Collision with non-fixed object indicator (1 if collided with non-fixed object as the first harmful event, 0 otherwise)	0.119 (0.128)	0.324 (0.334)	0.141 (0.127)	0.348 (0.334)	0.145 (0.114)	0.352 (0.319)
Driver characteristics						
Young aged driver indicator (1 if driver age below 30 years, 0 otherwise)	0.539 (0.595)	0.498 (0.490)	0.581 (0.571)	0.493 (0.495)	0.539 (0.623)	0.498 (0.484)
Middle aged driver indicator (1 if driver age between 30–49 years, 0 otherwise)	0.300 (0.298)	0.458 (0.457)	0.288 (0.306)	0.452 (0.461)	0.315 (0.276)	0.464 (0.447)
Middle aged driver with Sport Utility Vehicle (SUV) indicator (1 if driver age between 30–49 years driving SUV, 0 otherwise)	0.058 (0.078)	0.234 (0.269)	0.042 (0.100)	0.202 (0.300)	0.045 (0.074)	0.209 (0.262)
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise)	0.952 (0.965)	0.212 (0.183)	0.945 (0.962)	0.226 (0.191)	0.941 (0.952)	0.235 (0.213)
Exceeding speed limit by more than 10 mi/hr indicator (1 if travel exceeded the speed limit by more than 10 mi/hr, 0 otherwise)	0.082 (0.062)	0.275 (0.242)	0.080 (0.046)	0.271 (0.210)	0.072 (0.052)	0.260 (0.222)
Exceeding speed limit by more than 20 mi/hr indicator (1 if travel exceeded the speed limit by more than 20 mi/hr, 0 otherwise)	0.019 (0.012)	0.137 (0.109)	0.017 (0.013)	0.132 (0.113)	0.019 (0.005)	0.138 (0.077)

(*continued on next page*)

Table 2 (*continued*)

Variables	2015 Mean	2015 Std. Dev.	2016 Mean	2016 Std. Dev.	2017 Mean	2017 Std. Dev.
Driving below the speed limit by less than 10 mi/hr indicator (1 if travel speed is below the speed limit by more than 10 mi/hr, 0 otherwise)	0.139 (0.165)	0.346 (0.372)	0.119 (0.140)	0.324 (0.348)	0.136 (0.137)	0.343 (0.344)
Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise)	0.651 (0.643)	0.476 (0.478)	0.590 (0.658)	0.491 (0.474)	0.614 (0.591)	0.486 (0.491)
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise)	0.932 (0.953)	0.251 (0.211)	0.926 (0.944)	0.260 (0.228)	0.936 (0.958)	0.244 (0.200)
No ejection indicator (1 if driver was not ejected, 0 otherwise)	0.971 (0.979)	0.166 (0.140)	0.977 (0.985)	0.147 (0.119)	0.967 (0.983)	0.176 (0.127)
Other factors						
Non-geometry indicator (1 if crashes were identified not related to roadway geometry, 0 otherwise)	0.487 (0.483)	0.499 (0.499)	0.473 (0.436)	0.499 (0.496)	0.483 (0.502)	0.499 (0.500)

Std. Dev. = Standard Deviation.

in 2017 with traffic volumes below 40,000 vehicles/day. However, this low volume traffic was not found statistically significant for male drivers in all three years. Moreover, male drivers had higher probability of severe injury in 2015 and 2017 with traffic volume between 40,000–80,000 vehicles/day.

Continuing with Table 9, crashes occurring in darkness were found to be only significant for females in 2017, where darkness was associated with a lower probability of no injury and a higher probability of minor and severe injury. Regarding vehicle type, the pickup truck indicator was only significant for male drivers in 2015 and 2016, resulting in a lower probability of severe injury.

For roadway characteristics, the functional class of the roadway, roadway alignment, shoulder width, median, and surface condition were found statistically significant for male and female drivers over the study period. Female drivers had higher probability of severity injury on urban principal arterials/interstate crashes in 2017. However, this urban interstate indicator (1 if crash occurred on urban principal arterials/interstate, 0 otherwise) was not found statistically significant for 2015 and 2016 for female drivers and all three years for male drivers. Likewise, female drivers had higher probability of minor injury on non-

Table 3
Model results of mixed logit with heterogeneity in means and variance for male drivers involved in driving-too-fast-for-condition crashes in rainy weather, single-vehicle crashes in Florida during 2015.

Variables*	Parameter Estimates	t-stat.	Marginal Effects: No Injury	Minor Injury	Severe Injury
Constant [SI]	−0.413	1.69			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	3.212 (*5.129*)	2.57 (*3.27*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: no ejection indicator (1 if driver was not ejected, 0 otherwise)	−2.211	−1.80			
Heterogeneity in the variance of random parameter					
Constant [MI]: Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise)	−1.291	−3.46			
Spatial characteristics					
District 2 indicator (1 if crash occurred in District 2, 0 otherwise) [SI]	1.339	3.00	−0.0086	−0.0019	0.0106
District 4 indicator (1 if crash occurred in District 4, 0 otherwise) [NI]	0.619	2.06	0.0120	−0.0106	−0.0015
Temporal characteristics					
Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise) [MI]	−0.717	−1.77	0.0063	−0.0068	0.0004
Traffic characteristics					
Medium traffic volume indicator (1 if AADT between 40,000–80,0000 vehicles/day, 0 otherwise) [SI]	0.877	2.00	−0.0050	−0.0011	0.0061
Vehicle characteristics					
Pickup truck indicator (1 if pickup, 0 otherwise) [SI]	−2.211	−2.02	0.0014	0.0003	−0.0016
Roadway characteristics					
Most harmful median indicator [MI] (1 if most harmful event occurs in the median, 0 otherwise) [MI]	1.061	2.65	−0.0139	0.0144	−0.0005
Right curved segment indicator (1 if roadway curves to the right of travel direction, 0 otherwise) [MI]	−0.510	−2.61	0.0104	−0.0109	0.0005
Crash characteristics					
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) [NI]	−1.336	−3.91	−0.0295	0.0239	0.0056
Driver characteristics					
Driving below the speed limit by more than 20 mi/hr indicator (1 if travel speed is below the speed limit by more than 20 mi/hr, 0 otherwise) [MI]	0.894	1.94	−0.0065	0.0067	−0.0002
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise) [NI]	1.281	3.03	0.1275	−0.1077	−0.0198
Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise) [SI]	−0.890	−2.14	0.0075	0.0018	−0.0093
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [NI]	2.062	4.64	0.2006	−0.1721	−0.0285
Number of observations	1302				
Number of estimated parameters	17				
Log-likelihood at zero	−1430.393				
Log-likelihood at convergence	−764.784				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.465				

* SI = Severe Injury; MI = Minor Injury; NI = No Injury.

Table 4
Model results of mixed logit with heterogeneity in means and variance for male drivers involved in driving-too-fast-for-condition crashes in rainy weather, single-vehicle crashes in Florida during 2016.

Variables*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Constant [SI]	−0.536	−1.69			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	1.360 (*5.333*)	1.63 (*3.21*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: no ejection indicator (1 if driver was not ejected, 0 otherwise)	−2.922	−1.69			
Heterogeneity in the variance of random parameter					
Constant [MI]: Non-geometry indicator (1 if crashes were identified not related to roadway geometry, 0 otherwise)	−0.217	−1.97			
Spatial characteristics					
District 1 indicator (1 if crash occurred in District 1, 0 otherwise) [MI]	−1.152	−1.79	0.0088	−0.0091	0.0003
District 4 indicator (1 if crash occurred in District 4, 0 otherwise) [MI]	1.148	1.99	−0.0142	0.0146	−0.0004
Vehicle characteristics					
Pickup truck indicator (1 if pickup truck, 0 otherwise) [MI]	1.719	2.51	−0.0220	0.0227	−0.0007
Roadway characteristics					
Curved segment in the dark indicator (1 if roadway curves in travel direction in the dark, 0 otherwise) [MI]	1.695	2.91	−0.0045	−0.0007	0.0052
Straight segment in the dark indicator (1 if crash occurred on straight roadway segment in the dark, 0 otherwise) [MI]	1.161	2.10	−0.0180	0.0187	−0.0007
Crash characteristics					
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) [NI]	−1.643	−3.60	−0.0204	0.0136	0.0068
Driver characteristics					
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise) [NI]	1.102	1.97	0.0685	−0.0555	−0.0130
Exceeding speed limit by more than 10 mi/hr indicator (1 if travel speed exceeded the speed limit by more than 10 mi/hr, 0 otherwise) [MI]	1.635	1.93	−0.0081	0.0089	−0.0008
Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise) [SI]	−1.274	−2.58	0.0054	0.0006	−0.0060
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [NI]	2.653	5.81	0.1553	−0.1308	−0.0245
Number of observations	1350				
Number of estimated parameters	15				
Log-likelihood at zero	−1483.126				
Log-likelihood at convergence	−771.646				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.479				

* SI = Severe Injury; MI = Minor Injury; NI = No Injury.

interstate urban freeways in 2015. In addition, this urban freeway indicator (1 if crash occurred on urban freeway, 0 otherwise) was not found statistically significant for 2016 and 2017 for female drivers and all three years for male drivers. Male drivers had higher probability of severe injury on curved roadway in 2017. However, this curved segment indicator (1 if roadway curves to the right or left of travel direction, 0 otherwise) was not found statistically significant in 2015 and 2016 for male drivers and all three years for female drivers. Male drivers had higher probability of severe injury but lower probability of minor injury in 2015 on right curved roadway. Female drivers had lower probability of severe injury but higher probability of minor injury in 2017 on right curved roadway. This right curved segment indicator (1 if roadway curves to the right of travel direction, 0 otherwise) was not found statistically significant in 2016 either for male or female drivers. Female drivers had higher probability of severe and minor injury in 2016 and 2017 on roadways with narrow shoulder (shoulder width below 4 feet). This narrow shoulder indicator (1 if shoulder width is below 4 feet, 0 otherwise) was not found statistically significant for all three years for male drivers. In contrast, male drivers had higher probability of severe and minor injury in 2017 on roadways with shoulder width between 4–8 feet. This medium shoulder width indicator (1 if shoulder width is between 4–8 feet, 0 otherwise) was not found statistically significant for all three years for female drivers. Male drivers had higher probability of severe injury in 2016 but lower in 2017 for curved segments in the dark conditions. However, male drivers had higher probability of minor injury but lower probability of severe injury in 2016 on straight segments in dark conditions. For all three years, these two indicator variables (curved and straight segment in the dark conditions) were not found statistically significant in female models. Female drivers had higher probability of minor injury but lower probability of severe injury in 2015 and 2017 when road surface was found to be contributing factor in the crashes. This road surface indicator variable (1 if road surface condition was identified as contributing factor, 0 otherwise) was not found statistically significant for any years for male drivers.

Regarding crash characteristics, the non-collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) was found to be statistically significant in all time periods for both male and female drivers. Moreover, for both males and females these crash types reduced the probability of no injury and increased the probability of minor and severe injury. While the values of the marginal effects fluctuate a bit over time, this variable exhibits relative stability across genders and years. The other statistically significant crash characteristic is a collision with non-fixed object (1 if collided with non-fixed object as the first harmful event, 0 otherwise), which was found to be only significant for females in 2015, where it decreased the probability of minor injury and increased the probability of no injury and serious injury.

Driver characteristics specific to male and female drivers also played key role in injury severity determinations. Variables such as age, normal driving behavior (driving without any physical/emotional impairment), speed (exceeding or driving below the speed limit), alcohol use suspected, and restraint usage were found significant for male and female drivers over the study period. Female drivers of age below 30 years had lower severe and minor injury probability in 2017 and middle aged female drivers (30–49 years) driving sport utility vehicles (SUVs) were found to have higher probability of severe injury but lower probability of minor injury in 2015. Male drivers had a lower probability of severe injury but a higher probability of minor injury while exceeding the

Table 5
Model results of mixed logit with heterogeneity in means and variance for male drivers involved in driving-too-fast-for-condition crashes in rainy weather, single-vehicle crashes in Florida during 2017.

Variables*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Constant [SI]	0.498	1.64			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	2.522 (*5.472*)	3.95 (*4.22*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise)	−2.345	−3.46			
Heterogeneity in the variance of random parameter					
Constant [MI]: Young aged driver indicator (1 if driver age below 30 years, 0 otherwise)	−0.182	−1.65			
Spatial characteristics					
District 1 indicator (1 if crash occurred in District 1, 0 otherwise) [MI]	−1.771	−2.40	0.0093	−0.0102	0.0009
Temporal characteristics					
Late night indicator (1 if time of day is between 9 PM to 11:59 AM, 0 otherwise) [MI]	−1.317	−1.79	0.0062	−0.0070	0.0008
Second quarter indicator (1 if month of year is between April to June, 0 otherwise) [SI]	0.621	1.76	−0.0063	−0.0011	0.0073
Traffic characteristics					
Medium traffic volume indicator (1 if AADT between 40,000–80,0000 vehicles/day, 0 otherwise) [SI]	1.098	2.28	−0.0056	−0.0007	0.0063
Roadway characteristics					
Wide shoulder width indicator (1 if shoulder width 4–8 feet, 0 otherwise) [NI]	−1.510	−3.84	−0.0146	0.0077	0.0069
Curved segment in the dark indicator (1 if crash occurred on roadway curves in travel direction in the dark, 0 otherwise) [MI]	1.751	1.84	−0.0049	0.0054	−0.0005
Curved segment indicator (1 if roadway curves to the right or left of travel direction, 0 otherwise) [SI]	0.855	2.39	−0.0075	−0.0014	0.0089
Crash characteristics					
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) [NI]	−1.751	−4.69	−0.0219	0.0095	0.0124
Driver characteristics					
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise) [NI]	2.465	5.94	0.1604	−0.1134	−0.0470
Exceeding speed limit by more than 20 mi/hr indicator (1 if travel speed exceeded the speed limit by more than 20 mi/hr, 0 otherwise) [SI]	1.859	2.47	−0.0026	−0.0006	0.0032
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [NI]	3.152	7.92	0.2027	−0.1458	−0.0569
Number of observations	1329				
Number of estimated parameters	16				
Log-likelihood at zero	−1460.056				
Log-likelihood at convergence	−792.518				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.457				

* SI = Severe Injury; MI = Minor Injury; NI = No Injury.

Table 6
Model results of mixed logit with heterogeneity in means and variance for female drivers involved in driving-too-fast-for-condition crashes in rainy weather, single-vehicle crashes in Florida during 2015.

Variables*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Constant [SI]	2.111	1.63			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	3.047 (*4.498*)	2.29 (*2.85*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: Urban interstate indicator (1 if crash occurred on urban principal arterials/interstate, 0 otherwise)	1.142	1.88			
Heterogeneity in the variance of random parameter					
Constant [MI]: Medium traffic volume indicator (1 if AADT between 40,000–80,0000 vehicles/day, 0 otherwise)	−0.529	−1.73			
Spatial characteristics					
District 3 indicator (1 if crash occurred in District 3, 0 otherwise) [MI]	1.435	1.83			
Roadway characteristics					
Road surface indicator (1 if road surface condition was identified as contributing factor, 0 otherwise) [MI]	0.932	1.86	−0.0355	0.0375	−0.0020
Urban freeway indicator (1 if crash occurred on urban freeway, 0 otherwise) [MI]	1.691	1.91	−0.0130	0.0133	−0.0004
Crash characteristics					
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) [NI]	−2.841	−3.43	−0.0324	0.0212	0.0112
Collision with non-fixed object indicator (1 if collided with non-fixed object as the first harmful event, 0 otherwise) [MI]	−1.992	−2.02	0.0139	−0.0143	0.0004
Driver characteristics					
Middle aged driver with Sport Utility Vehicle (SUV) indicator (1 if driver age between 30–49 years driving SUV, 0 otherwise) [SI]	1.397	1.91	−0.0037	−0.0010	0.0047
Driving below the speed limit by less than 10 mi/hr indicator (1 if travel speed is below the speed limit by more than 10 mi/hr, 0 otherwise) [NI]	1.247	1.77	0.0153	−0.0136	−0.0017

(*continued on next page*)

Table 6 (*continued*)

Variables*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise) [SI]	−1.649	−1.89	0.0067	0.0017	−0.0084
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise) [NI]	3.210	2.66	0.2673	−0.2334	−0.0340
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [NI]	2.785	3.40	0.2277	−0.1998	−0.0279
Number of observations	734				
Number of estimated parameters	15				
Log-likelihood at zero	−806.381				
Log-likelihood at convergence	−485.396				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.398				

speed limit by more than 10 mi/hr. However, male drivers had higher probability of severe injury in 2017 while exceeding the speed limit more than 20 mi/hr (roughly, 2 percent of male drivers were observed exceeding the speed limit in this manner). In contrast, female drivers had a higher probability of severe injury but a lower probability of minor injury in 2017 while exceeding the speed limit by more than 10 mi/hr. Moreover, female drivers had a lower probability of severe and minor injury in 2015 and 2016 while driving below the speed limit by more than 10 mi/hr. Here, driving below the speed limit indicates some response to the adverse driving conditions, but not sufficient to avoid having the crash classified as having a speed too fast for conditions. Referring back to Fig. 1, this would be a speed adjustment somewhere to the left of point *D* on the *S*'*s*' curve, but not as far as point *B*, which would have the same crash risk as normal conditions. Interestingly, driving below the speed limit by less than 10 mi/hr indicator (1 if travel speed is below the speed limit by more than 10 mi/hr, 0 otherwise) was not found statistically significant for male drivers. These speed-related findings suggest a considerable effect of gender on speeding behavior in rainy weather conditions.

Regarding alcohol use, male and female drivers had lower probability of severe and minor injury in 2015 and 2016 when they were suspected of alcohol use. The restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) was one of just two variables found to be significant across both genders and all time periods (the other was the previously discussed non-collision indicator). While the marginal effect of this variables tended to vary from year to year and across genders,

Table 7
Model results of mixed logit with heterogeneity in means and variance for female drivers involved in driving-too-fast-for-condition crashes in rainy weather, single-vehicle crashes in Florida during 2016.

Variables*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Constant [SI]	1.652	1.78			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	3.914 (*6.060*)	3.84 (*2.46*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise)	−3.206	−2.52			
Heterogeneity in the variance of random parameter					
Constant [MI]: Middle aged driver indicator (1 if driver age between 30–49 years, 0 otherwise)	−0.617	−2.66			
Spatial characteristics					
District 7 indicator (1 if crash occurred in District 7, 0 otherwise) [SI]	0.783	1.64	−0.0060	−0.0010	0.0070
Temporal characteristics					
Afternoon peak indicator (1 if time of day is between 4 to 5:59 PM, 0 otherwise) [MI]	−1.781	−1.80	0.0145	−0.0163	0.0017
Traffic characteristics					
Medium traffic volume indicator (1 if AADT between 40,000–80,0000 vehicles/day, 0 otherwise) [SI]	−1.264	−2.00	0.0039	0.0006	−0.0045
Roadway characteristics					
Narrow shoulder width indicator (1 if shoulder width is below 4 feet, 0 otherwise) [MI]	−1.641	−1.84	0.0143	−0.0158	0.0016
Roadway surface with pickup truck indicator (1 if road surface contributed to crashes involving pickup truck, 0 otherwise) [MI]	2.625	1.72	−0.0070	0.0074	−0.0004
Crash characteristics					
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) [NI]	−1.845	−3.54	−0.0261	0.0108	0.0153
Driver characteristics					
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise) [NI]	1.622	2.61	0.1340	−0.0878	−0.0461
Driving below the speed limit by less than 10 mi/h indicator (1 if travel speed is below the speed limit by more than 10 mi/hr, 0 otherwise) [MI]	1.353	1.89	0.0125	−0.0091	−0.0034
Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise) [SI]	−1.096	−2.46	0.0198	0.0025	−0.0223
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [NI]	2.439	3.38	0.1980	−0.1311	−0.0670
Number of observations	688				
Number of estimated parameters	15				
Log-likelihood at zero	−755.845				
Log-likelihood at convergence	−490.475				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.351				

* SI = Severe Injury; MI = Minor Injury; NI = No Injury.

Table 8
Model results of mixed logit with heterogeneity in means and variance for female drivers involved in driving-too-fast-for-condition crashes in rainy weather, single-vehicle crashes in Florida during 2017.

Variables*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Constant [SI]	−1.265	−1.62			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	*3.234* (*2.370*)	*2.36* (*1.72*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise)	−2.809	−1.89			
Heterogeneity in the variance of random parameter					
Constant [MI]: Saturday indicator (1 if Saturday, 0 otherwise)	1.176	2.16			
Spatial characteristics					
District 1 indicator (1 if crash occurred in District 1, 0 otherwise) [MI]	−1.226	−1.82	0.0110	−0.0119	0.0009
Environmental characteristics					
Dark condition indicator (1 if crash occurred at the time of darkness, 0 otherwise) [NI]	−0.896	−2.30	−0.0315	0.0228	0.0086
Traffic characteristics					
Low traffic volume indicator (1 if AADT less than 40,000 vehicles/day, 0 otherwise) [SI]	1.850	3.77	−0.0259	−0.0056	0.0315
Roadway characteristics					
Narrow shoulder width indicator (1 if shoulder width is below 4 feet, 0 otherwise) [MI]	−1.561	−1.77	0.0094	−0.0108	0.0014
Right curved segment indicator (1 if roadway curves to the right of travel direction, 0 otherwise) [MI]	1.091	1.81	−0.0167	0.0184	−0.0017
Urban interstate indicator (1 if crash occurred on urban interstate, 0 otherwise) [SI]	1.481	2.77	−0.0120	−0.0029	0.0149
Road surface indicator (1 if road surface was identified as a contributing factor, 0 otherwise) [SI]	−1.419	−2.74	0.0113	0.0027	−0.0140
Crash characteristics					
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise) [NI]	−1.203	−2.51	−0.0155	0.0106	0.0049
Driver characteristics					
Young driver indicator (1 if drivers below 30 years, 0 otherwise) [NI]	0.511	1.64	0.0379	−0.0290	−0.0089
Exceeding speed limit by more than 10 mi/hr indicator (1 if travel speed exceeded the speed limit by more than 10 mi/hr, 0 otherwise) [SI]	1.512	2.16	−0.0048	−0.0014	0.0062
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [NI]	2.134	3.04	0.2520	−0.1910	−0.0610
Number of observations	670				
Number of estimated parameters	16				
Log-likelihood at zero	−736.070				
Log-likelihood at convergence	−480.316				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.347				

* SI = Severe Injury; MI = Minor Injury; NI = No Injury.

there is comparatively a good deal of stability in the effect of this variable with restraint usage consistently reducing the likelihood of minor and severe injury and increasing the likelihood of no injury.

In looking at other consistencies across time periods by gender (in addition to the non-collision and restraint usage indicators which were significant for both genders and all time periods), for crashes involving male drivers, just one other variable was found to be statistically significant across all three-time periods: the normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise). While driving without any physical/emotional impairment is statistically significant across all time periods, Table 9 shows considerable variation in marginal effects from one year to the next with, for example, the effect on severe-injury probabilities ranging from −0.0198 in 2015 to −0.0470 in 2017. It is noteworthy that driving without any physical/emotional impairment increased the probability of no injury for male drivers at about the same magnitude of female drivers in 2015 and 2016.

7. Summary and conclusions

Using single-vehicle crash data related to driving too fast for rainy conditions for male and female drivers in Florida from 2015–2017, this study used a random parameters logit model (with heterogeneity in mean and variance) to explore the temporal stability of factors determining male and female driver-injury severities over time. Three driver-injury levels were considered: no injury, minor injury (possible injury and non-incapacitating injury), and severe injury incapacitating injury and fatal injury). The estimated models showed a wide variety of factors significantly influencing driver-injury outcomes including spatial and temporal characteristics, overall traffic volume, vehicle and crash characteristics, roadway attributes, and driver factors.

Statistically significant differences were found between crashes involving male and female drivers, and both male and female crash injury-severity models exhibited statistically significant temporal instability over the three years considered (as indicated by likelihood ratio tests). This is not an unexpected finding given the abundance of recent crash research that has quantified temporal shifts in the determinants of crash likelihoods and their resulting severities (Mannering, 2018). Still this research indicates that, for speed-related adaptations to prevailing conditions, model estimation results that split male and female drivers-involved crashes can be used to help guide injury-severity mitigation policies.

The marginal effects of the individual explanatory variables also reflect the global temporal instability findings with considerable variation indicated over time. However, there were two explanatory variables that showed relative stability over time and across genders; an indicator variable for crashes involving non-collision factors (including overturn/rollover crashes) and an indicator variable for restraint usage (see Table 9). Policies that explicitly address these two variables such as continued efforts to increase safety belt usage, vehicle manufacturer regulations to minimize the probability of vehicle rollovers, or driver training relating to rollover avoidance) can have a long-term effect on reducing injury severities across genders. In addition, driver training that focuses speed adjustments in adverse conditions could fundamentally change the influence of explanatory variables on injury severity levels and reduce injury probabilities. Driver training would be a departure from the current approach that addresses speed adjustment to adverse conditions, which seems to be one of simply letting market-driven demand for advanced safety features (antilock brakes,

Table 9
Comparison of marginal effects in single-vehicle crashes over the years for male drivers, marginal effects for female drivers in parentheses.

Variables	No Injury			Minor Injury			Severe Injury		
	2015	2016	2017	2015	2016	2017	2015	2016	2017
Spatial characteristics									
District 1 indicator (1 if crash occurred in District 1, 0 otherwise)	–	0.0088	0.0093	–	−0.0091	−0.0102	–	0.0003	0.0009
	–	–	(0.0110)	–	–	(−0.0119)	–	–	(0.0009)
District 2 indicator (1 if crash occurred in District 2, 0 otherwise)	−0.0086	–	–	−0.0019	–	–	0.0106	–	–
District 4 indicator (1 if crash occurred in District 4, 0 otherwise)	0.0120	−0.0142	–	−0.0106	0.0146	–	−0.0015	−0.0004	–
District 7 indicator (1 if crash occurred in District 7, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	(−0.0060)	–	–	(−0.0010)	–	–	(0.0070)	–
Temporal characteristics									
Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	0.0063	–	–	−0.0068	–	–	0.0004	–	–
Late night indicator (1 if time of day is between 9 PM to 11:59 PM, 0 otherwise)	–	–	0.0062	–	–	−0.0070	–	–	0.0008
Afternoon peak indicator (1 if time of day is between 4 to 5:59 PM, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	(0.0145)	–	–	(−0.0163)	–	–	(0.0017)	–
Second quarter indicator (1 if month of year is between April to June, 0 otherwise)	–	–	−0.0063	–	–	−0.0011	–	–	0.0073
Traffic characteristics									
Low traffic condition indicator (1 if AADT is below 40,000 vehicles/day, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	–	(−0.0259)	–	–	(−0.0056)	–	–	(0.0315)
Medium traffic volume indicator (1 if AADT between 40,000–80,0000 vehicles/day, 0 otherwise)	−0.0050	–	−0.0056	−0.0011	–	−0.0007	0.0061	–	0.0063
	–	(0.0039)	–	–	(0.0006)	–	–	(−0.0045)	–
Environmental characteristics									
Dark indicator (1 if crash occurred at the time of darkness, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	–	(−0.0315)	–	–	(0.0228)	–	–	(0.0086)
Vehicle characteristics									
Pickup truck indicator (1 if pickup, 0 otherwise)	0.0014	−0.0220	–	0.0003	0.0227	–	−0.0016	−0.0007	–
Roadway characteristics									
Urban principal arterials/interstate indicator (1 if crash occurred on urban principal arterials/interstate, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	–	(−0.0120)	–	–	(−0.0029)	–	–	(0.0149)
Urban freeway indicator (1 if crash occurred on urban freeway, 0 otherwise)	–	–	–	–	–	–	–	–	–
	(−0.0130)	–	–	(0.0133)	–	–	(−0.0004)	–	–
Road surface indicator (1 if road surface condition was identified as contributing factor, 0 otherwise)	–	–	–	–	–	–	–	–	–
	(−0.0355)	–	(0.0113)	(0.0375)	–	(0.0027)	(−0.0020)	–	(−0.0140)
Curved segment indicator (1 if roadway curves to the right or left of travel direction, 0 otherwise)	–	–	−0.0075	–	–	−0.0014	–	–	0.0089
Narrow shoulder width indicator (1 if shoulder width is below 4 feet, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	(0.0143)	(0.0094)	–	(−0.0158)	(−0.0108)	–	(0.0016)	(0.0014)
Wide shoulder width indicator (1 if shoulder width is between 4–8 feet, 0 otherwise)	–	–	−0.0146	–	–	0.0077	–	–	0.0069
Right curved segment indicator (1 if roadway curves to the right of travel direction, 0 otherwise)	0.0104	–	–	−0.0109	–	–	0.0005	–	–
	–	–	(−0.0167)	–	–	(0.0184)	–	–	(−0.0017)
Curved segment in the dark indicator (1 if crash occurred on roadway curves in travel direction in the dark, 0 otherwise)	–	−0.0045	−0.0049	–	−0.0007	0.0054	–	0.0052	−0.0005
Most harmful median indicator (1 if most harmful event occurs in the median, 0 otherwise)	−0.0139	–	–	0.0144	–	–	−0.0005	–	–
Straight segment in the dark indicator (1 if crash occurred on straight roadway segment in the dark, 0 otherwise)	–	−0.0180	–	–	0.0187	–	–	−0.0007	–
Roadway surface with pickup truck indicator (1 if road surface contributed to crashes involving pickup truck, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	(−0.0070)	–	–	–	(0.0074)	–	(−0.0004)	–
Crash characteristics									
Non collision related factor indicator (1 if non-collision related factor including overturn/rollover, 0 otherwise)	−0.0295	−0.0204	−0.0219	0.0239	0.0136	0.0095	0.0056	0.0068	0.0124
	(−0.0324)	(−0.0261)	(−0.0155)	(0.0212)	(0.0108)	(0.0106)	(0.0112)	(0.0153)	(0.0049)
Collision with non-fixed object indicator (1 if collided with non-fixed object as the first harmful event, 0 otherwise)	–	–	–	–	–	–	–	–	–
	(0.0139)	–	–	(−0.0143)	–	–	(0.0004)	–	–
Driver characteristics									
Young driver indicator (1 if driver age below 30 years, 0 otherwise)	–	–	–	–	–	–	–	–	–
	–	–	(0.0379)	–	–	(−0.0290)	–	–	(−0.0089)
Middle aged driver with Sport Utility Vehicle (SUV) indicator (1 if driver age between 30–49 years driving SUV, 0 otherwise)	–	–	–	–	–	–	–	–	–
	(−0.0037)	–	–	(−0.0010)	–	–	(0.0047)	–	–

(*continued on next page*)

Table 9 (*continued*)

Variables	No Injury 2015	No Injury 2016	No Injury 2017	Minor Injury 2015	Minor Injury 2016	Minor Injury 2017	Severe Injury 2015	Severe Injury 2016	Severe Injury 2017
Normal driving indicator (1 if driving without any physical/emotional impairment, 0 otherwise)	0.1275	0.0685	0.1604	−0.1077	−0.0555	−0.1134	−0.0198	−0.0130	−0.0470
	(0.2673)	(0.1340)	–	(−0.2334)	(−0.0878)	–	(−0.0340)	(−0.0461)	–
Exceeding speed limit by more than 10 mi/hr indicator (1 if travel exceeded the speed limit by more than 10 mi/hr, 0 otherwise)	–	−0.0081	–	–	0.0089	–	–	−0.0008	–
	–	–	(−0.0048)	–	–	(−0.0014)	–	–	(0.0062)
Exceeding speed limit by more than 20 mi/hr indicator (1 if travel exceeded the speed limit by more than 20 mi/h, 0 otherwise)	−0.0065	–	−0.0026	0.0067	–	−0.0006	−0.0002	–	0.0032
Driving below the speed limit by less than 10 mi/hr indicator (1 if travel speed is below the speed limit by more than 10 mi/hr, 0 otherwise)	–	–	–	–	–	–	–	–	–
	(0.0153)	(0.0125)	–	(−0.0136)	(−0.0091)	–	(−0.0017)	(−0.0034)	–
Suspected Alcohol use indicator (1 if alcohol use is suspected in the crash involved driver, 0 otherwise)	0.0075	0.0054	–	0.0018	0.0006	–	−0.0093	−0.0060	–
	(0.0067)	(0.0198)	–	(0.0017)	(0.0025)	–	(−0.0084)	(−0.0223)	–
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise)	0.2006	0.1553	0.2027	−0.1721	−0.1308	−0.1458	−0.0285	−0.0245	−0.0569
	(0.2277)	(0.1980)	(0.2520)	(−0.1998)	(−0.1311)	(−0.1910)	(−0.0279)	(−0.0670)	(−0.0610)

electronic stability control, autonomous braking, traction control, etc.) gradually improve safety.

As with all studies, this study is not without its limitations. For example, although police officers are trained for consistency in interpretation, defining driving too fast for the conditions is still open to the interpretation of the officer, and a potential source of misinterpretation under different conditions, such as, traffic condition, weather conditions, and road-geometry conditions. If such misinterpretation occurs on a consistent basis, this could result in issues in difficulties uncovering causal effects (see the discussion of this point in Mannering et al., 2020). Another issue relates to the data coming from Florida where a mild climate precludes adverse weather conditions such as snow and ice. Exploring driving too fast for conditions under these more challenging weather conditions would be a fruitful direction for future research.

Author statement

The authors confirm that this paper has not been submitted elsewhere for publication consideration.

Declaration of Competing Interest

The authors have no conflicts of interest associated with this paper.

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