Analysis of pedestrian accident injury-severities at road junctions and crossings using an advanced random parameter modelling framework: the case of Scotland.

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ABSTRACT

This paper investigates the determinants of injury severities in pedestrian-motor vehicle accidents at signalised and unsignalised junctions, and at physically-controlled and human-controlled crossings in Scotland. The accident data were drawn from the official police crash report database of the UK spanning a period between 2010 and 2018. Correlated random parameter ordered probit models with heterogeneity in the means were developed in order to account for the multi-layered impact of unobserved heterogeneity on statistical estimation. The model estimation results showed that the severities of accident injuries are affected by roadway, location, weather, vehicle, and driver characteristics as well as temporal attributes (including time and day of the accident). Factors such as the urban context, lighting and weather conditions and road surface conditions were found to result in correlated random parameters, thus capturing the intricate, yet interactive effects of unobserved heterogeneity, and particularly the unobserved behavioural response of road users to different traffic control types at junctions and crossings. Vehicle type, driver’s gender and day-of-the-week were observed to influence the random parameters' distributions. Empirically, the results showcase variations in the determinants of injury severities at signalised and unsignalised junctions, and at physically-controlled and human-controlled crossings. Even though most of these variations were related to the magnitude of impact of the determinants, differences in the directional effects on injury severities were also identified, mainly for factors related to weather conditions, hazard presence on the road, and temporal characteristics of the accidents.

Keywords: Pedestrian accidents; injury severity; ordered probit model; signalised and unsignalised junctions; physically-controlled crossings; human-controlled crossings; correlated random parameters;

1. INTRODUCTION

Road casualties constitute one of the major public health concerns in the United Kingdom and worldwide. Vulnerable road users, principally pedestrians, cyclists and motorcyclists, have a greater propensity to casualties, as they account for more than half of all road traffic deaths (WHO, 2018). In the UK, pedestrian casualties accounted for 14% of all casualties in 2018, thus reflecting the second largest proportion of fatalities after car users (DfT, 2018). In Scotland, pedestrian casualties accounted for about 15% of total casualties from all traffic accidents in 2018 (Transport Scotland, 2018).

Road junctions have been long established as road elements where pedestrians face a higher risk of being involved in accidents with motor vehicles (European Transport Safety Council, 1999). Pedestrian-vehicle accidents in junctions have been investigated extensively in the literature (Ma et al., 2018; Zajac & Ivan, 2003; Zhang et al., 2008; Zheng, 2014; Jung et al., 2016). Previous evidence has shown that major determinants of injury severities include vehicle speeds, configuration and geometric characteristics of the junction, built environment and land-use characteristics, pedestrian characteristics, the presence of dedicated facilities for pedestrians as well as the desire lines of pedestrians. Furthermore, the level of traffic control implemented in junctions may influence the occurrence and severity of pedestrian-involved accidents (Tarko et al., 2012). Traffic signals are widely used in junctions to regulate traffic control, as they can spatially and temporally separate movements and potential conflicts between pedestrians and vehicles, thus enabling a reduction in the risk of hazardous conflicts that can result in accidents (Wong et al., 2007).

The level of pedestrian safety is also subject to the provision of dedicated pedestrian facilities. Previous research has established the safety benefits of facilities that physically provide protected, yet segregated paths for pedestrians, such as various types of crossings (e.g., signalised or sign-controlled crossings, zebra crossings and so on) or footbridges (Elvik et al., 2013; Pantangi et al., 2021a; Pantangi et al., 2021b; Sarwar et al., 2017). As an alternative to physical infrastructure, the presence of human control at crossings through crossing patrols also enhances pedestrian safety, especially for special cases of pedestrian movements, such as commute to school (Rosenbloom et al., 2008), which may include even more vulnerable users, e.g., children and parents. Despite the presence of physical or human control at pedestrian facilities, there is still potential for severe accidents, typically caused by traffic violations or risk-taking behaviours of drivers and/or pedestrians.

While the injury severities of pedestrian accidents have been individually explored for various junction and pedestrian crossing types in safety literature, there has been limited empirical research regarding how the factors determining injury severities of pedestrian-motor vehicle accidents vary by: (i) the level of traffic control at junctions; and (ii) the presence of physical facilities or human control at pedestrian crossings. Focusing on the type of traffic control, we separately consider injury severities of pedestrian-motor vehicle accidents at *signalised* and *unsignalised* junctions and *physically-controlled* and *human-controlled* crossings, respectively.

To account for unobserved heterogeneity, which may be present in the accident data, this study explores the determinants of injury severities for pedestrian-motor vehicle accidents using a correlated random parameters ordered probit approach with heterogeneity in the means. This modelling framework allows the parameter estimates to vary across the accident observations, thus facilitating the identification of varying impacts of the injury-severity determinants as well as of exogenous factors potentially controlling for such varying impacts of the injury-severity determinants. Furthermore, the correlation among the random parameters enables the recognition of interactive effects among the unobserved characteristics that may affect injury severities.

This paper contributes to empirical research about pedestrian-motor vehicle accident injuries in two ways: on the one hand, factors influencing injury severities are concurrently explored for several junction and pedestrian crossing types, thus enabling the identification of variations in the effects of the same factors. On the other hand, the statistical modelling framework can provide more robust empirical findings by addressing layers of unobserved heterogeneity, which were not simultaneously considered in prior studies of pedestrian safety.

2. PREVIOUS RESEARCH ON INJURY SEVERITIES AT JUNCTIONS AND CROSSINGS

Zajac & Ivan (2003) identified factors that significantly influenced injury severities of motor vehicle-crossing pedestrian crashes in rural Connecticut, U.S.A. using an ordered probit model. Whilst limiting the crashes to those where pedestrians were attempting to cross two-lane highways controlled by neither stop signs nor traffic signals, they found that factors that had significant influence on pedestrian injury severity were clear roadway width, alcohol use by either driver or pedestrian, age, and vehicle type.

Haleem et al. (2015) identified and compared the major factors affecting crash injury severity involving pedestrians at signalised and unsignalised intersections in Florida using a mixed logit approach. They identified major predictors of higher pedestrian severity risk at signalised intersections, including higher annual average daily traffic, speed limit, proportion of trucks, age, rainy weather, and dark lighting conditions. At unsignalised intersections, the identified factors included pedestrians walking along roadway, middle-aged and elderly pedestrians, at-fault pedestrians, vans, dark lighting conditions and higher speed limits.

Ma et al. (2018) investigated factors influencing injury severity at intersections for pedestrian involved crashes. They employed an ordered probit modelling approach to develop a model for examining the influence of various factors on pedestrian injury severity. They found that pedestrian injury severities vary by driver's age. Furthermore, their results showed that vehicle type, point of fist contact, and weather significantly impact pedestrian injury severity at intersections for all driver age categories investigated.

Using pedestrian and bicyclist involved crash data from the Fatality Analysis Reporting System in the U.S., Dong et al. (2019) used mixed generalised ordered logit models to investigate injury severities of vulnerable road users. Factors that were found to significantly influence the injury severities included age, alcohol use, motorist's previous crashes, number of occupants, junction profile, weather, and light conditions among others. Due to unobserved heterogeneity, the number of occupants, vehicle body type, interstate, and junction led to statistically significant random parameters.

Rothman et al. (2012) questioned the safety effects of traffic signals at midblock locations despite being established as one the most appropriate approaches to providing safe pedestrian crossings. They investigated pedestrian injuries at signalised midblock compared to signalised intersection locations in Toronto, Canada. The outcomes indicate that the odds of children and adults to sustain a major injury are higher at midblock locations compared to intersections, whereas, for seniors, the risk of sustaining a fatal injury at midblock locations is even higher.

Abdelwahab & Abdel-Aty (2001) investigated the use of multilayer perceptron and fuzzy adaptive resonance theory neural networks in understanding the relationship between factors including driver, vehicle environment, and roadway characteristics on driver injury severity. Their findings indicate that injuries in accidents at rural intersections are more severe than in accidents at urban intersections. Interestingly, they also found that drivers who are at fault in the traffic accident are less likely to experience severe injuries compared to those not at fault. Similar to Abdelwahab & Abdel-Aty (2001), who found gender differences in severity of injuries, Obeng (2011) found larger increases in the marginal effects of driver characteristics on the risk of severe injuries in females compared to males.

Recognising the importance of pedestrian involved vehicle crashes that occur at intersections, Zhu (2021) investigated the factors contributing to their severity based on a three-year record of crash data in Hong Kong. Artificial neural network was used to determine significant contributing factors for fatal and severe crashes. The author found an increase in the likelihood of fatal and severe vehicle-pedestrian crashes at intersections with light rainfall and at signalised junctions as well as at uncontrolled junctions.

In summary, from the array of studies reviewed, it can be deduced that several traditional methods of modelling pedestrian injury severity have been used, including discrete choice models, and Bayesian network methods among others, but with some limitations. Many of these studies do not capture a broad range of unobserved factors contributing to accidents and their severities. Furthermore, the models developed are limited in their capacity to concurrently capture both the likely correlations between the unobserved factors and the variations in the effects of the unobserved factors on injury severities.

To overcome these limitations, this study proposes an integrated modelling framework (i.e., the correlated random parameter ordered probit approach with heterogeneity in the means). Even though a few studies recently applied a similar modelling framework for the statistical analysis of accident injury severities (e.g., Fountas et al., 2021; Se et al., 2021; Ahmed et al., 2021), this approach has not been used to analyse pedestrian-vehicles accidents, to the best of the authors' knowledge.

3. METHODS

For the statistical analysis of the accident data, we employ an ordered probability framework with allowances for correlated random parameters and with a flexible structure for capturing heterogeneity in the means of the random parameters.

The traditional ordered probit model is formulated using a latent continuous variable, z_i, as follows:

$$z_i = \boldsymbol{\beta}\mathbf{X_i} + \varepsilon_i, y_i = j, if\ \mu_{j-1} < y_i < \mu_j,\ j = 1,2, \ldots..j \quad (1)$$

where $\boldsymbol{\beta}$ represents a vector of estimable parameters, $\boldsymbol{X_i}$ represents a vector of observable characteristics for accident observation i, y_i denotes an integer, which stands for the observed severity outcome of the accident injury, j denotes an integer representing the levels of injury-severity, the threshold parameters of the ordered model are represented by μ_j, which are ordered in nature. The random error component is denoted by ε_i, with the assumption for this being normally distributed.

Random parameters are integrated into the modelling framework to account for unobserved heterogeneity. This setting empowers the estimation of accident-specific parameter vectors, $\boldsymbol{\beta_i}$ for the explanatory variables included in $\mathbf{X}$ (Semple et al., 2021), as shown below:

$$\boldsymbol{\beta_i} = \boldsymbol{\beta} + \boldsymbol{\delta}\mathbf{K} + \Gamma\omega_i \quad (2)$$

Where the mean value of the random parameters' vector is represented by $\boldsymbol{\beta}$, Γ denotes a Cholesky matrix, $\mathbf{K}$ is a vector of exogenous variables that affect the means of the random parameters, $\boldsymbol{\delta}$ is a vector of coefficients for $\mathbf{K}$., a normally distributed random term is indicated by ω.

Considering the typical formulation of the random parameters (Washington et al., 2020), the random parameters vary across the observations in light of a pre-specified distribution, the mixing distribution. In this study, the normal distribution was selected to fit the random parameters' distribution. Previous evidence typically suggests the estimation of uncorrelated random parameters, implicitly assuming the existence of independent effects attributed to unobserved heterogeneity. Though, a fast-growing number of recent studies have revealed that possible dependence structures among unobserved characteristics may underpin their impact on model predictors. To account for this possibility, the random parameters are allowed to be correlated, hence, the off-diagonal elements of the Choleksy matrix are set to take non-zero values (Fountas et al., 2018b).

The covariance matrix of the random parameters, V, is given by multiplying a Cholesky matrix, Γ, and a Cholesky matrix prime, Γ^{ι}, as shown in Equation 3:

$$V = \Gamma\Gamma^{\iota} \tag{3}$$

As a result of the generalized formulation of the Cholesky matrix, the model's estimable parameters are both the diagonal and off-diagonal elements of the Cholesky matrix. Furthermore, the diagonal and off-diagonal values of the covariance matrix are used to compute the standard deviations of the correlated random parameters following a post-estimation procedure established by Fountas et al., 2018a .

The Simulated Maximum Likelihood Estimation (SMLE) method was used to calibrate the correlated random parameters model. As part of the SMLE , Halton draws were leveraged to obtain optimum numerical integrations for the simulation process (Halton,1960). For the estimations, 1000, 1200 and 1400 Halton draws have been used to stabilize the models' parameter estimates.

To capture the extent of correlation between the random parameters, correlation coefficients are computed. The definition of the correlation coefficient between two random parameters is given as:

$$Cor(\chi_{\kappa,}\chi_{\kappa\prime}) = \frac{Cov(\chi_{\kappa,}\chi_{\kappa\prime})}{\sigma_{\kappa}\sigma_{\kappa'}} \tag{4}$$

where $Cov(\chi_{\kappa,}\chi_{\kappa})$ denotes the covariance among the random parameters generated by the variables χ_{κ} and $\chi_{\kappa\prime}$, while, the standard deviations of their corresponding distributions are represented by σ_{κ} and $\sigma_{\kappa'}$.

The probability of each accident *i* to yield in an injury-severity outcome *j*, $(y = j)$ is expressed as:

$$P_i(y = j) = \Phi\left(\mu_j - \boldsymbol{\beta}_i\mathbf{X}_i\right) - \Phi(\mu_{j+1} - \boldsymbol{\beta}_i\boldsymbol{X}_i) \tag{5}$$

where Φ represents the cumulative function of the standard normal distribution, the other terms are as defined previously.

To ascertain the exact effects of the explanatory variables on the probabilities of all injury-severity levels, and especially of the interior levels, marginal effects are also estimated. Marginal effects demonstrate the change in the outcome probabilities as a result of a unit change in the independent variables (Washington et al., 2020). In this study, the vectors of explanatory variables in the estimated models contain only binary variables. Hence, their marginal effects are determined by the change in their values from "0" to "1", as shown is Equation 6:

$$\frac{P_i(y=j)}{\partial \mathbf{X}} = [\varphi(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}) - \varphi(\mu_j - \boldsymbol{\beta}\mathbf{X})]\boldsymbol{\beta} \quad (6)$$

where φ is the density function of the normal distribution and all other terms are as defined previously.

To evaluate the statistical fit of the estimated models, goodness-of-fit metrics were computed, namely the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC):

$$\text{AIC} = 2F - 2LL(\boldsymbol{\beta}) \quad (7)$$

$$\text{BIC} = -2LL(\boldsymbol{\beta}) + F\ln(N) \quad (8)$$

F is a scalar denoting how many parameters were estimated by the model, N indicates the size of the accident dataset used for modelling purposes, and all other terms are as previously defined.

4. EMPIRICAL SETTING

Data from the STATS19 database is used for the empirical analysis of this study. STATS19 is an accident database with information drawn from the police reports and is available to the public (Department for Transport, 2019). The dataset contains various fields of accident information, as extracted from the STATS19 form, which is used by the UK police for accident reporting purposes. Overall, these fields include characteristics such as accident time, date, and location, number and type of casualties (driver, passenger, pedestrian, and so on), socio-demographic traits of casualties (age, sex, type of residential location), vehicle characteristics (type, engine capacity, and condition), road design and type (e.g., single carriageway, dual carriageway, and so on). The dataset also includes information about prevailing weather and lighting conditions at the time of the accident. The reported injury outcomes are classified into three categories: slight, serious, and fatal injuries. The STATS19 dataset does not encompass accidents resulting in no injuries.

For this study, we draw a dataset of pedestrian-motor vehicle accidents occurred at signalised and unsignalised junctions, and at physically controlled and human-controlled crossings in Scotland over nine years, spanning from 2010 to 2018. During this period, there were 1841 and 5100 accidents cases at signalised and unsignalised junctions, respectively, while 4656 and 500 accident cases were observed at physically-controlled and human-controlled crossings, respectively. Table 2 shows the descriptive statistics of the key variables, which were identified as statistically significant in the analysis. Further classification of accidents by crossing and human control type, along with corresponding accident frequencies, is shown in Table 1. The latter also provides accident frequencies for signalised and unsignalised junctions.

Table 1. Classification of crossings and junctions based on traffic control

Physically-controlled crossings	(No) % of Accidents	Human-controlled crossings	(No)% of Accidents	Junction	(No) % of Accidents
Zebra crossing	(418) 8.9%	Control by school crossing patrol	(183) 36.6%	Signalised	(1841) 26.5%
Pelican, puffin, toucan or non-junction pedestrian light crossing	(2061) 44.3%	Control by other authorised person	(317) 63.4%	Unsignalised	(5100) 73.5%
Pedestrian phase at traffic signal	(1792) 38.5%				
Footbridge or subway	(23) 0.5%				
Central refuge	(362) 7.8%				

Table 2. **Descriptive statistics of key variables of pedestrian accidents at signalised and unsignalised junctions and physically and human-controlled crossings**

Variable description	Signalised junctions (N=1841)		Unsignalised junctions (N=5100)	
	Frequency	Percentage (%)	Frequency	Percentage (%)
Time (1 if evening peak hours, 0 otherwise)	483	26.24	-	-
Day (1 if weekend, 0 otherwise)	462	25.10	-	-
Speed limit (1 if speed limit is 40 mph, 0 otherwise)	44	2.39	-	-
Urban area (1 if the accident occurred in an urban area, 0 otherwise)	1745	94.79	4195	82.25
Weather conditions (1 if fine, 0 otherwise)	1358	73.76	3845	75.38
Lighting conditions (1 if daylight, 0 otherwise)	1172	63.66	-	-
Road surface condition (1 if dry, 0 otherwise)	1112	60.40	-	-
Vehicle type (1 if passenger car, 0 otherwise)	-	-	-	-
Road surface condition (1 if wet, 0 otherwise)	-	-	1779	34.88
Speed limit (1 if speed limit is 30 mph, 0 otherwise)	-	-	4571	89.63
Time (1 if morning peak hours, 0 otherwise)	-	-	662	12.98
Object in carriageway (1 if no object, 0 otherwise)	-	-	4990	97.84
Carriageway hazard (1 if no hazard, 0 otherwise)	-	-	4967	97.39
	Physically-controlled Crossings (N=4656)		**Human-Controlled Crossings (N=500)**	
Weather conditions (1 if fine, 0 otherwise)	3468	74.50	391	78.20
Gender (1 if male driver, 0 otherwise)	3035	65.19	314	62.80
Vehicle type (1 if passenger car, 0 otherwise)	3419	73.48	-	-
Lighting conditions (1 if daylight, 0 otherwise)	3094	66.45	-	-
Road surface condition (1 if wet, 0 otherwise)	1710	36.74	151	30.20

Variable description	Signalised junctions (N=1841)		Unsignalised junctions (N=5100)	
Carriageway hazard (1 if no hazard, 0 otherwise)	4577	98.30	490	98.00
Day (1 if weekend, 0 otherwise)	-	-	-	-
Speed limit (1 if speed limit is 20 mph, 0 otherwise)	-	-	45	9.00
Time (1 if evening peak hours, 0 otherwise)	-	-	95	19.00

5. RESULTS AND DISCUSSION

5.1 Model estimation results

The results (parameter estimates, correlation coefficients, Γ matrix elements, marginal effects) of the injury-severity models at signalised and unsignalised junctions, and at physically and human-controlled crossings are presented in Tables 3 to 10. For each of the aforementioned accident groups, Correlated Random Parameters Ordered Probit models with Heterogeneity in the Means (CRPOPHM) were estimated. Furthermore, a series of Likelihood Ratio Tests (LRT) were conducted to evaluate the statistical performance of the CRPOPHM models compared to lower order counterparts (i.e., fixed parameters and uncorrelated random parameters models). The LRT results showed that the CRPOPHM models are statistically superior than their counterparts at a confidence level greater than 95%. Hence, only the CRPOPHM models are presented and discussed. Positive parameter estimates indicate an increase in the likelihood of the most severe injury outcome (i.e., fatal injury), while negative parameters imply an increase in the likelihood of the slight injury outcome. For all models, the estimable parameters were found statistically significant considering a minimum 90% level of confidence, though, in most cases, the parameters were significant at a greater than 95% level of confidence.[1]

The boxplots in Figures 1-4 illustrate the random parameters' distributions. The lower and upper limits of the box reflect the interquartile range – 75th - 25th percentile, the thick line in the middle of the box represents the median, the red line indicates the zero value, and the whiskers are determined based on the minimum and maximum values of the distribution.

[1] The statistical analysis was conducted using the NLOGIT and SPSS software.

5.1.1 Pedestrian-motor vehicle accidents at signalised junctions

Seven variables were identified as statistically significant determinants of injury severities at signalised junctions. As shown in Table 3, four variables generated random parameters, which include the urban area, fine weather, daylight, and dry road surface. The distributions of these random parameters are visualised in Figure 1. The urban area variable is observed to reduce the likelihood of severe injuries for about 56% of the accident observations, while, for nearly 44% of the remaining observations, the likelihood of severe injuries increases. This may highlight the mixed exposure patterns of pedestrians to accidents in urban areas, which may depend on the characteristics of the roadway network and the level of interactions between urban land uses and pedestrian traffic. In a previous study, Ukkusuri et al. (2012) found a strong relationship between the built environment, transit, and road geometric design characteristics (distinguishing factors between urban and non-urban areas) and the total and fatal pedestrian-vehicle collisions. Similarly, daylight and dry road surface at the time of the accident are linked with a reduced likelihood of severe injuries for 51.63% and 94.64%, respectively, of the accident cases. Only the fine weather, contrary to other variables, was found to increase the likelihood of slight injuries for nearly 70% of the pedestrian accidents at signalised junctions. This is not surprising, as Edwards (1998) found that accidents in fine weather conditions were consistently more severe than accidents under all other conditions except fog, using data for England and Wales from 1981-1991. More recently, Fountas et al. (2020) showed that pedestrian-related accidents that occurred in Scotland are more likely to result in severe injuries under daylight and fine weather. Favourable visibility prompted by fine weather may lead to aggressive driving patterns, which typically amplify the casualties of vulnerable road users.

The variable indicating whether a passenger car was involved in the accident was found to influence the means of all random parameters (i.e., this variable was found to capture the heterogeneity in the means of random parameters in a statistically significant manner). For urban areas, fine weather, and dry road surface, the passenger car indicator induces an opposite effect from that implied by the sign of the mean of the random parameter distribution. To that end, car-pedestrian accidents that occurred at urban areas or on dry road surfaces are associated with a higher tendency for severe injuries compared to any other types of pedestrian accidents with similar area or road surface characteristics. This may be a result of the intense traffic volumes and interactions in urban areas, for both pedestrians and car users. The passenger car variable has the opposite influence on the mixing distribution of the fine weather, leading to a decrease of accident observations associated with severe injuries. As expected, fine weather improves visibility conditions and overall driving comfort, especially for car users, who are more likely to get affected by adverse weather conditions (Peng et al., 2018).

The model results also reveal that evening peak time, weekend, and 40 mph speed limit are statistically significant factors that exert a static impact across the accident observations, i.e., they result in fixed (non-random) parameters (see Table 3). More specifically, pedestrian accidents occurred at evening peak time and at roads with 40mph speed limit are more likely to yield serious or fatal injuries. Evening peak hours reflect traffic conditions with intense presence of vehicular and pedestrian movements, especially at signalised intersections. In Scotland, roads with 40 mph speed limits that include signalised intersections possibly indicate suburban or rural trunk roads crossing settlements where the presence of vulnerable road users is highly expected (Transport Scotland, 2012). Accidents involving pedestrians that occurred at weekends are less likely to generate severe injury outcomes. This finding is intuitive given the lower volumes of vehicles and pedestrians at signalised junctions on weekends, thus leading to the reduction of dangerous conflicts between pedestrians and motorised modes.

Table 3. Model estimation results for pedestrian accidents at junctions and crossings

Variables	***Signalised***		***Unsignalised***		***Physically-controlled***		***Human-controlled***	
	Coeff.	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***
Variables (Non-random parameters)								
Constant	-2.313	-6.42	-1.172	-6.18	-1.302	-6.54	-4.550	-3.24
Time (1 if evening peak hours, 0 otherwise)	0.935	5.51	-	-	-	-	-	-
Urban area (1 if the accident occurred in an urban area, 0 otherwise)	-	-	-0.099	-1.76	-	-	-	-
Day (1 if weekend, 0 otherwise)	-0.284	-1.67	-	-	-	-	-	-
Speed limit (1 if speed limit is 40 mph, 0 otherwise)	2.384	5.41	-	-	-	-	-	-
Weather conditions (1 if fine, 0 otherwise)	-	-	0.295	4.69	0.210	3.06	-	-
Carriage hazards (1 if No Hazard, 0 otherwise)	-	-	0.297	1.91	-	-	2.753	2.02

Gender (1 if driver's gender is male, 0 otherwise)	-	-	-	-	0.316	5.75	0.665	3.04
Variables (Random parameters)								
Urban area (1 if the accident occurred in an urban area, 0 otherwise)	-0.765	-1.95	-	-	-	-	-	-
SDPDF*	4.792	37.67	-	-	-	-	-	-
Weather conditions (1 if fine, 0 otherwise)	1.011	2.52	-	-	-	-	-0.559	-1.82
SDPDF*	2.176	33.06	-	-	-	-	2.048	16.56
Lighting conditions (1 if daylight, 0 otherwise)	-0.264	-0.76	-	-	-0.186	-2.71	-	-
SDPDF*	6.475	34.53	-	-	1.310	56.50	-	-
Road surface conditions **(1 if dry, 0 otherwise)**	-3.026	-7.15	-	-	0.370	4.69	0.528	1.75
SDPDF*	1.878	30.857	-	-	1.641	76.17	2.469	25.19
Speed limit (1 if speed limit is 30 mph [Unsignalised]; 20mph [Human-controlled], 0 otherwise)	-	-	-0.137	-1.18	-	-	-2.594	-3.04
SDPDF*	-	-	0.737	56.34	-	-	1.874	10.50
Time (1 if morning **peak hours [Unsignalised], Evening peak hours [Human-controlled], 0 otherwise)**	-	-	0.011	0.11	-	-	-1.425	-3.15
SDPDF*	-	-	0.776	79.67	-	-	1.123	12.31
Hit object in carriageway indicator (1 if No object, 0 otherwise)	-	-	-0.392	-2.15	-	-	-	-
SDPDF*	-	-	1.307	59.20	-	-	-	-
Road surface condition indicator (1 if wet, 0 otherwise)	-	-	0.475	5.48	-	-	-	-
SDPDF*	-	-	1.204	91.54	-	-	-	-
Vehicle type (1 if passenger car, 0 otherwise)	-	-	-	-	0.171	2.29	-	-
SDPDF*	-	-	-	-	1.268	83.11	-	-
Carriageway **hazards (1 if** no **Hazard, 0 otherwise)**					-0.307	-1.74	-	-
SDPDF*					1.397	50.79	-	-
Heterogeneity in means: Vehicle type (1 if passenger car, 0 otherwise)								
Urban area	0.672	2.19	-	-	-	-	-	-
Weather conditions	-2.229	-4.92	-	-	-	-	-0.230	-0.66
Lighting **conditions**	-1.298	-3.75	-	-	-0.081	-0.73	-	-
Road surface conditions (dry)	2.995	6.64	-0.219	-2.33	-0.263	-2.36	-0.147	-0.30
Speed limit	-	-	-0.087	-0.63	-	-	2.917	2.32
Time	-	-	0.276	2.16	-	-	2.724	3.65
Hit object in carriageway	-	-	0.353	2.60	-	-	-	-
Road surface condition (wet)	-	-	-	-	-	-	-	-
Vehicle type	-	-	-	-	0.529	4.35	-	-
Carriageway **hazards**	-	-	-	-	-0.292	-2.15	-	-
Threshold parameters for probabilities								
μ_1	8.694	14.64	2.273	33.87	2.730	32.59	4.522	8.15
N	1841		5100		4656		500	
***LL* (0)**	-1159.950		-3330.693		-3103.374		-275.329	

***LL* (β)**	-1135.892		-3282.667		-3054.017		-257.38	
Goodness-of-fit metrics								
AIC	2317.80		6611.30		6152.00		558.80	
BIC	2399.59		6710.46		6293.84		651.48	
Distributional characteristics of random parameters								
	Above zero	**Below zero**	**Above zero**	**Below zero**	**Above zero**	**Below zero**	**Above zero**	**Below zero**
Urban area	43.66	56.34	-	-	-	-	-	-
Weather conditions	67.89	32.11	-	-	-	-	39.24	60.76
Lighting **conditions**	48.37	51.63	-	-	44.35	55.65	-	-
Road surface condition	5.36	94.64	65.34	34.66	58.92	41.08	58.47	41.53
Speed limit	-	-	42.63	57.37	-	-	08.31	91.69
Time	-	-	50.57	49.43	-	-	10.22	89.78
Hit object in carriageway	-	-	38.21	61.79	-	-	-	-
Vehicle type	-	-	-	-	55.36	44.64	-	-
Carriageway **hazard**	-	-	-	-	41.30	58.70	-	-

*SDPDF: Standard deviation of parameter density function

Table 4. Diagonal and off-diagonal matrix [*t-stats*], and correlation coefficients (in parenthesis) of random parameters at signalised junctions

Variables	Urban area	Weather conditions	Lighting conditions	Road surface condition
Urban area (1 if the accident occurred in an urban area, 0 otherwise)	4.792 [13.75] (1.0000)	-	-	-
Weather conditions (1 if fine, 0 otherwise)	1.0766 [4.46] (0.4948)	1.891 [8.56] (1.0000)	-	-
Lighting conditions (1 if daylight, 0 otherwise)	3.0708[10.95] (0.4742)	-3.9076[-13.07] (-0.2898)	4.151[13.60] (1.0000)	-
Road surface conditions (1 if dry, 0 otherwise)	-0.0562[-0.25] (-0.0299)	1.8228[7.77] (0.8286)	-0.4093[-2.80] (-0.7396)	0.185 [1.90] (1.0000)

Table 5. Diagonal and off-diagonal matrix [*t-stats*], and correlation coefficients (in parenthesis) of random parameters for at unsignalised junctions

Variables	Speed Limit	Time	Hit object in carriageway	Road surface condition
Speed Limit (1 if speed limit is 30 mph, 0 otherwise)	0.737 [10.74] (1.0000)	-	-	-
Time (1 if Morning peak hours, 0 otherwise)	0.008 [0.12] (0.0098)	0.776 [11.84] (1.0000)	-	-
Hit object in carriageway (1 if No object, 0 otherwise)	-0.703 [-10.33] (-0.5377)	-0.716 [-21.78] (-0.5536)	0.837 [25.35] (1.0000)	-
Road surface conditions (1 if wet, 0 otherwise)	-0.133 [-2.95] (-0.1106)	0.615 [11.29] (0.5102)	1.008[20.54] (0.3156)	0.190[5.22] (1.0000)

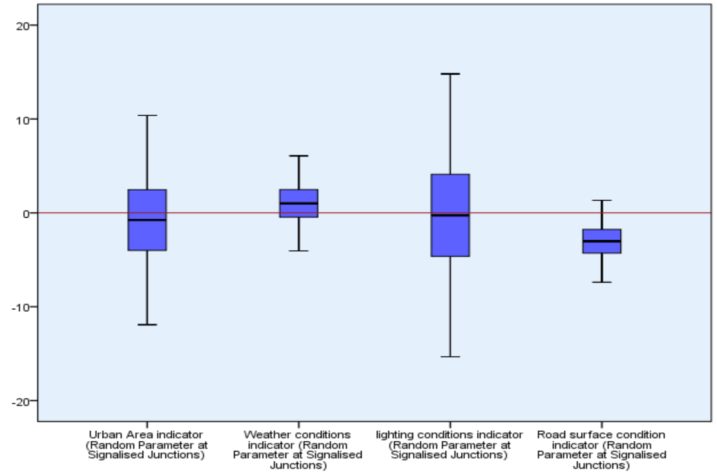

Figure 1 Boxplots illustrating the random parameters' distributions in the model for signalised junctions

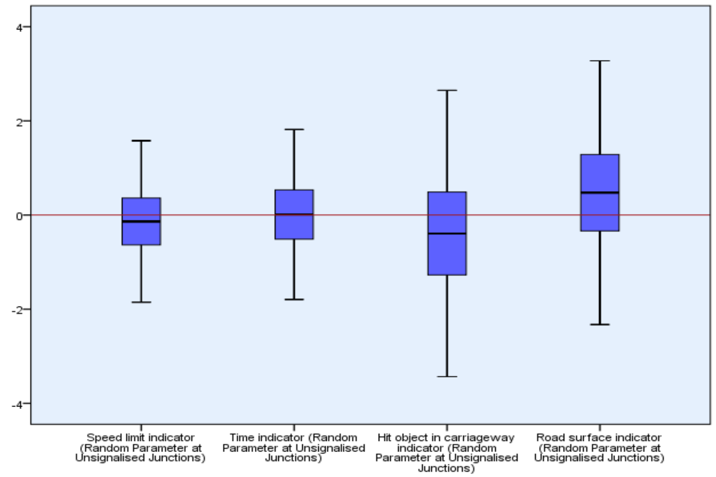

Figure 2 Boxplots illustrating the random parameters' distributions in the model for unsignalised junctions

5.1.2 Pedestrian-motor vehicle accidents at unsignalised junctions

Table 3 shows that the CRPOPHM model for pedestrian-motor vehicle accidents at unsignalised junctions contains four variables resulting to correlated random parameters: 30mph speed limit, morning peak hours, the no-object-in-carriageway indicator, and wet road surface. The distributions of the random parameters in this model are illustrated in Figure 2. The carriageways with a 30mph speed limit and those with no visible object at the time of the accident are linked with a higher likelihood of slight injuries for 57.37% and 61.79% of accident cases, respectively. Roads with 30mph speed limit either represent urban roads or rural roads within villages or any other types of small settlements (Transport Scotland, 2012). Given that urban roads are specifically captured through a different variable in the same model (see also Table 3), the effect of the 30mph speed limit possibly reflects the variation of driving patterns that are observed in uncontrolled or partially controlled junctions in rural areas (Hou et al, 2013), which have raised major safety concerns among the local communities of Scotland over the last few years (Cleland et al., 2020). Comparing this finding with a relevant effect in the model for signalised junctions, it is interesting to note the prevalence of severe injuries at signalised junctions on roads with 40mph speed limit, where both pedestrians and vehicles drivers reap the benefits of traffic signals, and other warning/information systems. This appears to contrast with Downey et al.'s (2019) finding, which shows that the pedestrian casualty rate is higher for unsignalised/priority-controlled junctions compared to signalised junctions.

Pedestrian-motor vehicle accidents that occurred at morning peak hours are associated with balanced effects on injury severities, as the likelihood of serious/fatal injuries increases for 50.57% of the observations. Wet road surfaces magnify the chances of pedestrian-motor vehicle accidents to be linked with severe injuries, as the specific variable increases the likelihood of serious and fatal injuries for 65.34% of the observations. Baireddy et al. (2018) also reported a prevalence of severe pedestrian-involved crashes on wet road surfaces under inclement weather. Focusing on variables with fixed parameters, fine weather and no hazard in carriageways are connected with more severe injuries, while the urban areas are linked to lower severity of injuries. In urban areas of Scotland, unsignalised junctions are primarily located in residential streets or non-built-up areas, where the interactions between motorized and pedestrian traffic may be less intense, whereas observed vehicular speeds are also lower.

Fine weather and the absence of apparent hazards on the carriageways may introduce risk-compensating impacts on drivers' or pedestrians' behaviours, as extensively discussed in Fountas et al.'s (2020) study.

The driver's gender further explains the heterogeneity in the means of the random parameters. The male driver indicator increases the mean of the random parameter for the no-object-in-carriageway indicator (which was originally negative), while it decreases the mean of the distribution for the wet road surface indicator (which was originally positive), as shown in Table 3. These findings imply that the involvement of a male driver increases the probability of severe injury in accidents where there was no visible object on the carriageway. On the contrary, male driver involvement decreases the proportion of accidents on wet road surface that yield injuries of lower severity. Likewise, the driver's gender is found to influence the 30mph speed limit and morning peak time variables at the same direction with that suggested by the original means of their distributions. Specifically, the results demonstrate that the male driver involvement in accidents during morning peak hours increases the likelihood of severe injuries. Male drivers have been long established as more prone to risk-taking behaviour, especially when the prevailing traffic conditions (as those in unsignalised junction environments) allow so (Hamed et al., 1997; Fountas et al., 2019). In contrast, male drivers on roads with a 30mph speed limit further increase the proportion of pedestrian-motor vehicle accidents resulting in slight injuries.

5.1.3 Pedestrian-motor vehicle accidents at physically-controlled crossings

Table 3 shows that six variables are identified as statistically significant factors of injury severities at physically-controlled crossings, out of which, four produced random parameters, including the passenger car indicator, daylight conditions, the wet road surface, and the absence of hazards on the carriageway. The mixed effects suggested by the random parameters are visualized through the boxplots of Figure 3, which provide the random parameters' distributions. Daylight and no-hazard-in-carriageway indicators are seen to reduce the likelihood of more severe injuries by about 56% and 59% of the accident observations, respectively, while the likelihood of severe injuries increases for the remaining accident observations. As in the model for signalised junctions, daylight may aid both pedestrians and drivers in properly comprehending and reacting to associated hazards via better visibility at the time of the accident, thereby reducing the potential for severe injuries. The effect of the no-hazard variable suggests that in the absence of hazardous objects, pedestrians and drivers are at lower risk of severe injuries in most of the cases; generally, roadside hazards have been long connected with higher impact velocity changes (delta-v) that may result in more severe injuries (Shannon et al., 2020).

On the contrary, the presence of a passenger car and wet road surface at the time of accident are associated with an increased likelihood of more severe injuries for about 55% and 59%, respectively, of the accident observations. The mixed trends for severe outcomes in pedestrian-car accidents may be attributed to the impact of various human factors of car drivers, such as age and cognitive state at the time of the accident, which are not available in the dataset (Mannering et al., 2016). It is not surprising the wet road surface contributes to higher chances of more severe injuries, as the roads tend to become more slippery for both pedestrians and vehicle users, and the friction between the road surface and the vehicle tyres reduces substantially. Crashes on wet roads were previously found to increase the probability of severe injuries (Aziz et al., 2013).

Pedestrian accidents occurred on weekends influence the means of all the random parameters. The weekend indicator imposes an opposite effect on the mean of the random parameter, only in the case of the wet road surface, where it reduces the originally positive mean, hence indicating an increased likelihood of slight injuries (see Table 3). Wet road surface may serve as an alert for driving caution, which may also extend to how the drivers interact with pedestrians in physically-controlled junctions, where there is anticipation for pedestrian movements. The weekend indicator is found to have an observable influence on the mixing distribution of the variables indicating passenger cars, daylight conditions, and no-hazard in carriageways by enhancing the main effect captured by the original means of the random parameters (see Table 3). Specifically, pedestrian accidents involving passenger cars are more likely to result in severe injuries when occurred at weekends. In contrast, the weekend variable increases the proportion of accidents under daylight conditions and on carriageways without hazards that are likely to result in slight injuries.

Focusing on variables with fixed parameters, fine weather at the time of the accident, and male drivers increase the likelihood of serious or fatal injuries, as shown in Table 3. As for unsignalised junctions, favourable weather conditions may trigger risk-compensating effects, especially for physically-controlled junctions, where drivers and pedestrians may feel more safe or confident due to the provision of crossing or channelisation facilities.

Table 6. Diagonal and Off-diagonal Matrix [*t-stats*], and Correlation Coefficients (in parenthesis) of Random Parameters for at Physically-Controlled Crossings

Variables	Vehicle type	Lighting conditions	Road surface condition	Carriageway hazard
Vehicle type (1 if Car, 0 otherwise)	1.268[18.97] (1.0000)	-	-	-
Lighting conditions (1 if daylight, 0 otherwise)	-1.133 [-19.48] (-0.8650)	0.657[11.56] (1.0000)	-	-
Road surface conditions (1 if wet, 0 otherwise)	-0.657 [-11.65] (-0.4003)	-1.199[-19.59] (-0.0209)	0.905 [15.90] (1.0000)	-
Carriageway hazard (1 if no Hazard, 0 otherwise)	-0.323 [-4.77] (-0.2315)	-0.350 [-6.61] (0.0747)	-1.229[-28.38] (-0.2098)	0.462 [17.27] (1.0000)

Table 7. Diagonal and off-diagonal matrix [*t-stats*], and correlation coefficients (in parenthesis) of random parameters at human-controlled crossings

Variables	Speed Limit	Time	Weather conditions	Road surface condition
Speed Limit (1 if speed limit is 20 mph, 0 otherwise)	1.874[2.87] (1.0000)	-	-	-
Time (1 if Evening peak hours, 0 otherwise)	-0.836 [-2.80] (-0.7448)	0.749 [2.08] (1.0000)	-	-
Weather conditions (1 if fine, 0 otherwise)	1.326 [7.75] (0.6474)	1.47 [8.08] (-0.0039)	0.531 [4.15] (1.0000)	-
Road surface conditions (1 if wet, 0 otherwise)	-2.199 [-7.87] (-0.8911)	0.460 [2.31] (0.7879)	0.644 [3.38] (-0.3759)	0.794[4.26] (1.0000)

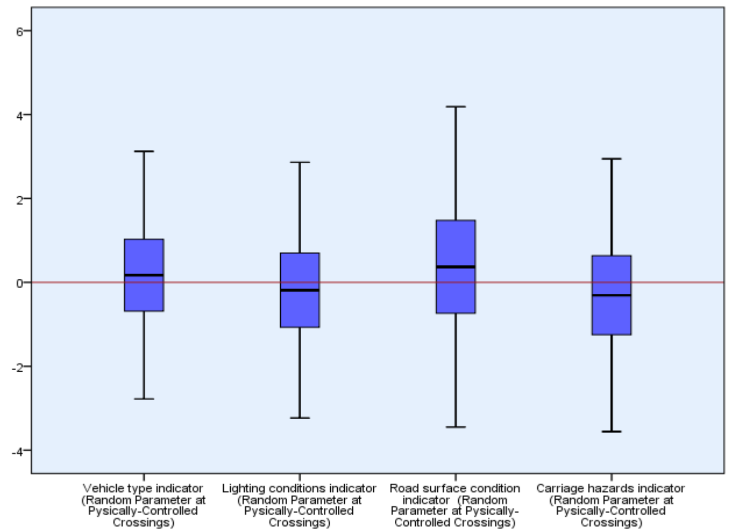

Figure 3 Boxplots illustrating the random parameters' distributions in the model for physically controlled crossings

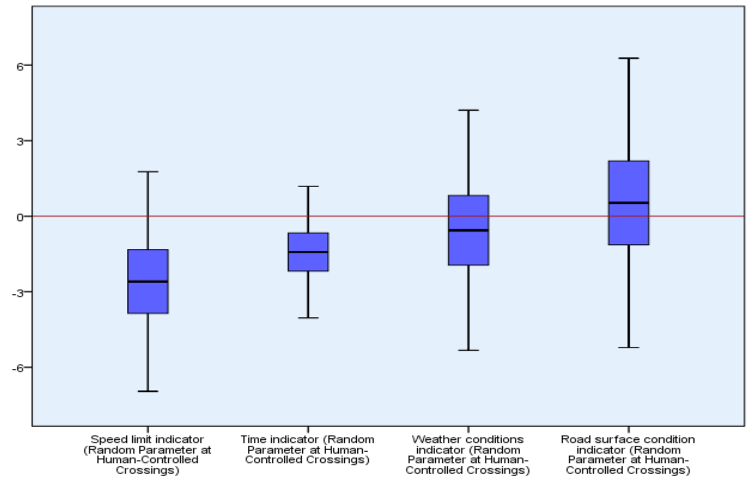

Figure 4 Boxplots illustrating the random parameters' distributions in the model for human-controlled crossings

5.1.4 Pedestrian-motor vehicle accidents at human-controlled crossings

Four factors, which include the 20mph speed limit, evening peak hours, fine weather, and wet road surface, result in correlated random parameters, as shown in Table 3. Out of these, only the wet road surface is mainly linked with a higher likelihood of more severe injuries, accounting for about 59% of the accident observations, as shown in the boxplot of Figure 4. This variable displays similar effects to its counterpart in the model for physically-controlled crossings. In contrast, carriageways with a 20mph speed limit, evening peak hours and fine weather are associated with a higher likelihood of slight injuries for vast majorities of accident observations, i.e., 91.69%, 89.78% and 60.76%, respectively (see Table 3). The lower speed patterns observed in roads with 20mph speed limits in conjunction with the presence of authorized patrol officers lead to safer and considerate behaviour, especially from drivers' side, which can justify the observed association with slight injuries.

Fine weather is found to favour slight injuries, as opposed to physically-controlled crossings. This finding may confirm the potential of human patrolling to encourage drivers and pedestrians complying with traffic rules and adopting safer traffic behaviour (Pantangi et al., 2020). Focusing on variables yielding fixed parameters, male drivers and no roadway hazard increase the likelihood of severe injuries, as also observed in physically-controlled crossings and unsignalised junctions, respectively.

The variable representing Monday, as the day-of-the-week when the accident occurred, explains the heterogeneity in the means of the random parameters. Specifically, the "Monday" variable changes the sign of the mean, from negative to positive, for the 20mph speed limit and evening peak hours, thus resulting to higher percentages of accidents with severe injuries. That is an interesting finding probably reflecting the more unsafe driving patterns typically observed in the first days of the week, as evidenced by the higher frequency of traffic violations relative to other days of the week (Zahid et al., 2020). It is also worth highlighting the magnitude of the Monday's effect on the two random parameters, as this is the only case in this study where the impact of the heterogeneity-in-the-means variable is strong enough to change the sign of the original means of the random parameters.

Table 8. Marginal effects of the explanatory variables for the estimated ordered probit models at signalised and unsignalised junctions

Variable description	CRPOPHM		
	Slight injury	Serious injury	Fatal injury
Signalised Junction			
Variables (Non-random parameters)			
Time (1 if the accident occurred during evening peak hours, 0 otherwise)	-0.0010	0.0008	0.00019
Day (1 if the accident occurred in the weekend, 0 otherwise)	0.00044	-0.00037	-0.000008
Speed Limit (1 if speed limit is 40 mph, 0 otherwise)	-0.00425	0.00378	0.000463
Variables (Random parameters)			
Urban area (1 if it is urban, 0 otherwise)	0.0219	-0.0378	0.0159
Light conditions (1 if daylight, 0 otherwise)	0.0382	-0.0293	-0.0089
Road surface condition (1 if dry, 0 otherwise)	0.0213	0.00092	-0.0223
Weather condition (1 if fine, 0 otherwise)	0.0034	-0.0086	0.0052
Unsignalised Junctions			
Variables (Non-random parameters)			
Urban area (1 if the accident occurred in an urban area, 0 otherwise)	0.0230	-0.0228	-0.00016
Weather conditions (1 if fine, 0 otherwise)	-0.0602	0.0598	0.00034
Carriageway hazard (1 if No Hazard, 0 otherwise)	-0.0561	0.0559	0.00027
Characteristics (Random parameters)			
Speed Limit (1 if speed limit is 30 mph, 0 otherwise)	0.0323	-0.0321	-0.00024
Time (1 if Morning peak hours, 0 otherwise)	-0.0025	0.0025	0.00002
Hit object in carriageway (1 if No object, 0 otherwise)	0.1047	-0.1036	-0.00110
Road surface condition (1 if wet, 0 otherwise)	-0.1137	0.1127	0.00094

Table 9. Marginal effects of the explanatory variables for the estimated ordered probit models for pedestrian accidents at physically and human-controlled crossings

Variable description	CRPOPHM		
	Slight injury	Serious injury	Fatal injury
Physically-controlled crossings			
Variables (Non-random parameters)			
Weather conditions (1 if fine, 0 otherwise)	-0.0430	0.0430	0.00005
Gender (1 if driver's gender is male, 0 otherwise)	-0.0652	0.0652	0.00007
Variables (Random parameters)			
Vehicle type (1 if passenger car, 0 otherwise)	-0.0356	0.0356	0.00004
Lighting conditions (1 if daylight, 0 otherwise)	0.0418	-0.0418	-0.00006
Road surface condition (1 if wet, 0 otherwise)	-0.0850	0.0848	0.00012
Carriageway hazard (1 if No Hazard, 0 otherwise)	0.0776	-0.0775	-0.00015
Human-controlled crossings			
Variables (Non-random parameters)			
Gender (1 if driver's gender is male, 0 otherwise)	-0.0584	0.0517	0.0068
Carriageway hazard (1 if no hazard, 0 otherwise)	-0.0804	0.0722	0.0082
Characteristics (Random parameters)			
Speed Limit (1 if speed limit is 20 mph, 0 otherwise)	0.2495	-0.2419	-0.0077
Time (1 if Evening peak hours, 0 otherwise)	0.1423	-0.1471	0.0048
Weather conditions (1 if fine, 0 otherwise)	0.1786	-0.1792	0.00063
Road surface condition (1 if wet, 0 otherwise)	-0.1011	0.0896	0.01154

5.2 Interpretation of the correlated random parameters

The correlation coefficients among the random parameters at signalised and unsignalised junctions, physically-controlled crossings and human-controlled crossings are presented in Tables 4 to 7, respectively. The correlation coefficients reflect the interactions among the unobserved effects captured by the random parameters.

Several negative correlations exist between pairs of random parameters related to accidents at signalised junctions. These are observed in the pairs formed by the urban area and dry surface, daylight and fine weather, and dry surface and daylight, with the correlation coefficients being -0.0299, -0.2898 and -0.7396, respectively. Negative correlations of the random parameters imply that the unobserved characteristics captured by the specific variables pose opposite influences on the injury outcomes. That means the injury severities feature contradictory effects, as the unobserved characteristics linked to one variable may favour slight injuries, while the unobserved characteristics linked to the other variable may favour severe injuries. The range of the unobserved characteristics that are captured by land use characteristics (i.e., urban area) and environmental conditions (lighting, weather, surface conditions) may be quite broad, but mainly relating to the behavioural responses of drivers and pedestrians to these factors, under the traffic context of signalised junctions.

Positive correlations are identified between the unobserved characteristics for the pairs fine weather and urban area, daylight and urban area, dry surface and fine weather - the correlation coefficients are 0.4948, 0.4742, and 0.8286, respectively. The positive coefficients imply unidirectional interactive influences (positive or negative) of the unobserved characteristics captured by these random parameters. For example, urban area and daylight are characteristics that generally favour slight injuries, as shown by the means of the corresponding random parameters.

Similarly, for the accidents at unsignalised junctions, Table 5 shows that there are negative coefficients of correlation for the following pairs of random parameters: no-object in carriageway and 30mph speed limit, wet road surface and 30mph speed limit, no-object in carriageway and morning peak time. Speed limits may serve as a significant source of unobserved heterogeneity, as the behavioural response to them may vary from driver to driver (Anastasopoulos & Mannering, 2016).

Such behavioural responses exhibit even greater variations when coupled with road conditions with quite heterogeneous implications on safety, such as the road surface.

For physically-controlled crossings, all the pairs of random parameters (except the no-hazard on the carriageway and daylight conditions) exhibit negative correlations. These are: daylight condition and passenger car (-0.8650), wet road surface and passenger car (-0.4003), no-hazard on the carriageway and passenger car (-0.2315), wet road surface and daylight condition (-0.0209), and no-hazard on the carriageway and wet road surface (-0.2098). Another interesting finding is that the passenger car, which has been long established as a major source of unobserved heterogeneity (Mannering et al., 2016), contributes to mixed effects in whichever pair of random parameters, as implied by the negative correlations.

Finally, for human-controlled crossings, there are negative correlations between the random parameter pairs of the evening peak time and 20mph speed limit, wet surface and 20mph limit, fine weather and evening peak time, and wet surface and fine weather, with the correlation coefficients being: 0.7448, -0.8911, -0.0039 and -0.3759, respectively. Positive correlations between the random parameters are observed for the pairs: fine weather and 20mph limit, wet road surface and evening peak time. As with unsignalised junction, the interactions between speed limit and road surface conditions unveil mixed effects. However, when 20mph speed limits are coupled with favourable weather, we observe evidence of homogeneity in the impact of unobserved characteristics, which may imply the limited range of users' behavioural responses to these factors in crossings with human patrolling presence.

5.3 Comparison of findings across the models

Table 10 summarises the observed impacts on the likelihoods of injury-severity outcomes of the variables that turned out statistically significant in all models. The relative magnitudes of the variable effects across models are also presented, as derived from the marginal effects in Tables 8 & 9. Fine weather was found to affect injury severities in all estimated models, either as random or fixed parameter. However, its effect is not consistent across all cases, as it increases the likelihood of severe injuries in unsignalised junctions and physically-controlled crossings, as opposed to the signalised junctions and human-controlled crossings where fine weather predominantly favours slight injuries, with the strongest effect being identified in the human-controlled crossings; the marginal effect for slight injuries is 0.179 (see Table 9). Road surface conditions are also observed to strongly affect injury outcomes across all models demonstrating mixed effects, with wet surfaces being mainly associated with more severe injuries. Notably, in the model for unsignalised junctions, we observe the most pronounced impact of this variable (the marginal effect for serious injury is 0.1127). As previously discussed, the driving conditions typically triggered by wet surfaces in combination with the level of traffic control in unsignalised junctions – that is appealing to risk-takers – may result in hazardous interactions between drivers and pedestrians. Another interesting finding arises from the no-hazard variable, which is linked with severe injuries in unsignalised and human-controlled junctions, but in physically-controlled junctions, the same factor exhibits a propensity towards slight injuries. It is worth mentioning that the absence of any apparent hazard on the carriageway demonstrates relatively strong effects across all models, as shown by the qualitative assessment of effects provided in Table 10.

Table 10. Comparative overview of the variables' effects across different models

Variable description	Signalised junctions	Unsignalised junctions	Physically controlled crossings	Human-controlled crossings
Carriageway hazard (1 if no hazard, 0 otherwise)	–	↑↑↑	[↓↓↓]	↑↑↑
Day (1 if weekend, 0 otherwise)	↓	–	–	–
Gender (1 if male driver, 0 otherwise)	–	–	↑↑↑	↑↑↑
Lighting conditions (1 if daylight, 0 otherwise)	[↓↓]	–	[↓↓]	–
Object in carriageway (1 if no object, 0 otherwise)	–	[↓↓↓↓]	–	–
Road surface condition (1 if dry, 0 otherwise)	[↓↓]	–	–	–
Road surface condition (1 if wet, 0 otherwise)	–	[↑↑↑↑]	[↑↑↑]	[↑↑↑↑]
Speed limit (1 if speed limit is 20 mph, 0 otherwise)	–	–	–	[↓↓↓↓]
Speed limit (1 if speed limit is 30 mph, 0 otherwise)	–	[↓↓]	–	–
Speed limit (1 if speed limit is 40 mph, 0 otherwise)	↑	–	–	–
Time (1 if evening peak hours, 0 otherwise)	↑	–	–	[↓↓↓↓]
Time (1 if morning peak hours, 0 otherwise)	–	[↑]	–	–
Urban area (1 if the accident occurred in an urban area, 0 otherwise)	[↓↓]	↓↓	–	–
Vehicle type (1 if passenger car, 0 otherwise)	–	–	[↑↑]	–
Weather conditions (1 if fine, 0 otherwise)	[↓]	↑↑	↑↑	[↓↓↓↓]

Table Key: "-" denotes a positive coefficient indicating higher likelihood of severe injuries; "-"denotes a negative coefficient indicating lower likelihood of severe injuries; "[…]" denotes a random parameter; "–" indicates that the variable is not statistically significant. The number of arrows, regardless of direction, provides a qualitative assessment of the relative magnitude of marginal effects, where: - = 0.000-0.009; -- = 0.010-0.049; ---= 0.050 – 0.099; ----≥0.100

6. SUMMARY OF FINDINGS AND CONCLUSIONS

This study provides a comprehensive investigation of the factors affecting injury severities in pedestrian-involved motor vehicle accidents considering different types of traffic control at junctions and pedestrian crossings. Thus, distinct injury-severity models are estimated for signalised and unsignalised junctions as well as physically-controlled and human-controlled pedestrian crossings. For the statistical analysis, we leveraged a correlated random parameter ordered probit approach, enriched with allowances for heterogeneity in the means of the random parameters. Due to its versatile capabilities, the employed modelling framework was proven capable of disentangling various angles of unobserved heterogeneity, demonstrating that the sources of unobserved effects on injury severities are dependent among them. The interactive effects of unobserved factors were captured by the correlation structure for random parameters, while the heterogeneity-in-the-means function unveiled another layer of unobserved impacts on injury severities, which directly influences the distributional characteristics of the random parameters.

The road surface conditions, posted speed limit and time-of-the-day were found to have heterogeneous impacts on injury severities, particularly at unsignalised junctions and at human-controlled crossings. In physically-controlled crossings, daylight and the absence of carriageway hazard introduced varying effects, but with higher propensity towards slight injuries, as opposed to passenger cars that also induced mixed patterns but with greater tendency towards severe injuries. In addition, the absence of an identifiable object on the road was found to induce varying effects across the accidents at unsignalised junctions featuring an overall strong trend towards slight injuries. Passenger cars and male drivers were found to affect the means of the random parameters at signalised and unsignalised junctions, respectively. Likewise, factors related to the day-of-the-week (weekend and Monday) were found to influence the mean of the random parameters for physically-controlled and human-controlled crossings.

Notable findings were drawn from the comparison of factors that were commonly identified as statistically significant in multiple models. The absence of any apparent hazard on the carriageway increased the likelihood of severe injuries at unsignalized junctions and at human-controlled crossings, whereas, at physically-controlled junctions, the same factor had opposite effect. Similar inconsistent effects were also observed for fine weather at the time of the accident. The results also disclosed effect disparities in accidents occurred at evening peak hours, which were strongly linked with slight injuries at human-controlled crossings, whereas at signalised junctions, evening peak hours favoured more severe injuries. Such findings are of key importance, especially for public authorities and policy makers, especially when designing safety countermeasures, as the sources of serious injury risk do evidently vary across different roadway facilities.

The outputs of this study can pave the way for policy implications. The consistently strong relationship of wet road surfaces with severe injuries across all cases highlights the urgency for better awareness of drivers and pedestrians about the significant injury risk posed by such surface conditions. This can be achieved either through traditional roadside signage or through vehicle-to-environment communication in vehicles featuring a higher level of automation. Injury risks arising from wet surfaces are paramount for Scotland, where climate conditions favour their frequent presence all year long (Fountas et al., 2020). In addition, the propensity of signalised junctions with 40mph speed limits to severe accidents may raise questions about the suitability of the specific speed limit and its capacity to curb speeding behaviours, especially in urban contexts. This finding could serve as supporting evidence for the further expansion of 20mph speed limits, primarily for built-up areas exhibiting significant pedestrian movements, as the specific intervention has proven efficient in bearing safety and public health benefits in Scotland (Nightingale et al., 2020).

Despite the insights gained by the statistical models, the data used for the analysis pose some limitations, mainly from an empirical perspective. For example, the lack of information about traffic signal settings (e.g., cycles, stages, or phases) did not allow the identification of the potential impact of cycle times or pedestrian phases on injury severities. Future research efforts can leverage richer datasets with more information about the traffic signal timings as well as more disaggregate information about the geometric design elements of intersections (e.g., angle, sight distance, horizontal and vertical clearance) and pedestrian facilities (e.g., refuges, curb types, and so on).

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