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Stability of factors influencing walking-along-the-road pedestrian injury severity outcomes under different lighting conditions: A random parameters logit approach with heterogeneity in means and out-of-sample predictions

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A R T I C L E I N F O

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A B S T R A C T

Pedestrians walking along the road's edge are more exposed and vulnerable than those on designated crosswalks. Often, they remain oblivious to the imminent perils of potential collisions with vehicles, making crashes involving these pedestrians relatively unique compared to others. While previous research has recognized that the surrounding lighting conditions influence traffic crashes, the effect of different lighting conditions on walking-along-the-road pedestrian injury severity outcomes remains unexplored. This study examines the variations in the impact of risk factors on walking-along-the-road pedestrian-involved crash injury severity across various lighting conditions. Preliminary stability tests on the walking-along-the-road pedestrian-involved crash data obtained from Ghana revealed that the effect of most risk factors on injury severity outcomes is likely to differ under each lighting condition, warranting the estimation of separate models for each lighting condition. Thus, the data were grouped based on the lighting conditions, and different models were estimated employing the random parameter logit model with heterogeneity in the means approach to capture different levels of unobserved heterogeneity in the crash data. From the results, heavy vehicles, shoulder presence, and aged drivers were found to cause fatal pedestrian walking-along-the-road severity outcomes during daylight conditions, indicators for male pedestrians and speeding were identified to have stronger associations with fatalities on roads with no light at night, and crashes occurring on Tuesdays and Wednesdays were likely to be severe on lit roads at night. From the marginal effect estimates, although some explanatory variables showed consistent effects across various lighting conditions in pedestrian walking-along-the-road crashes, such as pedestrians aged < 25 years and between 25 and 44 years exhibited significant variations in their impact across different lighting conditions, supporting the finding that the effect of risk factors are unstable. Further, the out-of-sample simulations underscored the shifts in factor effects between different lighting conditions, highlighting that enhancing visibility could play a pivotal role in significantly reducing fatalities associated with pedestrians walking along the road. Targeted engineering, education, and enforcement countermeasures are proposed from the interesting insights drawn to improve pedestrian safety locally and internationally.

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1. Introduction

In traffic safety, vulnerable road users (pedestrians, bicyclists, and motorcyclists) are cited as being disproportionately impacted by road traffic crashes. From the recent road safety statistics, this group of road users is identified to be involved in over 50 % of all traffic-related deaths worldwide (WHO, 2018a), and pedestrians, in particular, are noted as the most susceptible to fatalities (Li et al., 2021). Walking is one of the most common modes of transport in developing countries. However, road construction in developing countries does not adequately consider proper lighting and pedestrian protection facilities expected to protect vulnerable road users. Besides, developing countries' low pedestrian-centric safety standards also predispose walking-along-the-road pedestrians to vehicular conflicts, resulting in fatal collisions, unlike crossing-the-road pedestrians with some form of protection at signalized crossings (WHO, 2018a). Even though walking along the road's edge is an everyday activity in most developing countries, less attention has been paid to understanding the factors impacting the safety of this category of pedestrians and how the different lighting conditions influence them.

Pedestrians walking along the road's edge are particularly vulnerable to vehicle crashes. They are outside the designated pedestrian areas and often have less protection compared to pedestrians in crosswalks. Besides, depending on the lighting condition on the road, drivers and pedestrians may face visibility challenges, leading to an increased risk of collisions and can contribute to unique dynamics in vehicle–pedestrian crashes. Further, the space available for vehicles is reduced when pedestrians occupy and walk along the road space. This creates a unique interaction between pedestrians and vehicles, potentially leading to different collision patterns and outcomes. The vulnerability of these pedestrians can lead to more crashes with severe ramifications – thus, deserving attention from safety experts.

In the literature on pedestrian safety, walking-along-the-road pedestrian crashes are more frequent (53 %) compared to crossing pedestrian collisions (28 %) (Sivasankaran and Balasubramanian, 2020). Another study showed that walking along the road accounts for about 15 % of fatal pedestrian crash injuries with alarming consequences (NYMTC, 2002). Regardless, research focusing on investigating the factors influencing pedestrian injury severity outcomes of pedestrians walking along the road is scanty. Another crucial area that has not received attention by researchers is the determination of the factors influencing injury severity outcomes of pedestrians walking along the road while considering the lighting condition existing at the time of the crash (daylight, dark-but-lighted, and dark-but-not-lighted (streetlights off)). From the viewpoint of roadway lighting, the characteristics of traffic and pedestrians may differ depending on the lighting conditions at the time of the incident, namely daylight, night with lighting, and night without lighting (Fountas et al., 2020; Tamakloe et al., 2021). These lighting conditions can further impact the influence of explanatory factors on the severity of injuries. The disparities observed in crash outcomes under each lighting condition can be attributed to varying behaviors exhibited by drivers and pedestrians during daylight and dark conditions. Furthermore, unobserved factors related to traffic volume, travel intention, direction, and similar variables may also differ across lighting conditions – impacting injury severity outcomes differently. Understanding these variations of risk-factor effects on walking-along-the-road pedestrian injury severity outcomes is essential to guide the formulation of policies geared toward improving pedestrian safety.

Given the significance of walking as a means of transportation and the severity of injuries faced by pedestrians in developing countries primarily characterized by the lack of adequate pedestrian facilities and street lighting, it is crucial to conduct a comprehensive analysis to comprehend the influence of various factors on the mechanism behind crashes, which is primarily influenced by the surrounding lighting conditions during the incident. Thus, the main objective of this research is to examine the influence of risk factors on the severity of pedestrian injuries that occur while walking along roads under different lighting conditions in Ghana, a developing country in West Africa. The study contributes explicitly to the literature by (i) exploring the stability of factors influencing walking-along-the-road pedestrian injury severity outcomes under each lighting condition, (ii) identifying variables whose effects vary across different observations, and (iii) investigating the aggregate differences between walking-along-the-road pedestrian injury severity outcomes during the daylight, night-but-lighted, and night-but-unlighted conditions using an out-of-sample simulation technique. The study also contributes to the pedestrian safety literature in developing countries by employing an innovative econometric model, the random parameters logit model with heterogeneity in the means and variances approach to address the unobserved heterogeneity issue inherent in crash datasets. It is expected that this research will enhance our comprehension of the elements that impact the severity of injuries in pedestrian crashes occurring on roadways under varying lighting conditions. The findings of this study will contribute to identifying targeted and valuable countermeasures that can be implemented locally and internationally to mitigate pedestrian injuries.

2. Literature review

Crashes in developing countries have become a major public health concern. Over 93 % of the world's fatalities occur in these countries, and most of the casualties are pedestrians (WHO, 2020). To provide context and clarify the gap in the literature, a thorough review of the relevant literature on pedestrian injury severity studies from developing countries was conducted and presented in Table A1 in the appendix. In general, studies have shown that variables such as wide roadways, median-separator absence, and bad roadway surfaces tended to increase the propensity of fatal pedestrian crash injuries (Chen and Fan, 2019; Das et al., 2018a; Zafri et al., 2020). Other factors such as inclement weather, driver error, elderly pedestrians, heavy vehicles, high traffic volume, increased pedestrian-vehicle interactions, and encroachment of footpaths were identified as critical factors affecting the severity of pedestrian crashes in developing countries (Damsere-Derry et al., 2010; Hasanat-E-Rabbi et al., 2022; Obinguar and Iryo-Asano, 2021; Tay et al., 2011; Tjahjono et al., 2021).

A detailed analysis of the literature revealed that the poor transport infrastructure in developing countries, particularly regarding lighting conditions, accounts for an increased chance of crashes involving pedestrians and increased injury severities (Aidoo et al., 2013; Mujalli et al., 2019; Tamakloe et al., 2021). Many studies highlighted that fatal pedestrian-involved crashes are likely to occur late at night (Tulu et al., 2017; Verzosa and Miles, 2016), signifying that reduced visibility during such periods greatly impacted the severity of pedestrian crashes. Aidoo et al. (2013) showed that the chance of hit-and-run incidents involving pedestrians occurring at night without lighting was higher than when the streetlight was on. The study further found a high likelihood of hit-and-run casualties being hit again by other vehicles under dark conditions if not transported from the crash scene. Sullivan and Flannagan (2011) also identified differences in pedestrian crash risk across different lighting conditions, supporting the need to consider a more detailed analysis of the impact of pedestrian maneuver and lighting conditions on the injury severity outcome of vehicle–pedestrian crashes.

Regarding lighting conditions, Amoh-Gyimah et al. (2017) proved that the relative risk of pedestrian fatalities reduces by a more significant margin on dark-but-lighted roads (night but streetlights turned on) compared to dark-unlighted roads owing to the improved visibility at the time of the crash. Besides, both Aidoo et al. (2013) and Sivasankaran and Balasubramanian (2020) demonstrated that the chance of fatalities in vehicle–pedestrian crashes during dark conditions increases as drivers are likely to abandon injured casualties on dark-unlighted roads. Other studies also indicated that darkness increased the probability of pedestrian crash fatalities (Lee and Abdel-Aty, 2005; Sullivan and Flannagan, 2011).

Concerning the modeling approach, researchers tended to estimate single models using the entire dataset without considering the joint effects of key variables in the crash dataset. In recent years, there has been a growing body of literature exploring the variations in the impact of risk factors on crash injury severities through the estimation of separate models for each homogeneous sub-group of crash populations with similar characteristics to better understand their effect on crashes and propose more targeted policies. A few examples of these studies are summarized as follows. Focusing on temporal characteristics, some studies developed different models for different years (Behnood and Mannering, 2019; Hsu, 2016; Tamakloe et al., 2020). Some previous research also estimated separate models for different lighting conditions (Al-Bdairi et al., 2018; Ariannezhad and Wu, 2019; Hossain et al., 2022; Islam and Burton, 2020; Jafari Anarkooli and Hadji Hosseinlou, 2016; Uddin and Huynh, 2017). Further, the factors influencing injury severity outcomes, given the combined effects of lighting and weather conditions (Fountas et al., 2020) and lighting and pavement conditions (Tamakloe et al., 2021), have been conducted. Exploring the variability in the effects of risk factors under different combinations of pedestrian maneuver and lighting conditions could provide insights to improve pedestrian safety.

Researchers have investigated how different risk factors impact the severity of injuries under varying lighting conditions. They utilized various statistical models such as the ordered probit model, hierarchical ordered logit model, multinomial logit model, and mixed logit models. The ordered probit/logit models assume that the crash outcomes follow a specific order. However, some scholars argue that because the outcomes of traffic crashes are not ordered but discrete, it is more appropriate to use models that handle the non-ordered nature of crash outcomes (Al-Bdairi et al., 2018; Mannering and Bhat, 2014). Moreover, ordered response models impose limitations on the influence of variables and are more likely to underestimate less severe injury crashes (Ariannezhad and Wu, 2019; Islam and Mannering, 2006). As a result, multinomial logit models are commonly employed in the field of safety. Nevertheless, a significant drawback of multinomial logit models is the assumption about disturbance terms, which need to be independently and identically distributed. Violating this assumption can result in independence from irrelevant alternative properties (Washington et al., 2020). To address the limitations of multinomial logit models and nested logit models, mixed logit models are utilized. These models consider unobserved heterogeneity by introducing random parameters that allow certain explanatory variables to vary across observations. Unobserved heterogeneity can arise from different sources, like variations within variables or incomplete crash data. Neglecting this unobserved heterogeneity can lead to biased and inefficient parameter estimates (Mannering et al., 2016). However, traditional mixed logit models assume the same mean and variance for random parameters across all observations. Recent safety research has seen an increase in the use of more advanced mixed logit models that relax this assumption to better capture unobserved heterogeneity in the data. These advanced models, particularly the mixed logit models with heterogeneity in means and variances of random parameters, have provided improved results and insights that can be valuable for policymakers (Behnood and Mannering, 2017; Hou et al., 2022; Islam and Mannering, 2021; Seraneeprakarn et al., 2017). For this reason, this approach is employed in this study.

The limited access to transport services in developing countries has made walking an integral part of the urban transport system. However, due to the inadequate infrastructure for active mobility, the safety of pedestrians is jeopardized (Loo and Siiba, 2019). Walking-along-the-road crashes constitute a substantial number of fatality cases, and the lighting conditions significantly affect the chances and severity outcomes of collisions. From the reviewed literature, researchers have not considered estimating separate models to explore the variability in the effects of risk factors under different combinations of pedestrian maneuver and lighting conditions. As the factors influencing walking-along-the-road pedestrian crashes under different lighting conditions are likely to vary, conducting a more disaggregated study is imperative, which will lead to understanding and proposing more targeted countermeasures to improve traffic safety. Traffic safety studies acknowledged that the pedestrian maneuver prior to the crash, including walking along and crossing the road, is a significant proxy for measuring pedestrian exposure (Damsere-Derry et al., 2010). Thus, some researchers focused on exploring factors influencing crash severities, considering these proxies. For example, to properly understand how risk factors affect vehicle-crossing pedestrian crash injury severity outcomes, a study from Connecticut employed an ordered probit model to model vehicle-crossing pedestrian crashes extracted from a crash database (Zajac and Ivan, 2003). The study identified that roadway width, driver and pedestrian alcohol involvement, and aged pedestrians were critical determinants of fatal injury severity outcomes. The study further deduced that compact residential and downtown areas generally experienced lower severities. Compared to walking on the footpath. A study from Hong Kong showed that crossing the intersection led to more fatal crashes (Zeng et al., 2023). Similar findings from another highly developed territory were reported in a study from the United Kingdom (Salehian et al., 2023). Regarding factors contributing to walking-along-the-road crashes, a previous study identified that a lack of sidewalks, grassy walkable neighborhoods, and high levels of unemployment increased the chance of vehicle–pedestrian collisions (McMahon et al., 1999). Nevertheless, the authors did not consider the variations in risk factor effects considering different lighting conditions, and those from developing countries are scarce.

In general, numerous research works have examined pedestrian-vehicle crashes. However, there is a lack of comprehensive investigation into the diverse range of risk elements that impact pedestrian-vehicle accidents occurring while walking along the road, especially with a specific focus on the lighting conditions during these incidents, namely daylight, night with lights turned on, and night with lights turned off. Moreover, no previous research has successfully investigated the overall differences in the severity of injuries sustained by pedestrians walking along the road, considering various lighting conditions. A recent similar study on factors influencing pedestrian injury severity outcome presented a broader analysis, encompassing all pedestrian crashes without this differentiation (Alogaili and Mannering, 2022). This current study emphasizes examining crashes under varying lighting conditions. This extended analysis of lighting conditions provides a more comprehensive understanding of the factors influencing pedestrian injury severities. Specifically, in contrast, Alogaili and Mannering, (2022)'s work predominantly focused on daytime and nighttime conditions, with limited attention to nuanced lighting scenarios during nighttime. Therefore, our study offers a more specific and nuanced exploration of pedestrian injury severities among those walking along the road, particularly in different lighting conditions, setting it apart from the broader scope of Alogaili and Mannering, (2022)'s research. Addressing this gap, this study employs a random parameter logit model that considers variations in the mean and variance of random parameters.

3. Materials and methods

3.1. Data description

3.1.1. The magnitude of pedestrian safety problem in Ghana

Ghana is a natural resource-enriched country located in the western part of Africa, with an estimated population of 31.4 million people (Ghana Statistical Service, 2021). Generally, the country has a serious road safety problem. It was estimated in 2018 that there were 24.9 deaths per 100,000 persons, higher than the world average of 18.2 deaths per 100,000 persons. Road traffic crashes were identified as among Ghana's top 10 causes of death, and the cost of these crashes was estimated at 1.6 % of the country's Gross Domestic Product (Boateng, 2021). Speeding has been found to be the leading cause of crashes in the country (Afukaar, 2003).

Although walking forms the second most predominant mode of commuting, pedestrians continue to be disproportionally represented in all fatal road crashes in Ghana (Afukaar, 2003; Damsere-Derry et al., 2010; Essel and Spadaro, 2020). The number of pedestrian fatalities keeps increasing compared to other roadway users (NITA, 2020). Statistics show that about 40 % of all road traffic fatalities in the country involve pedestrians (Obeng-Atuah et al., 2017). According to the WHO, pedestrian fatalities in Ghana are the 6th highest compared to all other countries in the world and the third-highest among countries of similar income levels (11.5 deaths per 100,000 persons) (WHO, 2018b). A significant portion of the fatalities resulting from pedestrian crashes are hit-and-run cases, and these incidents typically take place in low-light or nighttime conditions (Aidoo et al., 2013).

In general, due to the cosmopolitan nature of most of its cities and the high space demand for commercial activities, there is often an increase in street parking and vehicle-human traffic conflicts, which pose a significant danger to pedestrians (Amoako et al., 2014). Similar to other developing countries, hawkers and vehicles mostly use sidewalks due to poor regulation enforcement mechanisms (Fig. 1). This unapproved change of use, coupled with inadequate pedestrian infrastructure, reduces the width of the sidewalks and further compels pedestrians to use lanes and shoulders of roads, which are unsafe for pedestrians (Lasmini and Indriastuti, 2010). Infrastructural challenges related to street lighting, a serious problem in Ghana, have also been tagged as a factor influencing pedestrian safety at night (Obeng-Atuah et al., 2017; Tamakloe et al., 2021). However, the number of preventable pedestrian-related deaths is highly unacceptable, demanding a rigorous analysis to identify critical policies for remedying the current situation.

3.1.2. Study data and framework

The pedestrian crash data employed for this study was procured from the Building and Road Research Institute crash bank of the Council for Scientific and Industrial Research, Ghana. In the event of a crash, experts from the Ghana Police Service are dispatched to the scene. The data collected are stored in the Micro-Accident Analysis Package developed by the Transport Research Laboratory, UK. In the crash form, pedestrian injury severity is categorized into three distinct groups: fatal, hospitalized/severe injuries, and injured-but-not-hospitalized/minor injuries. Fatal pedestrian injuries are the observations in which the pedestrian dies within 30 days of the vehicle–pedestrian crash. Hospitalized injuries (or serious injuries) are those observations in which the pedestrian is detained at the hospital for more than 24 h due to the nature of the injuries sustained. In injured-but-not-hospitalized or minor injury crashes, the pedestrian requires only first-aid attention, not hospitalization (Tamakloe et al., 2021).

The data includes all walking-along-the-road vehicle–pedestrian crashes on major roads in the country from 2014 to 2018. This timeline was selected based on data availability and adequacy regarding the number of observations for robust analysis. Although temporal instability of risk factors may be an issue, it could not be tested due to the limited number of observations in each data grouping used for the analysis.

Due to the motive of this study, specific attention is paid to lighting conditions and walking-along-the-road pedestrian crash variables. Thus, after cleaning the data by removing those observations with missing variable information, walking-along-the-road pedestrian crashes were extracted from the entire data and were divided based on the lighting condition: (i) walking-along-the-road pedestrian crashes during the daylighting condition (WDAY), (ii) walking-along-the-road pedestrian crashes during the night-but-lighted condition (WNLO), (iii) walking-along-the-road pedestrian crashes during the night-but-unlighted condition (WNNL). The data used for this study comprises, among other things, indicators corresponding to the temporal characteristics (day of the week), crash features such as the injury severity level, crash location, the manner of the crash, whether it occurred at an area with curved/inclined or straight/flat road, and whether it was a hit-and-run case (driver deciding to speed-off after a crash without helping their victims or reporting to the police). Besides, environmental features (such as clear or inclement weather conditions and lighting conditions), roadway characteristics such as the shoulder condition, surface condition (traffic control at the crash location, and pavement condition: good-tarred with no potholes/bad-rough/untarred or tarred with potholes), driver attributes (such as the gender of the driver, the age of driver), and the drivers' errors/faults that led to the crash) were considered. Notably, the determination of road surface quality in the dataset was based on information provided by the Ghana Police Service in the crash reports.

The total number of walking-along-the-road pedestrian crash observations (2014–2018) in the data was 4,053 (Table 1). It was observed that the majority of these crashes occurred on Saturdays (17 %, 680 observations). This study data also reveals that most of the pedestrian crashes occurred during clear weather (85 %), on straight roads (92 %), and on roads with shoulders (72 %) and no medians (74 %). Data on the location of the crash (rural/urban) was unavailable; thus, it was not reflected in this study. Further, 82 % of crashes occurred at midblocks (not-at-intersections) and sections without traffic control (79 %). The data revealed that 49 % of crashes involved cars against only 2 % of the "other vehicles" indicators, such as tractors and bicycles. It was also established that private-use vehicles were mainly engaged in pedestrian-

Fig. 1. Pedestrians walking along the road due to sidewalks taken over by street vendors.

Table 1
Descriptive statistics of explanatory variables.

Variables	WDAY		WNLO		WNNL		WT	
	Freq	%	Freq	%	Freq	%	Freq	%
Temporal and environmental characteristics								
Day of the week								
Sunday (1 if the day of the week is 'Sunday'; 0 otherwise)*	331	13	206	22	70	15	607	15
Monday (1 if the day of the week is 'Monday'; 0 otherwise)	368	14	128	13	57	12	553	14
Tuesday (1 if the day of the week is 'Tuesday'; 0 otherwise)	369	14	121	13	61	13	551	14
Wednesday (1 if the day of the week is 'Wednesday'; 0 otherwise)	340	13	120	13	41	9	501	12
Thursday (1 if the day of the week is 'Thursday'; 0 otherwise)	398	15	98	10	69	15	565	14
Friday (1 if the day of the week is 'Friday'; 0 otherwise)	395	15	129	14	72	15	596	15
Saturday (1 if the day of the week is 'Saturday'; 0 otherwise)	430	16	149	16	101	21	680	17
Weather condition								
Clear (1 if weather condition is 'clear'; 0 otherwise)	2,581	98	710	75	166	35	3457	85
Inclement (1 if weather condition is 'inclement'; 0 otherwise)*	50	2	241	25	305	65	596	15
Crash location characteristics								
Road description								
Other roads – curved/inclined (1 if road description is 'other roads – curved/inclined'; 0 otherwise)*	222	8	67	7	55	12	344	8
Straight/flat (1 if road description is 'straight/flat'; 0 otherwise)	2,409	92	884	93	416	88	3709	92
Road surface type								
Good (1 if road surface type is 'good'; 0 otherwise)	2,113	80	792	83	280	59	3185	79
Poor (1 if road surface type is 'poor'; 0 otherwise)*	518	20	159	17	191	41	868	21
Shoulder type								
No shoulder (1 if shoulder type is 'no shoulder'; 0 otherwise)*	732	28	257	27	165	35	1154	28
Shoulder present (1 if shoulder type is 'shoulder present'; 0 otherwise)	1,899	72	694	73	306	65	2899	72
Road separation								
No median (1 if road separation is 'no median'; 0 otherwise)*	1,919	73	671	71	409	87	2999	74
Median present (1 if road separation is 'median present'; 0 otherwise)	712	27	280	29	62	13	1054	26
Location type								
Not-at-intersection (1 if location type is 'not-at-intersection'; 0 otherwise)	2,148	82	772	81	421	89	3341	82
Other locations – roundabouts/intersections (1 if location type is 'other locations – roundabouts/intersections'; 0 otherwise)*	483	18	179	19	50	11	712	18
Traffic control								
No traffic control (1 if traffic control type is 'no traffic control'; 0 otherwise)*	2,067	79	713	75	418	89	3198	79
Other traffic control – stop sign/give way/pedestrian-X (1 if traffic control type is 'other traffic control – stop sign/give way/pedestrian-x'; 0 otherwise)	376	14	167	18	48	10	591	15
Signals (1 if traffic control type is 'signals'; 0 otherwise)	188	7	71	7	5	1	264	7
Crash characteristics								
Number of vehicles involved								
Multi-vehicle (1 if number of vehicles involved is 'multi-vehicle'; 0 otherwise)	569	22	217	23	57	12	843	21
Single-vehicle (1 if number of vehicles involved is 'single-vehicle'; 0 otherwise)*	2,062	78	734	77	414	88	3210	79
Hit & run								
Hit-and-run (1 if crash type is 'hit-and-run'; 0 otherwise)	49	2	27	3	7	1	83	2
Not-hit-and-run (1 if crash type is 'not-hit-and-run'; 0 otherwise)*	2,582	98	924	97	464	99	3970	98
Vehicle characteristics								
Vehicle type								
Bus/minibus (1 if vehicle type is 'bus/minibus'; 0 otherwise)	517	20	178	19	87	18	782	19
Car (1 if vehicle type is 'car'; 0 otherwise)	1,279	49	480	50	220	47	1979	49
Heavy goods vehicle (1 if vehicle type is 'heavy goods vehicle'; 0 otherwise)	277	11	103	11	40	8	420	10
Other vehicle types – bicycle, tractor (1 if vehicle type is 'other vehicle types – bicycle, tractor'; 0 otherwise)	45	2	8	1	8	2	61	2

(continued on next page)

Table 1 (*continued*)

Variables	WDAY		WNLO		WNNL		WT	
	Freq	%	Freq	%	Freq	%	Freq	%
Pickup (1 if vehicle type is 'pickup'; 0 otherwise)*	140	5	38	4	27	6	205	5
Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	373	14	144	15	89	19	606	15
Vehicle ownership/usage								
Bus/minibus (1 if vehicle ownership is 'bus/minibus'; 0 otherwise)*	493	19	174	18	82	17	749	18
Company vehicle (1 if vehicle ownership is 'company vehicle'; 0 otherwise)	285	11	98	10	48	10	431	11
Other owner – government/police/military/emergency (1 if vehicle ownership/usage is 'other owner – government/police/military/emergency'; 0 otherwise)	85	3	34	4	24	5	143	4
Private vehicle (1 if vehicle ownership is 'private vehicle'; 0 otherwise)	1,379	52	501	53	224	48	2104	52
Taxi (1 if vehicle ownership is 'taxi'; 0 otherwise)	389	15	144	15	93	20	626	15
Vehicle maneuver								
Going ahead (1 if vehicle maneuver is 'going ahead'; 0 otherwise)	2,463	94	902	95	434	92	3799	94
Other maneuver – right turn/left turn/u turn/others (1 if vehicle maneuver is 'other maneuver – right turn/left turn/u turn/others'; 0 otherwise)*	168	6	49	5	37	8	254	6
Vehicle defects								
Brake (1 if vehicle defect is 'Brake'; 0 otherwise)	147	6	39	4	19	4	205	5
No defect (1 if vehicle defect is 'no defect'; 0 otherwise)	2,181	83	779	82	410	87	3370	83
Other defects – tires/suspension/lights (1 if vehicle defect is 'other defects – tires/suspension/lights'; 0 otherwise)*	118	4	64	7	21	4	203	5
Steering (1 if vehicle defect is 'steering'; 0 otherwise)	185	7	69	7	21	4	275	7
Drivers characteristics and errors								
Driver sex								
Female (1 if driver/rider sex is 'female'; 0 otherwise)*	82	3	25	3	9	2	116	3
Male (1 if driver/rider sex is 'male '; 0 otherwise)	2,549	97	926	97	462	98	3937	97
Driver age								
25yrs-44yrs (1 if driver/rider age is '25yrs-44yrs'; 0 otherwise)*	1,851	70	677	71	320	68	2848	70
45yrs-64yrs (1 if driver/rider age is '45yrs-64yrs'; 0 otherwise)	461	18	142	15	85	18	688	17
<25yrs (1 if driver/rider age is '<25yrs'; 0 otherwise)	294	11	118	12	61	13	473	12
>64yrs (1 if driver/rider age is '>64yrs'; 0 otherwise)	25	1	14	1	5	1	44	1
Driver error								
Inattentive (1 if driver/rider error is 'inattentive'; 0 otherwise)	1,462	56	513	54	307	65	2282	56
Inexperienced (1 if driver/rider error is 'inexperienced'; 0 otherwise)	119	5	37	4	13	3	169	4
No error (1 if driver/rider error is 'no error'; 0 otherwise)*	285	11	93	10	26	6	404	10
Other errors – improper overtaking/improper turning/fatigued etc. (1 if driver/rider error is 'other errors – improper overtaking/improper turning/fatigued etc.'; 0 otherwise)	196	7	71	7	29	6	296	7
Speeding (1 if driver/rider error is 'speeding'; 0 otherwise)	506	19	220	23	92	20	818	20
Too close (1 if driver/rider error is 'too close'; 0 otherwise)	63	2	17	2	4	1	84	2
Casualty characteristics								
Casualty sex								
Female (1 if casualty sex is 'female'; 0 otherwise)*	1,166	44	318	33	169	36	1653	41
Male (1 if casualty sex is 'male '; 0 otherwise)	1,465	56	633	67	302	64	2400	59
Casualty age								
25yrs-44yrs (1 if casualty age is '25yrs-44yrs'; 0 otherwise)	1,109	42	435	46	169	36	1713	42
45yrs-64yrs (1 if casualty age is '45yrs-64yrs'; 0 otherwise)	435	17	160	17	112	24	707	17
<25yrs (1 if casualty age is '<25yrs'; 0 otherwise)	946	36	320	34	168	36	1434	35
>64yrs (1 if casualty age is '>64yrs'; 0 otherwise)*	141	5	36	4	22	5	199	5
Severity outcomes								

(*continued on next page*)

Table 1 (*continued*)

Variables	WDAY		WNLO		WNNL		WT	
	Freq	%	Freq	%	Freq	%	Freq	%
Fatal (1 if injury severity is 'fatal '; 0 otherwise)	399	15	183	19	105	22	687	17
Hospitalized (1 if injury severity is 'hospitalized'; 0 otherwise)	1,367	52	472	50	238	51	2077	51
Injury (1 if injury severity is 'injury'; 0 otherwise)	865	33	296	31	128	27	1289	32

Note: * = variable used as reference; WDAY = crashes involving walking-along-the-road pedestrians during the daytime; WNLO = crashes involving walking-along-the-road pedestrians during the night with streetlights turned on; WNNL = crashes involving walking-along-the-road pedestrians during the night with no streetlights lit or lights turned off; WT = crashes involving walking-along-the-road pedestrians

involved crashes in Ghana (52 %).

Most crashes (56 %) resulted from drivers of vehicles not paying attention and speeding (20 %). Most drivers fall between the ages of 25 to 44 years (70 %). Besides, the data shows that male drivers are over-represented in pedestrian-involved crashes, with fewer females (3 %) driving vehicles involved in crashes. This could be attributed to females being generally believed to drive with more care and attention than their male counterparts. Fewer female (41 %) pedestrian casualties were recorded compared to male pedestrian casualties (59 %), and most casualties fall within the age of 25–44 years (42 %). Elderly casualties of 65 years and above form the minority within the pedestrian casualty age group (5 %). The data shows that 51 % of pedestrian casualties sustained injuries requiring hospitalization; however, there was also a high fatality rate (17 %).

After segregating the data into various groupings, it was observed that most crashes occurred during daylight (2,631 observations) (see Table 1). The least pedestrian crashes occurred on dark roads (night-but-not-lighted, 471 observations). It is worth pointing out that severe injury crashes were more prominent (frequent) among the three injury severity levels even when the data was segregated. The study framework, which provides an overview of how the research presented in this paper was conducted, is shown in Fig. 2.

3.2. Estimation approach

In numerous studies, discrete outcome econometric models have been employed to examine the factors associated with injury severity outcomes in crashes. However, the reliability of the results and subsequent decisions drawn from them heavily rely on the quality and completeness of the crash data used. Mannering et al. (2016) argue that limited observable or reported information, as well as the quality of such information, can introduce biases in model results. This phenomenon, known as unobserved heterogeneity, has the potential to lead to the implementation of incorrect crash countermeasures. Therefore, addressing unobserved heterogeneity in crash severity studies is crucial to enhance statistical model inference. Utilizing heterogeneity models has become standard practice in this field (Mannering et al., 2016). Heterogeneity models allow analysts to obtain more accurate estimates by considering variations specific to each observation in the effects of explanatory variables (Alogaili and Mannering, 2022; Behnood and Al-Bdairi, 2020).

In this study, various estimation approaches, including the multinomial logit model (MNL), random parameter (mixed) logit model (RPL), and its variants (heterogeneity in means and variances), which addresses unobserved heterogeneity in the data, are examined to analyze the impact of crash-risk factors on pedestrian injury severity outcomes across different data subgroups. These subgroups are formed based on pedestrian maneuver and the prevailing lighting conditions at the time of the crash. The selection of the most suitable model is based on extensive testing and evaluation.

In order to develop a model, a severity function was developed to assess the likelihood of different levels of injury severity outcomes. Consider a linear function S_{ij} associated with the walking-along-the-road pedestrian-involved crash injury severity outcome i (fatal (FAT), hospitalized/severe (HSP), and minor/no injury (INJ)) for pedestrian j can be formulated as follows (Washington et al., 2003):

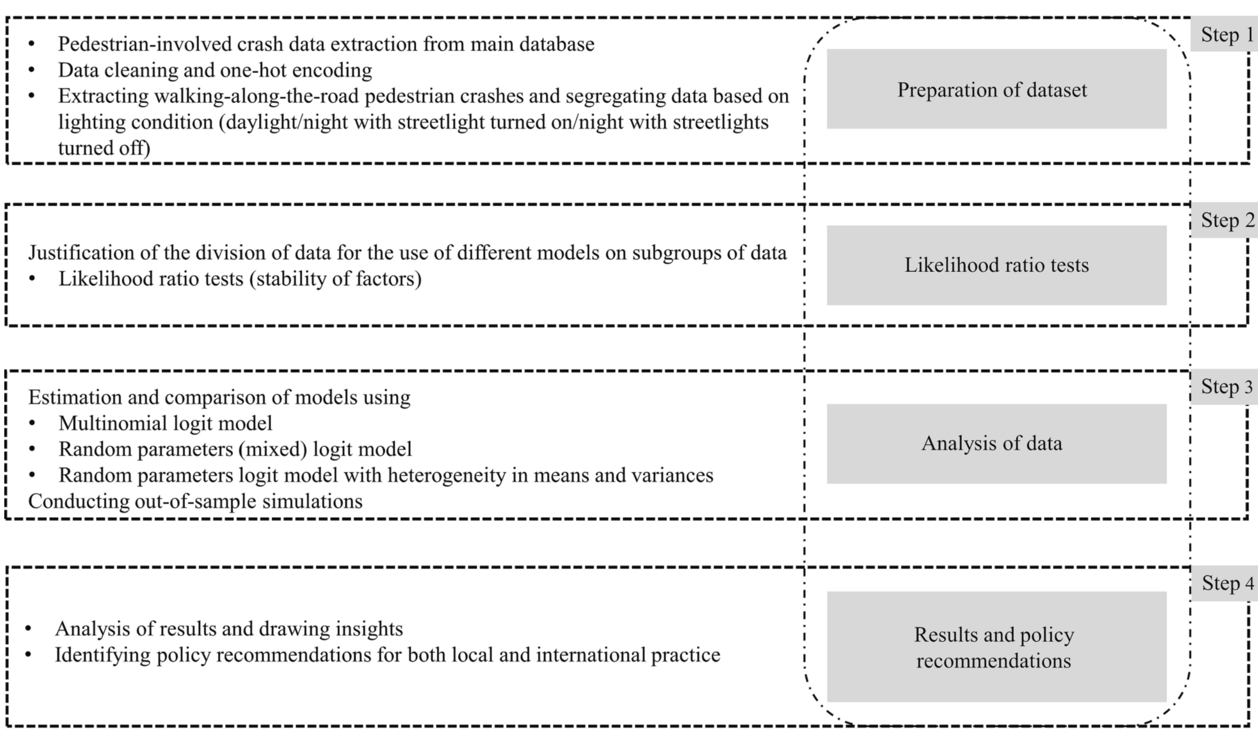

Fig. 2. Proposed study framework.

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

where S_{ij} refers to the likelihood function determining the probability that pedestrian j sustains an injury severity outcome of level i, $\boldsymbol{X}_{ij}$ connotes a vector of explanatory variables influencing the injury severity outcomes, $\boldsymbol{\beta}_i$ represents a vector of estimable parameters, and ε_{ij} is the error term assumed to follow an independent and identically distributed extreme value such as the Gumbel type 1. Consequently, by allowing the vector $\boldsymbol{\beta}_{ij}$ to assume a continuous density function such that the Prob ($\beta_n = \beta$)=$f(\beta|\varphi)$, the probability $P_j(i)$ that a pedestrian j will sustain an injury outcome i, is formulated as (McFadden and Train, 2000):

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

where $f(\beta|\varphi)$ refers to the probability density function of the vector $\boldsymbol{\beta}$, and φ corresponds to the vector of parameters of the density function in question. By allowing for heterogeneity in the means (and variances) of the random parameters, **Eq. (1)** is redeveloped such that the vector of estimable parameters $\boldsymbol{\beta}_i$ changes across the pedestrian crash observations as follows (Seraneeprakarn et al., 2017; Yu et al., 2020):

$$\boldsymbol{\beta}_i = \beta + \Theta_i \boldsymbol{Z}_i + \boldsymbol{\sigma}_i EXP(\psi_i \boldsymbol{Y}_i) \upsilon_i \tag{3}$$

where β corresponds the mean parameter estimate across all crashes, Θ_i represents the vector of estimable parameters, $\boldsymbol{Z}_i$ denotes a vector of explanatory variables accounting for heterogeneity in the means, $\boldsymbol{Y}_i$ corresponds to a vector of explanatory variables capturing heterogeneity in the standard deviation $\boldsymbol{\sigma}_i$ with ψ_i as the corresponding parameter vector, and the randomly distributed term that captures the observed heterogeneity across the pedestrian crash observations is represented by υ_i. This model would be reduced to a random parameters logit model with heterogeneity in means only model (RPLHM) if there were no variables in $\boldsymbol{Y}_i$ (Seraneeprakarn et al., 2017).

The normal distribution was selected for the random parameters after considering several distributional forms, such as the uniform, normal, lognormal, and triangular distributions. The normal distribution provided a better fit compared to the other distributional forms. The normal distribution has also been used in several other safety-related studies (Damsere-Derry et al., 2021; Li et al., 2021). The analysis was conducted using simulated maximum likelihoods with 1,000 Halton draws for accuracy and efficiency (Bhat, 2003; Halton, 1960). Finally, marginal effect (ME) estimates were computed to reflect the impact of significant crash-risk factors on pedestrian injury severity outcomes (Washington et al., 2020).

3.3. Transferability test

One of the main foci of this study is to statistically determine whether there are significant differences between different types of crashes categorized based on the lighting condition at the time of the crash (A = WDAY, B = WNLO, C = WNNL, T = ALL CRASHES). Two different likelihood ratio tests were conducted to verify the null hypothesis that the parameters in the individual models are equal and that the parameters obtained by estimating different models using different data groups are stable/transferable.

Regarding the first test, the test statistic employed is as follows (Washington et al., 2020):

$$X^2 = -2[LL(\beta_T) - LL(\beta_A) - LL(\beta_B) - LL(\beta_C)] \tag{8}$$

where $LL(\beta_T)$ is the log-likelihood at the convergence of a model estimated with the entire data from all subgroups under consideration T, $LL(\beta_A)$ is the log-likelihood at the convergence of the model using WDAY data, $LL(\beta_B)$ is the log-likelihood at the convergence of the model using WNLO data, and $LL(\beta_C)$ is the log-likelihood at the convergence of the model using WNNL data. The resulting X^2 statistic is χ^2 distributed with degrees of freedom (df) equal to the difference between the sum of the number of estimated parameters in A, B, and C and the number of estimated parameters in model T (Washington et al., 2020).

To further assess the transferability of factors influencing pedestrian crash injury severities among the different data subgroupings, the following log-likelihood ratio test was conducted as the second test:

$$X^2 = -2[LL(\beta_{m2m1}) - LL(\beta_{m1})] \tag{9}$$

where $m1$ and $m2$ correspond to any two different data subgroups, $LL(\beta_{m1})$ refers to the log-likelihood at the convergence of a model run using $m1$'s data. Note that there is no parameter restriction to subgroup $m2$'s converged parameters. $LL(\beta_{m2m1})$ corresponds to the log-likelihood at the convergence of a model estimated containing significant parameters from subgroup $m2$ using subgroup $m1$'s data. In this study, we reversed the tests using $LL(\beta_{m1m2})$ and $LL(\beta_{m2})$. The X^2 test statistic is χ^2 distributed with df equal to the number of parameters estimated in β_{m2m1} (or β_{m1m2}) (Washington et al., 2020).

The transferability tests were conducted by running traditional multinomial logit models using the various data groupings. For the transferability test conducted using **Eq. (8)**, the model estimate produced a X^2 of 102.86, which was χ^2 distributed with 28 degrees of freedom. The results indicate that the null hypothesis that all the parameters in the individual models are the same can be rejected with over a 99.99 % confidence level. Table 2 also presents results from the likelihood ratio test computed using **Eq. (9)**. The findings indicated that, in all of the two tests, the null hypothesis, which posited that the parameters were identical, could be disproven with a 95 % confidence level. Specifically, all tests produced a confidence level of over 95 %. This result informs the decision to fail to accept the null hypothesis that the effects of the indicator variables on pedestrian injury severity outcomes between any two data groups classified based on the different lighting conditions are the same. Together, the two series of transferability tests clearly indicate that the factors influencing pedestrian injury severities in Ghana across the various data groupings are unstable. Thus, as recommended in the literature (Mannering, 2018), it would be worthwhile to estimate separate models instead of a holistic model (a model containing the entire undivided dataset).

4. Results and discussions

After segmenting the data into the various groupings, two series of transferability/log-likelihood ratio tests were performed. The transferability analysis results clearly indicated that the factors influencing pedestrian injury severities in Ghana across the various data groupings are unstable – thus necessitating the estimation of different models for each data group. Based on this finding, separate models were estimated for each data segmentation. The model estimation results are presented in Table 3 (WT models), Table 4 (WDAY models), Table 5 (WNLO models), and Table 6 (WNNL models). Overall, the estimation results show plausible parameter signs. From the tables, all factors in the models estimated were found to be significant at 95 % confidence level. Similar to previous research, a few factors had low significance (at a 90 % confidence level) but were maintained in the models due to their

Table 2
Likelihood ratio test results (degree of freedom in parenthesis and confidence level in brackets).

m1	m2		
	WDAY	WNLO	WNNL
WDAY	–	96.28 (14) [>99.99 %]	63.26 (17) [>99.99 %]
WNLO	36.90 (21) [98.27 %]	–	27.95 (17) [95.45 %]
WNNL	52.68 (21) [99.98 %]	62.40 (14) [>99.99 %]	–

Table 3
Estimation results for pedestrian injury severity in walking-along-the-road crashes irrespective of lighting conditions (WT models).

Variables	MNL			RPL			RPLHM		
	Coefficient	Standard error	z-stats	Coefficient	Standard error	z-stats	Coefficient	Standard error	z-stats
Temporal and environmental characteristics									
Weather condition									
[FAT] Clear (1 if weather condition is 'clear'; 0 otherwise)	−0.431	0.113	−3.82	−1.376	0.564	−2.44	−1.455	0.584	−2.49
Std. dev. Of clear; normally distributed	–	–	–	2.173	0.876	2.48	2.365	0.863	2.74
Crash location characteristics									
Road description									
[FAT] Straight/flat (1 if road description is 'straight/flat'; 0 otherwise)	−0.476	0.139	−3.42	−1.382	0.671	−2.06	−1.309	0.639	−2.05
Std. dev. Of straight/flat; normally distributed	–	–	–	2.076	1.054	1.97	1.992	1.022	1.95
Shoulder type									
[INJ] Shoulder present (1 if shoulder type is 'shoulder present'; 0 otherwise)	−0.245	0.074	−3.30	−0.237	0.077	−3.08	−0.236	0.077	−3.06
Road separation									
[FAT] Median present (1 if road separation is 'median present'; 0 otherwise)	−0.380	0.116	−3.29	−0.782	0.312	−2.51	−0.806	0.312	−2.58
Traffic control									
[FAT] Signals (1 if traffic control type is 'signals'; 0 otherwise)	0.599	0.179	3.35	1.137	0.470	2.42	1.183	0.477	2.48
Crash characteristics									
Number of vehicles involved									
[FAT] Multi-vehicle (1 if number of vehicles involved is 'multi-vehicle'; 0 otherwise)	−0.274	0.118	−2.32	−0.507	0.259	−1.96	−0.494	0.261	−1.89
Hit & run									
[FAT] Hit-and-run (1 if crash type is 'hit-and-run'; 0 otherwise)	0.919	0.263	3.50	1.763	0.670	2.63	1.768	0.670	2.64
Vehicle characteristics									
Vehicle type									
[FAT] Bus/minibus (1 if vehicle type is 'bus/minibus'; 0 otherwise)	−0.333	0.133	−2.50	−0.627	0.292	−2.15	−0.658	0.300	−2.19
[FAT] Car (1 if vehicle type is 'car'; 0 otherwise)	−0.774	0.116	−6.65	−1.501	0.425	−3.53	−1.564	0.427	−3.66
[HSP] Other vehicle types – bicycle, tractor (1 if vehicle type is 'other vehicle types – bicycle, tractor'; 0 otherwise)	−0.495	0.277	−1.79	−0.606	0.305	−1.99	−0.585	0.306	−1.91
[FAT] Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	−1.050	0.158	−6.64	−1.997	0.569	−3.51	−2.033	0.560	−3.63
Vehicle ownership/usage									
[INJ] Other owner – government/police/military/emergency (1 if vehicle ownership/usage is 'other owner – government/police/military/emergency'; 0 otherwise)	−0.465	0.212	−2.19	−0.516	0.221	−2.33	−0.514	0.221	−2.33
[HSP] Taxi (1 if vehicle ownership is 'taxi'; 0 otherwise)	−0.197	0.090	−2.18	−0.209	0.095	−2.20	−0.210	0.095	−2.20
Vehicle defects									
[HSP] Brake (1 if vehicle defect is 'Brake'; 0 otherwise)	−0.342	0.191	−1.79	−0.495	0.218	−2.27	−0.509	0.218	−2.33
[HSP] No defect (1 if vehicle defect is 'no defect'; 0 otherwise)	−0.602	0.132	−4.56	−0.771	0.158	−4.87	−0.776	0.158	−4.92
[HSP] Other defects – tires/suspension/lights (1 if vehicle defect is 'other defects – tires/suspension/lights'; 0 otherwise)	−0.588	0.190	−3.09	−0.744	0.218	−3.42	−0.757	0.217	−3.49
Drivers characteristics and errors									
Driver sex									
[FAT] Male (1 if driver/rider sex is 'male '; 0 otherwise)	−0.590	0.247	−2.39	−1.226	0.610	−2.01	−1.292	0.624	−2.07
Driver errors									
[FAT] Speeding (1 if driver/rider error is 'speeding'; 0 otherwise)	0.530	0.102	5.21	0.996	0.330	3.02	1.015	0.326	3.11
Casualty characteristics									
Casualty sex									
[FAT] Male (1 if casualty sex is 'male '; 0 otherwise)	0.536	0.094	5.73	0.985	0.291	3.38	1.036	0.295	3.51
Casualty age									
[FAT] 25yrs-44yrs (1 if casualty age is '25yrs-44yrs'; 0 otherwise)	−0.989	0.178	−5.57	−1.865	0.588	−3.17	−1.908	0.587	−3.25
[FAT] 45yrs-64yrs (1 if casualty age is '45yrs-64yrs'; 0 otherwise)	−0.354	0.186	−1.90	−1.262	0.738	−1.71	−1.555	0.836	−1.86
Std. dev. Of 45yrs-64yrs; normally distributed				2.583	1.519	1.70	3.267	1.609	2.03
[FAT] < 25yrs (1 if casualty age is '<25yrs'; 0 otherwise)	−0.937	0.179	−5.24	−1.743	0.546	−3.19	−1.779	0.546	−3.26
Constants									
Constant [HSP]	−0.627	0.378	−1.66	−2.023	1.022	−1.98	−2.069	1.029	−2.01
Constant [INJ]	−1.504	0.363	−4.14	−3.067	1.047	−2.93	−3.120	1.051	−2.97
Heterogeneity in means									
Clear: Monday (1 if day of the week is 'Monday'; 0 otherwise)	–	–	–	–	–	–	−1.258	0.617	−2.04

(*continued on next page*)

Table 3 (*continued*)

Variables	MNL			RPL			RPLHM		
	Coefficient	Standard error	z-stats	Coefficient	Standard error	z-stats	Coefficient	Standard error	z-stats
Clear: Wednesday (1 if day of the week is 'Wednesday'; 0 otherwise)	–	–	–	–	–	–	1.135	0.604	1.88
Straight/flat: Monday (1 if day of the week is 'Monday'; 0 otherwise)	–	–	–	–	–	–	1.070	0.546	1.96
Straight/flat: Wednesday (1 if day of the week is 'Wednesday'; 0 otherwise)	–	–	–	–	–	–	−1.200	0.597	−2.01
Model statistics									
Number of observations	4053								
Log-likelihood at zero,$LL(0)$Log-likelihood at convergence,$LL(\beta)$	−4084.5504			−4084.5504			−4084.5504		
$\rho^2 = 1 - LL(\beta)/LL(0)$Akaike Information Criterion (AIC)	−3935.4836			−3931.2057			−3924.6429		
AIC/N	0.0365			0.0375			0.0391		
Number of observations	7919			7916.4			7911.3		
Log-likelihood at zero,$LL(0)$	1.954			1.953			1.952		

Note: MNL = multinomial logit model; RPL = random parameter logit model; RPLHM = random parameter logit with heterogeneity in means model.

importance (Se et al., 2021).

For the WT data, more than one significant random parameter with heterogeneity in the means of the random parameters was identified (Table 3). For the WDAY data, only one random parameter was identified, with a significant variable influencing the heterogeneity in its means (Table 4). Similarly, for the WNLO data, no variables were found to have an impact on the heterogeneity in the means of the identified random parameter, as indicated in Table 5. Lastly, no significant random parameters were identified in the WNNL data (Table 6).

Regarding the model selection, the goodness of fit measures in the tables show that the ρ^2 and log-likelihood values increase with increasing model complexity. AIC values were also found to decrease with model complexity. The RPLHM is the appropriate model for the WT data (Table 3). For the data subgroups, the RPLHM was the best model for the WDAY data, the RPL was also selected as the best model for the WNLO data, and the MNL was selected as the best model for the WNNL data. Table 7 displays the marginal effect estimates of the impacts of the explanatory variables that have demonstrated statistical significance in the selected models.

It is worth noting that all the indicators in Table 1 were used in the heterogeneity tests. Although heterogeneity in the means of random parameters was identified to be statistically significant in some models, heterogeneity in the variances of the random parameters was not determined to be statistically significant in any of the models estimated. A closer look at the parameter estimates shows considerable variation in the effect of some indicators identified to be statistically significant. To demonstrate this, marginal effects for each significant explanatory indicator in all the models defined for fatal injury, severe injury, and minor injury are presented in Table 7 for stability comparison. Table 8 also shows the distributional effect of random parameters across crash observations. The model fit is based on the ρ^2 values are slightly low for all models but are reasonable due to the robustness of the models applied. Previous studies using this technique considered lower values acceptable (Alnawmasi and Mannering, 2019; Se et al., 2021). The following sections present discussions of the modeling results, focusing on the instability of significant factors in the different groups explored.

4.1. Temporal and environmental characteristics

4.1.1. Day of the week

In general, crashes involving pedestrians walking along the road occurring on Mondays and Wednesdays during daylighting conditions were likely to have high injury severity outcomes (WDAY; Table 4). From the marginal effect estimates in Table 7, the probability of severe injury increases by 0.0107 on Mondays and 0.0105 on Wednesdays when a pedestrian walking along the road is hit by a vehicle. On lit roadways at night, walking-along-the-road crashes will likely be severe on Tuesdays and Thursdays (WNLO; Table 5). The probability of a pedestrian sustaining severe injury increases by 0.4965 and 0.0088 on Tuesday and Thursday, respectively. Again, whereas the probability of minor injury on Tuesdays increases by 0.0654 on dark roads with no light (WNNL), fatal injury increases by 0.0463. As illustrated in Fig. 3, there is high variability in the injury outcomes regarding the influence of the "Tuesday" variable in the WNLO and WNNL data, and the likelihood of severe injuries is highest on dark but lit roads.

The results suggest that walking-along-the-road crashes are likely to be severe during the day and are notably more severe on lit roads at night during the weekdays. During the weekdays, the number of pedestrians on the roads is likely higher, and street hawkers are also more likely to be on the sidewalk during the day or on lit roads. The occupation of the limited road space by hawkers and street vendors on weekdays further exposes them and pedestrians to crashes (Damsere-Derry et al., 2019; Obeng-Atuah et al., 2017). Besides, the haphazard way of driving on weekdays when traffic volumes are higher and the failure of drivers to adjust their speeds to the night conditions predisposes pedestrians to needlessly severe injuries in dark conditions (Damsere-Derry et al., 2010).

4.1.2. Weather condition

Considering the model containing the total data, walking-along-the-road pedestrian crashes occurring during clear weather conditions were likely to result in fatalities relative to crashes occurring in inclement weather conditions. The probability of fatalities increases by 0.0006, whereas severe and minor injuries decrease by 0.0003 (Table 7). Upon segregating the dataset into the various lighting conditions, it is clear that those crashes that occurred in the dark (unlit roads) as the pedestrian walked along the road were more likely to be severe, in line with the result reported in previous research (Amoh-Gyimah et al., 2017). The marginal effect estimates shows that the probability of severe injury crash outcomes increases by 0.0888 while that of fatalities decreases by 0.1344. Previous studies showed that severe injuries are expected during clear weather conditions as drivers are likely to drive carelessly during clear weather conditions (Behnood and Mannering, 2016; Zamani et al., 2021). Besides, many streetlights in Ghana are malfunctioning due to poor maintenance, and some surveyed pedestrians highlighted this issue as a major traffic safety problem in Ghana (Amoako et al., 2014). These are possible reasons for the increased injury severity outcomes, particularly when a crash occurs during clear weather conditions on dark roads. The findings highlight the importance of improving walking environments for pedestrians and providing adequate lighting at night.

Table 4
Estimation results for pedestrian injury severity in walking-along-the-road in daylighting condition crashes (WDAY models).

Variables	MNL			RPL			RPLHM		
	Coefficient	Standard error	z-stats	Coefficient	Standard error	z-stats	Coefficient	Standard error	z-stats
Temporal and environmental characteristics									
Day of the week									
[HSP] Monday (1 if day of the week is 'Monday'; 0 otherwise)	0.271	0.119	2.28	1.477	0.803	1.84	1.238	0.632	1.96
[INJ] Tuesday (1 if day of the week is 'Tuesday'; 0 otherwise)	0.317	0.121	2.63	0.519	0.204	2.54	0.531	0.202	2.63
[HSP] Wednesday (1 if day of the week is 'Wednesday'; 0 otherwise)	0.314	0.122	2.58	1.580	0.819	1.93	1.313	0.640	2.05
Crash location characteristics									
Road description									
[FAT] Straight/flat (1 if road description is 'straight/flat'; 0 otherwise)	−0.502	0.172	−2.92	−0.465	0.245	−1.90	−0.478	0.243	−1.97
Road surface type									
[INJ] Good (1 if road surface type is 'good'; 0 otherwise)	0.311	0.116	2.68	0.554	0.188	2.95	0.547	0.185	2.95
Shoulder type									
[INJ] Shoulder present (1 if shoulder type is 'shoulder present'; 0 otherwise)	−0.306	0.094	−3.26	−0.590	0.163	−3.62	−0.581	0.161	−3.61
Road separation									
[INJ] Median present (1 if road separation is 'median present'; 0 otherwise)	0.325	0.097	3.36	0.623	0.177	3.51	0.612	0.174	3.51
Crash characteristics									
Hit & run									
[HSP] Hit-and-run (1 if crash type is 'hit-and-run'; 0 otherwise)	−1.479	0.361	−4.10	−6.690	2.973	−2.25	−5.663	2.283	−2.48
Vehicle characteristics									
Vehicle type									
[INJ] Heavy goods vehicle (1 if vehicle type is 'heavy goods vehicle'; 0 otherwise)	−0.578	0.179	−3.23	−0.907	0.269	−3.37	−0.928	0.266	−3.49
[FAT] Pickup (1 if vehicle type is 'pickup'; 0 otherwise)	0.447	0.217	2.06	1.124	0.318	3.53	1.252	0.323	3.88
[FAT] Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	−0.398	0.197	−2.02	−0.443	0.246	−1.80	−0.445	0.246	−1.81
Vehicle ownership/usage									
[HSP] Company vehicle (1 if vehicle ownership is 'company vehicle'; 0 otherwise)	−0.402	0.155	−2.60	−1.045	0.649	−1.61	−1.006	0.544	−1.85
[FAT] Private vehicle (1 if vehicle ownership is 'private vehicle'; 0 otherwise)	−0.262	0.126	−2.08	−0.427	0.179	−2.38	−0.408	0.177	−2.30
[INJ] Taxi (1 if vehicle ownership is 'taxi'; 0 otherwise)	0.326	0.119	2.75	0.646	0.226	2.86	0.606	0.221	2.74
Vehicle defects									
[INJ] Steering (1 if vehicle defect is 'steering'; 0 otherwise)	−0.781	0.196	−3.99	−1.123	0.299	−3.75	−1.125	0.296	−3.80
Drivers characteristics and errors									
Driver age									
[INJ] > 64yrs (1 if driver/rider age is '>64yrs'; 0 otherwise)	−1.256	0.625	−2.01	−1.934	0.786	−2.46	−1.938	0.781	−2.48
Driver error									
[FAT] Speeding (1 if driver/rider error is 'speeding'; 0 otherwise)	0.565	0.130	4.35	0.973	0.190	5.11	0.963	0.190	5.08
Casualty characteristics									
Casualty sex									
[INJ] Male (1 if casualty sex is 'male '; 0 otherwise)	−0.225	0.085	−2.64	−0.630	0.152	−4.15	−0.603	0.151	−3.99
Casualty age									
[FAT] 25yrs-44yrs (1 if casualty age is '25yrs-44yrs'; 0 otherwise)	−0.573	0.119	−4.81	−1.251	0.498	−2.51	−1.294	0.533	−2.43
Std. dev. Of 25yrs-44yrs; normally distributed	–	–	–	1.660	0.761	2.18	1.700	0.783	2.17
Constants									
Constant [HSP]	0.539	0.183	2.95	0.792	0.352	2.25	0.682	0.319	2.14
Std. dev. Of constant [HSP]; normally distributed	–		–	7.254	2.879	2.52	5.961	2.129	2.80
Constant [INJ]	0.104	0.212	0.49	0.321	0.309	1.04	0.314	0.308	1.02
Heterogeneity in means									
Hospitalized: pickup (1 if vehicle type is 'pickup'; 0 otherwise)	–	–	–	–	–	–	1.744	0.811	2.15
Model statistics									
Number of observations	2631								
Log-likelihood at zero, $LL(0)$	−2609.8312			−2609.8312			−2609.8312		
Log-likelihood at convergence, $LL(\beta)$									
$\rho^2 = 1 - LL(\beta)/LL(0)$ Akaike Information Criterion (AIC)	−2509.8117			−2486.3681			−2484.1508		
AIC/N	0.0383			0.0473			0.0482		
Number of observations	5061.6			5020.7			5018.3		

(continued on next page)

Table 4 (*continued*)

Variables	**MNL**			**RPL**			**RPLHM**		
	Coefficient	**Standard error**	**z-stats**	**Coefficient**	**Standard error**	**z-stats**	**Coefficient**	**Standard error**	**z-stats**
Log-likelihood at zero,$LL(0)$	1.924			1.908			1.907		

Note: MNL = multinomial logit model; RPL = random parameter logit model; RPLHM = random parameter logit with RPLHM = random parameter logit with heterogeneity in means model, the heterogeneity in means model

Table 5
Estimation results for pedestrian injury severity in walking-along-the-road in the night-but-lighted condition crashes (WNLO models).

Variables	**MNL**			**RPL**		
	Coefficient	**Standard error**	**z-stats**	**Coefficient**	**Standard error**	**z-stats**
Temporal and environmental characteristics						
Day of the week						
[HSP] Tuesday (1 if day of the week is 'Tuesday'; 0 otherwise)	0.502	0.203	2.47	1.543	0.563	2.74
[HSP] Thursday (1 if day of the week is 'Thursday'; 0 otherwise)	0.449	0.221	2.03	1.102	0.499	2.21
Weather condition						
[INJ] Clear (1 if weather condition is 'clear'; 0 otherwise)	0.490	0.176	2.78	0.719	0.224	3.21
Crash location characteristics						
Traffic control						
[INJ] Other traffic control – stop sign/give way/pedestrian-X (1 if traffic control type is 'other traffic control – stop sign/give way/pedestrian-x'; 0 otherwise)	0.426	0.200	2.13	0.669	0.263	2.54
Vehicle characteristics						
Vehicle type						
[INJ] Car (1 if vehicle type is 'car'; 0 otherwise)	0.262	0.146	1.80	0.627	0.205	3.06
[FAT] Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	−0.625	0.262	−2.39	−1.022	0.310	−3.30
Vehicle defects						
[HSP] No defect (1 if vehicle defect is 'no defect'; 0 otherwise)	−0.624	0.218	−2.86	−1.112	0.545	−2.04
Std. dev. Of no defect; normally distributed	–	–	–	8.305	4.885	1.70
[HSP] Other defects – tires/suspension/lights (1 if vehicle defect is 'other defects – tires/suspension/lights'; 0 otherwise)	−0.628	0.331	−1.90	−0.755	0.354	−2.13
Drivers characteristics and errors						
Driver error						
[INJ] Inattentive (1 if driver/rider error is 'inattentive'; 0 otherwise)	0.549	0.155	3.54	0.765	0.200	3.82
Casualty characteristics						
Casualty sex						
[FAT] Male (1 if casualty sex is 'male '; 0 otherwise)	0.513	0.191	2.69	0.420	0.218	1.93
Casualty age						
[FAT] 25yrs-44yrs (1 if casualty age is '25yrs-44yrs'; 0 otherwise)	−0.481	0.203	−2.37	−0.766	0.247	−3.10
[FAT] < 25yrs (1 if casualty age is '<25yrs'; 0 otherwise)	−1.035	0.236	−4.39	−1.335	0.276	−4.84
Constants						
Constant [HSP]	1.137	0.293	3.88	0.655	0.329	1.99
Constant [INJ]	−0.671	0.302	−2.22	−1.541	0.389	−3.96
Model statistics						
Number of observations	951					
Log-likelihood at zero,$LL(0)$	−977.7194			−977.7194		
Log-likelihood at convergence,$LL(\beta)$	−939.4937			−929.5065		
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.0391			0.0493		
Akaike Information Criterion (AIC)	1907.0			1889.0		
AIC/N	2.005			1.986		

Note: MNL = multinomial logit model; RPL = random parameter logit model

4.2. Crash location characteristics

4.2.1. Road description

The "straight/flat road" indicator was significant in the WT and WDAY models. The model results reveal that walking-along-the-road pedestrian crashes will likely result in high-severity outcomes. The marginal effect estimate obtained from the WT model shows that the probability of severe injuries increased by 0.0083 when the crash occurred on a straight/flat road (Table 7). Interestingly, the marginal effect estimates for the WDAY model reveal that the probability of severe injury increases by 0.0084, and that of minor injury crashes rose by 0.0291 when the crash occurred during the daylighting condition as the pedestrian walked along the road (Table 7). Drivers are likely to drive carelessly when they perceive the road condition to be suitable (straight/flat), increasing their chances of hitting pedestrians walking along the road (Hong et al., 2020; Tamakloe et al., 2020). Moreover, the greater likelihood of minor injuries occurring during daylight hours could be attributed to improved visibility, enabling drivers to anticipate potential hazards and minimize the impact of collisions on pedestrians.

4.2.2. Road surface type

The indicator for "good road surfaces" (roads with no potholes) was identified to be significant only in the WDAY model. The parameter estimation results showed that walking-along-the-road pedestrian crashes would likely have lower severity outcomes. From the marginal effect estimates in Table 7, minor injuries during the day are likely, as the probability of this outcome increases by 0.0486 while that of fatal and severe injury reduces by 0.0290 and 0.0196, respectively. This result is reasonable as good road surfaces contribute to safer pedestrian conditions. When roads are free of potholes and provide a smooth driving space. Essentially, the risk of dodging potholes and hitting pedestrians at the edges of the roads, causing severe injuries or fatalities, is reduced. The findings suggest that the quality of road surfaces can significantly impact the severity outcomes of pedestrian crashes, further

Table 6
Estimation results for pedestrian injury severity in walking-along-the-road in the night-but-unlighted condition crashes (WNNL models).

Variables	MNL		
	Coefficient	Standard error	z-stats
Temporal and environmental characteristics			
Day of the week			
[HSP] Tuesday (1 if day of the week is 'Tuesday'; 0 otherwise)	−0.4861	0.2928	−1.66
Weather condition			
[FAT] Clear (1 if weather condition is 'clear'; 0 otherwise)	−0.9336	0.2899	−3.22
Crash location characteristics			
Road separation			
[INJ] Median present (1 if road separation is 'median present'; 0 otherwise)	1.0930	0.3070	3.56
Location type			
[HSP] Not-at-intersection (1 if location type is 'not-at-intersection'; 0 otherwise)	−0.7747	0.3297	−2.35
Vehicle characteristics			
Vehicle type			
[HSP] Bus/minibus (1 if vehicle type is 'bus/minibus'; 0 otherwise)	0.8017	0.2937	2.73
[FAT] Car (1 if vehicle type is 'car'; 0 otherwise)	−1.5291	0.3199	−4.78
[HSP] Heavy goods vehicle (1 if vehicle type is 'heavy goods vehicle'; 0 otherwise)	0.7439	0.3854	1.93
[INJ] Other vehicle types – bicycle, tractor (1 if vehicle type is 'other vehicle types – bicycle, tractor'; 0 otherwise)	1.5157	0.7430	2.04
[HSP] Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	−1.3363	0.3818	−3.50
Vehicle ownership/usage			
[FAT] Other owner – government/police/military/emergency (1 if vehicle ownership/usage is 'other owner – government/police/military/emergency'; 0 otherwise)	−1.2717	0.6203	−2.05
Drivers characteristics and errors			
Driver sex			
[HSP] Male (1 if driver/rider sex is 'male '; 0 otherwise)	−2.2119	1.0790	−2.05
[HSP] Speeding (1 if driver/rider error is 'speeding'; 0 otherwise)	0.7989	0.2916	2.74
Casualty characteristics			
Casualty sex			
[HSP] Male (1 if casualty sex is 'male '; 0 otherwise)	0.9848	0.2905	3.39
Casualty age			
[FAT] 25yrs-44yrs (1 if casualty age is '25yrs-44yrs'; 0 otherwise)	−0.8918	0.2934	−3.04
[FAT] < 25yrs (1 if casualty age is '<25yrs'; 0 otherwise)	−1.1334	0.2998	−3.78
Constants			
Constant [HSP]	2.5268	1.1919	2.12
Constant [INJ]	−1.0448	0.3943	−2.65
Model statistics			
Number of observations	471		
Log-likelihood at zero,$LL(0)$	−486.8120		
Log-likelihood at convergence,$LL(\beta)$	−434.7504		
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.1069		
Akaike Information Criterion (AIC)	903.5		
AIC/N	1.918		
Note: MNL = multinomial logit model			

emphasizing the importance of maintaining well-maintained roads to enhance pedestrian safety. Poor road surface conditions, characterized by the presence of potholes, amplify the risk of traffic crashes. A research investigation into the correlation between road surface quality and the severity of road crashes in Indonesia unveiled a positive connection. The findings from this study unequivocally indicate that enhancements to road surfaces are linked to a reduction in road fatalities (Sari and Yudhistira, 2021).

4.2.3. *Shoulder presence*

Compared to roads without shoulders, those with shoulders seem more dangerous for pedestrians walking along the road, irrespective of the lighting condition. It is notable from the marginal effect estimates that those crashes occurring during the daylight on roads with shoulders are more likely to result in fatalities (Table 7). In particular, the probability of fatalities increases by 0.0287 when it occurs on a shoulder-present road. This finding could be due to street vendors' occupation of the sidewalks during the daytime – forcing pedestrians onto the roadway and increasing their chances of crashes. In line with the findings presented in this research, an earlier study discovered that roads lacking shoulders or those with overgrown shoulders were linked to a reduced likelihood of pedestrians experiencing severe injuries. The authors suggested that this phenomenon was probably because pedestrians were less inclined to utilize these particular road sections (Amoh-Gyimah et al., 2017).

4.2.4. *Road separation*

In the unsegregated data, walking-along-the-road crashes generally were found to have a high chance of severe injury outcomes at median-present segments. The probability of observing severe injuries increases by 0.0069 at a segment with a median. At these segments, the likelihood of minor injuries increases by 0.0042, while fatal injuries decrease by 0.0110. However, after segregating the data based on the lighting condition, it was identified that the probability of observing minor injury outcomes in walking-along-the-road pedestrian crashes during the day or on dark roads with no lights increases by 0.0179 and 0.2004, while that of the other severity outcomes decreases substantially (Table 7). A previous study identified that median presence reduced the chance of observing fatalities (Chung, 2018). Nevertheless, the findings reported in this study are reasonable, as median-separated roads (plantings, barriers, painted markings, or posts) create a psychological effect that promotes increased caution among both pedestrians and drivers.

4.2.5. *Location type*

The indicator for "not-at-intersections" was significant only in the model related to crashes occurring on dark-unlit roads. Table 7 shows the highest marginal effect estimate for minor injury (0.1042). Besides, severe injury outcomes decreased by 0.1779, and the probability of fatalities increased by 0.0737. The results indicate that walking-along-the-road pedestrian-vehicle crashes on dark unlit non-intersections are more likely to be minor injuries than those at intersection segments. Compared to non-intersection segments, intersections are well known to be hazardous locations where different streams of traffic flow (Tay, 2015). Vehicles rushing to negotiate a curve at intersections at higher speeds are likely to hit pedestrians walking along the road. In addition, poor visibility due to darkness is likely the leading cause of these crashes. Although speeds at non-intersections are likely higher, the chance of skidding off or running into pedestrians at the edge of the road is likely to be reduced at these sections as they do not involve making sharper curves as in the case of intersections – reducing the chance of severe or fatal collisions with pedestrians. These findings concur with previous studies (Islam and Jones, 2014).

4.2.6. *Traffic control*

In the segregated data (WNLO), the findings demonstrated that it is likely to observe minor injuries at roadway sections with other traffic control types such as stop signs/give way/pedestrian-X on lit roads at night. The likelihood of minor injuries increased by 0.0167, whereas fatal and severe injuries decreased by 0.0096 and 0.0071 (Table 7). Pedestrians and drivers may take additional safety precautions in dark conditions. In dark roadway conditions, drivers tend to exercise more caution and drive at slower speeds. Besides, the limited visibility can make it more difficult for drivers to detect pedestrians in time to take

Table 7
Comparison of marginal effects of the statistically significant explanatory variables in the models for vehicle–pedestrian walking-on-the-road crashes in different lighting conditions (defined for fatal injury severity [FAT], severe injuries needing hospitalization [HSP], and minor injuries [INJ]).

Variables	WT			WDAY			WNLO			WNNL		
	FAT	HSP	INJ	FAT	HSP	INJ	FAT	HSP	INJ	FAT	HSP	INJ
Temporal and environmental characteristics												
Day of the week												
[HSP] Monday (1 if the day of the week is 'Monday'; 0 otherwise)	–	–	–	−0.0033	**0.0107**	−0.0074	–	–	–	–	–	–
[HSP] Tuesday (1 if the day of the week is 'Tuesday'; 0 otherwise)	–	–	–	–	–	–	−0.3404	**0.4965**	−0.1561	0.0463	−0.1117	**0.0654**
[INJ] Tuesday (1 if the day of the week is 'Tuesday'; 0 otherwise)	–	–	–	−0.0049	−0.0035	**0.0084**	–	–	–	–	–	–
[HSP] Wednesday (1 if the day of the week is 'Wednesday'; 0 otherwise)	–	–	–	−0.0035	**0.0105**	−0.0070	–	–	–	–	–	–
[HSP] Thursday (1 if the day of the week is 'Thursday'; 0 otherwise)	–	–	–	–	–	–	−0.0037	**0.0088**	−0.0052	–	–	–
Weather condition												
[FAT] Clear (1 if the weather condition is 'clear'; 0 otherwise)	**0.0006**	−0.0003	−0.0003	–	–	–	–	–	–	−0.1344	**0.0888**	0.0456
[INJ] Clear (1 if the weather condition is 'clear'; 0 otherwise)	–	–	–	–	–	–	−0.0491	−0.0245	**0.0736**	–	–	–
Crash location characteristics												
Road description												
[FAT] Straight/flat (1 if the road description is 'straight/flat'; 0 otherwise)	−0.0134	**0.0083**	0.0051	−0.0375	0.0084	**0.0291**	–	–	–	–	–	–
Shoulder type												
[INJ] Shoulder present (1 if shoulder type is 'shoulder present'; 0 otherwise)	0.0041	**0.0297**	−0.0338	**0.0287**	0.0174	−0.0462	–	–	–	–	–	–
Road surface type												
[INJ] Good (1 if road surface type is 'good'; 0 otherwise)	–	–	–	−0.0290	−0.0196	**0.0486**	–	–	–	–	–	–
Road separation												
[FAT] Median present (1 if road separation is 'median present'; 0 otherwise)	−0.0110	**0.0069**	0.0042	–	–	–	–	–	–	–	–	–
[INJ] Median present (1 if road separation is 'median present'; 0 otherwise)	–	–	–	−0.0098	−0.0080	**0.0179**	–	–	–	−0.0533	−0.1471	**0.2004**
Location type												
[HSP] Not at intersection (1 if location type is 'not at intersection'; 0 otherwise)	–	–	–	–	–	–	–	–	–	0.0737	−0.1779	**0.1042**
Traffic control												
[INJ] Other traffic control - stop sign/give way/pedestrian-X (1 if traffic control type is 'other traffic control - stop sign/give way/pedestrian-x'; 0 otherwise)	–	–	–	–	–	–	−0.0096	−0.0071	**0.0167**	–	–	–
[FAT] Signals (1 if traffic control type is 'signals'; 0 otherwise)	**0.0054**	−0.0033	−0.0021	–	–	–	–	–	–	–	–	–
Crash characteristics												
Number of vehicles involved												
[FAT] Multi-vehicle (1 if number of vehicles involved is 'multi-vehicle'; 0 otherwise)	−0.0059	**0.0037**	0.0022	–	–	–	–	–	–	–	–	–

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Table 7 (*continued*)

Variables	WT			WDAY			WNLO			WNNL		
	FAT	HSP	INJ	FAT	HSP	INJ	FAT	HSP	INJ	FAT	HSP	INJ
Hit & run												
[FAT] Hit-and-run (1 if crash type is 'hit-and-run'; 0 otherwise)	**0.0033**	−0.0020	−0.0013	–	–	–	–	–	–	–	–	–
[HSP] Hit-and-run (1 if crash type is 'hit-and-run'; 0 otherwise)	–	–	–	0.3973	−1.3545	**0.9572**	–	–	–	–	–	–
Vehicle characteristics												
Vehicle type												
[FAT] Bus/minibus (1 if vehicle type is 'bus/minibus'; 0 otherwise)	−0.0092	**0.0057**	0.0034	–	–	–	–	–	–	–	–	–
[HSP] Bus/minibus (1 if vehicle type is 'bus/minibus'; 0 otherwise)	–	–	–	–	–	–	–	–	–	−0.2047	**0.2690**	−0.0643
[FAT] Car (1 if vehicle type is 'car'; 0 otherwise)	−0.0461	**0.0278**	0.0182	–	–	–	–	–	–	–	–	–
[INJ] Car (1 if vehicle type is 'car'; 0 otherwise)	–	–	–	–	–	–	−0.0288	−0.0153	**0.0442**	–	–	–
[HSP] Heavy goods vehicle (1 if vehicle type is 'heavy goods vehicle'; 0 otherwise)	–	–	–	–	–	–	–	–	–	−0.0708	**0.1709**	−0.1001
[INJ] Heavy goods vehicle (1 if vehicle type is 'heavy goods vehicle'; 0 otherwise)	–	–	–	**0.0077**	0.0030	−0.0106	–	–	–	–	–	–
[FAT] Pickup (1 if vehicle type is 'pickup'; 0 otherwise)	–	–	–	**0.0069**	−0.0023	−0.0046	–	–	–	–	–	–
[FAT] Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	−0.0171	**0.0106**	0.0065	−0.0045	0.0009	**0.0036**	−0.0156	0.0036	**0.0120**	–	–	–
[HSP] Powered two-wheeler (1 if vehicle type is 'powered two-wheeler'; 0 otherwise)	–	–	–	–	–	–	–	–	–	−0.1924	**0.1272**	0.0652
[HSP] Other vehicle types - bicycle, tractor (1 if vehicle type is 'other vehicle types - bicycle, tractor'; 0 otherwise)	0.0004	−0.0017	**0.0013**	–	–	–	–	–	–	–	–	–
[INJ] Other vehicle types - bicycle, tractor (1 if vehicle type is 'other vehicle types - bicycle, tractor'; 0 otherwise)	–	–	–	–	–	–	–	–	–	−0.0740	−0.2039	**0.2779**
Vehicle ownership/usage												
[HSP] Company vehicle (1 if vehicle ownership is 'company vehicle'; 0 otherwise)	–	–	–	0.0034	−0.0069	0.0034	–	–	–	–	–	–
[FAT] Other owner - government/police/military/emergency (1 if vehicle ownership/usage is 'other owner - government/police/military/emergency'; 0 otherwise)	–	–	–	–	–	–	–	–	–	−0.1831	**0.1210**	0.0621
[INJ] Other owner - government/police/military/emergency (1 if vehicle ownership/usage is 'other owner - government/police/military/emergency'; 0 otherwise)	0.0005	**0.0023**	−0.0028	–	–	–	–	–	–	–	–	–
[FAT] Private vehicle (1 if vehicle ownership is 'private vehicle'; 0 otherwise)	–	–	–	−0.0175	0.0037	**0.0138**	–	–	–	–	–	–

(*continued on next page*)

Table 7 (*continued*)

Variables	WT			WDAY			WNLO			WNNL		
	FAT	HSP	INJ	FAT	HSP	INJ	FAT	HSP	INJ	FAT	HSP	INJ
[HSP] Taxi (1 if vehicle ownership is 'taxi'; 0 otherwise)	0.0012	−0.0073	**0.0061**	–	–	–	–	–	–	–	–	–
[INJ] Taxi (1 if vehicle ownership is 'taxi'; 0 otherwise)	–	–	–	−0.0059	−0.0042	**0.0102**	–	–	–	–	–	–
Vehicle defects												
[HSP] Break (1 if vehicle defect is 'break'; 0 otherwise)	0.0012	−0.0055	**0.0042**	–	–	–	–	–	–	–	–	–
[HSP] No defect (1 if vehicle defect is 'no defect'; 0 otherwise)	**0.1979**	−0.2725	0.0746	–	–	–	0.0086	−0.0221	**0.0134**	–	–	–
[HSP] Other defects - tyres/suspension/lights (1 if vehicle defect is 'other defects - tyres/suspension/lights'; 0 otherwise)	0.0017	−0.0084	**0.0067**	–	–	–	0.0043	−0.0107	**0.0064**	–	–	–
[INJ] Steering (1 if vehicle defect is 'steering'; 0 otherwise)	–	–	–	**0.0053**	0.0024	−0.0077	–	–	–	–	–	–
Drivers characteristics and errors												
Driver sex												
[FAT] Male (1 if driver/rider sex is 'male '; 0 otherwise)	−0.0830	**0.0512**	0.0318	–	–	–	–	–	–	–	–	–
[HSP] Male (1 if driver/rider sex is 'male '; 0 otherwise)	–	–	–	–	–	–	–	–	–	0.2105	−0.5081	**0.2976**
Driver age												
[INJ] > 64yrs (1 if driver/rider age is '>64yrs'; 0 otherwise)	–	–	–	**0.0010**	0.0004	−0.0014	–	–	–	–	–	–
Driver error												
[FAT] Speeding (1 if driver/rider error is 'speeding'; 0 otherwise)	**0.0160**	−0.0098	−0.0061	**0.0199**	−0.0050	−0.0149	–	–	–	–	–	–
[HSP] Speeding (1 if driver/rider error is 'speeding'; 0 otherwise)	–	–	–	–	–	–	–	–	–	**0.1150**	−0.0760	−0.0390
[INJ] Inattentive (1 if driver/rider error is 'inattentive'; 0 otherwise)	–	–	–	–	–	–	−0.0377	−0.0180	**0.0556**	–	–	–
Casualty characteristics												
Casualty sex												
[FAT] Male (1 if casualty sex is 'male '; 0 otherwise)	**0.0460**	−0.0284	−0.0176	–	–	–	**0.0354**	−0.0094	−0.0260	–	–	–
[HSP] Male (1 if casualty sex is 'male '; 0 otherwise)	–	–	–	–	–	–	–	–	–	**0.1418**	−0.0937	−0.0481
[INJ] Male (1 if casualty sex is 'male '; 0 otherwise)	–	–	–	**0.0235**	0.0135	−0.0370	–	–	–	–	–	–
Casualty age												
[FAT] < 25yrs (1 if casualty age is '<25yrs'; 0 otherwise)	−0.0424	**0.0261**	0.0162	–	–	–	−0.0428	0.0102	**0.0326**	−0.1632	**0.1079**	0.0553
[FAT] 25yrs-44yrs (1 if casualty age is '25yrs-44yrs'; 0 otherwise)	−0.0503	**0.0311**	0.0192	−0.0052	−0.0010	**0.0062**	−0.0439	0.0111	**0.0328**	−0.1284	**0.0849**	0.0435
[FAT] 45yrs-64yrs (1 if casualty age is '45yrs-64yrs'; 0 otherwise)	−0.0009	**0.0006**	0.0004	–	–	–	–	–	–	–	–	–

Note: WT = all crashes involving pedestrians walking along the edge of the road; WDAY = crashes involving "walking-along-the-road" pedestrians during the daytime; WNLO = crashes involving "walking-along-the-road" pedestrians during the night with streetlights turned on; WNNL = crashes involving "walking-along-the-road" pedestrians during the night with no streetlights lit or lights turned off; FAT = fatal crash; HSP = hospitalized/severe injury crash; INJ = injured-but-not-hospitalized/minor injury

Table 8
Distributional effect of random parameters across crash observations.

Model name	Random parameter (RP)	Mean of RP	Std. dev. of RP	Decreasing likelihood (%)	Increasing likelihood (%)
WNLO	[HSP] No defect	−1.1123	8.3051	55.33	44.67
WDAY	[FAT] 25yrs-44yrs casualty age	−1.2940	1.6996	77.68	22.32
WDAY	Constant [HSP]	0.6822	5.9607	45.44	54.56

evasive actions, resulting in collisions at lower speeds. The reduced impact speed decreases the likelihood of fatal injuries and increases the chances of minor injuries. This discovery aligns with existing literature, which demonstrates that traffic signs play a crucial role in reducing the likelihood of pedestrian fatalities and severe injuries (Kim et al., 2010).

4.3. Crash characteristics

4.3.1. Number of vehicles involved

The impact of the indicator for "multi-vehicle crashes" on pedestrian injury severity outcomes was also explored. The model results revealed that pedestrians involved in crashes as they walked along the road were less likely to experience fatal injuries but more likely to have severe injuries in a multi-vehicle crash (Table 7; WT data; Marginal effect estimates: FAT: 0.0059, HSP: 0.0037, and INJ: 0.0022). During a multi-vehicle crash, visibility can be compromised due to obstructed views or sudden environmental changes. This reduced visibility makes it more difficult for drivers to spot pedestrians and react in time to avoid a collision, increasing the chances of severe pedestrian injuries. Further, multi-vehicle crashes can result in secondary collisions or chain-reaction crashes, where additional vehicles may hit pedestrians initially uninvolved in the primary crash. These subsequent impacts can have severe consequences for pedestrians and increase the likelihood of severe injuries. Notably, the impact force on the pedestrian would be much lower than when the vehicle did not hit another vehicle. Thus, it is likely that the fatality in the multi-vehicle case would be lower compared to the single-vehicle crash case. In the literature, single-vehicle crashes are likely to be more fatal compared to multi-vehicle crashes (Barua and Tay, 2010).

4.3.2. Hit & run

The influence of the hit-and-run indicator on injury severity outcomes was identified to show some level of variability (see Fig. 4). Hit-and-run pedestrian crashes occurring as the pedestrian walks along the road in the full data (WT) were identified to have a high propensity for fatal ramifications (see Table 4). From the marginal effects estimate in Table 7, this indicator increases fatal injury by 0.0033 in the unsegregated data. The probability of severe and minor injury decreases by 0.0020 and 0.0013. Drivers often flee the scene in hit-and-run crashes irrespective of the lighting condition due to the fear of being penalized. The association of the hit-and-run indicator variable with fatal injury outcomes is consistent with previous research (Aidoo et al., 2013).

Interestingly, upon segregating the data, it was clear that the probability for minor injuries increased highest by 0.9572 and that of fatalities increases by 0.3973, while severe injuries decreased by 1.3545 during the daytime (see Fig. 4). Hit-and-run crashes are more likely to occur at night time relative to day time (Jiang et al., 2016; Tay et al., 2008). Besides, witnesses or nearby individuals will likely notice a hit-and-run crash in daylight. This increases the chances of someone immediately calling for emergency medical assistance, resulting in a quicker response time and prompt medical attention, which can help mitigate the severity of injuries. Besides, the heightened visibility during the day enables drivers to better anticipate potential dangers and take evasive actions, reducing the severity of the impact and resulting in minor injuries rather than more severe ones.

4.4. Vehicle characteristics

4.4.1. Vehicle type

Regarding the effect of the vehicle type, it can be observed from the results that fatalities are less likely in PTW-pedestrian crashes. The variability in the impact of this indicator on injury outcomes is visualized in Fig. 5. Specifically, whereas severe injuries are more likely in the full unsegregated data, minor injuries are observed to be more probable in walking-along-the-road crashes during daylight or dark-but-lit conditions. This finding is intuitive as the PTW riders are likely to see and

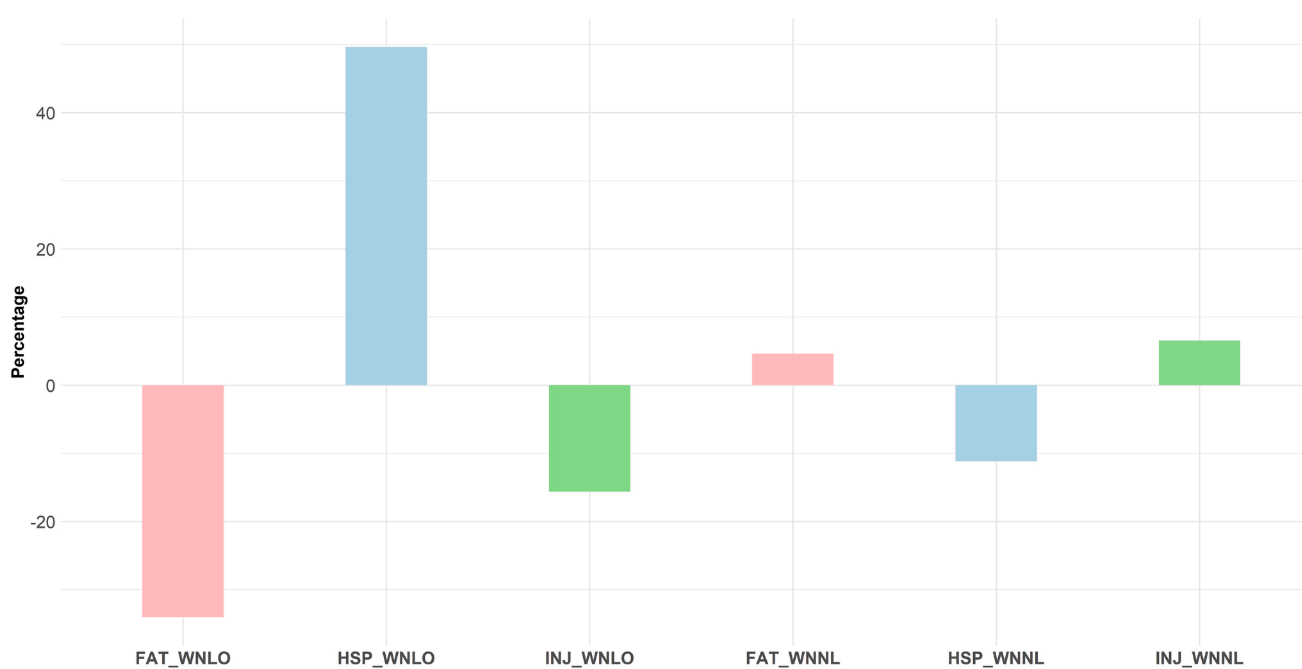


Fig. 3. The marginal effect of the indicator variable for "Tuesday" (defined for hospitalized/severe crash).

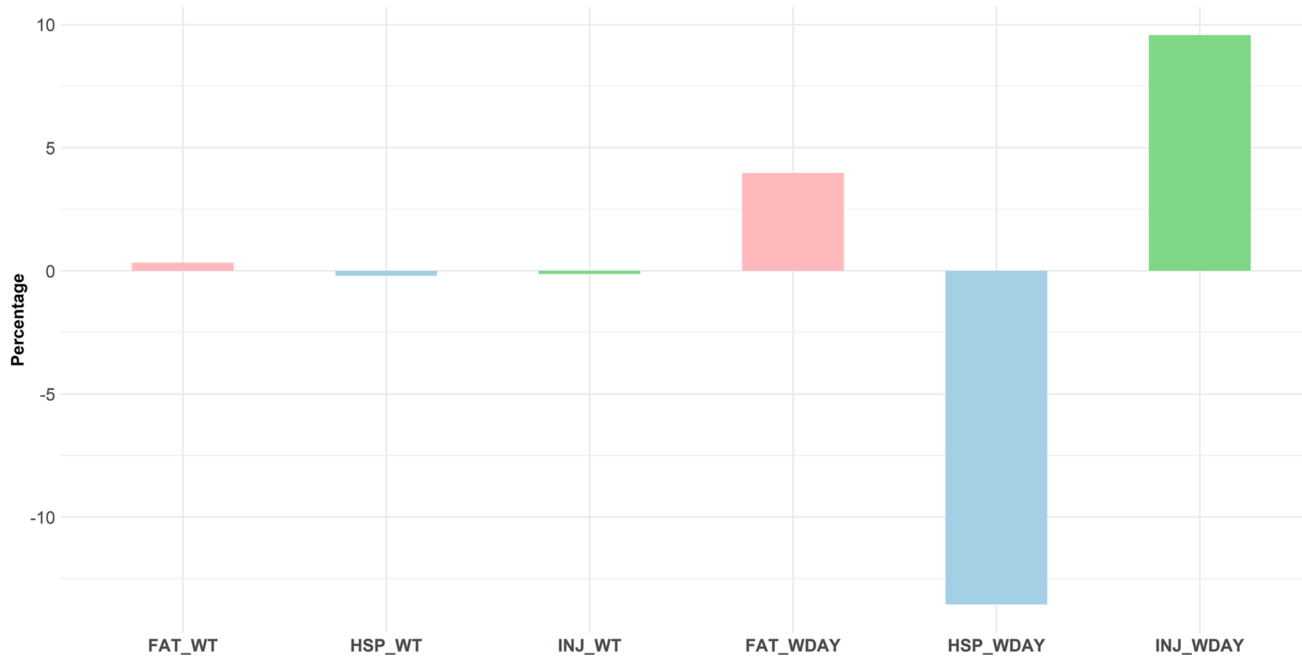


Fig. 4. The marginal effect of the indicator variable for “hit-and-run”.

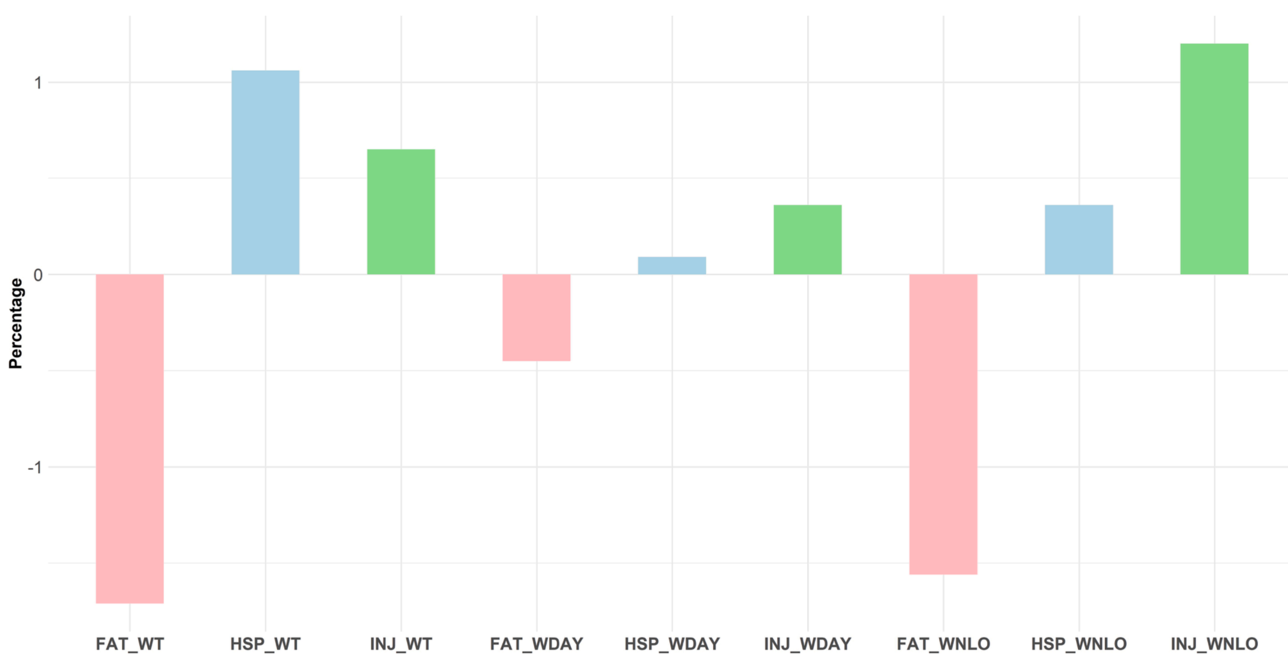


Fig. 5. The marginal effect of the indicator variable for “PTW” (defined for fatal injury).

try to dodge the pedestrian in the road space, reducing the level of impact. The literature found that pedestrian crashes involving PTWs are more prone to happen in dark conditions at night, especially when it’s raining, and the roads are wet, with curves in the road. The authors suggest that darkness and poor lighting conditions reduce visibility and reaction times for pedestrians and riders, leading to longer braking distances and more severe crashes. As a result, these nighttime incidents are likely to result in more serious injuries than crashes during the day (Montella et al., 2012).

It was established that the “bus/minibus involvement” indicator increased the probability of severe injury crash outcomes (Table 6, WNNL data). The marginal effect estimates in Table 7 revealed that the bus/minibus indicator significantly decreases fatal injury outcomes but increases severe injury outcomes in the WNNL model. Consistent with prior research, minibus accidents occurring at night are anticipated to result in more serious injuries (Sam et al., 2018). This finding is reasonable, again, as minibus drivers tend to exceed speed limits during nighttime when roads are less congested, regardless of the limited visibility caused by darkness. This behavior can lead to slower reaction times, longer braking distances, and raises the risk of more severe crashes at night (unlit roads), outweighing the chances of minor injuries.

Further, the marginal effects estimates show that heavy goods vehicles (HGV) and pickups were generally likely to be involved in fatal and severe injury crashes irrespective of the lighting condition at the crash’s time (Table 7). This result is consistent with previous research that shows that the severity of injuries is directly related to the vehicle mass (they are unable to reduce speeds on impact due to their mass) – thus, heavy vehicles cause more havoc compared to cars (Chen and Fan, 2019; Damsere-Derry et al., 2010; Tay et al., 2011; Verzosa and Miles, 2016).

4.4.2. Vehicle ownership/usage

Several indicator variables, such as company vehicle status, private vehicle usage status, taxi usage status, and "other ownership", were explored to investigate their impact on pedestrian crash injury severity outcomes. First, vehicles identified as belonging to companies were found to have a high propensity for fatal injuries in walking-along-the-road crashes during the day (WDAY; Table 4). The positive marginal effect estimate for fatal injury in Table 7 confirms this result. Drivers operating company-owned vehicles might be pressured to meet deadlines or delivery targets, leading to potentially aggressive or careless driving behaviors. Further, company drivers might be more susceptible to distractions related to their work, such as using onboard devices, communicating with dispatch, or navigating unfamiliar routes. These are likely reasons for this result. In the existing literature, it was observed that the ownership of trucks by companies influenced the severity of injuries resulting from crashes. The size of the company emerged as a significant factor in this regard. Specifically, medium-sized company trucks were more frequently associated with single-fatality accidents, while larger companies were less likely to be involved in more severe accidents. Additionally, trucks owned by interstate companies were more susceptible to fatal accidents, possibly due to their longer travel distances (Zheng et al., 2018). It is worth noting that in the current study, there was no available data specifying the types of companies to which each vehicle belonged. Further analysis is required to understand the underlying reasons for these findings.

In Table 7, the indicator for "private vehicle usage" increased the probability of minor injuries during the day when a pedestrian walking along the edge of the road is involved in a crash. The indicator variable "other vehicle ownership" (such as government, policy, military, or emergency response vehicles) also increases the chance of severe injury in pedestrian-involved crashes when the pedestrian is involved in the crash as s/he walks along a dark-unlit road at night. Vehicles used as taxis were found to cause minor injury crashes when they hit pedestrians walking along the road during the day. These results are plausible as private vehicle drivers often drive more carefully compared to drivers who don't drive their own vehicles. Injury severity in the case of taxis is also minor - many people use their vehicles as taxis. Notably, this outcome differs from what has been documented in existing research. A prior investigation indicated that shared taxi drivers often exhibit reckless driving behavior, leading to greater injury severity when they collide with vulnerable road users (Ouni and Belloumi, 2018).

4.4.3. Vehicle defects

Upon exploring the impact of vehicle defects on pedestrian injury severity outcomes, the study identified that steering defects increased the probability of fatal injury by 0.0053 when the defective vehicle crashes with a pedestrian walking along the edge of the road during the day (Table 4). During the day, pedestrian volumes are high. A steer-defective vehicle may exhibit unpredictable movements, swerving unexpectedly toward pedestrians. This unpredictability can catch pedestrians off guard, leaving them less time to react or find a safe position, thereby increasing the likelihood of fatal injuries. Previous research demonstrated that Ghana experiences a higher occurrence of fatal crashes caused by defective steering systems (Agyemang et al., 2021).

Crashes involving vehicles with brake defects were more likely to yield minor injuries with a reduced possibility of fatal injuries in lit road conditions at night (Table 7). Defective brakes have been found to cause secondary crashes with severe injuries (Xie et al., 2018). However, pedestrians walking along the road can have some time to take cover. The finding in this study is also likely due to the driver's alertness and increased reaction time in such eventualities. This allows the driver to take evasive actions, potentially reducing the severity of injuries.

The "no defects" indicator in the full data model (WT) yields fatal injury with a probability increasing by 0.1979 while that of severe injuries decreases by 0.2725 (Table 7). However, during the night-but-lit condition (WNLO) this variable was identified to be more likely to cause minor injuries. In the WNLO model, this indicator was found to be a random parameter with a mean and a standard deviation of -1.112 and 8.305. As detailed in Table 8, this explanatory variable increases the likelihood of severe injuries for 44.67 % of the data and decreases the chance of severe injury by 55.33 % of the WNLO crash observations.

4.5. Driver's characteristics and errors

4.5.1. Driver sex

The model containing the unsegregated data (WT) shows that walking-along-the-road pedestrian crashes involving male drivers are likely severe. While the probability of severe injury increases by 0.0512, that of minor injury also increases by 0.0318, and that of fatalities decreases by 0.0830 (Table 7). However, upon segregating the data based on the lighting condition, the probability of minor injuries was found to be more likely on dark unlit roads. This probability is likely to increase by 0.2976, and that of severe injuries decreases by 0.5081. However, there is a substantial chance of fatal injury when the crash occurs in dark conditions. The likelihood of fatal injury increases by 0.2105. Research shows that male drivers are often overconfident and drive recklessly compared to their female counterparts. Besides, studies show that they are likely to drive under the influence of alcohol or drugs at night (Das et al., 2018b; Jiang and Ren, 2020; Tay et al., 2011). These behaviors could reduce their chance of spotting a pedestrian on time to avoid a crash.

4.5.2. Driver age

The indicator for "elderly driver" (>64yrs) was found to be significant only in the model with WDAY data. From the marginal effects estimates, the likelihood of fatal injury increases by 0.0010, and severe injury increases by 0.0004 in a WDAY pedestrian crash (Table 7). The chance of minor injuries decreases by 0.0014. This finding suggests that fatal injury is more likely if an elderly driver crashes into a pedestrian walking along the road's edge during daylighting conditions. This observation is because older drivers may react slowly in critical situations due to reduced cognitive abilities and physical strength (Park and Bae, 2020).

4.5.3. Driver error

The indicator variable for "speeding" was statistically significant and increased the propensity for fatal injury outcomes in most models estimated. The probability of fatalities increased by 0.0160, 0.0199, and 0.1150 in the WT, WDAY, and WNNL models (Table 7). A previous study showed that speeding is Ghana's most dominant cause of pedestrian fatality (Afukaar, 2003). Clearly, fatalities are highly expected when a crash occurs on a dark unlit road at night compared to daylight in speeding crashes. This finding is intuitive and consistent with previous literature (Chen and Fan, 2019; Tay et al., 2011; Verzosa and Miles, 2016). In dark conditions, the reduced visibility reduces the reaction time available to both parties involved. This combination of higher speeds and limited reaction time increases the likelihood of fatal injuries in pedestrian-vehicle crashes.

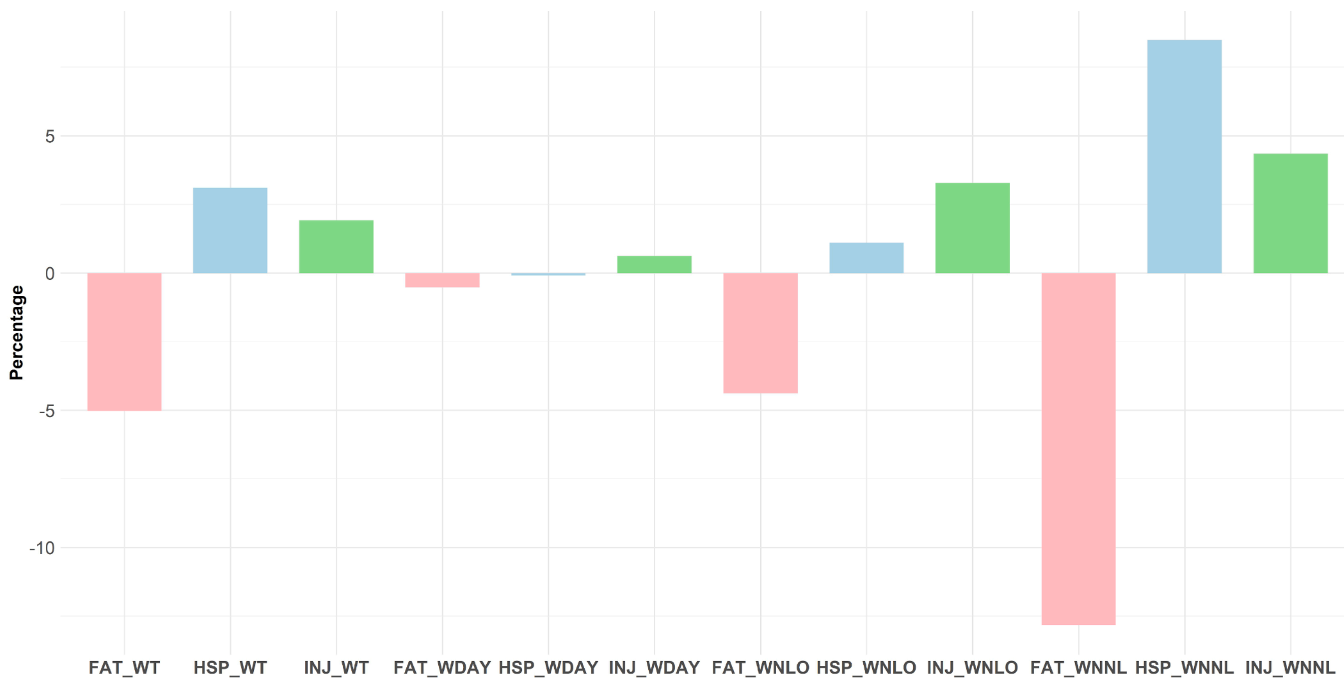
Inattentiveness was significant in the WNLO model. According to the results in Table 7, minor injuries are more likely when the crash involves a pedestrian walking along a lit road at night (WNLO data; Marginal effect estimates: FAT: -0.0377; HSP: -0.0180; INJ: 0.0556). Inattentive driving has been previously reported to be a factor impacting the safety of pedestrians in Ghana (Obeng-Atuah et al., 2017). Inattentiveness is when a driver is distracted from driving as s/he engages in other activities, robbing them of precious seconds needed to react in critical situations. Inattentive drivers may not be moving at high speeds.

Besides, even though the road is dark, the fact that it is lit (WNLO) can improve the visibility of both the driver and the pedestrian. This increased visibility, coupled with the slow-moving vehicle, gives the driver some level of awareness of the pedestrian's presence, giving them a better chance of taking evasive action or reducing the impact during the crash and the pedestrian injury severity.

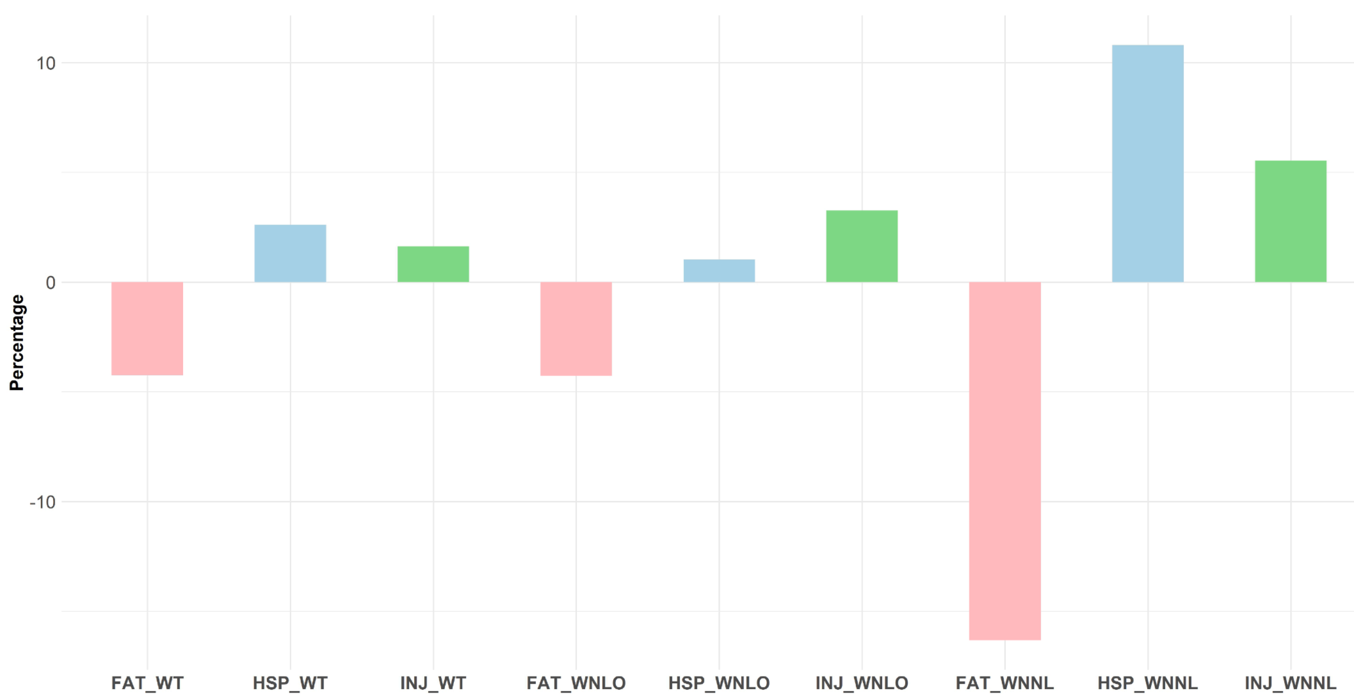
4.6. Pedestrian casualty characteristics

4.6.1. Casualty sex

Pedestrian casualty sex was significant in all of the models. From the marginal effect estimates presented in Table 7, it is observed that male pedestrians have increased probabilities for fatal injuries and reduced probabilities for severe and minor injuries compared to their female



(a) Marginal effect: casualty age 25yrs-44yrs (defined for fatal injury)



(b) Marginal effect: casualty age <25yrs (defined for fatal injury)

Fig. 6. Marginal effects of key casualty age-related variables showing variation in factor effects.

counterparts, irrespective of the lighting condition. The literature indicates that males have a higher chance of sustaining fatal injuries as they are less careful and mostly do not adhere to traffic regulations. The authors also noted that males are more likely to drink alcohol during the night, increasing their chance of fatal collisions when using unprotected road spaces due to poor perception and reaction to oncoming vehicles (Obeng-Atuah et al., 2017).

4.6.2. Casualty age

Significant variations between the effect of the indicators for age on severity outcomes were established. Relative to elderly pedestrians, walking-along-the-road pedestrians between the ages of 25 to 44 years are more likely to result in severe injuries at night when the roads are unlit – consistent with the literature that older pedestrians are more likely to be involved in fatal crashes at night compared to younger pedestrians (Pour-Rouholamin and Zhou, 2016). The likelihood of severe injuries increases by 0.0849, minor injuries increase by 0.0435, and fatal injuries decrease by 0.1284 when crashes occur on unlit roads at night. Besides, the chance of observing minor injuries among this age group increases highest during the daytime and on lit roads at night (see Fig. 6 (a)). The casualty age "25yrs-44yrs" indicator in the WDAY model is a random parameter. From Table 8, it is shown that this indicator decreases the likelihood of fatal injury for 77.68 % of the WDAY crash observations and increases the probability of fatal injury for 22.32 % of the WDAY crash observations.

Similarly, relative to old pedestrians, younger pedestrians below the age of 25 years are also likely to experience severe injuries (not fatal) on dark-unlit roads but minor injuries on dark-but-lit roads at night. This variable also showed high variability concerning its impact on injury severity outcomes. The findings depict an increased severity in dark unlit roads among younger pedestrians compared to lit roads or daylighting conditions (see Fig. 6(b)). This finding is reasonable as younger pedestrians walking along the road can spot dangerous circumstances on lit roads or during daylight and react faster than their elderly counterparts, making them more likely to sustain minor injuries. It is, however, difficult for them and drivers to spot and avoid crashes in darker conditions – thus resulting in severe injuries.

4.7. Heterogeneity in means and variances

The heterogeneity in the means and variances of the random parameters were tested. Concerning the model estimated using the WT data, the clear weather and straight/flat indicator variables were identified to produce a random parameter with heterogeneity in the mean (Table 3). For the clear weather indicator, the variables for "Monday" reduced the likelihood of fatal injury severity outcomes in walking-along-the-road pedestrian crashes. Mondays often witness higher traffic volume as people return to work after the weekend. The increased number of vehicles on the road can lead to more minor injury crashes due to congestion. Besides, fatal crashes on Wednesdays may involve other factors, such as tiredness and reckless behavior due to less congested roads during the midweek.

Interestingly, the indicator for "Wednesday" further raised the possibility of increased injury severity outcomes, making fatal injury crashes more likely in walking-along-the-road maneuvers on Wednesdays during clear weather conditions. The indicator for Monday increased the propensity for fatal injuries on straight/flat roads, and that of Wednesday reduced the probability of fatal injuries on straight/flat roads. Additionally, on Wednesdays, drivers may experience midweek distractions or increased stress levels that can divert their attention from the road. Distractions, such as work-related pressures or personal obligations, coupled with the perception of driving on a good straight road, can contribute to minor accidents with reduced severity of pedestrian injuries (Hong et al., 2020). As shown in Table 4 (WDAY), the indicator for 25yrs-44yrs was a random parameter. However, no variable affected the heterogeneity in the means and variances of this random parameter.

4.8. Comparison of out-of-sample and within-sample predictions

Taking a broader look at the summary of marginal effects presented in Table 7, the impact of risk factors on the severity of injuries changed depending on the lighting conditions considered. While observing the shifts in the influence of specific variables across different lighting conditions is interesting, the cumulative effect of these shifts explored via performing out-of-sample simulations, holds particular significance for transportation safety experts. In the literature, researchers conducted out-of-sample predictions to confirm the non-transferability of or differences between overturned and hit-fixed-object crashes (Yan et al., 2022), crashes occurring on weekdays, weekends, and holidays (Se et al., 2022), crashes involving male and female motorcyclists (Wang et al., 2022), crashes involving restraint and unrestrained drivers (Se et al., 2023), crashes occurring during the daytime and nighttime (Alogaili and Mannering, 2022), and crashes occurring in different years (Islam et al., 2020). Specifically, out-of-sample simulation conducted by Se et al. (2023) indisputably illustrated that utilizing seatbelts is likely to offer advantages by leading to a substantial decrease in the fatality rate associated with single-vehicle run-off-road accidents caused by speeding. Besides, according to Alogaili and Mannering (2022), pedestrian-vehicle accidents that occur during the day might result in injuries that are up to 16.45 % less severe than incidents that occur at night. It should be noted that generating out-of-sample predictions using the randomly generated parameters models, as estimated in this study, is a non-trivial task. This is because obtaining estimated injury probabilities for individual crashes requires simulating the entire random parameter distribution, similar to the process employed during parameter estimation. Merely using the means of the random parameters would result in significantly biased probability estimates. The literature has provided a comprehensive explanation, discussion, and empirical evaluation of this technique (Alogaili and Mannering, 2022; Hou et al., 2022; Xu et al., 2021). In order to delve deeper into this matter, the parameters obtained from each estimated model were utilized to predict individual injury severities considering the actual crash characteristics observed. These predictions were then compared with out-of-sample predictions obtained as in previous studies (Alnawmasi and Mannering, 2022; Alogaili and Mannering, 2022).

This proposed predictive comparison aims to assess how the overall aggregate probabilities of injury severity change under different lighting conditions while considering the actual characteristics of the crashes. To initiate the prediction for scenarios outside each dataset, the focus is initially placed on comparing pedestrian-involved crashes that occur during daylight (WDAY), night with lighting (WNLO), and night without lighting (WNNL). Presumably, the higher severity of pedestrian injuries observed at night is primarily due to fatigue or reduced visibility caused by insufficient lighting compared to daytime conditions. An intriguing question would be, for example, how the pedestrian injury severity distributions would change for night crashes with lighting if we used daytime parameter estimates to forecast them.

To execute the simulation of predictions beyond the observed data, the originally approximated parameters obtained from the reference dataset will be employed within a simulation technique akin to the one utilized in the model estimation process. The assessment of predictions made for scenarios outside the original dataset and those within it involves a comparison achieved by quantifying probability differences. To illustrate, the likelihood of the severity of injuries from daytime pedestrian accidents is computed using a model established from nighttime collision data (referred to as out-of-sample predictive probability). This probability is then contrasted with the computed probability derived from the nighttime data using a model tailored to nighttime pedestrian accidents (referred to as within-sample probability or "observed" probability). For the traditional fixed parameter MNL, the predicted probabilities are directly calculated using **Eq. (2)**. However, for the random parameter models, the calculation of both the out-of-sample probability and within-sample probability can be executed using the subsequent equation (Alnawmasi and Mannering, 2022; Hou et al., 2022; Wang et al., 2022).

$$P_j(i) = \frac{1}{N}\sum_{n=1}^{N}\frac{exp\left[\left(\beta_i + \Theta_{ij}\mathbf{Z}_{ij} + \boldsymbol{\sigma}_{ij}EXP\left(\psi_{ij}\mathbf{Y}_{ij}\right)v_{ij}\right)\mathbf{X}_{ij}\right]}{\sum_{i=1}^{I}exp\left[\left(\beta_i + \Theta_{ij}\mathbf{Z}_{ij} + \boldsymbol{\sigma}_{ij}EXP\left(\psi_{ij}\mathbf{Y}_{ij}\right)v_{ij}\right)\mathbf{X}_{ij}\right]} \tag{10}$$

where N represents the total number of Halton draws applied. In this study, 1,000 Halton draws are applied. The remaining variables have been explained in the previous equations.

The outcomes of this out-of-sample simulation, which summarizes the changes in predicting pedestrian injury severity are provided in Table 9. These offer a concise overview of the changes in the forecasted average walking-along-the-road pedestrian injury severity under varying lighting conditions. These are also visualized in Figs. 7 to 9. In Fig. 7, we employed WDAY models to predict injury severity for WNLO and WNNL based on their observed characteristics. In Fig. 8, we utilized WNLO models to predict injury severity for WDAY and WNNL based on their observed characteristics. Finally, in Fig. 9, we employed WNNL models to predict injury severity for WDAY and WNLO based on their observed characteristics.

The predictions of pedestrian injury severity outcomes, as shown in Fig. 7**(a) and 7(b)**, are relatively similar when using the estimated models based on WDAY. Although there is notable variation in individual crash predictions in this figure, the average values for injury severity levels indicate that using WDAY model to predict WNLO injury severity leads to overestimating severe (hospitalized) and minor injury outcomes. Specifically, in Fig. 7**(a)**, severe and minor injury outcomes are overestimated by 0.0207 and 0.015, respectively, signifying a higher propensity for severe injury. Similarly, in Fig. 7**(b)**, severe (hospitalized) injury severity and minor injury outcomes are overestimated by 0.0163 and 0.0385, respectively, when the WDAY model predicts WNNL injury severity outcomes – signifying a higher propensity for minor injury. Therefore, if the explanatory variables were the same for every pedestrian-involved crash in WNLO and WNNL, the estimated WDAY model would predict a higher number of severe and minor injury crashes compared to the actual observations. However, the results also indicate that fatal injuries are underestimated, with an average underestimation of 0.0357 in Fig. 7(a) and 0.0548 in Fig. 7(b). Consequently, when using the WDAY model, one would have expected fewer fatal injury crashes. This result clearly demonstrates that improving lighting conditions at night will provide a substantial advantage by reducing the fatality rate of crashes.

The WNLO model is used to predict the severity of crash injuries in both daylight (WDAY) and night-but-unlit (WNLL) conditions, and the results are depicted in Fig. 8(a) and 8(b), respectively. It is observed that the WNLO model tends to underestimate severe injuries and overestimate fatal and minor injuries when the WDAY data is applied. Consequently, if WDAY parameters were applied, it would be expected that more fatal injuries would have occurred during daylighting conditions while fewer severe injuries would have been observed. This shows that night conditions are likely to increase the fatality of crashes. The WNLO model slightly underestimates fatal injuries while overestimating severe and minor injuries when the WNNL data is used. Thus, at night, when streetlights are turned on, it would be expected that fewer fatalities would occur, along with an increase in the number of severe and minor injuries during night-but-unlit conditions.

Table 9
Summary of changes in walking-along-the-road pedestrian injury severity prediction means between different lighting conditions.

Data	Fatal	Hospitalised	Injured-not-hospitalised
WDAY model predicts WNLO injury severity	−0.0357	0.0207	0.0150
WDAY model predicts WNNL injury severity	−0.0548	0.0163	0.0385
WNLO model predicts WDAY injury severity	0.0229	−0.0258	0.0029
WNLO model predicts WNNL injury severity	−0.0025	0.0009	0.0033
WNNL model predicts WDAY injury severity	−0.0345	0.0417	−0.0072
WNNL model predicts WNLO injury severity	−0.0394	0.0375	0.0019

The WNNL model used to predict the severity of individual crash injuries during daytime (WDAY) and nighttime-but-lit (WNLO) conditions are depicted in Fig. 9(a) and 9(b), respectively. The findings indicate that the WNNL models tend to miscalculate the number of fatal and minor injuries, underestimating them while overestimating the occurrence of serious injuries. Consequently, if the WDAY data were applied, a higher number of serious injuries would have been anticipated during daylighting conditions, accompanied by fewer fatal and minor injuries. Additionally, using the WNLO data displays a similar pattern, underestimating fatal injuries and overestimating severe and minor injuries in WNLO data. Therefore, if WNLO data were utilized, fewer fatal injuries would have been expected compared to the observed data, while more severe injuries would have been predicted during the night-but-lit conditions.

The results from the prediction simulations displayed in Figs. 7 through 9 indicate compelling indications regarding the significant overall variability in pedestrian injury severities. Additionally, the findings imply that although parameter values play a crucial role in predicting individual crashes, they do not substantially influence the total number of crashes categorized by injury severity.

5. Conclusion

5.1. Summary

Although walking-along-the-road crashes constitute a significant proportion of fatal roadway crashes, limited attention has been paid to identifying the factors influencing their severity outcomes. Besides, there is no knowledge of how risk factors' impact varies under different lighting conditions, particularly in developing countries with transport facility deficits such as poor street lighting. This study explored the potential variation in the effect of crash-risk factors on walking-along-the-road pedestrian-involved crash injury severity in a developing country, considering different lighting conditions at the time of the crash. In addition, walking-along-the-road pedestrian-vehicle crash data occurring in Ghana between 2014 and 2018 was obtained for this study. Variants of the MNL, including the RPLHM model, were used for analyses to identify possible random parameters and establish the relationships between them.

Upon conducting a preliminary transferability/stability analysis, it was determined that the effects of risk factors differed for each data combination (walking-along-the-road pedestrian crash grouped based on lighting conditions). The predictive comparison results reveal evidence of instability among the WDAY, WNLO, and WNNL models when using their respective parameter estimates to predict probabilities. Specifically, when predicting injury severity outcomes in the dataset, there was significant variation in the out-of-sample simulation results, indicating clear signs of instability.

Generally, in the unsegregated data, fatal pedestrian walking-along-the-road crashes were linked with clear weather, traffic signal presence, hit-and-run, non-defective vehicles, speeding, and male pedestrians. Upon analyzing the data and considering the prevailing lighting conditions during the crashes, notable variations in the impact of risk factors were observed. Specifically, while these factors were found to cause fatal pedestrian injuries in the overall model (WT), they were more likely to result in minor injuries under specific conditions. These conditions include clear weather on dark unlit roads, signals and non-defective vehicles on dark-but-lit roads, and hit-and-run crashes that occurred during daylight hours. Regardless of the lighting conditions, it

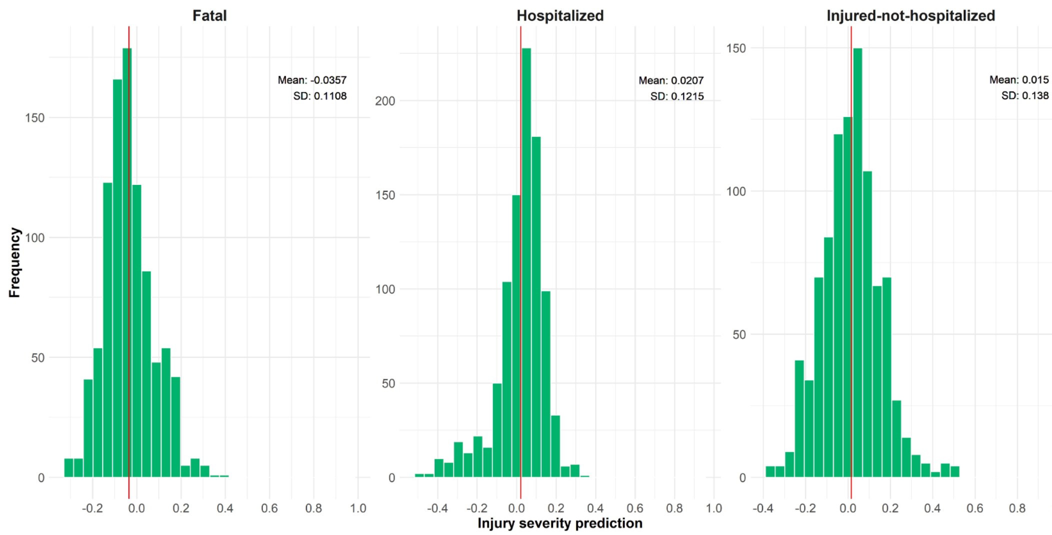
Table A1
Factors influencing the severity of pedestrian-involved crashes in developing countries.

Category	Variables	Effect (sign)	References
Temporal features	Day and evening time (06:00–10:00,11:00–15:00,16:00–19:00,20:00–23:00), morning peak, evening peak	Negative	(Amoh-Gyimah et al., 2017; Obinguar and Iryo-Asano, 2021)
	Weekend, night-time (18:00 – 08:59), dawn/dusk, late night (1 am – 5 am)	Positive	(Amoh-Gyimah et al., 2017; Damsere-Derry et al., 2010; Park and Bae, 2020; Tulu et al., 2017; Verzosa and Miles, 2016; Zafri et al., 2020)
Roadway characteristics	One-way traffic, fair road surface, 3–4 lanes, straight and flat, tarred and good, tarred with potholes, shoulder condition poor/overgrown, no shoulder, wet, speed camera	Negative	(Amoh-Gyimah et al., 2017; Hasanat-E-Rabbi et al., 2022; Obinguar and Iryo-Asano, 2021; Park and Bae, 2020; Verzosa and Miles, 2016; Zafri et al., 2020)
	Undivided road, bad road surface, >5 lanes, median absence/presence, straight and flat	Positive	(Chen and Fan, 2019; Das et al., 2018a; Hasanat-E-Rabbi et al., 2022; Obinguar and Iryo-Asano, 2021; Zafri et al., 2020) The study from Bangladesh by Zafri et al. (2020) had contrasting findings.
Drivers' characteristics	Driver owns a vehicle, male, age under 30, over 65, female	Negative	(Chen and Fan, 2019; Kim et al., 2017; Saha et al., 2021; Tay et al., 2011; Tulu et al., 2017) A study from South Korea by Tay et al. (2011) mentions that drivers over 65 are less likely to be involved in fatal pedestrian crash injuries.
	31–40 years, age above 40, primary school education level and below, 2–5 years driving experience, owner of the vehicle – other (friend, family), male, drunk, inattentiveness to yield sign	Positive	(Besharati and Tavakoli Kashani, 2018; Hasanat-E-Rabbi et al., 2022; Kim et al., 2017; Park and Bae, 2020; Saha et al., 2021; Tay et al., 2011; Tjahjono et al., 2021; Tulu et al., 2017) Tjahjono et al. (2021) show that male drivers are likely to cause fatal crashes when they hit pedestrians crossing the road.
Pedestrian characteristics	41–50 years, male, <13 years, female	Negative	(Das et al., 2018a; Hasanat-E-Rabbi et al., 2022; Kim et al., 2017; Park and Bae, 2020; Tay et al., 2011; Verzosa and Miles, 2016) The study from South Korea by Tay et al. (2011) and Park and Bae (2020), and from the Philippines by Verzosa and Miles (2016) show that males are less likely to be involved in fatal pedestrian crash injuries (inconsistency) The study from South Korea by Kim et al. (2017) shows that younger pedestrians are likely to be involved in fatal crashes.
	Less than 18 years, more than 50 years, >60 yrs., male, female, elderly pedestrians	Positive	(Besharati and Tavakoli Kashani, 2018; Hasanat-E-Rabbi et al., 2022; Kim et al., 2017; Obinguar and Iryo-Asano, 2021; Saha et al., 2021; Tay et al., 2011; Tjahjono et al., 2021; Tulu et al., 2017; Verzosa and Miles, 2016) The study from South Korea by Kim et al. (2017) mentions that females are associated with fatalities.
Pedestrian activity	Crossing	Positive	(Damsere-Derry et al., 2010; Hasanat-E-Rabbi et al., 2022; Sarkar et al., 2011)
Weather characteristics	Clear, good	Negative	(Amoh-Gyimah et al., 2017; Zafri et al., 2020)
	Rain, cloud, fog, snow	Positive	(Kim et al., 2017; Mujalli et al., 2019; Park and Bae, 2020; Sarkar et al., 2011; Tay et al., 2011)
Lighting condition	Night – no light, night – light, dark	Positive	(Amoh-Gyimah et al., 2017; Chen and Fan, 2019; Mujalli et al., 2019; Saha et al., 2021; Zafri et al., 2020)
Crash characteristics	Multi-vehicle–pedestrian involved	Positive	(Verzosa and Miles, 2016)
Crash location	School, church, hospital areas, three-legged intersections, police-controlled intersection, outside of roadway, shoulder, at roadside, at sidewalk,	Negative	(Chen and Fan, 2019; Kim et al., 2017; Saha et al., 2021; Tay et al., 2011; Tulu et al., 2017; Zafri et al., 2020)
	Not-at-intersection, crosswalk, non-signalized intersection, residential area, high income, and low-income inhabitants, four-way intersection, 50 m from zebra crossing, close to transit station, near the alley, three-way intersection,	Positive	(Amoh-Gyimah et al., 2017; Damsere-Derry et al., 2010; Saha et al., 2021; Tay et al., 2011; Tjahjono et al., 2021; Tulu et al., 2017; Verzosa and Miles, 2016) The study from Bangladesh by Saha et al. (2021) was inconsistent. Tay et al. (2011) showed that intersections are likely places for fatal pedestrian crash injuries.
Vehicle characteristics	Non-motorized vehicle, motorcycle	Negative	(Tjahjono et al., 2021; Tulu et al., 2017)
	Bus, truck, car, van, medium vehicle, heavy vehicle, tractor, special vehicle	Positive	(Chen and Fan, 2019; Hasanat-E-Rabbi et al., 2022; Kim et al., 2017; Obinguar and Iryo-Asano, 2021; Saha et al., 2021; Sarkar et al., 2011; Tay et al., 2011; Tulu et al., 2017; Verzosa and Miles, 2016; Zafri et al., 2020)
Traffic characteristics	Speed (<60 km/h)	Negative	(Tulu et al., 2017)
	AADT > 9,000, high pedestrian-vehicle interactions, speed (>60 km/h), off-peak, high traffic volume, speed limit above 50mph, speed limit (35-50mph)	Positive	(Chakraborty et al., 2019; Chen and Fan, 2019; Damsere-Derry et al., 2010; Das et al., 2018a; Mukherjee and Mitra, 2020; Rahimi et al., 2020; Tulu et al., 2017; Zafri et al., 2020) The speed limit identified by Chen and Fan (2019)'s study seems lower compared to others

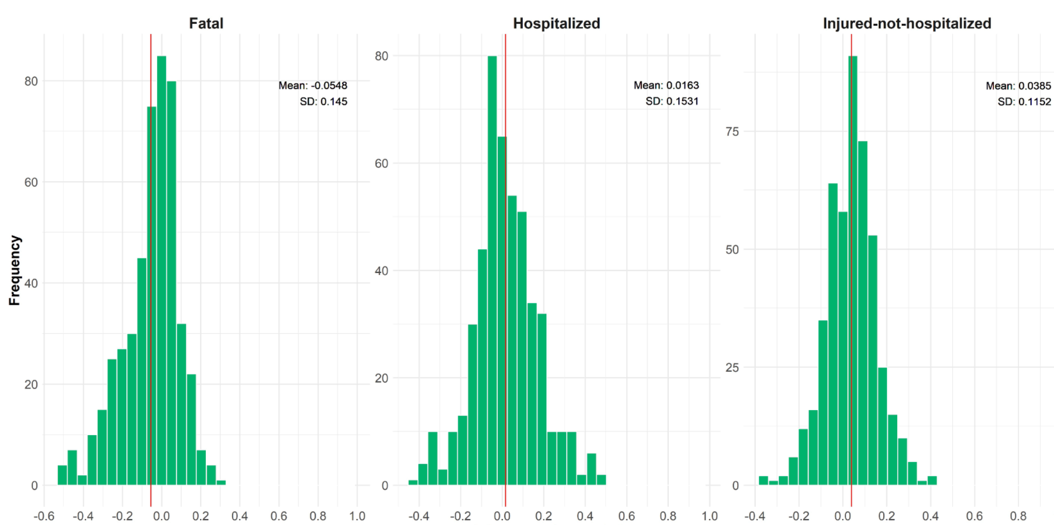
(*continued on next page*)

Table A1 (*continued*)

Category	Variables	Effect (sign)	References
Others	Road width < 6 m, road width between 6 and 12 m, population density, financial independence, doctors per thousand people	Negative	(Amoh-Gyimah et al., 2017; Kim et al., 2017) The study from South Korea by Kim et al. (2017) shows inconsistencies regarding population density.
	Population density (pop/km), encroachment of footpath, open space land use rate, proximity to the intersection, airbag deployment, percentage of elderly, road width > 6, poor sight distance, absence of pedestrian signal	Positive	(Kim et al., 2017; Mukherjee and Mitra, 2020; Obinguar and Iryo-Asano, 2021; Rahimi et al., 2020)



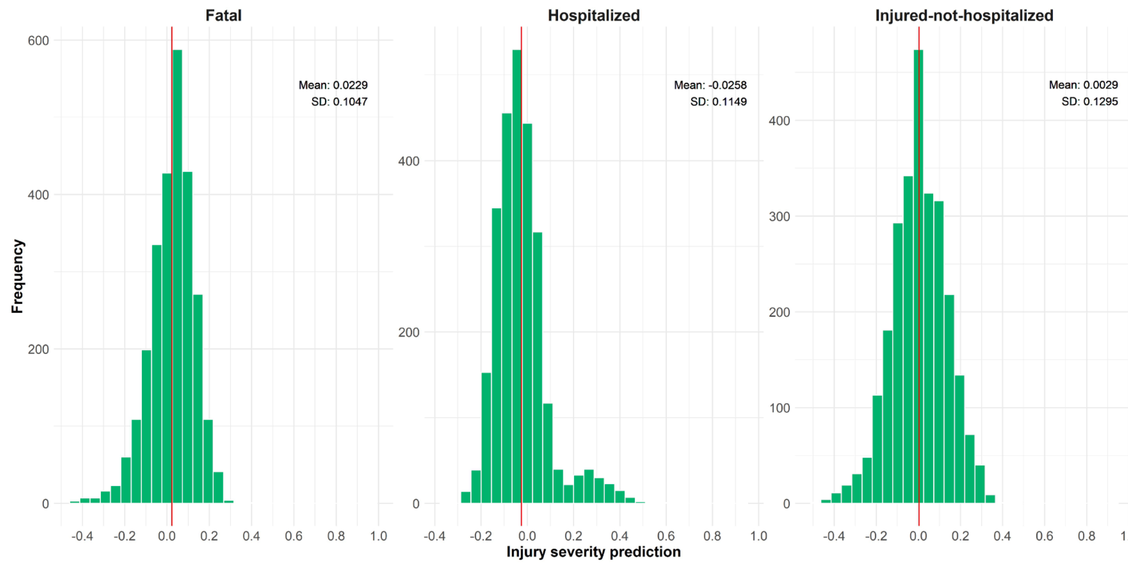
(a) Difference between the pedestrian WDAY estimated model predicted injury probabilities using WNLO data and the WDAY “observed” probabilities.



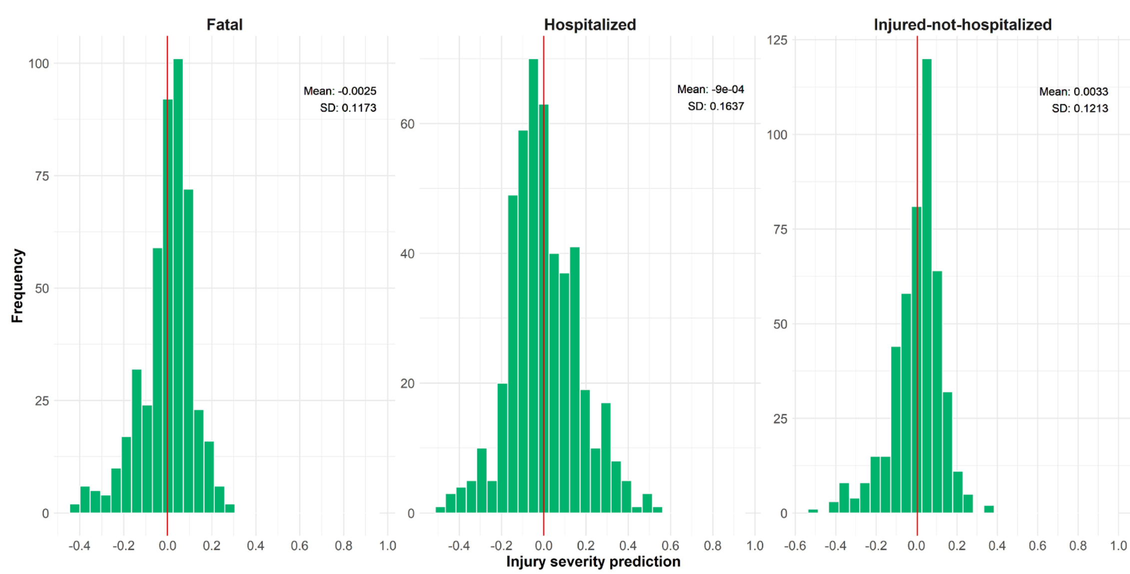
(b) Difference between the pedestrian WDAY estimated model predicted injury probabilities using WNNL data and the WDAY “observed” probabilities.

Fig. 7. Out-of-sample predictions based on the WDAY estimated models.

was consistently observed that factors such as speeding and male casualties consistently resulted in fatal injuries. Particularly, the risk of fatality was heightened in dark and unlit conditions. Further, severe pedestrian injuries are expected on Tuesdays on dark-but-lit roads, but minor injuries are likely to occur on dark-unlit roads and during daylighting conditions. Several factors, such as pickups, HGVs, shoulder presence, and drivers above 64 years, showed a higher association with fatalities during the daytime. Indicator variables for non-defective



(a) Difference between the pedestrian WNLO estimated model predicted injury probabilities using WDAY data and the WNLO "observed" probabilities.



(b) Difference between the pedestrian WNLO estimated model predicted injury probabilities using WNNL data and the WNLO "observed" probabilities.

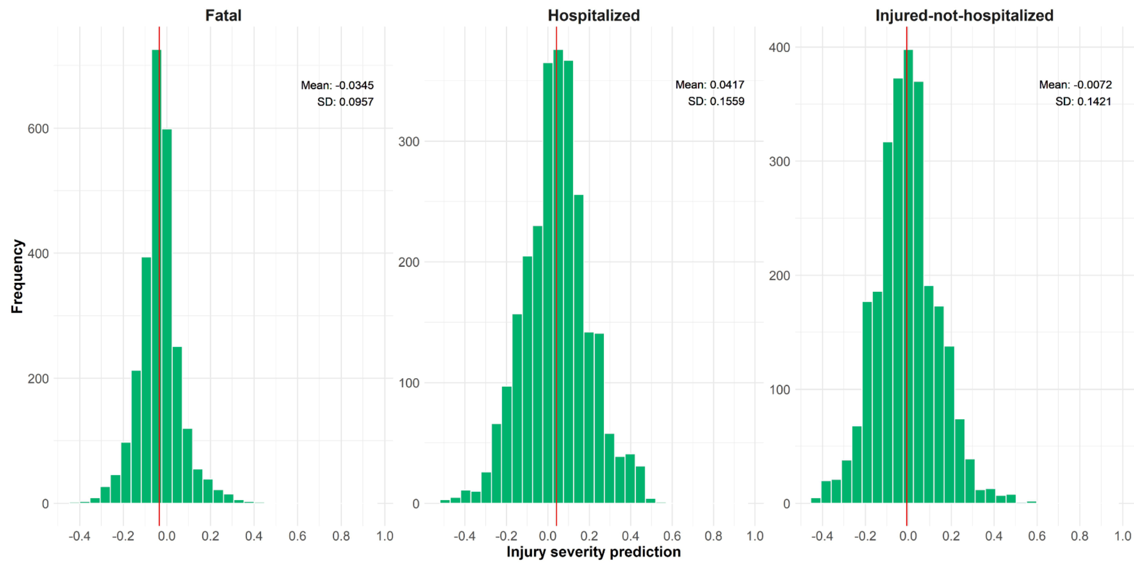
Fig. 8. Out-of-sample predictions based on the WNLO estimated models.

vehicles and pedestrians aged 25–44 had negative heterogeneous effects on pedestrian injury severity outcomes. Besides, a few variables resulted in significant heterogeneity in the means of these random parameters, providing additional insights into the presence of unobserved heterogeneity in the data. The simulation results unequivocally illustrate that improved visibility will likely confer a significant safety advantage. Consequently, enhancing nighttime lighting could substantially mitigate the risk of fatalities for pedestrians walking along roadsides.

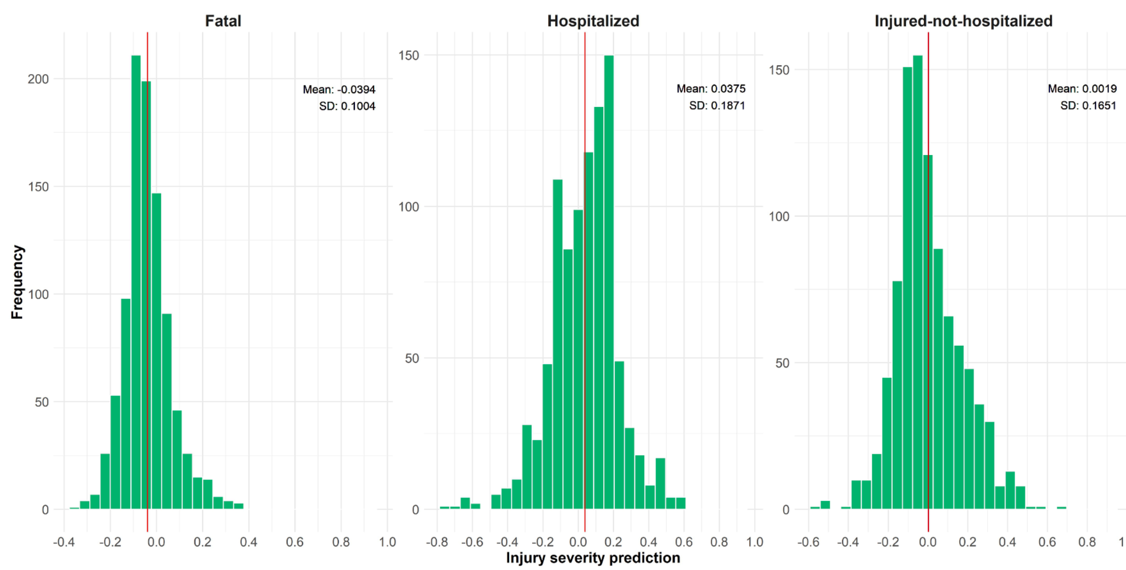
5.2. Policy suggestions

The study results suggest a series of engineering, education, and enforcement countermeasures for local and international practice. First, regarding the educational aspect, to help improve the harmony of both motorized and non-motorized road users, there is the need to educate and encourage drivers/riders to always adopt pedestrian-first measures as they drive. Besides, special educational campaigns should be targeted at the general populace on how to use roadways safely. It would also be worthwhile to reinforce road safety by introducing it into the educational curriculum of all school-going children.

Further, the association between walking-along-the-road -related crashes and severe/fatal injury in Ghana at night is likely due to reduced visibility, the inadequacy of pedestrian protection facilities, and the attitude of pedestrians and drivers. While education could address the attitudinal challenges, engineering measures such as constructing pedestrian barriers and protected sidewalks are recommended. Most



(a) Difference between the pedestrian WNNL estimated model predicted injury probabilities using WDAY data and the WNNL "observed" probabilities.



(b) Difference between the pedestrian WNNL estimated model predicted injury probabilities using WNLO data and the WNNL "observed" probabilities.

Fig. 9. Out-of-sample predictions based on the WNNL estimated models.

roads in Ghana were solely designed to move traffic (Afukaar, 2003). Retrofitting dangerous roadways by adding sidewalks clearly separated from the travel lanes using barriers and pedestrian-friendly facilities could reduce crashes. These sidewalks should be placed on both sides of the roadway in urban centers, transit locations, and school zones. Creating paved shoulders for pedestrians is worthwhile in situations where sidewalks are impractical. Further, safety engineers must provide pavement and sidewalk visibility enhancements to increase the visibility of pedestrians at night. These enhancements include lighting systems, *retro*-reflective pavement markings, and advance signing. Like other developing countries, Ghana does not have good urban speed laws (WHO, 2018b); thus, drivers drive haphazardly, making it difficult to avoid a crash when a pedestrian suddenly appears in the road space. Thus, it would be worthwhile to consider reducing the speed limits on most roadways with high pedestrian activity (using speed bumps where necessary). Other countermeasures, such as road diets and the construction of pedestrian refuge islands.

Finally, creating a safe road space for pedestrians and drivers is crucial. To achieve this, stricter enforcement needs to be established. First, it would be worthwhile to introduce automatic enforcement, such as speed and mobile phone detection cameras, to identify and punish drivers inattentive and overspeeding drivers. To further monitor and control how HGVs, commercial, and company vehicle drivers operate their vehicles on the roadways, policies should be enacted to ensure that operators of such vehicles install digital tachographs on the vehicles. These vehicles' speed and driving patterns could then be accessed and examined to identify and punish drivers who flout traffic regulations. Finally, in the long term, developing a driver penalty point system is crucial to control, penalize, and re-educate drivers who continue to break traffic rules. The association of elderly drivers with fatal pedestrian crash injuries during the day highlights the need to consider allowing elderly drivers to undergo physical and cognitive examinations yearly for a driver's license renewal. Elderly drivers may be given some driving limitations preventing them from using risky road segments. Unlike the current system, which does not distinguish between elderly and young drivers at renewals, this system could help reduce the number of drivers with visibility defects on the roads. There is also the need to enforce laws to prevent the occupation of sidewalks by street vendors. Besides, stricter rules must be made to punish drivers who engage in hit-and-run to deter others from engaging in such behavior.

5.3. Study limitations

As with every research, this study has a few limitations. Although the data used for the analysis spans the period from 2014 to 2018, a temporal stability test was not considered as the data segregation into each year results in significantly smaller sample sizes, likely affecting the quality of the results. A separate analysis of the temporal variations of risk factors will be considered in the future. It is also important to acknowledge that our study did not distinguish between crashes involving pedestrians walking on the footpath or road verge. Additionally, we analyzed all crashes occurring within intersections or roundabouts with those on road segments together instead of segregating them due to data limitations. Future research could benefit from separate analyses of these scenarios to gain insights into how risk factors affect injury severity outcomes within each context. In the out-of-sample prediction analysis, we have not explored the transferability of parameters estimated from the aggregated model. This might an intriguing avenue for future research.

CRediT authorship contribution statement

Reuben Tamakloe: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Data curation, Validation. **Emmanuel Kofi Adanu:** Formal analysis, Investigation, Writing – review & editing, Data curation, Validation. **Jonathan Atandzi:** Investigation, Writing – original draft, Writing – review & editing, Visualization. **Subasish Das:** Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Validation. **Dominique Lord:** Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Validation. **Dong-joo Park:** Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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