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Analysis of pedestrian accident severity by considering temporal instability and heterogeneity

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ABSTRACT

The aim of this study was to investigate the effects of temporal instability and possible heterogeneity on pedestrian accident severity, 48786 accident data from 2018 to 2021 in the UK STATS database were used as the study object, and accident severity was used as the dependent variable, and 49 accident characteristics were selected as independent variables from 6 characteristics of accident pedestrian, driver, vehicle, road, environment and time to construct the pedestrian accident mean heterogeneity random-parameter logit model and examined its temporal stability. The results of model estimation and likelihood ratio tests indicate that the variables affecting pedestrian injury severity are highly variable and not stable over the years. And further demonstrates the potential of models that address unobserved heterogeneity for significant relationships in pedestrian accident severity analyses.

1. Introduction

1.1. Background

Pedestrians have an injury risk that is approximately four times higher than that of other road users [1]. In Europe, pedestrians account for 27 % of road traffic fatalities [2]. In South Korea, approximately 22.4 % of all traffic accidents involve pedestrians, and 37.6 % of all traffic fatalities are pedestrians [3]. In 2021, 4086 road traffic accidents involving pedestrians occurred in China, and these accidents resulted in 1413 deaths, 3017 injuries, and direct property losses of 23.45 million RMB [4]. Exploring the factors that affect the severity of pedestrian injuries might reveal methods of reducing pedestrian fatalities and injuries, thereby providing valuable guidance for transportation planners and decision-makers to make accurate and effective decisions.

1.2. Literature review

Studies on pedestrian accidents have commonly investigated the frequency of pedestrian accidents occurring in specific road

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sections or factors related to the severity of pedestrian injuries. Road design is a significant contributor to serious pedestrian injuries and deaths. Gálvez-Pérez et al. [5]found that the elderly pedestrian collisions could be avoided with the existence of a wider sidewalk in the district and a greater traffic lights density. Unlike younger pedestrian accidents, these accidents are much more favored in ageing districts with higher traffic flows. G. Tiwari et al. [6] found that pedestrians are more than 2.3 times more likely to die from a pedestrian crash in rural areas than in urban areas. This is because rural areas have higher vehicle speeds combined with fewer separated facilities for pedestrians, such as sidewalks, trails, and paths, compared to urban areas. Stoker, P. et al. [7] found that design of the roadway and development of different land uses can either increase or reduce pedestrian road traffic injury. Sergio et al. [8] presented the Walking Behavior Questionnaire (WBQ), which identifies traffic violations as an issue of road user safety, to thoroughly describe the validation of an instrument for measuring the walking risky and positive behavior on the road, using the Walking Behavior Questionnaire. Francisco et al. [9] evaluated the differences between safe and dangerous driving behaviors from the perspectives of pedestrians and drivers, and the results showed that pedestrians had a very negative evaluation of the driver's road behavior. At the same time, drivers believe that their own behavior is more appropriate than the behavior of other drivers. Women and older adults consider themselves "safer" users. On the contrary, young drivers report a higher frequency of self rated unsafe behavior.

The aforementioned scholars have analyzed the factors affecting the severity of pedestrian accidents from a macro perspective by considering aggregated accident data. However, the effects of these factors on accident severity should not be assumed to remain constant over time [10]. Ignoring changes in the relationships between the aforementioned factors and accident severity over time (temporal instability) might result in biased estimations or even incorrect results [11]. Behnood et al. [12] studied traffic accidents in Chicago and found that the effects of factors such as highway geometry, vehicle characteristics, and driver characteristics on driver injury severity vary considerably with each year. Hosseini et al. [13] investigated data from bicycle collisions in Los Angeles, California, from 2012 to 2017 and found that the effects of certain factors, such as cyclists over the age of 55 years, cyclist negligence, and rear-end collisions, differed between years; the reason for these changes was unclear. Ijaz et al. [14]used motorcycle collision data for 2017 to 2019 from Rawalpindi, Pakistan, to examine the temporal instability of factors affecting the severity of helmeted and unhelmeted motorcycle collision injuries. They found that the likelihood of fatal injuries in unhelmeted collisions might be lower during nonpeak hours than during peak hours, and helmeted collisions are more likely to result in fatal and minor injuries on workdays than on weekends.

Traffic accidents are complex, and data from the police or other organizations might not include all factors affecting the severity of collision injuries [15]. Guo et al. [16] emphasized that heterogeneity should be considered in analyses of accident severity. Neural networks [17], Bayesian networks [18], and other methods can be used for this task; however, the most common approach used for this task is the random-parameter method. Azimi et al. [19] examined the heterogeneity of factors influencing accident severity by using a random-parameter ordered logit model. Wen et al. [20] used the random parameter Logit model to discuss the heterogeneity of rollover accidents. The research shows that age and gender obey normal distribution respectively, and the impact of young drivers and male drivers on the degree of injury in accidents is different. Venkataraman et al. [21] proposed a random-parameter negative binomial model to analyze collision frequency; this model can capture some of the heterogeneity, which can provide detailed information on the factors of accident occurrence and be used to predict the occurrence of accidents.

Traditional random-parameter methods require assuming that the model parameters follow a normal or uniform distribution so that factor heterogeneity can be observed. However, if the data are similar for some observations or groups, these distributions might be insufficient for capturing all the heterogeneity in the data [22]. A common approach for addressing heterogeneity is to use finite mixture models in which groups of observed values with uniform variable effects are estimated, which enables the heterogeneity of multiple factors to be captured. Yu et al. [23] proposed a hybrid latent-class analysis model to address the heterogeneity of the effects of road geometry features on risk factors. Adanu et al. [24] used a latent-class logit model to study the factors affecting motor vehicle collision accidents on weekdays and weekends and found that drunk driving and fatigue were significantly correlated with accident severity. Xie et al. [25] compared multinomial logit models and reported that the latent-class logit model was the most effective model for fitting single-vehicle accidents on rural roads.

1.3. Objective

In summary, analyses of factors affecting accident severity have mostly relied on models such as the random-parameter logit model and latent-class, random-parameter logit model to account for the unobserved heterogeneity in the data. However, few comparative analyses of the results obtained from different modeling methods have been performed, and the potential heterogeneity in the mean (or variance) of the data has rarely been investigated.

Moreover, some influencing factors have temporal instability; thus, different fitting results might be obtained for these factors in different timeframes. This aspect is often ignored in pedestrian accident analysis. Therefore, the potential temporal instability and unobserved heterogeneity of factors affecting accidents must be studied to obtain more accurate knowledge regarding the causal factors of pedestrian accidents; this knowledge can be used as a reference by relevant authorities to improve pedestrian safety.

In this study, pedestrian accident data between 2018 and 2021 from the UK STATs19 database were analyzed. A multicollinearity diagnostic was used to evaluate factors affecting accident severity that belonged to six categories: pedestrians, drivers, vehicles, roads, environments, and time. Data for each year were analyzed, and the data were regrouped in accordance with identified temporal instabilities. An improved random-parameter logit model was then developed for quantitatively and qualitatively analyzing the influencing factors and for observing the potential heterogeneity and temporal instability in them. Finally, the effectiveness of the proposed model was verified by examining its Akaike information criterion (AIC) value, Bayesian information criterion (BIC) value, McFadden's pseudo R2 value, and fitting results.

Analyzing the influence of pedestrian accident factors on accident severity in terms of temporal instability and possible heterogeneity to uncover additional accidents influencing factors can provide theoretical support for reducing the severity of pedestrian accidents.

This paper is organized as follows. Section 1 reviews recent research on factors related to accident severity, with a focus on pedestrian accidents, and discusses the shortcomings of previous studies. Section 2 describes the proposed random-parameter logit model, which considers mean heterogeneity and can be used for time grouping analysis. Section 3 presents the results of the pedestrian accident severity model constructed in this study. Section 4 describes the mean heterogeneity of multiple factors, the applicability of the proposed method on the basis of the optimal fitting results, and a critical evaluation of the results. Finally, Section 5 presents the conclusion of this study.

2. Materials and methods

2.1. Data source and processing

The STATs19 database (https://data.gov.uk/dataset/) is a road accident database that was established by the United Kingdom in 1949. This database has a standardized format, and the road traffic accident statistics in it are obtained from police reports. The database comprises three documents: STATs19AccData, STATs19VehData, and STATs19CasData for accidents, vehicles, and casualties data, respectively. In this study, we selected road accident data from 2018 to 2021 and coded the independent and dependent variables.

(1) Dependent variable coding

The severity of accidents in the STATS19 database was classified into three categories: fatal, serious injury, and slight injury. The meaning of each code is presented in Table 1.

(2) Independent Variable Encoding

The selected independent variables were classified as related to the pedestrian, driver, vehicle, road, environment, or time of the accident. Multicollinearity might occur in complex models that fit multiple variables and leads to unstable analysis results, nonunique solutions, or results that are inconsistent with reality. In this study, the variance inflation factor (VIF) was used identify collinearity among the independent variables [26]. The VIF is calculated as in Eq. (1) below:

$$VIF_{X_i} = \frac{1}{1 - R^2_{X_i}} \tag{1}$$

where $R^2_{X_i}$ is the square of the negative correlation coefficient between an independent variable X_i and the other independent variables when they are used as predictors in regression analysis. A VIF_{X_i} value of greater than 10 indicates the presence of severe multicollinearity among the in-dependent variables.

All the intersection control variables had VIF values of greater than 10; thus, they were directly excluded from this study [27]. Consequently, the intersection control modes were coded dichotomously as intersection control or no intersection control. Ultimately, 49 independent variables were coded after preprocessing (Table 2).

2.2. Temporal instability test

Temporal instability refers to variables having dissimilar or even opposite fitting results for different periods or combinations. Two likelihood ratio tests were used to assess temporal instability.

The first set of likelihood ratio tests was conducted to examine the stability of parameter estimation between years. The test statistic followed a χ^2 distribution, whose mathematical model is formulated as in Eq. (2) below [28]:

$$\chi^2 = -2\left[LL\left(\beta_{t_2,\mathrm{t}_1}\right) - LL\left(\beta_{t_1}\right)\right] \tag{2}$$

where t_1 and t_2 denote two years in the accident data set, $LL\left(\beta_{t_2,\mathrm{t}_1}\right)$ is the log-likelihood at convergence of a model containing parameters from t_2 while using data subset t_1, and is the log-likelihood at convergence of the model using subset t_1.

The results of the likelihood ratio tests for different periods are presented in Table 3. In all 12 tests, the null hypothesis was rejected

Table 1
Dependent variable coding.

Variable Attributes	Variable Symbol	Variable Description	Explanation
Accident Severity	1	Fatal	Died at the scene or within 30 days
	2	Serious Injury	Hospitalization required, such as shock, fractures, amputations, concussions, etc.
	3	Slight Injury	Minor injuries, abrasions, contusions, etc. that do not require medical treatment

Table 2
Variable symbols and descriptions.

Parameter Symbols	Variable Description	Parameter Symbols	Variable Description	Parameter Symbols	Variable Description
–	Spring[a]	Xi17	No intersection control	Xi33	Turn left
Xi1	Summer	–	No crossing facilities[a]	Xi34	Turn right
Xi2	Autumn	Xi18	Crosswalks	Xi35	Overtake
Xi3	Winter	Xi19	Crossing bridges	–	Ahead[a]
–	Within the week[a]	Xi20	Pedestrian signals	Xi36	Rear
Xi4	Weekend	–	Daytime[a]	Xi37	Right
–	Flat peak period[a]	Xi21	Nighttime illumination	Xi38	Left
Xi5	Peak Period	Xi22	Nighttime without lighting	Xi39	Other
–	Ring Road[a]	–	Sunny[a]	–	Driver is male[a]
Xi6	Single carriageway	Xi23	Rain	Xi40	Driver is famale
Xi7	Dual carriageway	Xi24	Snow, fog	–	Driver <20 years old[a]
Xi8	Freeway turnoff	–	Dry[a]	Xi41	Driver 20–29 years old
–	<20 mph[a]	Xi25	Humid	Xi42	Driver 30–39 years old
Xi9	30 mph	Xi26	Frost, snow	Xi43	Driver 40–49 years old
Xi10	40 mph	–	Urban[a]	Xi44	Driver >50 years old
Xi11	>50mph	Xi27	Suburban	–	Pedestrian is male[a]
–	None[a]	–	Bicycle[a]	Xi45	Pedestrian is famale
Xi12	Roundabout	Xi28	Motorcycles	–	Pedestrian <20 years old[a]
Xi13	T/Misplaced intersection	Xi29	Cars	Xi46	Pedestrian 20–29 years old
Xi14	Highway fork	Xi30	Trucks	Xi47	Pedestrian 30–39 years old
Xi15	crossroad	Xi31	Other motor vehicles	Xi48	Pedestrian 40–49 years old
Xi16	Other intersection	–	Start, stop[a]	Xi49	Pedestrian >50 years old
–	Intersection control[a]	Xi32	Straight ahead		

[1] Variables with.
[a] denote the reference category, and i has a value of 1 and 2 for fatal accidents and severe injury, respectively.

at a 99.99 % confidence level, which indicated that separate models should be produced for each year and that time instability exists [29].

The second group of likelihood ratio tests was intended to examine the time instability of pedestrian injury severity by jointly testing the model across all years. The test statistic was calculated as in Eq. (3) below :

$$\chi^2 = -2\left[LL(\beta_T) - \sum\nolimits_{2018}^{2021} LL(\beta_i)\right] \tag{3}$$

where $LL(\beta_T)$ is the log-likelihood value at convergence of the model that includes all the data from 2018 to 2021 and $LL(\beta_i)$ is the log-likelihood value at convergence of the model for year i.

The results of the likelihood ratio test for the joint model are presented in Table 4.

The likelihood ratio test for the combined model reveals that the null hypothesis can be rejected; that is, time instability exists.

2.3. Random-parameter logit model with mean heterogeneity

Accident records differ between localities because of various factors; thus, data for some factors are heterogeneous. The main sources of heterogeneity in pedestrian accident data are shown in Fig. 1.

Although the random-parameter logit model can address heterogeneity in data, it cannot determine whether the parameters are affected by other systematic factors [30]. To address this problem, the following improvement is proposed for the random-parameter logit model:

First, a random term is added to an independent variable to create a new parameter β_{si} as in Eq. (4) below:

$$\beta_{si} = \beta_i + \Gamma_i V_{si} \tag{4}$$

where i indicates death, serious injury, or minor injury; β_i is a fixed parameter; Γ_i is a coefficient matrix indicating the covariance and

Table 3
Results of likelihood ratio tests for various periods.

a	b			
	2018	2019	2020	2021
2018	–	3.099 [>99.99 %]	7.296 [>99.99 %]	5.083 [>99.99 %]
2019	47.817 [>99.99 %]	–	14.625 [>99.99 %]	55.823 [>99.99 %]
2020	51.887 [>99.99 %]	36.233 [>99.99 %]	–	40.555 [>99.99 %]
2021	84.654 [>99.99 %]	94.956 [>99.99 %]	31.601 [>99.99 %]	–

[2] Values in parentheses represent the confidence level.

Table 4
Results of the likelihood ratio test for the joint model.

$LL(\beta_T)$	$LL(\beta_{T2018})$	$LL(\beta_{T2019})$	$LL(\beta_{T2020})$	$LL(\beta_{T2021})$	χ^2	Confidence level
−30145.263	−7494.423	−7315.233	−7647.875	−7674.795	25.874	>99.99 %

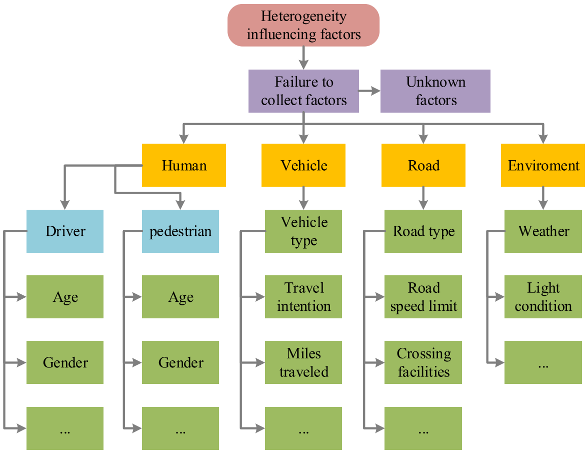

Fig. 1. Sources of heterogeneity in pedestrian accident data.

potential correlation between random parameters; and V_{si} is a random term whose covariance matrix is a unit matrix and has mean 0.

The random-parameter logit model does not explain the possible influences leading to the random coefficients. That is, consider the possibility of unobserved heterogeneity appearing in the mean of the parameters. To this end, a random-parameter logit model with mean heterogeneity is introduced by adding the mean heterogeneity vector. The term β_{si} is the vector of estimated parameters that vary between incidents, and it is expressed as in Eq. (5) below:

$$\beta_{si} = \beta_i + \Delta\omega_i + \Gamma_i V_{si} \tag{5}$$

Where ωi is the vector of mean heterogeneity associated with the attributes of people, vehicles, roads, and environment. Δ is the corresponding vector of estimated parameters.

Bhat's experiment indicated that if the sample size and the number of parameters are large, the use of Halton sequences can reduce the sample size required to obtain favorable results by 90 % [31]. Therefore, the Halton sequence method was adopted to estimate the probability density function values in the present study.

The expressions for the utility function and probability density function of the random-parameter logit model with mean heterogeneity are as in Eq. (6) and Eq. (7) below:

$$T_{si} = \beta_{si} X_{si} + \varepsilon_{ni} = (\beta_{si} + \Delta\omega_i + \Gamma_i V_{si}) X_{si} + \varepsilon_{ni} \tag{6}$$

$$P_s(X_n|\beta_{si}) = \int \frac{\exp(\beta_{si} X_s)}{\sum \exp(\beta_{si} X_s)} f(\beta_{si}|\theta) d\beta_{si} \tag{7}$$

where T_{si} is the utility function for an accident s with severity i, X_s is the independent variable affecting the severity of the accident, ε_{ni} is the error term, and $P_s(X_n|\beta_{si})$ is the probability density function of accidents.

2.4. Mean marginal effect

The random-parameter model with mean heterogeneity alone cannot quantitatively analyze the effect of a factor on pedestrian injury severity; thus, the average marginal effect (AME) method was employed in this study. The AME is the average change in the probability of each accident severity level if a selected variable in the model is changed by one unit and is computed as in Eq. (8) below:

$$M_{y=k|x_i} = \frac{\sum_{i=1}^{n} p(y_i = k|x_i = 1) - p(y_i = k|x_i = 0)}{n} \tag{8}$$

where n is the number of accidents, $M_{y=k|x_i}$ is the AME of factor x on the severity of an accident of type k, $p(y_i = k|x_i = 1)$ is the probability of accident severity for variable n when $x_i = 1$, and $p(y_i = k|x_i = 0)$ is the probability of occurrence of accident severity for variable I when $x_i = 0$.

2.5. Evaluation indices for goodness of fit

The goodness of fit of the developed models was evaluated using McFadden's pseudo R^2 value, the AIC, and the BIC, which are calculated as in Eq. (9), Eq. (10) and Eq. (11) below:

$$R^2 = 1 - \frac{\ln L}{\ln L_0} \tag{9}$$

$$AIC = -2\ln(L) + 2q \tag{10}$$

$$BIC = -z\ln(L) + k\ln(n) \tag{11}$$

where q is the number of parameters in the model, n is the number of accidents, ln*(L)* is the log-likelihood value at convergence,and ln *(L_0)* is the log-likelihood value of the initial model fit.

3. Results

3.1. Model construction results

The estimation results for the random-parameter logit model with mean heterogeneity are presented in this section. The random parameters in the model were assumed to be potentially influenced by other random terms; thus, the distributions generated by the random parameters were transformed into fixed effect values to reduce the potential effect of heterogeneity on the model.

3.1.1. Parameter estimation results

The model construction results are presented in Table 5, and 37 pedestrian accident factor variables were significant in the random-parameter logit model with mean heterogeneity.

3.1.2. Mean heterogeneity of random parameters

According to Table 6, the random variable of a speed limit of 30 mph in 2018 had mean heterogeneity for two variables: female drivers and female injured pedestrians. The random variables of no lighting at night in 2019 and a pedestrian age of >50 years had mean heterogeneity with the variables of snow and foggy weather. The random variable of no lighting at night in 2020 had mean heterogeneity with the variable of roads with zebra crossings. The random variable of trucks in 2021 had mean heterogeneity with the varia-ble of pedestrians aged 40–49 years, and the random variable of lighting at night had mean heterogeneity with the variable of a speed limit of 30 mph.

Table 5
Model construction results.

		2018		2019		2020		2021	
Dependent variable	Variable Symbols	Parameter	Standard deviation	Parameter	Standard deviation	Parameter	Standard deviation	Parameter	Standard deviation
Death	X19	−2.370***	1.026***	–	–	–	–	−0.396**	1.102*
	X111	1.472***	1.084	–	–	–	–	–	–
	X121	–	–	–	–	–	–	0.67131*	0.85878*
	X122	–	–	1.373***	1.085***	1.072***	0.909***	–	–
	X130	–	–	1.163***	1.361**	–	–	1.467**	1.589***
	X132	−2.519***	3.200***	–	–	–	–	–	–
	X133	−0.905***	0.850**	–	–	–	–	–	–
	X135	–	–	–	–	–	–	1.051*	0.673**
	X137	–	–	–	–	–	–	−1.577***	0.907***
	X138	−4.312***	2.884***	0.627*	0.631**	−3.343***	2.477***	−1.163**	0.402**
	X140	−2.156***	1.085**	–	–	–	–	–	–
	X143	−2.125***	0.693**	–	–	–	–	–	–
	X145	–	–	−1.247**	1.405***	–	–	–	–
	X149	–	–	–	–	1.720***	1.230***	1.856***	1.481**
Severe injuries	X218	–	–	−0.609**	2.585**	–	–	–	–
	X221	–	–	0.490***	0.300***	–	–	–	–
	X232	–	–	–	–	0.266***	0.532***	–	–
	X236	–	–	−0.511**	0.513***	–	–	−0.284**	0.682**
	X239	–	–	–	–	−0.609**	1.218**	–	–
	X243	–	–	–	–	–	–	−0.342**	0.240**
	X249	0.507***	0.627*	0.737***	0.947***	0.603**	1.206**	–	–

[3] The ***, ** and * in the results indicate confidence levels of 99 %, 95 % and 90 %, respectively.

Table 6
Mean heterogeneity of random parameters.

	2018		2019		2020		2021	
	Variables	Parameter	Variables	Parameter	Variables	Parameter	Variables	Parameter
Death	X19:X140	−1.393**	X122:X124	1.142**	X122:X118	−2.133***	X130:X148	0.997***
	X19:X145	−0.920***	–	–	–	–	X121:X19	−0.201***
	X111:X122	2.164**	–	–	–	–	–	–
Severe injuries	–	–	X249:X124	1.303	–	–	–	–

[4] The ***and ** in the results indicate confidence levels of 99 % and 95 %, respectively.

3.1.3. Results of the marginal effect calculations

The AMEs of nonsignificant safety factors for the four years from 2018 to 2021, which were not random parameters, are presented in Table 7.

3.2. Model construction results

Section 3.1 provides preliminary evidence that the effects of various factors on pedestrian accident severity vary considerably between years. If some parameters are assumed to be stochastic and normally distributed, the model indicates that unobserved heterogeneity in accidents exists. In this section, a selected subset of significant variables are further analyzed. The statistics of normal distributions are reported as means (standard deviations).

3.2.1. Pedestrian

(1) Gender

Female gender was a significant factor for fatal accidents; accident severity for women in 2019 was normally distributed, with the

Table 7
AME values of the nonsignificant safety factors.

		2018	2019	2020	2021
Dependent variable	Variable Symbols	AME value			
Death	X13	–	−0.69 %	–	−0.19 %
	X15	−0.80 %	–	–	–
	X111	–	3.17 %	4.06 %	4.02 %
	X118	–	–	−1.18 %	–
	X121	–	−1.20 %	−1.81 %	–
	X122	1.68 %	–	–	–
	X130	–	–	3.18 %	–
	X132	–	2.04 %	1.74 %	0.88 %
	X135	–	–	1.67 %	–
	X137	−1.11 %	−1.16 %	−1.41 %	–
	X139	–	–	−3.17 %	–
	X140	–	–	–	−0.67 %
	X143	–	–	–	−0.40 %
	X145	−0.10 %	–	–	–
	X147	−0.84 %	–	−1.59 %	−1.42 %
	X138	–	1.87 %	−1.53 %	−1.94 %
Severe injuries	X21	–	–	−2.53 %	–
	X27	–	–	–	0.43 %
	X210	0.83 %	1.22 %	1.53 %	0.77 %
	X211	–		11.47 %	14.39 %
	X218	−3.56 %	–	−4.11 %	–
	X221	0.55 %	–	0.53 %	0.97 %
	X222	–	–	0.58 %	0.77 %
	X223	–	−3.93 %	–	–
	X225	–	4.77 %	2.56 %	–
	X229	−1.11 %	–	–	–
	X232	0.99 %	–	–	0.53 %
	X236	–	–	−0.62 %	–
	X238	–	–	–	−0.66 %
	X239	−0.51 %	−0.42 %	–	–
	X242	–	−5.57 %	–	–
	X243	−0.74 %	−0.91 %	–	–
	X244	–	−0.46 %	–	–

mean value being −1.247 (1.405). The probability of an accident involving a female pedestrian being nonfatal was 81.33 %. This is consistent with some previous findings and can be explained by behavioural differences between males and females, with males being more likely to engage in risky behaviours when travelling, and females being more sensitive to traffic safety and more cautious in their travels, according to previous research [32].

(2) Age

There was no significant effect of pedestrian age older than 50 years on fatal accidents in 2018 and 2019. In contrast, the parameters in the pedestrian fatal accident model for 2020 obeyed a normal distribution with a mean of 1.720 and a standard deviation of 1.230. That is, when pedestrians are older than 50 years old, the probability of increasing pedestrian mortality is 91.92 %. Similarly, The parameters in the 2021 pedestrian fatality model obey a normal distribution with a mean of 1.856 and a standard deviation of 1.481. That is, the probability of increasing pedestrian fatalities when pedestrians are older than 50 years old is 89.44 %.

In 2018, 2019, and 2020, the effects of a pedestrian being over 50 years old on the probability of severe injury were modeled as normally distributed random parameters with mean values of 0.507 (0.627), 0.737 (0.947), and 0.603 (1.206), respectively. For these distributions, the probabilities of the variable being less than 0 were 20.9 %, 21.77 %, and 30.85 %, respectively; thus, the corresponding increases in the probability of serious pedestrian injury in this age group were 79.1 %, 78.23 %, and 69.15 % in 2018–2020, respectively. Similar results have been found in a number of previous studies, Their frail bodies and increased risk of diseases such as cardiovascular disease and osteoporosis may lead to an increase in serious injuries following accidents in this age group [33].

By contrast, the variables of a pedestrian age of 30–39 years and a pedestrian age of 40–49 years had temporal instability. For pedestrians aged 30–39 years, the AME values for fatal accidents in 2018, 2020, and 2021 indicated a decrease in the probability of death by 0.84 %, 1.59 %, and 1.42 %, respectively. These results might be attributable to the physical fitness of pedestrians in this age group, which enables them to better withstand vehicle collisions.

The probability of death for pedestrians aged 40–49 years decreased by 1.53 % and 1.94 % in 2020 and 2021, respectively. However, in 2019, their probability of death in-creased by 1.87 %, which indicated temporal instability. This result is consistent with the results of Ali et al. [15]and might be attributable to the deteriorating physiological functions of older adults and a psychological fear of traffic accidents.

3.2.2. *Driver*

(1) Gender

For fatal pedestrian accidents in 2018, the effect of a driver being a woman on accident severity was modeled as a normally distributed random variable with a mean of −2.156 (1.085); the probability of the aforementioned parameter being less than 0 was 97.67 %, which indicated that the probability of fatal outcomes significantly decreased by 97.67 % if the driver was a woman. This result can be attributed to female drivers being more attentive and cautious than are male drivers, who tend to be more aggressive, which might increase the likelihood of severe accidents [34].

(2) Age

The normal distributions for driver age of 40–49 years had mean values of −2.125 (0.693) and −0.342 (0.240) for 2018 and 2021, respectively, which indicated that pedestrian fatalities were avoided in 99.89 % and 92.36 % of accidents. These results might be attributable to the cautious driving style and fast reaction time of experienced middle-aged drivers [35].

The results for the AME indicate that a driver age of 30–39 years was associated with a 5.57 % lower risk of severe pedestrian injury in 2019. A driver age of 40–49 years was associated with a 0.74 % and 0.91 % lower risk of severe pedestrian injury in 2018 and 2019, respectively, and a 0.4 % lower risk of pedestrian death in 2021.

3.2.3. *Vehicle type*

Vehicle type is correlated with pedestrian accident severity. The involvement of trucks in pedestrian fatalities was modeled as a normally distributed random variable; the distributions for 2019 and 2021 had mean values of 1.163 (1.361) and 1.467 (1.589), respectively, which indicated that accidents involving trucks had an 80.23 % and 82.12 % probability of causing pedestrian fatalities in 2019 and 2021, respectively. The unobserved heterogeneity associated with the factor of truck involvement can be explained by differences in truck weight, type, and cargo [11].

3.2.4. *Road*

(1) Road speed limit of 30 mph

In the 2018 and 2021 pedestrian fatality models, the normal distributions for a road speed limit of 30 mph had mean values of −2.370 (1.026) and −0.396 (1.102), respectively, which indicated that reducing the speed limit to 30 mph decreased the probability of pedestrian death by 98.96 % and 64.06 % in 2018 and 2021, respectively. Random parameters can reflect differences in outcomes at that speed limit and the possible presence of unobserved factors on injury outcomes at that speed limit. Moradi et al. found that Iranian drivers were more likely to exceed the speed limit on roads with the lowest speeds, leading to more serious accidents [36].

(2) Road speed limit of >50 mph

The effect of a road speed limit of >50 mph on pedestrian fatalities was stable in 2019, 2020, and 2021; this factor was associated with 3.17 %, 4.06 %, and 4.02 % higher probabilities of pedestrian death in 2019–2021, respectively. However, in the model for 2018, the normal distribution had a mean value of 1.472 (1.084), which indicated that a speed limit of >50 mph increased the probability of death by 91.31 %. This result is consistent with the findings of previous research. As speed increases, decision-making time decreases and kinetic energy increases, which ultimately results in more severe injuries and fatalities [37].

(3) Pedestrian crossing facilities

The only significant variable related to pedestrian crossings was the zebra crossing. The presence of a zebra crossing reduced the probability of a pedestrian fatality by 1.18 % in 2020 and reduced the probability of severe injury by 3.56 % and 4.11 % in 2018 and 2020, respectively. For 2019, the corresponding normal distribution in the severe injury accident model had a mean of −0.609 (2.585), which indicated that the presence of a zebra crossing reduced the probability of severe injury by 59.48 %.

The aforementioned results indicate that zebra crossings significantly reduced accident severity in all years and for all injury types. This result might be attributable to the fact that zebra crossings can act as a warning to drivers, which results in accidents that cause less harm to pedestrians. Pfortmueller et al. [38] found a correlation between higher traffic control on pedestrian crossings and a lower probability of severe injury.

3.2.5. Environment

(1) Nighttime illumination

Nighttime illumination reduced fatalities in pedestrian accidents by 1.20 % and 1.81 % in 2018 and 2020, respectively. In the 2021 pedestrian fatality model, the normally distributed random parameter of pedestrian accidents had a mean of 0.671 (0.859), which indicated that nighttime illumination increased the probability of pedestrian fatality by 78.23 %.

For 2018, 2020, and 2021, nighttime illumination had a stable effect on the serious injury rate, with increases of 0.55 %, 0.53 %, and 0.97 %, respectively, being observed in this rate. The normally distributed random variable of the 2019 model had a mean of 0.490 (0.300), which indicated that nighttime illumination increased the probability of serious pedestrian injury by 94.84 %. Random parameters can reflect differences in outcomes in the presence of light at night as well as the possible presence of unobserved factors influencing injury outcomes in the presence of light, and it has been found that the presence of light at night significantly reduces the severity of accidents, but that there are some streets that are lit but have inconsistent street lighting and poor illumination, which can lead to more serious accidents [39].

(2) Nighttime without lighting

For pedestrian fatality accidents in 2018, accidents at night without lighting were associated with an increase of 1.68 % in the probability of pedestrian death. The normal distributions of accidents at night without lighting had mean values of 1.373 (1.085) and 1.072 (0.909) for 2019 and 2020, respectively, which indicated that unlit nighttime accidents were associated with an 89.8 % and 88.1 % increased probability of pedestrian death in 2019 and 2020, respectively.

(3) Weather

Weather conditions, such as rainy, snowy, or foggy weather, were significant variables only in the pedestrian severe injury accident models for 2019 and 2020. Rainy days in 2019 reduced the probability of severe pedestrian injury by 3.93 %, and snowy and foggy days in 2019 and 2020 had a marginal effect on such injury; they increased the probability of severe pedestrian injury by 4.77 % and 2.56 % in 2019 and 2020, respectively. The afore-mentioned findings are consistent with the results of Zhai et al. [35].

3.2.6. Time

Compared with other seasons, the pedestrian fatality probability was 0.69 % and 0.19 % lower in winter for the 2019 and 2021 pedestrian fatality models, respectively, and the pe-destrian severe injury probability was 2.53 % lower in 2020.

4. Discussion

4.1. Multifactor heterogeneity inference

Certain random parameters generate fixed effects in the presence of other influencing factors. The results that can be used to eliminate heterogeneity, thereby improving the homogeneity of the analysis, are described as follows.

In the 2018 accident data, the random parameter of a speed limit of 30 mph had mean heterogeneity for accidents caused by female drivers or involving female pedestrians; the probability of a fatality decreased when the speed limit was 30 mph. Mean heterogeneity was also observed for accidents occurring in poorly lit conditions at night and with a speed limit of >50 mph; the probability of pedestrian death increased under these conditions.

In the 2019 accident data, female drivers and pedestrians aged >50 years had mean heterogeneity with accidents caused by snow and fog, which increased the probability of pedestrian fatalities.

In the 2020 accident data, female drivers had mean heterogeneity in accidents involving zebra crossings; the probability of pedestrian death decreased for an accident involving a female driver and zebra crossing.

In the 2021 accident data, well-lit conditions at night had mean heterogeneity with a road speed limit of 30 mph; thus, if the lighting at night was adequate, a speed limit of 30 mph decreased the probability of pedestrian deaths. Moreover, truck involvement increased pedestrian deaths for individuals aged between 40 and 49 years.

4.2. Test of model fit

To assess the effectiveness of the proposed random-parameter logit model with het-erogeneity, a multinomial logit model, stochastic-parameter logit model that does not consider mean heterogeneity, and stochastic-parameter logit model that considers mean heterogeneity were constructed and then evaluated using three metrics: the AIC value, BIC value, and R^2 value (Table 8).

Smaller AIC and BIC values and larger R^2 values indicated better fit. The results in Table 8 indicate that the random-parameter logit model incorporating mean heterogeneity had smaller AIC and BIC values and a larger R^2 value than did the multinomial logit model and Random-parameter logit model. Thus, the proposed random-parameter logit model was deemed the optimal model for fitting the severity of pedestrian accidents.

4.3. Limitations

The random-parameter analysis for the 2019 model revealed that crossing facilities can increase pedestrian safety; however, pedestrians must actively and correctly use these facilities. Some pedestrians might choose risky actions, such as jaywalking. In the future, heterogeneity in pedestrian risky behavior and the effects of crossing facilities should be further explored.

The model constructed and modified in this study can only be used for data that has undergone complex and tedious preprocessing for standardization. In addition, substantial data are required to avoid parameter fitting bias in the model. In future research, improvements can be made to the proposed model and different time intervals based on other standards can be used for further investigating temporal instability.

4.4. Security improvement measures

Based on the results of the analysis of each significant factor and the analysis of mean heterogeneity, combined with the previous related literature research, the countermeasures to improve the safety of pedestrians are proposed from the two aspects of human factors and road environment.

First of all, we need to popularise the knowledge of road safety, enhance the traffic safety awareness of every urban resident, so that every pedestrian can do to develop good travel habits, do not venture, do not impulsive, in addition to strengthening the correct concept of pedestrians to comply with the road traffic regulations, the formation of a healthy road traffic culture. In the elderly and children more intersections, road sections placed reasonable warning signs and set up a reasonable speed limit, and strengthen the traffic guidance, while in the daily to strengthen their safety awareness to enhance the protection effect. Some pedestrian accidents are caused by drivers' unsafe behaviour, and managers can enhance the management of traffic violations to reduce drivers' dangerous behaviour. Drivers in the driving school test training and test content, increase the psychological and physical qualities, road safety knowledge, driving skills requirements. Also need the relevant departments from time to time to drivers to popularise safety knowledge and awareness of the hazards of traffic accidents, enhance the driver's driving judgement, adaptability, common traffic hazards have the ability to identify and advocate the road vulnerable groups of courtesy and care.

The road speed limit has an impact on the severity of pedestrian accidents, which for the road speed limit is greater than 50mph factors significantly increase the probability of pedestrian deaths and serious injuries, therefore, for these road sections, should be

Table 8
Test results of the three models.

Model	Evaluation Indicators	2018	2019	2020	2021
Multinomial logit Model	*AIC/n*	1.274	1.506	1.525	1.508
	BIC/n	1.289	1.520	1.536	1.517
	R^2	0.236	0.159	0.131	0.128
Random-parameter logit model	*AIC/n*	1.266	1.504	1.518	1.197
	BIC/n	1.287	1.514	1.537	1.512
	R^2	0.426	0.317	0.265	0.301
Random-parameter logit model considering mean heterogeneity	*AIC/n*	1.263	1.501	1.519	1.489
	BIC/n	1.282	1.513	1.537	1.505
	R^2	0.429	0.317	0.308	0.315

based on the field investigation of the local department, to determine the optimal speed limit of the road, in addition to real-time collection of road traffic information, environmental information and other data, combined with the relevant algorithms to derive the optimal speed limit value of the current road, and through the appropriate facilities to inform drivers. And through the corresponding facilities to inform the driver, so as to achieve in the enhancement of road safety at the same time can also enhance the efficiency of road traffic.

Properly installed pedestrian crossing facilities can guide pedestrians to comply with traffic rules and greatly reduce the probability of pedestrian accidents. At present, there is no road design specification in the road before the completion of a clear pedestrian crossing area, therefore, the need for road planning and design process, combined with the road near the traffic district traffic flow forecasts, the environment near the road section and the land use situation, the near and far future development of the foundation, the ability to have the demand for places, from the pedestrians travelling psychological considerations, moderately ahead of the planning and layout of the pedestrian street crossing infrastructure. For the more dangerous road junctions that already exist, or road sections with high pedestrian flow, installing pavements where there are no pavements, increasing the width of narrow pavements, completely isolating the pavement from the road by installing a pavement buffer zone, as well as appropriately paving the pavements can greatly reduce the severity of accidents.

The relevant departments should first check the road without lights, to do with the conditions of the road without lighting equipment for comprehensive lighting facilities. The existing lighting facilities but poor conditions, strengthen the road lighting, in addition to set up anti-glare facilities, to prevent the glare of the headlights of the opposite vehicle, improve the driver's visual distance at the same time to eliminate the driver's nervousness at night, reduce the incidence of accidents.

5. Conclusions

(1) In this study, the UK STATs19 road accident database was used to develop a pedestrian accident severity model by selecting 49 variables related to the pedestrian, driver, vehicle, road, environment, and time of an accident as independent variables and death, serious injury, and slight injury as dependent variables on the basis of a multicollinearity diagnostic.

(2) Two likelihood ratio tests revealed time instability in the accident data from 2018 to 2021. For fatal accidents, the four variables of a speed limit of >50 mph, straight vehicle movement, collision on the right side, and collision on the left side were significant in the accident severity model in all four years. For serious injuries, the two variables of a speed limit of 40 mph and night lighting were significant in all four years. The other variables were only significant in some years, which indicated temporal instability. However, in the serious injury model, the significant variables of night lighting, straight vehicle movement, collision on the left side, and pedestrians aged 40–49 years had substantial temporal in-stability; their effects on accident severity were opposite in different years.

(3) In the pedestrian fatality model for different years, a random-parameter logit model that considers mean heterogeneity captured heterogeneity for 14 variables: road speed limits of 30 mph and >50 mph, straight vehicle movement, left turn, collision on the left side, collision on the right side, female drivers, female pedestrians, drivers aged 40–49 years, pedestrian aged >50 years, trucks, no night lighting, night lighting, and overtaking. In the pedestrian serious injury model for different years, a random-parameter logit model that considers mean heterogeneity captured heterogeneity for seven variables: pedestrians aged >50 years, zebra crossings, night lighting, collision from the rear, straight movement, collision at other locations, and drivers aged 40–49 years.

(4) Compared with the multinomial logit model and the random-parameter logit model that considers mean heterogeneity, the random-parameter logit model that considers mean heterogeneity had better fitting performance and could better estimate the influence of other systemic factors on the estimated factors, thereby reducing possible heterogeneity.

Data availability statement

Data will be made available on request.

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CRediT authorship contribution statement

Pingfei Li: Methodology, Funding acquisition, Data curation, Conceptualization. **Chengyi Zhao:** Writing – original draft, Data curation. **Min Li:** Writing – review & editing. **Daowen Zhang:** Writing – review & editing, Supervision. **Qirui Luo:** Validation. **Chenglong Zhang:** Investigation. **Wenhao Hu:** Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Wenhao Hu reports financial support was provided by state administration for market regulation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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