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Unconstrained and partially constrained temporal modelling of pedestrian injury severities

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ABSTRACT
This study aims to explore the phenomenon of pedestrian crash severity by investigating how pedestrian injury levels have evolved in incidents occurring prior to (2019), during (2020), and after (2021) the COVID-19 lockdowns. Using Louisiana crash data, distinct annual models for pedestrian injury severity (categorised as severe (fatal and severe), minor (moderate and minor), and no injury) were developed using a random parameters logit approach, accounting for potential heterogeneity in means and variances of random parameters. Likelihood ratio tests were employed to assess the overall stability of model estimates across the studied years, and a comparison was made between partially constrained and unconstrained temporal modelling approaches. The results reveal statistically significant differences in injury severity before, during, and after the COVID-19 pandemic.

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KEYWORDS
Pedestrian crash; temporal instability; random parameters models; heterogeneity in means; COVID-19

Introduction

Apart from its widespread popularity as a recreational and fitness activity, walking is increasingly recognised as a crucial and sustainable means of transportation. Nevertheless, pedestrians, along with cyclists, moped riders, and motorcyclists, stand out as the most susceptible road users, facing a higher likelihood of sustaining severe injuries in the event of a collision compared to occupants of cars and trucks. In a recent report, the Governors Highway Safety Association (GHSA) revealed alarming statistics regarding pedestrian fatalities on U.S. roadways. According to preliminary data reported by State Highway Safety Offices (SHSOs), 3,434 pedestrians lost their lives in the first half of 2022. A subsequent report analysing comprehensive state-reported data for the entire year of 2022 highlighted the persistent danger faced by pedestrians on the roads. The data disclosed a grim reality, with 2.37 pedestrian deaths per billion vehicle miles travelled (VMT) in 2022, marking an increase and continuing a troubling trend that began in 2020 (GHSA 2023).

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The escalating frequency of pedestrian crashes and the corresponding increase in injury severity underscore the need for in-depth study of pedestrian safety. The present study's exploration of pedestrian crash severity over the years preceding, during, and following the COVID-19 lockdowns, particularly within the context of Louisiana, contributes valuable insights into the complex factors influencing the outcomes of vehicle-pedestrian collisions. Recently, Alnawmasi and Mannering (2023) analysed the impact of day/night and COVID-19 lockdowns on bicyclist injury severities in vehicle-bicycle crashes. Yearly models were estimated using a random parameters logit approach, considering various factors affecting injury severity. Following the methodological framework of previous works, (Alnawmasi and Mannering 2023; Dzinyela et al. 2024), the current study adopted a partial constraint random parameter logit approach, accounting for potential heterogeneity in means of random parameters which enhances the understanding the influence of different variables. The partial constraint random parameter logit approach enables us to examine the temporal stability of each variable used in the model, to find exploratory variables that significantly change over time and variables that were stable over the years. While this approach does not deviate significantly from the fully unconstrained approach employed in previous studies (Alnawmasi and Mannering 2022; Alnawmasi and Mannering 2023; Islam and Mannering 2021), it enables the distinction between temporally stable and unstable variables over the years, thereby helping with better inference. By examining the stability of model estimates across different years and comparing temporal modelling approaches, the study establishes a robust foundation for understanding the temporal dynamics of pedestrian injury severity. Additionally, the incorporation of a comprehensive array of variables, encompassing pedestrian and vehicle driver details, road and environmental conditions, and temporal characteristics, reflects a systematic and thorough approach.

The adoption of a partially constrained temporal model using econometric methods, such as the random parameters logit approach, is essential for this study due to its ability to capture the nuanced shifts in parameters over different time periods (pre-, during, and post-COVID-19). Unlike Empirical Bayesian (EB) methods, which are primarily useful for improving estimates in the presence of small sample sizes or spatial data, or Propensity Score Matching (PSM), which addresses selection bias but lacks temporal dimension consideration, econometric methods excel in accommodating unobserved heterogeneity and temporal dynamics. The random parameters logit model provides the flexibility to model complex relationships and interactions between variables, crucial for understanding how external shocks like the COVID-19 pandemic can alter the relationships between predictor variables and pedestrian injury severity. This approach offers a comprehensive analysis of how factors influencing pedestrian crash outcomes evolve over time, which is critical for identifying and understanding the significant parameter shifts driven by changes in health control policies and travel behaviours during and after the pandemic.

Literature review

The literature review is divided into two sections: (1) studies on pedestrian crash severity analysis, and (2) studies on temporal instability analysis in crash severity analysis.

Studies on pedestrian crashes

In the recent years, many researchers focused on pedestrian related crash data analysis. Chen and Fan (2019) used a multinomial logit (MNL) model to analyse pedestrian-vehicle crash severity in North Carolina. Significant factors for severe outcomes included poor driver condition, motorcycle or heavy truck involvement, older pedestrian age, weekend crashes, low light conditions, curved roads, wet surfaces, specific road types, and high-speed limits. Sze and Wong (2007) investigated the injury risk of pedestrian casualties in traffic crashes using binary logistic regression. Results indicated a declining trend in pedestrian injury risk, accounting for demographic, road environment, and other factors. Xiao et al. (2023) employed latent cluster analysis to identify homogeneous clusters within the pedestrian-vehicle crash dataset and then proposed an unbalanced panel mixed ordered probit model to analyse these clusters. The model provided valuable insights into significant variables affecting injury severity, considering the heterogeneity issue and variations among different places. The findings suggested that this model can be an alternative approach to understanding and addressing the factors influencing injury severity in pedestrian-vehicle crashes. Xu et al. (2020) investigated pedestrian injury severity in traffic crashes while considering both spatial and temporal heterogeneity using a geographically and temporally weighted regression (GTWR) model. The GTWR model outperformed the standard geographically weighted regression (GWR) and temporally weighted regression (TWR) models in terms of goodness-of-fit and F statistics.

Tay et al. (2011) employed a multinomial logit model to investigate the factors influencing the severity of pedestrian-vehicle collisions. Model results revealed that various factors, including collisions with heavy vehicles, intoxicated or male drivers under 65, elderly or female pedestrians, and pedestrian crashes occurring in adverse conditions like bad weather, at night, on high-speed roads, on road links, in tunnels, on bridges, or on wider roads were linked to fatal/serious injuries. Furthermore, Dovom et al. (2012) found that factors such as pedestrian age, the type of vehicle involved in the crash, and the crash location significantly influenced the probability of death at the crash scene using binary logistic models and forensic medical data from the Mashhad region. Similarly, Davis (2001) developed an ordered discrete outcome model to examine the relationship between the severity of injury sustained by pedestrians when struck by vehicles and the speed of the striking vehicle. Considering different age groups for the analysis, model findings indicated that injury severity patterns were similar for children and adults. However, elderly pedestrians tended to experience more severe injuries in lower impact speed crashes compared to the other two groups.

Eluru, Bhat, and Hensher (2008) proposed the mixed generalised ordered-response logit (MGORL) model, an extension of the existing ordered-response models. Model results showed the elasticity effects of injury severity determinants were similar for pedestrians and bicyclists, with key factors including age, speed limits, crash location, and time of day. Guo et al. (2020) introduced a two-level random intercept model for predicting pedestrian crash severity, considering interdependent characteristics using the Bayesian modelling approach with Colorado's pedestrian crash data. Factors influencing pedestrian crashes included age, vehicle type, and driver speed at intersections, while road and lighting conditions, seatbelt use, and driver speed impact urban road sections. In addition, Guo et al. (2017) analysed pedestrian-involved crashes to understand the impact of demographics and neighbourhood environment on pedestrian injury severity using a mixed effects logistic model. Older pedestrians and males were found to be random, suggesting the need for customised safety programmes. Other findings indicated pedestrians in higher-income areas were less likely to sustain severe injuries, while low-income areas exhibited more unsafe pedestrian behaviours. Similarly, Xin et al. (2017) investigated the effects of neighborhood characteristics and the built environment on pedestrian injury severity using data from pedestrian-vehicle using random parameter generalised ordered probit model with heterogeneity in means and variances. The analysis identified three significant factors: African American community, school zone, and bus stop area, which influenced pedestrian injury severity. Additionally, elderly pedestrians involved in intersection-related crashes were more likely to suffer severe injuries compared to younger pedestrians. Kim et al. (2010) used a mixed logit model to examine pedestrian-injury severity in pedestrian-vehicle collisions and found several factors like darkness without streetlights, involvement of trucks, freeway location, speeding, older pedestrians and collisions with a drinking motorist linked with fatal injuries. Furthermore Kim, Kho, and Kim (2017) examined factors affecting injury severity in pedestrian crashes, considering both crash and municipality characteristics. It identified significant factors at the crash level, including intoxicated drivers, elderly pedestrians, wide roads, and adverse weather conditions. Municipality-level factors, such as low population density, limited financial independence, and a higher percentage of elderly residents, were also linked to more severe crashes. Municipalities with the highest pedestrian fatality rates have rates 7.4 times higher than those with the lowest rates. Lu et al. (2020) used a partial proportional odds (PPO) model to analyse factors that affected Pedestrian Injury Severity (PIS) while considering the ordered nature of severity levels. The results indicated that factors like local drivers, trucks, holidays, clear weather, and hit-and-run contributed to higher PIS. Similarly, Salehian et al. (2023) identified factors like pedestrian location, lighting conditions, and road type influencing injury severity at intersections and non-intersections on rural roads by employing Latent Class Analysis and the Ordered Probit model.

Studies on temporal instability analysis

Several studies were conducted to investigate temporal instability. Ahmed and Ahmed (2022) analysed driver injury severity on a rural mountainous highway corridor during different weather conditions. Separate models were developed for each year, and a random-intercept Bayesian logistic approach was used. The analysis revealed temporal instability in many factors, with some showing stability during clear weather conditions. The study recommended countermeasures like warning signs, variable message signs and connected vehicle technology. Alnawmasi and Mannering (2019) examined the temporal instability of factors influencing motorcyclist injury severity in single-vehicle motorcycle crashes in Florida. Random parameters multinomial logit models were employed, and likelihood ratio tests were conducted to assess the stability of model estimates across time periods. The results revealed significant temporal instability in motorcyclist injury severity models, likely attributed to changes in technology, economic conditions, road user behaviour, and riders' skills over time. Fanyu et al. (2021) also employed correlated and uncorrelated random parameter to examine the influence of various truck classes on non-truck-involved crash severity and found temporal instability in crash severity factors. Islam, Alnawmasi, and

Mannering (2020) focused on work-zone-related crashes in Florida, revealing an increase in injury severities. Random parameters logit models were used to examine single-vehicle work zone crashes. The analysis incorporated various factors affecting driver injury severity. Notably, the model showed significant differences in parameters for each year, indicating temporal instability. However, it's essential to note that these variations may not solely stem from changes in driver behaviour over time. Islam and Mannering (2021) investigated the impact of inappropriate speed adjustment to adverse conditions on crash-injury severities, focusing on differences between male and female drivers and how these differences evolved over time. It analysed single-vehicle crashes in rainy weather with identified driver actions contributing to the crashes. Random parameters multinomial logit models were used to estimate driver injury severity. The results revealed significant disparities in injury severities between male and female drivers, with statistically significant temporal instability in the effects of factors over time. Li, Song, and Fan (2021) investigated how various factors influence pedestrian injury severity during different time periods. Random parameters logit models were employed, while accounting for unobserved heterogeneity in means and variances. Factors included pedestrian, driver, crash, locality, roadway, time, environment, traffic control, and work zone characteristics. Song, Fan, and Li (2021) analysed multi-vehicle crashes involving alcohol impaired (Blood Alcohol Concentration or BAC over 0.05) or drug-impaired drivers. A random parameters logit model was employed to identify significant factors and assess the impact of economic conditions on them. The study underscored the importance of considering time-of-day variations, temporal instability, and inherent heterogeneity when addressing alcohol and drug-impaired crashes, especially in the post-recession period. Yan et al. (2023) focused on injury severity in nighttime single-vehicle crashes among drivers of different age groups and investigated how these factors vary over time. The study employed random parameters logit models with heterogeneity in means to assess temporal instability and transferability of nighttime crash severity predictors among different age groups. The results revealed emphasised the need to account for temporal instability and age-related differences in crash prediction.

Zubaidi et al. (2021) examined injury severity factors for drivers at unsignalized yield sign intersections, considering both temporal stability and unobserved heterogeneity. Random parameters, random parameters with mean heterogeneity, and random parameters with mean and variance heterogeneity, were employed. Likelihood ratio tests revealed temporal instability in the data over the four years. The analysis identified 28 unstable variables, with some like crashes within metropolitan areas and on dry pavement, remained stable. The study suggested accounting for temporal instability to formulate effective countermeasures. Wang et al. (2021) used correlated mixed logit models with temporal instability to estimate injury severity and vehicle damage in intersection crashes. The study found temporal instability in both injury severity and vehicle damage models. Yan et al. (2021) focused on injury severity in alcohol-impaired driving crashes and how these factors vary weekly and over time. It employed hierarchical ordered probit models with random thresholds to examine three injury severity categories: no injury, minor injury, and severe injury. The study assessed the weekly transferability and temporal stability of the models through likelihood ratio tests and analyses the marginal effects of explanatory variables. The findings suggest that some factors exhibited weekly variations and temporal instability, while others demonstrated relative weekly transferability and temporal stability. Mannering (2018) challenged

Table 1. Pedestrian crashes by year and injury types.

Year	Severe Injury (SI)	Minor Injury (MI)	No Injury (NI)	Yearly Total
2019	301	617	802	1720
2020	322	495	596	1413
2021	369	512	617	1498
Total	992	1624	2015	4631

the common assumption in statistical analyses of highway safety data that model parameters remained temporally stable over time. The review of this literature suggested that temporal instability exists due to behavioural reasons, a notion supported by recent crash-data analyses. The paper then discussed the implications of this temporal instability for contemporary crash-data modelling methods and concluded by addressing how it can be accounted for to improve the interpretation of crash data-analysis findings. Behnood and Mannering (2019) examined factors influencing injury severities in large-truck crashes in Los Angeles, considering morning and afternoon periods and year-to-year variations. Random parameters logit models were used to account for unobserved heterogeneity, and likelihood ratio tests assessed model transferability across different times of day and years. The results revealed instability in the effects of certain factors on injury severities, but several variables exhibited consistent effects, providing insights for regulating truck operations by time of day.

Data collection

This study collected three years (2019–2021) of vehicle-pedestrian crash data from Louisiana. Table 1 presents a comprehensive overview of pedestrian crashes spanning the years 2019–2021, delineating the occurrences of Severe Injuries (SI), Minor Injuries (MI), and No Injuries (NI) for each respective year. SI includes fatal (K) and incapacitating (A) injuries, MI includes non-incapacitating (B) and minor (C) injuries, and NI includes no injury (O) or property damage only (PDO) crashes. As the frequency of fatal injuries is lower than that of other injury outcomes, making the KABCO segmentation of the data highly imbalanced. To address this and due to sample sizes, fatal and incapacitating injuries are combined into one group representing severe outcomes of crashes. The second category includes non-incapacitating and minor injuries, providing a mid-level injury outcome representing moderate injury levels. Lastly, crashes with no injuries or only property damage, which have a high frequency, are not combined with any other category and represent the lower injury severity outcomes. This approach of categorising injury severity into three levels has been adopted in previous research (Alnawmasi and Mannering 2019; Yu, Ma, and Shen 2021). The cumulative data reveals a total of 992 Severe Injuries, 1624 Minor Injuries, and 2015 No Injuries, contributing to an aggregate of 4631 pedestrian crashes over the three-year period. The percentage change in Severe Injuries from 2019 to 2021 reflects a notable increase of 22.59%, signifying a rise in severe incidents. Conversely, Minor Injuries showed a decline of approximately 17.03%, and No Injuries exhibited a more pronounced decrease of 23.07% during the same timeframe. Breaking down the specifics, in 2019, Severe Injuries constituted approximately 17.5% of the total cases, totaling 301 reported incidents. Minor Injuries accounted for approximately 35.9%, amounting to 617 incidents, while No Injuries comprised around 46.6%, reflecting 802 cases. The cumulative injuries for the year amounted to 1720 reported cases. In 2020, Severe Injuries made up around 22.8% of the total cases, with 322 reported incidents. Minor Injuries constituted approximately 35.0%, totaling 495 incidents, while No Injuries accounted for roughly 42.2%, comprising 596 cases. The total reported injuries for 2020 stood at 1413. In 2021, Severe Injuries saw a rise, comprising approximately 24.7% of the total cases, with 369 reported incidents. Minor Injuries slightly increased to approximately 34.2%, totaling 512 incidents. No Injuries also experienced a slight increase, accounting for approximately 41.1%, with 617 reported cases. The total injuries reported for that year amounted to 1498. Analysing the percentage changes from 2020 to 2021 reveals a 14.6% increase in Severe Injuries, a 3.4% increase in Minor Injuries, and a 3.5% increase in No Injuries. In total, there was a 6% increase in overall reported injuries during this period.

Data description

Table 2 presents descriptive statistics for key explanatory variables that exhibited significance in the estimated models for the years 2019, 2020, and 2021. All variables in the table are indicator variables, taking the value of 1 when the conditions specified in the variable name are met, and 0 otherwise. For instance, the variable 'Truck or Van' takes the value of 1 when the vehicle type is a truck or van, and it takes the value of 0 when the vehicle type is different. These statistics provide insights into the means and standard deviations for each

Table 2. Descriptive statistics of key explanatory variables that were significant in the models estimated.

	2019		2020		2021	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Pedestrian Condition						
Pedestrian's alcohol-only impairment (1 if yes; 0 otherwise)	0.052	0.222	0.048	0.214	0.048	0.214
Pedestrian crossing, entering road at intersection (1 if yes; 0 otherwise)	0.264	0.441	0.195	0.397	0.212	0.408
Pedestrian crossing, entering road at midblock (1 if yes; 0 otherwise)	0.203	0.402	0.237	0.425	0.215	0.411
Inattentive pedestrian (1 if yes; 0 otherwise)	0.204	0.403	0.188	0.390	0.206	0.405
Pedestrian in normal condition (1 if yes; 0 otherwise)	0.429	0.495	0.386	0.487	0.377	0.485
Season						
Fall (1 if yes; 0 otherwise)	0.280	0.449	0.284	0.451	0.294	0.456
Summer (1 if yes; 0 otherwise)	0.213	0.410	0.211	0.408	0.217	0.412
Spring (1 if yes; 0 otherwise)	0.259	0.438	0.200	0.400	0.230	0.421
Winter (1 if yes; 0 otherwise)	0.247	0.431	0.306	0.461	0.260	0.439
Lighting Condition						
Darkness with streetlight (1 if yes; 0 otherwise)	0.274	0.446	0.255	0.436	0.268	0.443
Darkness without streetlight (1 if yes; 0 otherwise)	0.139	0.346	0.163	0.369	0.178	0.383
Daylight (1 if yes; 0 otherwise)	0.484	0.500	0.481	0.500	0.453	0.498
Location Characteristics						
Business area (1 if yes; 0 otherwise)	0.263	0.440	0.240	0.427	0.246	0.431
Business and residential area (1 if yes; 0 otherwise)	0.365	0.482	0.338	0.473	0.342	0.474
Open country (1 if yes; 0 otherwise)	0.045	0.208	0.054	0.226	0.051	0.219
Residential area (1 if yes; 0 otherwise)	0.280	0.449	0.326	0.469	0.308	0.462

(*continued*).

Table 2. Continued.

	2019		2020		2021	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Road Type						
One-way road (1 if yes; 0 otherwise)	0.137	0.343	0.108	0.310	0.111	0.314
Divided two-way road (1 if yes; 0 otherwise)	0.227	0.419	0.206	0.404	0.228	0.420
Undivided two-way road (1 if yes; 0 otherwise)	0.585	0.493	0.638	0.481	0.607	0.488
Two-way road with barrier (1 if yes; 0 otherwise)	0.032	0.176	0.030	0.170	0.037	0.188
Vehicle Characteristics						
Running lights in daytime (1 if yes; 0 otherwise)	0.061	0.239	0.072	0.259	0.068	0.252
Headlights Off (1 if yes; 0 otherwise)	0.160	0.367	0.153	0.360	0.152	0.359
Headlights On (1 if yes; 0 otherwise)	0.404	0.491	0.420	0.494	0.427	0.495
Vehicle Type						
Passenger Car (1 if yes; 0 otherwise)	0.426	0.495	0.417	0.493	0.426	0.495
Truck or Van (1 if yes; 0 otherwise)	0.235	0.424	0.270	0.444	0.230	0.421
SUV (1 if yes; 0 otherwise)	0.238	0.426	0.211	0.408	0.236	0.424
Crash Type						
Rear end (1 if yes; 0 otherwise)	0.033	0.179	0.042	0.202	0.042	0.201
Right angle (1 if yes; 0 otherwise)	0.053	0.224	0.049	0.216	0.057	0.231
Non-collision with motor vehicle (1 if yes; 0 if no)	0.690	0.463	0.774	0.418	0.702	0.458
Driver's characteristics						
Driver's age 25–45 (1 if yes; 0 otherwise)	0.333	0.471	0.302	0.459	0.316	0.465
Driver's age 46–45 (1 if yes; 0 otherwise)	0.208	0.406	0.207	0.405	0.212	0.408
Driver's age older than 65 (1 if yes; 0 otherwise)	0.098	0.298	0.089	0.285	0.091	0.287
Young driver (1 if younger than 25; 0 otherwise)	0.116	0.321	0.153	0.360	0.147	0.354
Driver's Condition						
Distracted driver (1 if yes; 0 otherwise)	0.025	0.156	0.025	0.155	0.031	0.174
Inattentive driver (1 if yes; 0 otherwise)	0.130	0.336	0.153	0.360	0.148	0.355
Driver in normal condition (1 if yes; 0 otherwise)	0.509	0.500	0.495	0.500	0.495	0.500
Prior movement, making a left turn (1 if yes; 0 otherwise)	0.103	0.304	0.074	0.262	0.069	0.254
Prior movement, proceeding straight ahead (1 if yes; 0 otherwise)	0.578	0.494	0.619	0.486	0.619	0.486
Driver's alcohol & drug impairment (1 if yes; 0 otherwise)	0.002	0.048	0.004	0.065	0.007	0.081
Driver's alcohol-only impairment (1 if yes; 0 otherwise)	0.029	0.168	0.024	0.153	0.029	0.167
Driver's drug-only impairment (1 if yes; 0 otherwise)	0.004	0.064	0.008	0.088	0.006	0.077
Not impaired driver (1 if yes; 0 otherwise)	0.662	0.473	0.677	0.468	0.680	0.467

variable across the specified years, shedding light on various factors that may influence pedestrian crash severity. These factors encompass pedestrian conditions, season, lighting conditions, location characteristics, road type, vehicle characteristics, crash type, driver's characteristics, and driver's condition. The statistics allow for a comprehensive understanding of the characteristics and their variations over the study period, providing valuable information for the analysis and interpretation of pedestrian crash severity models.

Estimation methods

Theory

In this study, we have examined various factors that influence the severity of pedestrian crashes, categorising them into three outcomes: Severe Injury (SI), Minor Injury (MI), and No Injury (NI). Previous studies have employed a range of methodological approaches to examine pedestrian injury severity. For instance, (Hossain et al. 2024; Liu, Li, and Ng 2024) utilised the binary logit model to investigate injury severity in pedestrian crashes. (Barbour et al. 2024; Gang 2024; Tamakloe et al. 2023) employed multinomial logit modelling to analyze factors influencing pedestrian injuries. Additionally, numerous studies employed ordered probit modelling (Olowosegun et al. 2022; Salehian et al. 2023). Furthermore, there is a growing body of research utilising machine learning and deep learning techniques for analysing such factors (Elalouf, Birfir, and Rosenbloom 2023; Khan, Das, and Liu 2024). For our study, we employed a random parameters logit model, considering heterogeneity in means. The multinomial logit model, an unordered probability model, was chosen over the ordered logit and probit models because ordered models can produce biased and inconsistent estimates when there is underreporting, which is common in no-injury crash datasets. This problem does not affect unordered models like the multinomial logit model (see Savolainen and Mannering 2007). Other limitations with the probit and logit ordered models are the limitations placed by these models on a variable, influence (Geedipally, Turner, and Patil 2011; Savolainen and Mannering 2007). Kropko (2007) also found the multinomial logit to nearly always provide more accurate results than the probit models computer simulations. With the strength of multinomial logit models over the ordered logit and probit models, the choice of the multinomial logit model was justified. This approach allowed us to investigate potential factors influencing injury severity among pedestrians involved in crashes. The multinomial logit (MNL) model is well-suited for modelling choices among a set of discrete, non-ordered alternatives, as it does not assume any inherent order among the choices. Additionally, MNL modelling offers flexibility in utility specification, making it more advanced than ordered probit modelling. It allows for the incorporation of a wide range of explanatory variables that influence the probability of each injury severity outcome. Unlike ordered discrete choice models, which impose a monotonic effect on the dependent variables, the MNL model allows for a non-monotonic effect. This means that the relationship between explanatory variables and injury severity outcomes can vary in different directions and is not constrained to follow a single, increasing (or decreasing) pattern, thereby better capturing the complex nature of injury severities in this research. Furthermore, we assessed the stability of these factors over time, as suggested by (Mannering, Shankar, and Bhat 2016). To establish this model, we began by defining a function that determines the severity of injuries sustained by pedestrians (Washington et al. 2020) as:

$$S_{ij} = \boldsymbol{\beta}_i \boldsymbol{X}_{ij} + \varepsilon_{ij} \tag{1}$$

Here, S_{ij} represents the function determining the probability of pedestrian injury severity at level i in crash j, $\boldsymbol{X}_{ij}$ is a vector of explanatory variables that alter the outcome of injury severity level i. $\boldsymbol{\beta}_i$ is the vector of estimable parameters and ε_{ij} represents the error term, assumed to follow an independent and identically distributed extreme value distribution. If the error term is presumed to follow generalised extreme value distribution, the result is standardised multinomial logit (McFadden 1981):

$$P_j(i) = \frac{EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{ij})}{\sum_{\forall I} EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{ij})} \tag{2}$$

Where $P_j(i)$ represents the probability that crash j will lead to pedestrian injury severity level i. To accommodate the possibility of parameters being random and varying across observations in the vector $\boldsymbol{\beta}_i$, Equation (2) modifies as (Train 2009),

$$P_j(i) = \int \frac{EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{ij})}{\sum_{\forall I} EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{ij})} f(\beta|\varphi) d\beta \tag{3}$$

Where $f(\beta|\varphi)$ denotes the probability density function of $\boldsymbol{\beta}_i$ with φ describing the characteristics of the density function.

To account for potential variations in the means and variances of random parameters, $\boldsymbol{\beta}_{ij}$ is defined to vary across different crashes, and it is an estimable vector as: (Alnawmasi and Mannering 2019; Behnood and Mannering 2019, 2017; Mannering, Shankar, and Bhat 2016; Pang et al. 2022; Seraneeprakarn et al. 2017; Waseem, Ahmed, and Saeed 2019; Washington et al. 2020);

$$\boldsymbol{\beta}_{ij} = \beta_i + \Theta_{ij} \boldsymbol{Z}_{ij} \tag{4}$$

Where the mean parameter estimate β_i is associated with the mean value across all crashes. The vector $\boldsymbol{Z}_{ij}$ represents a set of crash specific independent variables that accommodate variations in means influencing the severity of pedestrian injury level i, while Θ_{ij} is the corresponding vector of estimable parameters.

Previous studies (Adanu, Dzinyela, and Agyemang 2023; Alnawmasi and Mannering 2019; Dzinyela et al. 2024; Mannering, Shankar, and Bhat 2016) have demonstrated that normal distribution is statistically superior to other distributions. Therefore, we adopted the assumption that random parameters follow a normal distribution. We applied a simulated maximum likelihood approach with 1000 Halton draws to the model (Bhat 2001; McFadden and Train 2000; Train 2009; Washington et al. 2020). Marginal effects are computed for each explanatory variable to assess the impact of one-unit change in each explanatory variable on pedestrian injury severity.

Temporal stability tests

In safety literature, it is widely acknowledged that the impact of explanatory variables in statistical models for crash likelihoods and outcomes experiences temporal variations due to a range of factors like shifts in traffic flow patterns, advancements in vehicle technologies, fluctuations in weather conditions, changes in road infrastructure, economic influences on travel behaviours, regulatory adjustments, and the effectiveness of public awareness campaigns. The dynamic interplay of these factors necessitates a comprehensive understanding to adapt safety measures effectively and mitigate variations in road safety outcomes over time (Mannering 2018b).

To empirically investigate whether models for pedestrian injury severity exhibit significant differences during the years spanning from 2019 to 2021, a series of likelihood ratio tests were performed. These tests aimed to compare the models developed each year, with the objective of ascertaining the stability of estimated parameters over time. Two primary types of likelihood-ratio tests are commonly employed to assess whether the impacts of explanatory variables exhibit significant variations across different time periods: the global test and the pairwise test. The global test is conducted using a model estimated from the complete dataset encompassing all time periods and individual models representing each specific time period within the dataset. This assessment is carried out by computing Equation (5). The test statistic follows a chi-squared distribution (with degrees of freedom equivalent to the number of estimated parameters), as outlined in (Washington et al. 2020).

$$X^2 = -2[LL(\beta_T) - \sum_{t}^{T} LL(\beta_t)] \tag{5}$$

In this context, $LL(\beta_T)$represents the log-likelihood of the converged model using the complete dataset spanning all time periods (referred to as the full model), $LL(\beta_t)$is the log-likelihood at convergence for a model specific to the t^{th} time period, and T stands for the total number of time periods. The resulting statistic, X^2, follows a chi-squared distribution, with degrees of freedom equivalent to the difference between the total number of parameters included in the model for each time period and the number of parameters in the full model.

To assess the temporal stability of parameters between any two of the time periods, the following pairwise test can be utilised:

$$X^2 = -2[LL(\beta_{t_2,t_1}) - LL(\beta_{t_1})] \tag{6}$$

Where $LL(\beta_{t_2,t_1})$ represents the log-likelihood at model convergence using data from time-period t_2, with parameters converged based on data from time-period t_1, and $LL(\beta_{t_1})$ stands for the log-likelihood at model convergence using data from time-period t_1, with parameters no longer restricted to those from time-period t_2, as seen in $LL(\beta_{t_2 t_1})$. This test was also reversed, exchanging time-period t_1 and t_2 to obtain two test results for each year's comparison. The resulting X^2follows a chi-squared distribution and is employed to determine whether the null hypothesis, suggesting that the parameters are equal in the two years, can be confidently rejected. The results, as shown in Table 3, demonstrate that the null hypothesis of model estimates being consistent from one year to the next can be confidently rejected with over 99% confidence, indicating statistically significant variations from year to year.

Table 3. Likelihood ratio test results between different time periods based on random parameters logit with heterogeneity in means. (confidence level with degrees of freedom in parenthesis and χ^2 values in brackets).

	t_2		
t_1	2019	2020	2021
2019	–	83.6793(19) [> 99.99%]	80.02078(21) [> 99.99%]
2020	92.14089(21) [> 99.99%]	–	63.1616(21) [> 99.99%]
2021	99.07531(21) [> 99.99%]	82.80236(19) [> 99.99%]	–

Constrained vs. Unconstrained temporal modeling

In terms of modelling, there are three general approaches to addressing temporal shifts in parameters: fully temporally constrained parameters, temporally unconstrained parameters, and partially temporally constrained parameters. Fully temporally constrained parameters entail forcing all model parameters to remain constant over time, which is a common practice when pooling multiple years of data without considering the potential for parameter shifts. Temporally unconstrained parameters involve splitting the data into time periods and estimating separate models for each period, allowing all parameters to vary from one time to the next. The results obtained through temporal data splitting are equivalent to those from using all the data at once and creating time-specific variables. Partially temporally constrained parameters involve using all the data and conducting statistical tests to determine if specific parameters from one or more time periods can be combined. This approach, often implemented with maximum likelihood estimation and likelihood ratio tests, typically results in a model where the impact of some variables changes from one time period to another, while the effects of other variables remain relatively stable across one or more time periods (Alnawmasi and Mannering 2023; Dzinyela et al. 2024).

The temporally unconstrained likelihood ratio test results in Table 3 indicate significant shifts in model parameters over time concerning pedestrian crash severity. To estimate the partially temporally constrained model, all three years of data (2019, 2020, and 2021) are considered, and variables are defined for each year. It’s essential to note that this approach results in the same estimation as separately estimating unconstrained models for each year. Subsequently, within this all-years model, a series of likelihood ratio tests is conducted to ascertain whether constraining parameters for individual variables over one or more years is statistically justified. The comparison involves evaluating unconstrained temporal parameters (derived from splitting the data temporally by year or using all years with time-specific variables) against partially temporally constrained parameters (where the statistical similarity of some parameters over time is tested, and if confirmed, these parameters are constrained to remain the same over time while allowing others to vary). The statistical test is represented as (Alnawmasi and Mannering 2023):

$$\mathrm{X}^2 = -2[LL(\beta_C) - LL(\beta_U)] \tag{6}$$

Where $LL(\beta_U)$ signifies the log-likelihood at convergence of the unconstrained parameters, where all parameters for a specific variable are permitted to vary for each period. In contrast, $LL(\beta_C)$stands for the log-likelihood at convergence of the constrained parameters where the variable’s parameter is constrained to maintain the same value over one or more time periods. The resulting X^2 statistic follows a chi-squared distribution and is employed to assess whether the null hypothesis, implying that the constrained and unconstrained parameters are equivalent, can be confidently rejected. The degrees of freedom correspond to the difference in the number of parameters estimated. If the null hypothesis is confidently rejected, it supports the use of unconstrained parameters, signifying separate yearly parameters for each variable. In the event that the null hypothesis cannot be confidently rejected, the constrained model is estimated appropriate. This testing procedure is conducted for each variable within the model.

Model estimation results

Table 1 contains information on the counts of pedestrian injury severities for each level spanning from 2019 to 2021. For a concise overview of the key variables that played a significant role in the modelling process and influenced the severity of pedestrian injuries, please refer to Table 2. In this study, we employed a random parameters logit model with heterogeneity in means (RPLHMV). The results of temporally unconstrained parameter estimation for the random parameters logit model, accounting for heterogeneity in means, regarding injury severities from pedestrian crashes during the years 2019–2021, can be found in Appendix Tables A.1–A.3.

The primary focus of this paper lies in the presentation of the parameter estimation results under partial temporal constraints, as depicted in Table 4. Our analysis suggests that we cannot definitively conclude that the unconstrained and partially constrained models exhibit significant differences from each other. This conclusion is supported by the results of likelihood ratio tests, which indicate that the null hypothesis, positing the equality of the partially constrained and unconstrained models, cannot be convincingly rejected. The test statistic for this is (Alnawmasi and Mannering 2023):

$$X^2 = -2[LL(\beta_{PC}) - LL(\beta_{U,2019}) - LL(\beta_{U,2020}) - LL(\beta_{U,2021})] \quad (7)$$

where $LL(\beta_{U,2019}), LL(\beta_{U,2020}), LL(\beta_{U,2021})$ represent the log-likelihood at convergence of the unconstrained parameters, where all parameters for a specific variable are allowed to vary for each respective year (detailed estimation results are provided in the appendix). Additionally, $LL(\beta_{PC})$ represents the log-likelihood at convergence of the model with partially constrained parameters, where some variables have their parameter values constrained to be the same across one or more time periods. The resulting value X^2 follows a χ^2distribution and is used to assess whether the null hypothesis, which posits that the constrained and unconstrained parameters are equal, can be rejected. The degrees of freedom for this statistic are determined by the difference in the number of estimated parameters. For this specific model, the computed statistic is $-2 * [-4552.61$ - $(-1666.61–1382.65–1496.98)] = 12.74$ with 13 degrees of freedom $(21 + 19 + 21 - 48)$. This means that the null hypothesis that the unconstrained and partially constrained models are the same can only be rejected with 46.81% confidence. Consequently, we cannot conclusively assert that the unconstrained and partially constrained models are significantly different from each other. However, with the partially constrained models, one can identify explanatory variables that are temporally stable or unstable over the years under study. It's important to note that the appendix tables (Table A1, Table A2, and Table A3) reveal that all estimated models exhibit at least one statistically significant random parameter, some of which display statistically significant heterogeneity in the means and variances. Shifting our focus to the partially temporally constrained model results in Table 4, it becomes evident that the constant defined for severe injuries remains consistent in 2019, 2020 and 2021.

Variables producing the same parameter value across all years

In Table 4, which incorporates data from all years in the model, three variables consistently demonstrate unchanging and statistically significant effects over time. Firstly, pedestrian

Table 4. Partially temporally constrained random parameters logit with heterogeneity in means results for pedestrian-vehicle crash-injury severities (parameters defined for: [NI] No Injury; [MI] Minor Injury; [SI] Severe Injury; years [2019], [2020], [2021])

			Marginal Effects		
Variable Description	Estimated Parameter	t-stat	Severe	Minor	No Injury
Constant [SI] [2019,2020,2021]	0.84979	11.78			
Variables producing the same parameter value across all years					
Pedestrian crossing, entering road at intersection [NI][2019,2020,2021]	0.33265	3.92	−0.0101	0.0143	−0.0043
Pedestrian crossing, entering road at midblock [MI][2019,2020,2021]	−0.77386	−5.7	0.0075	0.0056	−0.0131
Darkness without streetlight [NI][2019,20202021]	1.13941	7.19	−0.0137	−0.0105	0.0243
Random Parameters (Normally distributed)					
Undivided two-way road [NI][2019]	−2.72682	−2.47	−0.0025	−0.0025	0.0051
Standard deviation undivided two-way road [2019]	4.72792	2.97			
Passenger car [MI][2019]	−0.38431	−0.86	−0.0038	0.0061	−0.0023
Standard deviation Passenger car [2019]	3.15818	1.97			
Driver's age 25–45 [SI][2019]	−0.63248	−2.93	−0.0063	0.005	0.0013
Standard deviation [2019]	1.79793	1.77			
Undivided two-way road [NI][2020]	−1.1704	−1.95	−0.0045	−0.004	0.0085
Standard deviation of undivided two-way road [2020]	4.22348	3.61			
Undivided two-way road [NI][2021]	−0.74153	−2.59	0.0045	0.004	−0.0085
Standard deviation of undivided two-way road [2021]	1.24009	2.16			
Heterogeneity in mean of the random parameter					
Undivided two-way road: Daylight [2019]	−2.13405	−2.16			
Undivided two-way road: Daylight [2020]	−2.75408	−2.97			
Undivided two-way road: Inattentive pedestrian [2021]	−0.63966	−2.43			
Crash characteristics					
Prior movement, making a left turn [MI][2021]	0.55034	2.58	−0.0024	0.0029	−0.0005
Prior movement, making a left turn [NI] [2019]	−1.31021	−2.37	0.001	0.0006	−0.0016
Prior movement, making a left turn [NI][2020]	−1.71389	−2.05	0.0005	0.0004	−0.0009
Prior movement, proceeding straight ahead [SI][2019]	−0.39094	−3.11	−0.0132	0.0093	0.0039
Prior movement, proceeding straight ahead [NI][2020]	0.79157	4.71	−0.0079	−0.0078	0.0157
Prior movement, proceeding straight ahead [SI] [2021]	−0.61814	−6.03	−0.0264	0.0169	0.0095
Vehicle headlights off [NI][2021]	−1.49201	−4.86	0.0028	0.002	−0.0047
Crash type, non-collision with motor vehicle [MI][2020]	0.69748	6.83	−0.0273	0.0353	−0.008
Driver characteristics					
Driver's age less than 25 years [NI][2021]	0.52168	2.44	−0.0019	−0.0018	0.0037
Driver's age 25–45 [NI][2020,2021]	0.36737	3.06	−0.0049	−0.0046	0.0095
Driver's age 46–65 [SI][2019]	−0.27249	−1.84	−0.004	0.0031	0.0009
Driver's age older than 65 years [NI][2020]	−1.11891	−2.08	0.0008	0.0007	−0.0015

(*continued*).

Table 4. Continued.

Variable Description	Estimated Parameter	t-stat	Marginal Effects		
			Severe	Minor	No Injury
Driver's age older than 65 years [MI][2021]	−0.30576	−1.54	0.0014	−0.0018	0.0004
Driver's alcohol-only impairment [NI][2020,2021]	1.07552	2.98	−0.0013	−0.0013	0.0026
Inattentive driver [NI][2019,2020]	−1.13077	−3.91	0.003	0.0021	−0.0051
Pedestrian characteristics					
Inattentive pedestrian [NI][2020]	−1.2476	−3.58	0.0021	0.0021	−0.0043
Pedestrian alcohol impairment [SI][2019]	−0.95491	−2.96	−0.0028	0.002	0.0008
Roadway and Environmental Characteristics					
Darkness with streetlights [SI][2019]	−0.31119	−2.06	−0.0051	0.0035	0.0016
Darkness with streetlights [SI][2020]	−0.49963	−3.57	−0.0074	0.0055	0.0019
Darkness with streetlights [SI][2021]	−0.42722	−3.39	−0.0078	0.0051	0.0027
Summer [SI][2021]	−0.27498	−2.06	−0.0041	0.0027	0.0015
Winter [SI] [2020]	0.365	2.89	0.0072	−0.0054	−0.0018
Roadway/Spatial Characteristics					
Open country [MI][2021]	−0.70615	−2.2	0.0009	−0.0016	0.0007
Open country [NI] [2019]	1.25119	3.06	−0.0014	−0.0011	0.0026
Residential area [NI] [2020]	−0.6609	−2.3	0.0023	0.0019	−0.0042
Residential area [SI] [2019]	0.31762	2.1	0.0052	−0.004	−0.0012
One way road [NI] [2019]	−1.04497	−3.92	0.0023	0.0015	−0.0038
Divided two-way road. [SI] [2020]	−0.39632	−2.74	−0.0052	0.0034	0.0018
Divided two-way road with barrier [SI][2021]	−0.87811	−2.55	−0.0017	0.0008	0.0009
Vehicle characteristics					
SUV [NI] [2019]	−0.48571	−2.15	0.0015	0.0015	−0.003
Passenger car [NI] [2021]	−0.32609	−2.34	0.0033	0.0029	−0.0062
Model Statistics					
Log-likelihood at convergence, LL(β)	−4552.61				
Log-likelihood at zero, LL (0)	−5087.67				
$\rho 2 = 1 - \text{LL}(\beta)/\text{LL}(0)$	0.11				
Corrected $\rho 2 = 1 - [\text{LL}(\beta)\text{-}48]/\text{LL}(0)$	0.10				
Number of observations	4631				

crossings at intersections consistently lead to a reduction in the likelihood of no pedestrian injuries and severe pedestrian injuries, supported by the marginal effects detailed in Table 4, emphasising the importance of using designated intersections for pedestrian safety. Secondly, pedestrian crossings at midblock locations consistently contribute to a higher probability of severe and minor pedestrian injuries. Thirdly, the absence of streetlights in dark conditions consistently leads to a lower probability of severe and minor pedestrian injuries.

Variables producing random parameters

When examining variables that produce random parameters, the 'undivided two-way road' consistently exhibited statistically significant random parameters in each yearly model (Table A1, Table A2, and Table A3). The findings in Table 4 demonstrate that this indicator had statistically significant random parameters in the years 2019, 2020, and 2021, resulting in variations in the likelihood of pedestrian injury severities. Specifically, crashes occurring on undivided two-way roads were associated with higher probabilities of no injuries for pedestrians in 2019 and 2020 while simultaneously reducing the probability of minor and severe injuries. In contrast, in 2021, crashes on undivided two-way roads were linked to a higher probability of severe and minor injuries for pedestrians, with a decrease in the likelihood of no pedestrian injuries. Of all the parameters, it was observed that 'daylight' had a negative impact on the mean of the random parameter 'undivided two-way road' in 2019 and 2020, resulting in a decrease in the mean of 'undivided two-way road.' Additionally, the presence of 'inattentive pedestrians' also caused a downward shift in the mean of the random parameter 'undivided two-way road' in 2021. Furthermore, in 2019, the parameter representing drivers aged between 25 and 45 years old was identified as a random factor, indicating an increased likelihood of minor pedestrian injuries and no pedestrian injuries, as well as a decreased likelihood of severe pedestrian injuries. Additionally, the parameter associated with passenger car in 2019 was recognised as a random parameter, demonstrating an elevated probability of minor pedestrian injuries.

Variables producing fixed parameters

Analyzing crash characteristics, we observe varying patterns in pedestrian injury severities over different years. Left-turn collisions were linked to a higher likelihood of minor injuries in 2021, while in 2019 and 2020, they were associated with a higher likelihood of severe and minor injuries. For crashes occurring while proceeding straight ahead, they had a higher likelihood of minor and no injuries in 2019 and 2021, while in 2020, only the likelihood of no injuries increased for such incidents. Regarding crashes with the vehicle's lights turned off, this factor became significant only in 2021, and it was linked to an increased in probability of severe and minor pedestrian injuries. The final variable in crash characteristics, the indicator 'crash type, non-collision with a motor vehicle,' demonstrated statistical significance in 2020, indicating a heightened likelihood of minor injuries to pedestrians. Shifting our focus to driver characteristics, the model results in Table 4 indicate that young drivers aged less than 25 years old were associated with a higher likelihood of no pedestrian injuries in 2021. For drivers that were aged 25–45 years old the likelihood of no injuries increased in 2020 and 2021. Additionally, drivers aged 46–65 in 2019 demonstrated a decreased likelihood of severe injuries, with the marginal effect suggesting a greater propensity for minor injuries in the event of a pedestrian collision and the lowest probability of severe injuries. In 2020, drivers older than 65 years were associated with a higher likelihood of both severe and minor injuries. Conversely, in 2021, they were linked to a higher likelihood of severe injuries and no pedestrian injuries In 2020 and 2021, drivers impaired by alcohol exhibited a heightened probability of no pedestrian injuries altogether, along with the same reduced likelihood of experiencing severe and minor injuries for pedestrians. In contrast, inattentive drivers in 2019 and 2020 demonstrated a reduced likelihood of escaping pedestrian injuries, with a higher propensity for sustaining severe pedestrian injuries, as indicated by the marginal effects in Table 4.

In terms of pedestrian characteristics, inattentive pedestrians were found to be associated with a reduced probability of no pedestrian injury. The marginal effect indicates approximately the same likelihood for inattentive pedestrians to sustain severe or minor injuries in 2020. In 2019, impaired pedestrians under the influence of alcohol exhibited a decreased probability of sustaining severe injuries. According to the marginal effect, pedestrians affected by alcohol were 0.002 more likely to experience minor injuries and 0.0028 less likely to endure severe injuries. The increased likelihood of no pedestrian injuries while drivers were impaired and the decreased likelihood of severe injuries for impaired pedestrians could be attributed to the findings of Saeed et al. (2020). Their study suggests that pedestrian injury patterns in alcohol-impaired incidents are not isolated but are influenced by local and neighbouring areas' alcohol-related crash rates, the abundance of alcohol-related businesses, and regional influences. Additionally, residents near state borders may cross into neighbouring states to avoid stricter alcohol regulations, contributing to increased crash rates and shaping the overall injury outcomes.

Regarding roadway and environmental characteristics, the presence of streetlights in dark conditions heightened the likelihood of sustaining no visible or minor injuries in 2019, 2020, and 2021. Across all three years, the probability of minor pedestrian injuries was consistently higher than that of no pedestrian injuries, indicating that pedestrians are more likely to incur minor injuries in well-lit areas during darkness. This could be attributed to increased visibility provided by streetlights, potentially justifying the reduced likelihood of severe injuries in such illuminated environments. Furthermore, the decreased likelihood of severe injuries can be attributed to the improved visibility afforded by streetlights, thereby reducing the probability of sustaining severe injuries. In 2020, the probability of severe pedestrian injuries increased during the winter due to factors such as adverse weather conditions and reduced visibility. However, in the following summer of 2021, the likelihood of pedestrians sustaining severe injuries decreased, likely as a result of improved weather conditions and increased visibility during that season.

In terms of road and spatial characteristics, in 2019, crashes that occurred in open country areas were associated with a higher probability of pedestrians sustaining no injuries. The likelihood was decreased for both minor and sever injuries. The marginal effects revealed a lower likelihood of pedestrian sustaining severe injuries compared to minor injuries for crashes occurring in these areas. However, in 2021, the likelihood of pedestrians sustaining minor injuries decreased in crashes in these areas, while the likelihood of severe injuries and no injuries increased. This increase was more pronounced for severe injuries compared to no injuries. Additionally, in residential areas, the probability of pedestrians sustaining severe injuries increased in 2019, while the probabilities of minor and no injuries both decreased. Specifically, it is less likely for pedestrians to sustain minor injuries in such areas. In contrast, the likelihood of no pedestrian injuries further decreased for crashes that occurred in residential areas in 2020, with an increase observed in both severe and minor injuries. Notably, the rise is more pronounced for severe injuries. Crashes taking place on one-way roads in 2019 were lined to a heightened likelihood of both severe and minor pedestrian injuries, with a more pronounced impact observed specifically in severe injuries. However, for divided two-way roads, the probability of severe pedestrian injuries decreased in 2020, signifying a safer environment for pedestrians involved in crashes on such roads during that year. Pedestrians involved in a crash on those roads were more likely to sustain minor injuries compared to no visible injury. This trend remained consistent in 2021, as crashes that occurred on divided two-way roads with barriers had a lower likelihood of pedestrians sustaining severe injuries, but the likelihood of sustaining no injuries was higher than that of minor injuries.

Table 5. Average (standard deviation) differences in estimated model-predicted vs. observed pedestrian injury probabilities.

Year	No Injury	Minor Injury	Severe Injury
2019–2020	−0.039 (0.104)	−0.003 (0.119)	0.043 (0.104)
2020–2021	−0.014 (0.113)	0.007 (0.117)	0.007 (0.104)

In terms of variables related to vehicle characteristics, SUVs in 2019 were linked to an increase in the likelihood of both severe and minor injuries by the same magnitude (0.0015), while the likelihood of no injuries decreased. The category 'passenger car' was also associated with a higher probability of sustaining both severe and minor injuries and a lower likelihood of no injuries. Marginal effects indicate that the probability of sustaining severe injuries was more pronounced than that of minor injuries for such crashes.

Out-of-sample predictions

For out-of-sample predictions, we employ the estimated parameters from 2019, using them in conjunction with observed 2020 crash data to forecast the resulting injury severities. We then compare these predictions to those generated for 2020 crashes using the parameters and data from that same year. This out-of-sample prediction approach is necessary as it involves estimating injury probabilities using parameters from a distinct sample. It's important to note that using only the means of the random parameters can lead to significantly biased probability estimates. For a more in-depth understanding of this technique, Hou et al. (2022) provide a comprehensive explanation, discussion, and empirical assessment.

The results of the out-of-sample simulations are presented in Table 5. The difference between the predicted severity probabilities for pedestrians in 2020, using 2019-estimated parameters with 2020 data, and using 2020 data with 2020 estimated parameters, show that the prediction of pedestrian injury outcomes was very close. Using the mean of the predicted pedestrian injury severity probabilities, the 2019 model overestimated severe injuries by an average of 0.0426 and underestimated minor and no injury by 0.0032 and 0.0395 respectively. The disparities in predicted severity probabilities for pedestrians in 2021, when utilising 2020-estimated parameters with 2021 data and comparing to using 2021 data with 2021 estimated parameters, reveal that the proportions of severe and minor injuries are expected to be 0.0071 and 0.0073 higher, respectively, while the proportion of no injuries is projected to be 0.0144 lower. Based on these results, the 2019 model parameters predicting 2020 severe injuries and the 2020 model parameters predicting 2021 severe injuries would have predicted more severe injuries than actually occurred. In spite of the unclear reasons why there are less severe injuries as compared to what was predicted, one could argue that the progression of vehicle technologies, road designs and also various safety campaigns are producing beneficial results.

Figure 1 summarise the distribution of differences between the pedestrian 2019 estimated model predicted injury probabilities using 2020 data and 2019 'observed' probabilities and Figure 2 summarise difference between the pedestrian 2020 estimated model predicted injury probabilities using 2021 data and 2020 'observed' probabilities.

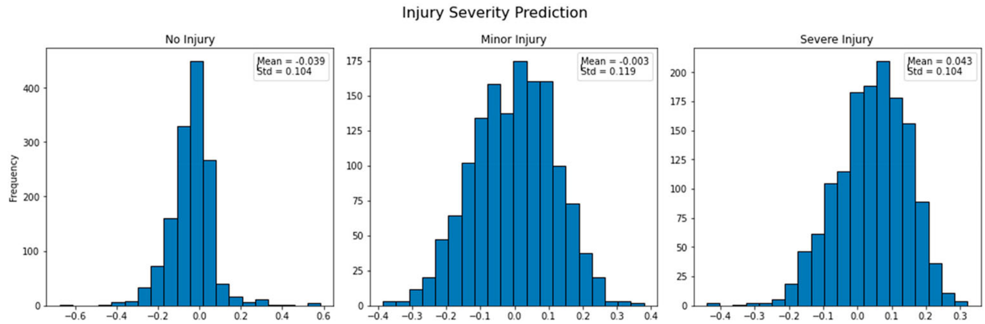

Figure 1. Difference between the pedestrian 2019 estimated model predicted injury probabilities using 2020 data and 2019 'observed' probabilities.

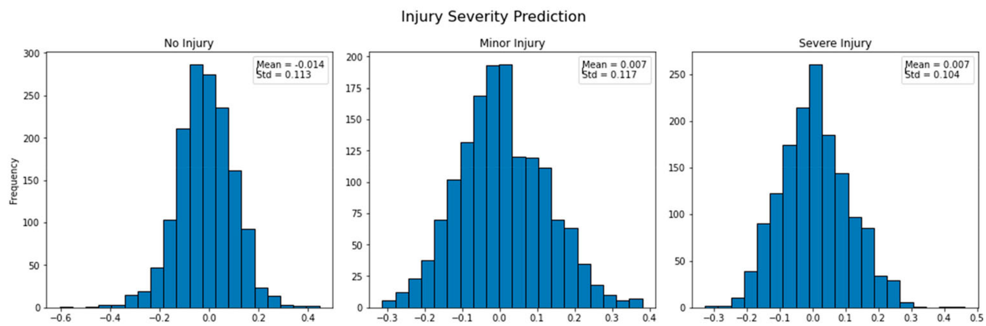

Figure 2. Difference between the pedestrian 2020 estimated model predicted injury probabilities using 2021 data and 2020 'observed' probabilities.

Key findings

This study encompasses a comprehensive analysis of factors influencing the severity of pedestrian injuries from 2019 to 2021. Key variables and their significance are presented in Tables 1 and 3, offering an essential overview. The study employs a random parameters logit model with heterogeneity in means, providing detailed results in Table A1, Table A2, and Table A3 in the appendix. The focus lies in comparing unconstrained and partially constrained models, with the likelihood ratio tests suggesting that differences between these models are not statistically significant. Table A1, Table A2, and Table A3 present the results of a temporally unconstrained random parameters logit model with heterogeneity in means for pedestrian-vehicle crash-injury severities in 2019, 2020, 2021 respectively. The estimated parameters are provided for three injury categories: Severe Injury (SI), Minor Injury (MI), and No Injury (NI). Table 4 provides insights from a partially temporally constrained random parameters logit model, capturing heterogeneity in means for pedestrian-vehicle crash-injury severities across 2019, 2020, and 2021. Pedestrian crossing, entering at intersection, pedestrian crossing, entering at midblock, and darkness with streetlight produced the same parameter value across all years. Notable findings include the impact of the constant term (2019,2020,2021), winter season (2020), and residential area (2019) on severe injuries, making a left turn (2021), non-collision with a motor vehicle (2020) on minor injuries, pedestrian crossing or entering the road at an intersection (2019, 2020, 2021), darkness without streetlight (2019, 2020, 2021), proceeding straight ahead (2020), young driver aged less than 25 years old (2021), and driver aged between 25–45 years old (2020,2021), as well as driver's alcohol-only impairment (2020, 2021), all exhibited a positive impact on injury probabilities over all years of the study. In each category, these variables increased the likelihood of crash severity. Regarding the variables with a negative impact on injury severity probabilities, the study identifies that driver aged between 25–45 years old (2019), proceeding straight ahead (2019, 2021), drivers aged 46–65 (2019), pedestrians with alcohol impairment (2019), incidents occurring in darkness with streetlights (2019, 2020, 2021), summer season (2021), and incidents on a divided two-way road (2020) or a divided two-way road with a barrier (2021) all contribute to a decreased likelihood of severe injuries. Similarly, for minor injuries, variables including pedestrian crossing or entering the road at midblock (2019, 2020, 2021), passenger car (2019), older drivers aged over 65 years (2021), and incidents occurring in open country areas (2021) exhibited a negative impact which indicated reduced probabilities of pedestrian injury severities. In the category of no injury, variables such as scenarios on undivided two-way roads (2019), making a left turn (2019, 2020), incidents with vehicle headlights off (2021), involvement of drivers older than 65 years (2020), inattentive drivers (2019, 2020), and inattentive pedestrians (2020), incidents in residential areas (2020), on one-way roads (2019), and those involving SUVs (2019) and passenger cars (2021) contributed to a reduced likelihood of injuries.

The marginal effects of some variables were observed to differ before, during, and after the COVID-19 pandemic. For example, crashes on open county roads in 2019 (pre-COVID) were less likely to result in severe injuries, whereas crashes in 2021 (post-COVID) were more likely to cause severe injuries. Additionally, the variable for pedestrian crossing, entering road at midblock increased the probability of severe injury in 2020 (during COVID) compared to pre-COVID and post-COVID periods, where it reduced the likelihood of severe injury. These findings align with previous studies, such as Islam et al. (2023), which attributed severe crashes during the COVID period to an increased likelihood of risky drivers travelling. Mannering (2018) also noted fundamental changes in driver behaviour, vehicle technology, and weather conditions over the years, contributing to temporal trends in crash data. Out-of-sample predictions further indicate an increase in the probability of severe injuries over the years. These findings underscore the importance of evaluating crashes at disaggregated levels, as aggregating data may obscure relevant information.

Random parameter undivided two-way road exhibits variations across the years, displaying heterogeneous mean effects. In the years 2019 and 2020, daylight conditions contributed to a downward shift in the mean of the random parameter for undivided two-way roads. This suggests that crashes occurring on undivided two-way roads during daylight hours tend to be less severe than those happening during nighttime. Furthermore, in the year 2021, the presence of inattentive pedestrians caused a similar downward shift in the mean of the random parameter for undivided two-way roads. This implies that crashes involving undivided two-way roads and inattentive pedestrians during this year were associated with reduced severity compared to other scenarios. The observed variations highlight the dynamic nature of these factors over time and their impact on the severity of crashes on undivided two-way roads.

Conclusions

This study undertook a careful examination of pedestrian injury severity from 2019 to 2021, employing a random parameters logit model with heterogeneity in means. The investigation revealed significant insights into the impact of various factors on pedestrian-vehicle crash injury severities. The detailed presentation of key variables and their significance provides a valuable resource for understanding the nuances of pedestrian safety. The focus on comparing unconstrained and partially constrained models through likelihood ratio tests further strengthens the analytical framework. The findings illuminate noteworthy patterns in the influence of specific variables on injury probabilities across the studied years. Factors such as road characteristics, driver behaviour, and environmental conditions were shown to play crucial roles in shaping the severity of pedestrian injuries. The temporal analysis indicated statistically significant differences in injury severity before, during, and after the COVID-19 pandemic, highlighting the importance of considering temporal dynamics in pedestrian safety research. By identifying the variables that significantly impact pedestrian injury severity, policymakers and traffic safety professionals can formulate targeted strategies to mitigate risks and enhance pedestrian safety on roadways. The detailed insights provided by this study encourages future research efforts aimed at reducing the alarming trend of pedestrian injuries observed in recent years.

It is important to recognise several limitations in this study that may influence the interpretation and generalisation of the findings. Firstly, the geographical focus on pedestrian-vehicle crashes in Louisiana raises concerns about the applicability of the results to regions with distinct traffic dynamics and infrastructure. Additionally, reliance on data reported by state police officers might be associated with potential biases and variations in reporting practices across jurisdictions, non-reporting, missing information, unavailability of near-crash information impacting the accuracy and completeness of the dataset. For instance, the absence of detailed demographic information about the pedestrians, such as age and gender, can be considered as a limitation. The data provided only includes behavioural information. Future studies can incorporate these demographic factors to better understand their influence on the injury severity of pedestrians in crashes. The temporal scope of three years may not capture long-term trends or subtle shifts in pedestrian safety patterns. The chosen modelling approach, while powerful, simplifies real-world complexities and assumes independence of irrelevant alternatives. External factors such as socioeconomic variables, urban planning policies, and unaccounted-for changes in pedestrian behaviour could also influence the outcomes. Furthermore, the study identifies associations but does not establish causation, and the observed relationships may be confounded by unexplored variables. Lastly, the impact of the COVID-19 pandemic on pedestrian safety, though acknowledged, may not be comprehensively captured. Even though much of 2020 was dominated by the Covid-19 pandemic, subsequent research endeavours could explore the occurrences of crashes during the specific months coinciding with the emergence of Covid-19 and subsequent implementations of lockdown measures, up to the point where these restrictions were eased. Despite these limitations, this research serves as a valuable starting point, highlighting the need for future studies that address these constraints to enhance the depth and breadth of knowledge in pedestrian safety research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix: Estimation results for temporally unconstrained models

Table A1. Temporally unconstrained random parameters logit with heterogeneity in means results for pedestrian-vehicle crash-injury severities for 2019 (parameters defined for: [NI] No Injury; [MI] Minor Injury; [SI] Severe Injury).

			Marginal Effects		
Variable Description	Estimated Parameter	t-stat	*Severe*	Minor	No Injury
Constant [SI]	0.96	6.64			
Random Parameters (Normally distributed)					
Undivided two-way road [NI]	−3.14	−2.02	−0.0069	−0.0073	0.0141
Standard deviation of undivided two-way road	5.41	2.43			
Driver's aged 25–45 [SI]	−0.72	−3.01	−0.0167	0.0129	0.0038
Standard deviation of Driver's age 25–45	2.07	2.1			
Passenger car [MI]	−0.60	−0.9	−0.0099	0.0165	−0.0067
Standard deviation of passenger car	4.21	1.75			
Heterogeneity in mean of the random parameter					
Undivided two-way road: Daylight	−2.37	−1.88			
Crash Characteristics					
Prior movement, proceeding straight ahead [SI]	−0.45	−3.1	−0.0378	0.0265	0.0113
Prior movement, making a left turn [NI]	−1.22	−2.1	0.0024	0.0014	−0.0038
Driver Characteristics					
Driver's age 46–65 [SI]	−0.32	−1.96	−0.0123	0.0094	0.0029
Inattentive driver [NI]	−1.49	−2.78	0.0042	0.0027	−0.0069
Pedestrian Characteristics					
Pedestrian alcohol impairment [SI]	−0.99	−2.99	−0.0074	0.0054	0.002
Pedestrian crossing, entering road at midblock [MI]	0.35	1.9	−0.0074	0.01	−0.0025
Pedestrian crossing, entering road at intersection [NI]	−0.84	−3.1	0.0073	0.0043	−0.0116
Roadway and Environmental Characteristics					
Darkness with streetlights [SI]	−0.38	−2.28	−0.0155	0.0104	0.0051
Darkness without streetlights [NI]	1.36	3.45	−0.0088	−0.0065	0.0153
Roadway/Spatial Characteristics					
Residential area [SI]	0.29	1.73	0.0117	−0.009	−0.0027
One-way road [NI]	−1.04	−3.76	0.0061	0.0037	−0.0097
Open country [NI]	1.31	2.99	−0.0038	−0.0028	0.0066
Vehicle characteristics					
SUV [NI]	−0.49	−2.05	0.0039	0.0039	−0.0078
Model Statistics					
Log-likelihood at convergence, LL(β)	−1666.61				
Log-likelihood at zero, LL (0)	−1889.61				
$\rho 2 = 1 - \mathrm{LL}(\beta)/\mathrm{LL}\ (0)$	0.12				
Corrected $\rho 2 = 1 - [\mathrm{LL}(\beta) - 21]/\mathrm{LL}\ (0)$	0.11				
Number of observations	1720				

Table A2. Temporally unconstrained random parameters logit with heterogeneity in means results for pedestrian-vehicle crash-injury severities for 2020 (parameters defined for: [NI] No Injury; [MI] Minor Injury; [SI] Severe Injury).

			Marginal Effects		
Variable Description	Estimated Parameter	t-stat	*Severe*	Minor	No Injury
Constant [SI]	0.93	7.11			
Random Parameters (Normally distributed)					
Undivided two-way road [NI]	−1.07	−1.82	−0.0153	−0.0132	0.0285
Standard deviation of undivided two-way road	4.1	3.58			
Heterogeneity in mean of the random parameter					
Undivided two-way road: Daylight	−2.75	−3.00			
Crash Characteristics					
Prior movement, proceeding straight ahead [NI]	0.83	4.34	−0.0274	−0.0269	0.0543
Prior movement, making a left turn [NI]	−1.57	−1.91	0.0016	0.0013	−0.0029
Crash type, non-collision with motor vehicle [MI]	0.77	5.68	−0.0983	0.1272	−0.0289
Driver Characteristics					
Inattentive driver [NI]	−0.94	−2.6	0.0048	0.0036	−0.0083
Driver's alcohol-only impairment [NI]	1.66	2.39	−0.0019	−0.0023	0.0042
Driver's age 25–45 [NI]	0.47	2.28	−0.008	−0.0077	0.0157
Driver's age older than 65 [NI]	−1.09	−2.01	0.0026	0.0023	−0.0049
Pedestrian Characteristics					
Pedestrian crossing, entering road at midblock [MI]	2.19	−0.0115	0.0157	−0.0042	2.19
Pedestrian crossing, entering road at intersection [NI]	−0.98	−3.58	0.007	0.0059	−0.0129
Inattentive pedestrian [NI]	−1.23	−3.53	0.007	0.007	−0.014
Roadway and Environmental Characteristics					
Darkness with streetlights [SI]	−0.51	−3.56	−0.0244	0.0182	0.0062
Winter [SI]	0.34	2.65	0.022	−0.0166	−0.0055
Darkness without streetlight [NI]	0.98	3.48	−0.0102	−0.0083	0.0185
Roadway/Spatial Characteristics					
Divided two-way road [SI]	−2.87	−0.0183	0.0121	0.0062	−2.87
Residential area [NI]	−0.65	−2.28	0.0076	0.0063	−0.0139
Model Statistics					
Log-likelihood at convergence, LL(β)	−1382.65				
Log-likelihood at zero, LL (0)	−1552.33916				
$\rho 2 = 1 - \text{LL}(\beta)/\text{LL}(0)$	0.11				
Corrected $\rho 2 = 1 - [\text{LL}(\beta) - 19]/\text{LL}(0)$	0.10				
Number of observations	1413				

Table A3. Temporally unconstrained random parameters logit with heterogeneity in means results for pedestrian-vehicle crash-injury severities for 2021 (parameters defined for: [NI] No Injury; [MI] Minor Injury; [SI] Severe Injury).

			Marginal Effects		
Variable description	Estimated Parameter	t-stat	*Severe*	Minor	No Injury
Constant [SI]	0.67	5.84			
Random Parameters (Normally distributed)					
Undivided two-way road [NI]	−0.72	−2.21	0.0153	0.0138	−0.0291
Standard deviation of Undivided two-way road	1.16	1.68			
Heterogeneity in mean of the random parameter					
Undivided two-way road: Inattentive pedestrian	−0.62	−2.37			
Crash Characteristics					
Prior movement, proceeding straight ahead [SI]	−0.52	−4.29	−0.0686	0.0436	0.025
Prior movement, making a left turn [MI]	0.52	2.34	−0.0069	0.0085	−0.0016
Vehicle headlights off [NI]	−1.47	−4.78	0.0086	0.006	−0.0146
Driver Characteristics					
Driver's alcohol-only impairment [NI]	0.84	2.08	−0.0022	−0.0021	0.0043
Distracted driver [MI]	−0.57	−1.59	0.0022	−0.0031	0.0009
Inattentive driver [SI]	0.28	1.77	0.0095	−0.0064	−0.003
Driver's age older than 65 [MI]	−0.32	−1.58	0.0044	−0.0058	0.0014
Driver's aged 25–45 [NI]	0.28	1.92	−0.0072	−0.0068	0.014
Young driver [NI]	0.49	2.28	−0.0056	−0.0052	0.0108
Pedestrian Characteristics					
Pedestrian crossing, entering road at midblock [MI]	0.33	2.41	−0.0103	0.0161	−0.0058
Pedestrian crossing, entering road at intersection [NI]	−0.65	−3.41	0.0085	0.0068	−0.0153
Roadway and Environmental Characteristics					
Darkness with streetlights [SI]	−0.38	−2.9	−0.0214	0.0138	0.0076
Summer [SI]	−0.23	−1.71	−0.0109	0.007	0.0039
Darkness without streetlights [NI]	1.17	5.01	−0.0228	−0.018	0.0408
Roadway/Spatial Characteristics					
Two-way road with barrier [SI]	−0.85	−2.43	−0.005	0.0022	0.0028
Open country [MI]	−0.71	−2.18	0.0026	−0.0049	0.0022
Vehicle characteristics					
Passenger car [NI]	−0.34	−2.42	0.0108	0.0098	−0.0205
Model Statistics					
Log-likelihood at convergence, LL(β)	−1496.98				
Log-likelihood at zero, LL (0)	−1645.72				
$\rho 2 = 1 - \text{LL}(\beta)/\text{LL (0)}$	0.09				
Corrected $\rho 2 = 1 - [\text{LL}(\beta)\text{-21}]/\text{LL (0)}$	0.08				
Number of observations	1498				