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Identifying the Factors That Increase the Probability of an Injury or Fatal Traffic Crash in an Urban Context in Jordan

Tasneem Miqdady and Juan de Oña *

TRYSE Research Group, Department of Civil Engineering, University of Granada, ETSI Caminos, Canales y Puertos, c/ Severo Ochoa, s/n, 18071 Granada, Spain; tasneem@correo.ugr.es

* Correspondence: jdona@ugr.es

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Abstract: The lack of robust studies carried out on urban roads in developing countries makes it difficult to enhance traffic safety, ensuring sustainable roads and cities. This study analyzes the contribution of a number of explanatory variables behind crashes involving injuries on arterial roads in Irbid (Jordan). Five binary logistic regression models were calibrated for a crash dataset from 2014–2018: one for the full database, and the others for the four main crash causes identified by Jordanian Traffic Police reports. The models show that whatever the crash cause, the three most significant factors linked to an injury or fatality lie in urban road sections that are in large-scale neighborhood areas, have fewer than six accesses per kilometer, and have a low traffic volume (under 500 veh/h/ln). Some of these results agree with previous studies in other countries. Jordan's governmental agencies concerned with urban road safety might use these results to develop appropriate plans and implement priority actions for each crash cause, in addition to undertaking further research for comparative purposes.

Keywords: crash severity; collision crashes; arterial roads; urban context; logistic regression; crash cause; injury; sustainable roads

1. Introduction

Traffic crashes stand as the foremost obstacle to sustainable roadways. Indeed, traffic crashes are a growing worldwide problem that lead to a tremendous loss of human resources, with economic consequences as well. There were 1.35 million road deaths in 2016, and about 75% of all crash injuries occur in urban areas [1]. As urbanization has accelerated and urban traffic is more complicated, the problem of traffic crashes in urban contexts increases and it is more acute in developing countries, where around 0.5 million deaths and up to 15 million injuries are caused by urban road crashes [2]. As a case study of developing countries, Jordan traffic crashes with serious injuries and fatalities amounted to terribly tragic numbers in 2012, for which reason the Public Police Department and the ministries of Public Work and Municipalities developed a five-year safety plan (2013–2017) to decrease the figures by 20% by the end of 2017. In reality, the reduction was even greater: a 27% reduction in injuries, and a 35% reduction in fatalities. However, Jordan urban contexts specifically still suffer from a lack of safety plans to control the traffic crash problem. As successful plans for safety, and hence sustainability, depend on a profound understanding of crash causes and contexts, extensive data collection is also necessary [3]. In this respect, urban road safety studies in Jordan became more viable in 2014, when police started to report crashes directly in situ using GPS systems.

In light of this improvement, many factors connected to crash location (i.e., geometric design and urban context factors) could be addressed in urban crash studies in a developing country, such as Jordan. The main contribution of this study to the literature is the possibility of analyzing the influence of several crash location factors on the severity of traffic crashes in a developing country in an urban context. This study presents, for the first time, a clear understanding of Jordanian urban crashes and to what extent this context affects traffic crash severity. In addition, for more insight, the study hypothesizes that the heterogeneity due to crash cause could be studied and will show a variable effect, since it also reflects the driving behavior effects on Jordanian urban roads. With this intention, the analysis is replicated for each cause alone for comparison purposes.

Simply, the present study aims to identify the main variables influencing the occurrence of traffic injuries or fatalities on urban arterial roads in Jordan. Furthermore, differences are identified according to the crash cause within several categories reported by the police. The findings contribute to Jordanian urban traffic safety studies, which are very limited in number to date (e.g., Mujalli et al. [4,5]). The results are compared with those of similar studies in other countries, whether developed (Das et al. [6]; Abdel-Aty and Abdelwahab [7]; Ma et al. [8]; Wang et al. [9]; Haleem and Abdel-Aty [10]; Russo et al. [11]; Garrido et al. [12]; Zhuanglin et al. [13]) or developing (Al Ghamidi [14]; Altwaijri et al. [15]; Hassan and Al-Faleh [16]; Hosseinpour et al. [17]).

The paper is organized as follows: after this brief introduction, the literature review section presents existing traffic severity studies in the urban context, focusing on the main explanatory variables affecting severity; the crash data section describes the database used for analysis, the main preprocessing tasks, and some descriptive statistics; the model section presents the methodology followed; the analysis and comparison sections summarize and highlight the main outcomes obtained through the analysis; and finally, some conclusions and policy implications are offered in the last section.

2. Literature Review

Although 75% of traffic crashes occur in urban infrastructures, the amount of studies examining them is much lower compared to the literature analyzing rural crashes [2], including crash severity analysis. Nevertheless, worldwide crash severity studies (in both developed and developing countries) consider several types of urban infrastructures. For example, crash severity was examined at arterial sections [14,15,18–23], urban signalized [19,20] and unsignalized [10] intersections, urban freeway segments [22], toll plazas [20], and other urban segments [17,24].

Some studies analyzing crash severity in urban contexts have considered the type of crash as one of the independent variables [15,16,21,23], while other studies have restricted their analysis to one type, such as head-on crash severities [17] or rollover crash severities [24]. This kind of study allows us to reduce the heterogeneity and provide more robust outputs. In addition, the effect of non-vehicle–vehicle crashes (i.e., crashes with motorcycles, bicycles, pedestrians) has also been studied in analyzing traffic behavior effects on urban crash severity [21,23,25,26].

Most of the studies that analyze crash severity in urban areas only consider as explanatory factors the variables registered in the crash reports, whatever the type of section or the crash type concerned. This paper focuses mainly on arterial sections and collision crashes (not pedestrian or roll-over crashes). In developed countries, several studies [20–23] found that the driver's age and gender, vehicle type, seatbelt use, alcohol, lighting, weather and road surface conditions, and time and distance from the intersection are significant variables. Some studies in developing countries [14–16] have identified a similar pattern regarding age, time, road surface, lighting conditions, whether single vehicle is involved, day of the week, crash location, and head-on point of collision. Those variables were also reported as significant in defining crash severity. Regarding traffic flow and speed variables, studies in both developed and developing countries suggested that low traffic volumes (hourly or daily) are also related to severe crashes [22,23]. In the same way, crashes at sections with higher speed limits showed greater tendencies to involve injuries or fatalities [14–16,19,20]. Moreover, sharing the road with heavy vehicles and light truck vehicles was positively associated with higher severity [24].

The previous variables were widely studied in both urban and interurban sections without major differences in their effect on crash severity. However, geometric design variables have shown significant effects on crash severity at urban road sections. Previous studies [17–19,24] have considered a great variety of geometric factors for urban roads because of their richness of design elements and characteristics. For instance, Harvey and Aultman-Hall [18] examined arterial streetscape design and traffic safety in urban areas by evaluating the effect of several street landscape design variables (i.e., width, building to building across the street; length, centerline distance between intersections; height, average building height; width–height ratio; street wall continuity; building per length; and tree coverage area) on crash severity. Ma et al. [19] also established statistical relationships to relate severe crashes to a variety of geometric design factors. They found that a higher number of severe crashes was associated with a longer length of the road segment, fewer lanes per direction, more side accesses per kilometer, and the presence of bus stops. Additionally, Hosseinpour et al. [17] analyzed the effect of road characteristics and revealed that horizontal curvature, paved shoulder width, type of terrain, and side friction were associated with more severe crashes; yet, access points and the presence of a median reduced the probability of severe head-on crashes on federal urban segments. Anarkooli et al. [24] also had the same results for single-vehicle rollover crash severity on the same segments.

Not only is the design of the urban road section important, but the urban design of the region where the road section is located could also be of relevance. Previous studies [17,18,24] have also suggested that the urban context, or the landscape of a region, could have a plausible effect on traffic behavior, as well as traffic safety. Nevertheless, there is still a lack of analyses on the urban context effect on crash severity. Briefly, Harvey and Aultman-Hall [18] found that accidents in smaller, more enclosed street landscapes were less likely than those in larger, more open streetscapes to cause injury or fatal crashes. Furthermore, in-fill development and street tree planting could be used as safety countermeasures. In developing countries, Hosseinpour et al. [17] and Anarkooli et al. [24] showed that land use and the type of terrain have significant effects on crash severity.

Turning to Jordan traffic safety studies, in general, most crash studies are concerned with frequency prediction (crash rates), not the severity probabilities. Moreover, many studies deal with rural areas or the whole country's crash characteristics. By way of illustration, Al-Masaeid [27] studied traffic accident characteristics in Jordan with an extensive evaluation of the 2008 policy implementation, highlighting this law enforcement and other measures and their very positive impact on safety. Al-Omari et al. [28] studied traffic crash trends in Jordan over thirteen years (1998-2010), analyzing the distribution of crash types, severity level, age group involvement, etc. Their study also correlated traffic crashes to variables such as time, traffic speed, and pavement condition. Al-Omari et al. [29] studied the spatial–temporal incidence of crashes in Irbid City using GIS (Geographic Information Systems) and fuzzy logic to predict the riskiest spots depending on road section and intersection parameters.

Finally, studying crash severity on Jordanian urban roads started with Mujalli et al. [4], who used the variables included in the Jordanian Traffic Police reports to identify factors affecting the crash severity. They identified the number of vehicles involved, accident pattern, number of directions, accident type, lighting, surface condition, and speed limit as the variables that contribute to the occurrence of high-severity crashes. Furthermore, Mujalli et al. [5] analyzed pedestrian–vehicle crashes, finding that road type, number of lanes, speed limit, lighting, and adverse weather conditions affect the risk of fatality or severe injury.

This study follows the line of Mujalli et al. [4], in that, aside from defining the factors that have significant effects, it also determines to what extent these factors could increase or decrease the probability of crash injuries. Additionally, this study adds some new urban factors to the analysis (e.g., neighborhood scale, land use, on-street parking) for the first time in a traffic safety study set in Jordan.

3. Data Collection and Description of Variables

Careful and extensive data collection is key to drawing sound conclusions. In Jordan, the Police Traffic Central Department is the crash database reference. Traffic policemen fill out accident reports that include crash location based on GPS coordinates, and other data (crash type, cause, time, weather, etc.). This study covers a five-year period (2014–2018), in which 21,662 traffic crashes were registered on 39 arterial road sections in Irbid City, the second most populated city in Jordan.

The original severity data consider four categories: property damage only, slight injury, serious injury, and fatality. Since urban networks generally produce a low number of injuries or fatal crashes, and to ensure a sufficient number of observations for estimation purposes and following previous studies [6,30], severity data are grouped into two categories: (1) property damage only (PDO) and (2) injury or fatality (INJ). Hence, in this study, the target variable of severity is binary.

The crashes were also classified by type into three different categories: 20,742 collisions, 640 crashes involving pedestrians, and 280 run-off-road crashes. Only 1653 of those crashes entailed injuries, while all the rest caused property damage only (PDO). Given the low number of run-off-road and pedestrian crashes, this study focuses on collision crashes only (i.e., head-on, rear-end, sideswipe, and with fixed object crashes) and does not consider pedestrian and run-off-road crashes that should be analyzed in further studies.

As mentioned previously, Jordan's crash database provides the data adopted in this study as variables: number of vehicles involved, season, time of day, type of day, accident cause, weather conditions, and state of pavement surface.

Additionally, traffic data were obtained from camera videotapes and derived from calculations following the procedures and equations of Garber and Hoel [31] and Homburger et al. [32]. These variables are hourly traffic volume, percentage of heavy vehicles, and 85th percentile of speed.

In an effort to be more comprehensive and to increase the novelty of this study, several geometric and urban characteristics were considered according to the Highway Safety Manual (HSM [33]) and previous studies. The set includes: distance from the following intersection, road cross-section type (two-lane two-way or multilane two-way), geometric consistency (a qualitative evaluation by an expert of the consistency of the geometric design and construction), sufficient building setbacks (according to Jordan's Ministry of Public Works laws), presence of on-street parking, nominal clear zone of trees (based on American Association of State Highway and Transportation Officials [34]), neighborhood scale (a qualitative measure of the massing of buildings and spaces) [35], number of accesses to the section, and land use.

Afterwards, traffic, geometric, and urban characteristics were combined with the section at hand using the GIS platform, which connects the section parameters to the GPS crash coordinates. All variable categories and descriptions, along with a summary of collision data for Irbid City, are listed in Table 1.

Table 1. Explanatory variable description.

Variables *	Variable Levels	No. of Crashes	INJ ** (%)
Distance from intersection **(DI)**			
Heavy vehicles % (**HVEH**)			
Number of vehicles involved **(VINV)**	For single-vehicle crash ***(SNG)***	1018	16.9
	For two-vehicle crash ***(TWO)***	18421	3.30
	For more than two-vehicle crash ***(MUL)***	1303	7.68
Season **(SEAS)**	if in autumn (Sep, Oct, Nov) ***(AUT)***	2635	4.74
	if in winter (Dec, Jan, Feb) ***(WIN)***	6129	6.27
	if in spring (Mar, Apr, May) ***(SPR)***	6577	3.57
	if in summer (Jun, Jul, Aug) ***(SUM)***	5401	2.50
Time of the day **(TIME)**	if during 0:00–5:59 ***(0–6)***	359	9.19
	if during 6:00–11:59 ***(6–12)***	3786	4.25
	if during 12:00–17:59 ***(12–18)***	9623	4.08
	if during 18:00–23:59 ***(18–0)***	6974	4.19
Day type **(DAY)**	if during the day after the weekend (Sun) ***(AW)***	3487	4.04
	if during the day before the weekend (Thu) ***(BW)***	3796	3.66
	if during weekend holiday (Fri, Sat) ***(WE)***	8140	4.35
	if during regular workday ***(WD)***	5319	4.60

Table 1. *Cont.*

Variables *	Variable Levels	No. of Crashes	INJ ** (%)
Crash cause (**CAUS**)	if due to unsafe lane changes ***(LCH)***	2372	3.92
	if due to exceeding speed limit ***(LIM)***	904	5.64
	if due to driving without taking safety precautions ***(SAF)***	8872	4.14
	if due to failing to obey traffic control devices ***(TCD)***	4815	4.09
	If due to tailgating ***(TAI)***	3779	4.53
Weather condition (**WEAT**)	if in good weather (clear or cloudy) ***(GW)***	18,178	3.16
	if in rainy weather ***(RAI)***	2211	12.26
	if in other bad conditions (foggy, snowy, windy, etc.) ***(OTH)***	353	9.92
Pavement Surface **(PAVE)**	if on dry pavement (***Dry***)	18449	3.70
	if on wet pavement after raining (***WET***)	2144	7.88
	if on other bad surface conditions (oily, muddy, icy, etc.) (***OTH***)	149	18.12
Traffic volume **(TRAF)**	if traffic volume in the segment is low (350-500 veh/h/ln) ***(LV)***	2020	17.38
	if traffic volume in the segment is moderate (501-700 veh/h/ln) ***(MV)***	11,139	4.60
	if traffic volume in the segment is high (>701 veh/h/ln) ***(HV)***	7583	0.21
Geometric consistency **(CONS)**	if segment curve consistency is perfect, width of lane and median is standard, perfect design of intersections, presence of safety elements ***(A)***	1533	5.22
	if segment curve consistency is good, width of lane and median is standard, good design of intersections, presence of safety elements ***(B)***	9525	4.16
	if segment curve consistency is good, width of lane and median is less than standard, bad design of intersections, presence of safety elements ***(C)***	8689	4.14
	if segment curve consistency is bad, width of lane and median is less than standard, bad design of intersections, absence of safety elements ***(D)***	995	4.22
Cross section (**SECT**)	if in a two-lane two-way road section ***(TLN)***	5542	4.24
	if in a multilane two-way road section ***(MLN)***	15,200	4.24
85th-percentile speed **(SP85)**	if in a segment of 85^{th} % speed <50 km/h ***(LSP)***	18,634	1.91
	if in a segment of 85^{th} % speed >50 km/h ***(HSP)***	2108	24.86
Sufficient building setbacks **(BUIL)**	if in a segment where on both sides buildings are settled on the standard setbacks ***(SUF)***	11,027	3.81
	if in a segment where on both sides buildings are not settled on the standard setbacks ***(NSUF)***	9715	4.73
On-street parking **(PARK)**	if there is on-street parking in the segment ***(EX)***	10,119	0.85
	if there is no on-street parking ***(NEX)***	10623	7.47
Trees in nominal clear zone **(TREE)**	if the trees in the segment curb are in the nominal clear zone ***(IN)***	11,012	2.07
	if trees exceed the nominal clear zone ***(EXC)***	9730	16.69
Neighborhood scale **(NESC)**	if in a large-scale neighborhood ***(LAR)***	8104	9.79
	if in a small-scale neighborhood ***(SMA)***	12,638	0.68
Number of accesses per km **(ACCE)**	if the number of accesses to the segment >6 ***(HN)***	12,266	0.70
	if the number of accesses to the segment ≤ 6 ***(LN)***	8476	9.36

Table 1. *Cont.*

Variables *	Variable Levels	No. of Crashes	INJ ** (%)
Land use **(LUSE)**	if in a commercial zone ***(COM)***	9569	3.85
	if in a residential zone ***(RES)***	6360	4.61
	if in an industrial zone ***(IND)***	2155	4.87
	if in a non-categorized zone ***(NC)***	2658	4.25

Note: * All variables are categorical except DI and HVEH, which are continuous; ** INJ: injury or fatality.

Crash cause data were used for segmentation purposes to identify the specific effect of the same explanatory variables for each cause, this was supposed to deal with heterogeneity of the data and consider driving behavior as much as possible. The Jordanian Traffic Police reports identify five main crash causes: unsafe lane changes (LCH), exceeding speed limit (LIM), driving without taking safety precautions (SAF), failing to obey traffic control devices (TCD), and tailgating (TAI). Table 2 offers a crash data summary, classified by crash causes.

Table 2. Explanatory variables and data summary of crash causes.

Variables *		**LCH**		**LIM**		**SAF**		**TCD**		**TAI**	
main	levels	total	INJ	total	INJ	total	INJ	total	INJ	total	INJ
DI	Cont.	2372	93	904	51	8872	367	4815	197	3779	9
HVEH	Cont.	2372	93	904	51	8872	367	4815	197	3779	9
VINV	SNG	125	22	49	10	417	70	261	46	166	24
	TWO	2099	65	776	30	7882	258	4243	127	3421	127
	MUL	148	6	79	11	573	39	311	24	192	20
SEAS	AUT	340	11	134	5	1107	47	583	25	471	37
	WIN	643	46	271	23	2580	151	1477	98	1158	66
	SPR	768	24	306	19	2853	97	1497	56	1171	39
	SUM	621	12	193	4	2332	72	1276	18	979	29
TIME	0-6	53	5	16	4	140	14	74	7	76	3
	6-12	475	20	178	10	1590	76	820	26	723	29
	12-18	1096	36	428	16	4128	135	2281	103	1690	103
	18-0	748	32	282	21	3014	142	1640	61	1290	36
DAY	AW	393	22	170	10	1529	50	815	21	580	38
	BW	417	19	159	6	1688	56	884	34	648	24
	WE	939	39	361	14	3364	156	1888	76	1588	69
	WD	623	13	214	21	2291	105	1228	66	963	40
WEAT	GW	2137	61	792	33	7776	238	4207	125	3266	116
	RAI	192	31	101	15	949	119	525	60	444	46
	OTH	43	1	11	3	147	10	83	12	69	9
PAVE	DRY	2169	78	801	37	7898	279	4248	144	3333	145
	WET	174	13	93	10	904	74	547	47	426	25
	OTH	29	2	10	4	70	14	20	6	20	1
TRAF	LV	229	48	110	19	858	141	483	80	340	63
	MV	1302	42	492	31	4727	220	2591	114	2027	105
	HV	841	3	302	1	3287	6	1741	3	1412	3
CONS	A	159	7	55	4	668	32	366	19	285	18
	B	1029	37	383	17	4062	171	2219	80	1732	74
	C	1098	46	414	26	3705	148	2005	88	1567	70
	D	86	3	52	4	437	16	225	10	195	9
SECT	TLN	648	30	241	14	2372	87	1283	52	998	52
	MLN	1724	63	663	37	6500	280	3532	145	2781	119

Table 2. *Cont.*

Variables *		LCH		LIM		SAF		TCD		TAI	
SP85	LSP	2136	33	809	8	7995	154	4378	76	3316	84
	HSP	236	60	95	43	877	213	437	121	463	87
BUIL	SUF	1236	46	491	24	4719	177	2567	99	2014	74
	NSUF	1136	47	413	27	4153	190	2248	98	1765	97
PARK	EX	1137	7	455	5	4296	37	2350	20	1845	17
	NEX	1199	86	449	46	4576	330	2465	177	1934	154
TREE	IN	1200	27	455	11	4795	90	2556	58	2006	42
	EXC	1172	66	449	40	4077	277	2559	139	1773	129
NESC	LAR	934	78	354	48	3456	335	1887	175	1473	157
	SMA	1438	15	550	3	5416	32	2928	22	2306	14
ACCE	HN	1397	9	538	10	5236	31	2789	19	2306	17
	LN	975	84	366	41	3636	336	2026	178	1473	154
LUSE	COM	1086	38	410	25	4122	147	2204	87	1747	71
	RES	746	38	302	13	2717	124	1464	62	1131	56
	IND	240	6	90	9	901	46	528	21	396	23
	NC	300	11	102	4	1132	50	619	27	505	21

Note: * LCH: unsafe lane changes; LIM: exceeding speed limit; SAF: driving without taking safety precautions; TCD: failing to obey traffic control devices; TAI: tailgating.

4. Methodological Approach

In view of the binary categories of crash severity (dependent variables) that resulted after aggregation, and given the need to predict the probability of the outcomes rather than the outcomes themselves, a binary logistic model was chosen to represent the relationship between the level of severity (personal damage only versus injury) and the set of the explanatory variables. According to Long [36], logit and probit models provide very similar results in terms of marginal effects (i.e., the effects on the predicted mean of the outcome, keeping other covariates at the mean or averaging them over observed values) for independent variables. However, logit models have the advantage of generating coefficients that can be transformed into odds ratios.

For this reason, most studies that analyze traffic crash severity use different types of logit models (e.g., binary logit, multinomial logit, ordered logit, nested logit, random parameters logit, or generalized ordered logit) [37].

This study uses a binary logit model because the dependent variable (Y) only takes two values: injury or fatal crashes (Y = 1) and property damage only crashes (Y = 0). The probability that an injuring or fatal crash will occur or not is modeled as a logistic distribution in Equation (1):

$$\pi(x) = \frac{\exp[g(x)]}{1+\exp[g(x)]} \tag{1}$$

The logit of the multiple logistic regression model is given by Equation (2):

$$g(x) = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_j + \sum_{j=1}^{p} \beta_j\, x_j \tag{2}$$

where $\pi(x)$ is the conditional probability of an injury or fatal crash, which is equal to the number of injuries or fatal crashes divided by the total number of crashes. In turn, xj is the value of the jth independent variable, with β_j as the corresponding coefficient, for j = 1,2, . . . p, and p is the number of independent variables. β_0 is the intercept.

The maximum likelihood method is employed to measure the association using the following likelihood function (Equation (3)):

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)\ y_{\mathrm{i}}\ [1 - \pi(x_i)]1 - \ y_i \quad (3)$$

where y_i is the ith observed outcome, with the value of either 0 or 1, and $i = 1,2, \ldots, n$, where n is the number of observations. By maximizing the log likelihood (LL) expression in Equation (4):

$$\mathrm{L}(\beta) = \ \ln[l(\beta)] = \sum_{i=1}^{n} \{\mathrm{y}_i\ \ln[\ \pi(x_i)] + \left(1 - \mathrm{y}_i\right)\ \ln[1 - \pi(x_i)]\} \quad (4)$$

the best estimate of β can be obtained.

The influence of attribute k on crash severity can be revealed by the odds ratio (OR) of Equation (5):

$$\mathrm{OR}\ = \exp\left(\beta_j\right) \quad (5)$$

With a 95% confidence level, the odds ratio provides the relative amount by which the odds ratios of the crash severity increase (OR greater than 1.0) or decrease (OR less than 1.0) when the value of the predictive value is increased by 1.0 unit. Because the standard deviations among variables differ substantially, the effect of a "unit standard deviation change" can be evaluated instead of a "unit change". In other words, Equation (6) shows that for a standard deviation change in k, the odds are expected to change by a factor, holding all other variables constant:

$$\exp(\mathrm{ORStdk})\ =\ \exp(\beta j\, *(\mathrm{SD\ of\ k})) \quad (6)$$

The modeling procedure began with the assessment of correlation in the dataset. The correlation matrix showed that two variables (weather and pavement surface conditions) were strongly correlated. In order to develop meaningful model estimations, and to ensure reasonable magnitudes and signs of the coefficients, it was advisable to exclude one of those variables from the model. The selection of the variable to be removed was based on the condition that the model fit will not vary significantly, and the removed variable is the one with a higher correlation with all variables. Accordingly, weather condition was excluded from the models.

A reference category was, moreover, chosen for each variable. It was the one permitting the odds for other categories of the same variable to be equal to or more than 1 (i.e., to show categories that directly increase the injury probability in the results table).

Binary logit models for the entire database (general model) and for each one of the crash causes reported by the police (i.e., unsafe lane changes, LCH; exceeding speed limit, LIM; driving without taking safety precautions, SAF; failing to obey traffic control devices, TCD; and tailgating, TAI) were developed using STATA 15/MP. Because the main purpose of this study is not to predict or forecast crash severity but rather to identify the extent of the effects of all studied factors, insignificant explanatory variables are retained in the models.

During application of the same fit assessment and model developing procedure on the exceeding speed limit (LIM) crashes, the model gave overestimated results. This was obviously due to the low number of observations (904 crashes), so we do not report or interpret these particular results.

The fitted binary logit model for the entire database and the remaining four causes considered are shown in Table 3. Essentially, it shows the factor estimation results for the category INJ (when the crash outcome is fatality or injury) when the category property damage only (PDO) crashes is the base category. It also includes some goodness-of-fit statistics, such as number of observations, Nagelkerke R-square value, log-likelihood at convergence, log-likelihood at zero, chi-square test, and degree of freedom.

5. Analysis of the General Model

Calculating the unit standard deviation change in the odds ratio for each variable when holding the other variables constant, Table 3 shows the factors' estimated effects across the entire database.

Table 3. Binary logit model's estimation of factors´ effect on injury probability.

	Exp. Variables	General Model	LCH Model	TAI Model	TCD Model	SAF Model
		e^BStdX *	e^BStdX	e^BStdX	e^BStdX	e^BStdX
Continuous variables						
DI		**1.334**	1.398	**1.272**	**1.543**	**1.335**
HVEH		**0.881**	0.882	0.866	0.935	0.881
Categorical variables						
VINV	SNG	**1.513**	**1.653**	**1.480**	**1.693**	**1.418**
	TWO	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	MUL	**1.309**	1.184	1.192	**1.367**	**1.322**
SEAS	AUT	**1.154**	**1.724**	**1.417**	**1.366**	0.916
	WIN	**1.478**	**2.300**	**1.547**	**1.969**	**1.248**
	SPR	**1.172**	1.405	1.091	1.288	1.100
	SUM	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
TIME	0-6	**1.140**	1.251	0.902	1.083	**1.220**
	6-12	1.038	0.837	1.245	1.058	1.039
	12-18	1.006	0.735	**1.547**	1.230	**0.811**
	18-24	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
DAY	AW	1.079	1.174	1.212	0.878	1.077
	BW	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	WE	1.135	0.901	1.081	0.903	**1.294**
	WD	1.073	0.641	0.959	1.117	1.126
PAVE	DRY	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	WET	1.090	1.164	0.977	1.060	**1.179**
	OTH	**1.176**	1.120	0.974	**1.228**	1.117
TRAF	LV	**3.767**	**4.044**	**4.092**	**3.744**	**3.871**
	MV	**4.691**	2.692	**6.088**	**4.363**	**5.261**
	HV	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
CONS	A	1.109	1.323	1.342	0.939	1.205
	B	**1.322**	2.250	1.181	1.080	**1.572**
	C	1.310	2.208	1.362	1.075	1.457
	D	Ref. cat.	Ref. cat.	Ref. cat	Ref. cat.	Ref. cat.
SECT	TLN	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	MLN	1.090	0.928	1.130	1.076	1.175
SP85	LSP	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	HSP	**2.564**	**2.967**	**2.572**	**2.613**	**2.523**
BUIL	SUF	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	NSUF	**1.338**	1.060	**1.657**	1.055	**1.406**
PARK	EX	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	NEX	**3.087**	**4.992**	**3.081**	**2.942**	3.015
TREE	IN	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	EXC	**1.699**	1.401	**1.876**	**1.543**	**1.756**
NESC	LAR	**6.740**	**4.342**	**8.087**	**6.857**	**7.951**
	SMA	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
ACCE	HN	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	LN	**4.101**	**5.537**	**4.806**	**4.146**	**4.114**

Table 3. *Cont.*

	Exp. Variables	General Model	LCH Model	TAI Model	TCD Model	SAF Model
		e^BStdX *	e^BStdX	e^BStdX	e^BStdX	e^BStdX
LUSE	COM	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.	Ref. cat.
	RES	**1.288**	1.216	1.225	1.258	**1.357**
	IND	**2.134**	1.359	**2.115**	**2.128**	**2.306**
	NC	**2.846**	**2.142**	**3.343**	**2.660**	**3.134**
Constant		***0.000***	***0.000***	***0.000***	***0.000***	***0.000***
No. observations		*20742*	2372	3779	4815	8872
Nag. R^2		*0.711*	*0.757*	*0.713*	*0.728*	*0.717*
−2LL with constant only		*7277*	*785*	*1392*	*1645*	*2539*
−2 LL with variables		*2382*	*215*	*454*	*506*	*975*
X^2, df = 30		*4896*	*569*	*938*	*1139*	*2081*

Bold values are statistically significant at 95% level of confidence, * change in odds for standard deviation increase in X.

In the case of the continuous explanatory variables, for a standard deviation increase in the log of crash distance from the nearest intersection (DI), the odds of an injuring crash are 1.334 times greater. Similar results were found in China's urban context [13], supposing that an increase in DI produces higher speeds and higher crash severity. Meanwhile, a heavy vehicle percentage increase (HVEH) makes the odds of an injuring crash decrease to 0.88 (12% less likely to produce an injuring crash), indicating that this factor activates driver cognition and perception due to previous knowledge of existing traffic conditions [17].

5.1. Crash Report Factors

In view of Table 3, for the variables taken from police reports, with a standard deviation unit change:

Single-vehicle crashes (SNG VINV) have higher odds (1.5 times greater injuring crash probability) than two- and multiple-vehicle crashes. This could be because single-vehicle crashes usually accompany uncontrolled speeds or sudden obstacles that make the crash riskier. Indeed, this finding has been reported by previous studies (e.g., [4,15,21,38]).

During winter (WIN), followed by spring and then autumn, the odds of injuring crashes increase. Russo et al. [11] reported an opposite effect, with winter entailing a lower severity of crashes, but also more cautious driving behavior and low speeds, but these results were under more adverse weather conditions (snow, ice).

In terms of time (TIME), nighttime (0–6) with low traffic flow, higher speed, and lighting problems is riskier than daytime (the odds of an injuring crash being 1.14 times greater). These results agree with those of many previous studies (e.g., [4,12,22]).

Day factor is not significant in the model, and its effect is limited to the category weekend days (WE DAY), which is 1.13 times more likely to induce an injuring crash. Similar results were reported by Hassan and Al-Faleh [16], unlike the findings of Russo et al. [11], which could be attributed to a difference in traffic flow patterns and driver behavior over different days in different countries.

In comparison with a dry surface, wet pavement has no significant effect, yet other bad pavement surface conditions (oily, muddy, etc.) do indeed. Similarly, Hassan and Al-Faleh [16] and Mujalli et al. [4] found that unexpected surface conditions could highly increase crash severity. Still, other studies point to a higher effect of dry pavement (e.g., [6,12,15]) due to less cautious driving under such conditions.

5.2. Traffic Factors

As in previous studies (e.g., [4,6,22,39]), the results show that low and medium traffic volumes (between 350–700 veh/h/ln) for a standard deviation unit change have a highly significant effect on increasing injuring crashes (respective probabilities 3.7 and 4.7 times greater). Those studies also agree that high travel speed is a significant factor, being 2.56 times more likely to produce an injuring crash. In fact, low traffic volumes stimulate drivers to travel at high speeds, which may produce more severe crashes.

5.3. Geometric Design Factors

When dealing with geometric variables, for a standard deviation unit change, the following results were reported:

The segment cross section (SECT) showed a low (insignificant) effect. In general, a two-lane two-way section is less likely to induce injuring crashes than a multilane two-way section. This could be related to lower speeds and restricted driving in two-lane two-way sections compared to multilane sections.

In studying the effect of segment geometric consistency (CONS), the results show that a good consistency (B, C) could increase driver comfort, which leads to higher speeds and a higher possibility of injuring crashes (1.3 times more). A bad design (D) (i.e., bad segment curve consistency, width of lane and median less than standard, bad design of intersections, or absence of safety elements) could increase driver caution and attention, thus decreasing the probability of an injuring crash. These results agree with previous ones (e.g., [7–10,17]).

A low number of accesses to the segment (LN ACCE) is a factor that could reduce driver attention and perception due to previous knowledge of the built-in environment. So, as previously reported by Hosseinpour et al. [17], drivers tend to travel less carefully and faster. These segments are therefore about four times more likely to be involved in injuring crashes. The same interpretation is evoked for the existence of on-street parking (PARK). Several studies [40–42] hold that on-street parking makes a positive contribution to road safety, although parking itself does not improve safety if studied alone.

5.4. Urban Factors

The results also show that urban context factors contribute to driver visibility, attention, and comfort. For example, for a standard deviation unit change, if the road section has buildings that are not tied to the stipulated governmental setbacks (NSUF BUIL), the probability of injuring crashes is almost 1.4 times greater. Additionally, when trees are not within the clear zone (EXC TREE), which can affect the driver visibility of the back-view and road signs (especially for large vehicles), the odds ratio of injuring crashes is about 1.7 times more.

In addition, this study considers the neighborhood scale (NESC) and land use (LUSE). The effect of such factors has been analyzed and discussed in previous studies [18,43], and it is thought that widely dispersed developments and low density often increase vehicle miles traveled, this magnitude being directly related to higher crash rates and severity. Our study also showed that being in a large-scale neighborhood increases the odds ratio of injuring crashes by a factor of 6.7. When comparing different land use types, the results show that non-categorized zones (NC) have the highest injuring crash probability, followed by industrial and residential, if commercial zones are the reference category (2.8, 2.1, and 1.3 times greater, respectively). Several studies (e.g., [17,43–47]) present similar findings about the outcomes of crashes in segments with intense activity (commercial, residential, etc.).

6. Analysis of Reported Causes' Models

This section illustrates the key results depending on the crash cause:

6.1. Driving without Taking Necessary Safety Precautions

The last column in Table 3 provides the results for the crashes caused by driving without taking the necessary safety precautions (SAF), which are the most frequent (see Table 1), and have the highest percentages of fatalities or injuries.

In this case, the categories most related to crashes involving injury or fatality are: single-vehicle crashes (SNG VINV), winter (WIN SEAS), from 12 a.m. to 6 a.m. (0–6 TIME), during the weekend holiday (WE DAY), wet pavement surface (WET PAVE), low and medium traffic volumes in the segment (LV, MV TRAF), good geometric consistency (B CONS), multilane two-way road sections (MLN SECT), high 85th percentile speed (HSP SP85), when on both sides buildings are not settled on the standard setbacks (NSUF BUIL), there is no on-street parking (NEX PARK), trees exceed the nominal clear zone (EXC TREE), a large neighborhood (LAR NESC), few accesses in the segment (equal to or fewer than six accesses per kilometer) (LN ACCE), and non-categorized or industrial land use (NC and IND LUSE). The results are the same as for the general model, except pavement surface condition; the fact that wet pavement implied higher risk than other bad conditions could be related to low safety precautions for the vehicles.

The categories that reduce the probability of injuring/fatal crashes coincide with those of the general model, except for the season of the year (the safest season is autumn), and the time of the day (the safest period being from 12 p.m. to 6 p.m.). It may be that drivers exhibit more compliance to safety precautions in these times of the day and the year.

Finally, as for the general model, a crash is more likely to involve injury/fatality when it is further from an intersection (DI), and it is less likely to do so when the percentage of heavy vehicles (HVEH) is greater.

6.2. Failing to Obey Traffic Control Devices

Running red lights, failing to obey stop signs or other control devices that regulate traffic priorities, or unsafe reversing are examples of what we refer to as failing to obey traffic control devices (TCD).

The results for an injury or fatality outcome are similar to those for the general model, except for two variables: type of day and geometric consistency. Table 3 shows that a regular workday (WD DAY) rather than a weekend day entails the highest probability of injuring or fatal crashes; the categories that reduce the probability of injuring or fatal crashes are day after the weekend (Sunday) (AW DAY) and perfect consistency (A CONS). This finding reflects the degree of compliance with safety precautions—for both driver and vehicle— in Jordan under these conditions.

As for the previous models, a crash is more likely to cause injury when it is more distant from an intersection (DI), while it is less likely when the percentage of heavy vehicles is greater (HVEH).

6.3. Tailgating (TAI)

The closer a car is to the one in front of it, the less time a driver has to react to sudden stops in order to avoid a collision. Tailgating (TAI) is a leading cause of rear-end car crashes and multiple-car collisions.

Since injuring or fatal crashes most often result from high speeds and free-flowing traffic, it is logically difficult to analyze injuring crashes in conjunction with tailgating. Table 3 shows this to be the model most different from the general model. In this case, the converse effect is for the factors time of the day, day type, pavement surface, and consistency. The categories with the highest probability of injuring or fatal crashes for these variables are: from 12 p.m. to 6 p.m. (12–18 TIME), when the pavement is dry (DRY PAVE), and with perfect or bad geometric consistency (A,C CONS), so the risk possibility could stem from bad behavior or bad road design. In contrast, the categories that reduce the probability of injuring or fatal crashes are: from 12 a.m. to 6 a.m. (0-6 TIME) because at nighttime drivers do not usually tailgate, wet and other bad surface conditions (oily, muddy, icy) (WET, OTH PAVE), and bad consistency (D CONS).

Again, the crash is more likely to cause injury with increasing distance from an intersection (DI), and less likely when the percentage of heavy vehicles (HVEH) increases.

Additionally, an increase in some urban factor effects is obvious, such as non-sufficient building setbacks (NSUF BUIL, 32%), trees exceeding the nominal clearance zone (EXC TREE, 17%), and large-scale neighborhood (LAR NESC, 134%). These figures indicate to what extent visibility could affect driver behavior and imply an injuring crash, even due to tailgating.

6.4. Unsafe Lane Changes (LCH)

Changing lanes without taking the time to look and make an unsafe maneuver is a leading cause of sideswipe collisions, and the fourth leading cause of crashes in the urban context of Irbid. Table 3 presents results largely similar to those of the general model, yet for some variable categories, opposite effects were observed: time of day, type of day, and cross-section type. Thus, for the following categories the probability of an injury or fatality outcome was reduced: from 6 a.m. to 12 p.m., from 12 p.m. to 6 p.m. (6–12, 12–18 TIME, since morning and afternoon hours tend to have high traffic density and it is more difficult to change lanes), weekend days and regular days (WE, WD DAY, which tend to have less aggressive driving or maneuvers), and multilane two-way road sections (MLN SECT, as lane changes in this type of cross-sections are predictable, and the driver is ready to respond to such movement).

Despite the non-significance of both continuous variables in this case, a crash is more likely to involve injury when further from the intersection (DI), and less likely when there are more heavy vehicles (HVEH).

7. Comparison of Models

When comparing the five models to each other, some key similarities and differences in the variable effects stand out. In general, the percentage of heavy vehicles (HVEH), geometric consistency (CONS) and the type of cross section (SECT) were not statistically significant in most models.

At the same time, a number of categorical variables present noteworthy differences among the models:

- Season: summer is the safest season for all the models except for SAF, which shows autumn to be the safest season.
- Time of the day: for all the models except TAI, the period from 12 a.m. to 6 a.m. presents the highest odds ratio for injuring crashes. The TAI model's highest odds ratio is for the period 12 p.m. to 6 p.m. The safest time frame likewise presents differences among the models: 6 p.m. to 12 a.m. for the general model and TCD; 12 p.m. to 6 p.m. for LCH and SAF; and 12 a.m. to 6 a.m. for the TAI model.
- Type of day: the general and SAF models present similar results for this variable, the highest odds ratios being for weekend holiday and the lowest ones for the day before the weekend. LCH and TAI models give similar results, with the highest odds ratios for after the weekend and the lowest ones for regular workdays. However, the TCD model gives just the opposite results: the highest odds ratios for regular workdays and the lowest ones for after the weekend.
- Pavement surface: for all the models except TAI, other bad surface conditions is the variable presenting the highest odds ratio for injuring crashes. The TAI model's highest odds ratio is for dry pavement, though this is the safest category for all the other models. Other bad surface conditions constitutes the safest category for the TAI model.
- Geometric consistency: segment curves with good consistency present the highest odds ratios for all the models except TAI, whose highest one corresponds to low consistency. Segment curves with bad consistency present the lowest odds ratios, with the exception of the TCD model, whose lowest odds ratio is for perfect consistency.
- Cross section: multilane two-way road sections present the highest odds ratios for the models, with the exception of LCH, which designates two-lane two-way roads sections.

Although the values of odds ratios vary among the models, they present similar trends for certain categorical variables. Table 4 offers a summary of all the statistically significant (at a 95% confidence level) categories of factors that increase the possibility of inducing crashes with injuries or fatalities (displayed in descending order of influence).

Table 4. Summary of important factors increasing injuring crashes in an urban context.

Factors	Type of Factor
Large-scale neighborhood	Urban
Number of accesses to the segment < 6 per km	Geometric
Low traffic volume (<500 veh/h/ln)	Traffic
No on-street parking	Geometric
Non-categorized and industrial land use	Urban
High 85th % speed (>50 km/h)	Traffic
Single-vehicle crash	Crash report
Winter and autumn seasons	Crash report
Trees exceeding the nominal clear zone	Urban
Distance from intersection	Crash report

8. Conclusions

This study has examined the influence of 17 factors on the injury probability of collision crashes in an urban context within a developing country, in this case Jordan. While injuries from crashes in urban areas constitute a worldwide problem, it is even more serious in developing countries, as their databases contain limited information for analysis and extrapolation. Since 2014, the crash database in Jordan managed by the Police Traffic Central Department has improved, now including the locations of crashes using GPS coordinates. This makes it possible to complement the database statistics with further information, such as traffic volume, speed, and other variables related to the road characteristics or the urban context (road cross section, geometric consistency, land use, etc.).

The modeling involved the complete database and each one of the subsets of crash causes reported by the police (i.e., driving without taking safety precautions, failing to obey traffic control devices, tailgating, and unsafe lane changes). The results show that most of the variables considered in the analysis have a significant effect on severity. Whatever the model considered, the distance from an intersection, the number of vehicles involved in the crash, the season, traffic volume, 85th percentile of speed, the presence of on-street parking, the neighborhood scale, the number of accesses, and land use proved to be significant variables. In addition, all previous factors except the season showed a homogeneous effect (e.g., in all models, a single vehicle increased the probabilities of injury from crashes, while two-vehicle involvement decreased the probabilities). This homogeneous behavior is also observed for two other variables that are not significant in all the models considered: sufficient building setbacks and trees in the nominal clear zone.

In all models, the probability of a crash with injury or fatality increases as the distance from the intersection increases; when the number of heavy vehicles decreases; when there is only one vehicle involved in the crash; when the traffic volume is low (under 500 veh/h/ln); when the link speed is over 50 km/h; in segments when the buildings are not settled on the standard setbacks; when there is no on-street parking; when trees exceed the nominal clear zone; in large-scale neighborhood areas; when the number of accesses per kilometer is under six; and in zones with non-categorized or industrial land use. Although it is not possible to generalize the results for all the models in the case of the other variables considered in the analysis, some general patterns emerge, with the exception of the type of day. In most of the models (four out of five), the probability of an injuring crash increases during winter, from 12 a.m. to 6 a.m., when the pavement surface is in bad condition other than wet (oily, muddy, icy), in curves with good consistency, and in multilane two-way road sections.

These results, consistent with previous studies in other developed and developing countries, provide a broader view of Jordan´s problem with urban traffic crashes. The results expounded here could be used by Jordanian governmental agencies, or agencies in developing countries, to design and implement long-term traffic safety plans. Firstly, they could help reduce injuring crashes in urban areas, and secondly improve road quality as a base for sustainable cities. For example, specific sustainable countermeasures could be undertaken in large-scale neighborhoods, or traffic controls could be increased in low-volume arterials and in multilane two-way road sections.

Certain limitations might affect the results of this study: reporting errors in collecting the urban context data, GPS technical errors, and human errors because of unreliability in accident reports. Further replications of the model with larger, more comprehensive and reliable samples—including factors overlooked in this study, such as driver and vehicle characteristics, and dealing with other crash and road types—could enhance our understanding of how the urban context affects traffic safety.

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References

1. World Health Organization. *Global Status Report on Road Safety 2018*; World Health Organization: Geneva, Switzerland, 2018.
2. World Bank. *Cities on the Move: Chapter 5 (Urban Transport Safety and Security)*; World Bank: Washington, DC, USA, 2002; p. 65.
3. Heydari, S.; Hickford, A.; McIlroy, R.; Turner, J.; Bachani, A.M. Road Safety in Low-Income Countries: State of Knowledge and Future Directions. *Sustainability* **2019**, *11*, 6249. [CrossRef]
4. Mujalli, R.O.; Lopez, G.; Garach, L. Bayes classifiers for imbalanced traffic accidents datasets. *Accid. Anal. Prev.* **2015**, *88*, 37–51. [CrossRef]
5. Mujalli, R.O.; Garach, L.; Lopez, G.; Al-Rousan, T. Evaluation of injury severity for pedestrian-vehicle crashes in Jordan using extracted rules. *J. Transp. Eng. Part A* **2019**, *145*. [CrossRef]
6. Das, A.; Abdel-Aty, M.; Pande, A. Using conditional inference forests to identify the Factors Affecting Crash Severity on Arterial Corridors. *J. Saf. Res.* **2009**, *40*, 317–327. [CrossRef]
7. Abdel-Aty, M.A.; Abdelwahab, H.T. Predicting injury severity levels in traffic crashes: A modeling comparison. *J. Transp. Eng.* **2004**, *130*, 204–210. [CrossRef]
8. Ma, J.; Kockelman, K.M.; Damien, P. A multivariate poisson-lognormal regression model for prediction of crash counts by severity, using bayesian methods. *Accid. Anal. Prev.* **2008**, *40*, 964–975. [CrossRef]
9. Wang, C.; Quddus, M.A.; Ison, S.G. Predicting accident frequency at their severity levels and its application in site ranking using a two-stage mixed multivariate model. *Accid. Anal. Prev.* **2011**, *43*, 1979–1990. [CrossRef]
10. Haleem, K.; Abdel-Aty, M. Examining traffic crash injury severity at unsignalized intersections. *J. Saf. Res.* **2010**, *41*, 347–357. [CrossRef]
11. Russo, B.J.; Savolainen, P.T.; Schneider, W.H.; Anastasopoulos, P.C. Comparison of factors affecting injury severity in angle collisions by fault status using a random parameters bivariate ordered probit model. *Anal. Methods Accid. Res.* **2014**, *2*, 21–29. [CrossRef]
12. Garrido, R.; Bastosa, A.; Almeidab, A.; Elvas, J.P. Prediction of road crash severity using the ordered probit model. In 17th Meeting of the Euro Working Group on Transportation (EWGT2014), Sevilla, Spain. *Transp. Res. Procedia* **2014**, *3*, 214–223. [CrossRef]

13. Zhuanglin, M.; Chunfu, S.; Hao, Y.; Sheqiang, M.A. Analysis of the Logistic Model for Crash Severity on Urban Road Environment. In Proceedings of the IEEE Intelligent Vehicles Symposium conference, Xi'an, China, 3–5 June 2009; pp. 983–987.
14. Al-Ghamdi, A. Using logistic regression to estimate the influence of crash factors on crash severity. *Accid. Anal. Prev.* **2002**, *34*, 729–741. [CrossRef]
15. Altwaijri, S.A.; Quddus, M.A.; Bristow, A.L. Analysing the Severity and Frequency of Traffic Crashes in Riyadh City Using Statistical Models. *Int. J. Transp. Sci. Technol.* **2012**, *1*, 351–364. [CrossRef]
16. Hassan, H.M.; Al-Faleh, H. Exploring the risk factors associated with the size and severity of roadway crashes in Riyadh. *J. Saf. Res.* **2013**, *47*, 67–74. [CrossRef]
17. Hosseinpour, H.; Yahaya, A.S.; Sadullah, A.F. Exploring the effects of roadway characteristics on the frequency and severity of head-on crashes: Case studies from Malaysian Federal Roads. *Accid. Anal. Prev.* **2014**, *62*, 209–222. [CrossRef]
18. Harvey, C.; Aultman-Hall, L. Urban streetscape design and crash severity. *Transp. Res. Rec.* **2019**, *2500*, 1–8. [CrossRef]
19. Ma, M.; Yan, X.; Abdel-Aty, M.; Huang, H.; Wang, X. Safety analysis of urban arterials under mixed-traffic patterns in Beijing. *Transp. Res. Rec.* **2010**, *2193*, 105–115. [CrossRef]
20. Abdel-Aty, M.A. Analysis of driver injury severity levels at multiple locations using ordered probit models. *J. Saf. Res.* **2003**, *34*, 597–603. [CrossRef]
21. Theofilatos, A.; Graham, D.; Yannis, G. Factors Affecting Accident Severity Inside and Outside Urban Areas in Greece. *Traffic Inj. Prev.* **2012**, *13*, 458–467. [CrossRef]
22. Haleem, K.; Gan, A. Identifying traditional and nontraditional predictors of crash injury severity on major urban roadways. *Traffic Inj. Prev.* **2011**, *12*, 223–234. [CrossRef]
23. Das, A.; Pande, A.; Abdel-Aty, M.; Santos, J. Urban arterial crash characteristics related with proximity to intersections and injury severity. *Transp. Res. Rec.* **2008**, *2083*, 137–144. [CrossRef]
24. Anarkooli, A.J.; Hosseinpour, M.; Kardar, A. Investigation of factors affecting the injury severity of single-vehicle rollover crashes: A random-effects generalized ordered probit model. *Accid. Anal. Prev.* **2017**, *106*, 399–410. [CrossRef] [PubMed]
25. Alfonso, M.; Maurizio, S. A Study on cyclists behaviour and bicycles kinematic. *Int. J. Transp. Dev. Integr.* **2020**, *4*, 14–28.
26. Alfonso, M.; Luca, M.; Maurizio, S. Analysis of the Relationship between Turning Signal Detection and Motorcycle Driver's Characteristics on Urban Roads; A Case Study. *Sensors* **2019**, *19*, 1802–1817.
27. Al-Masaeid, H. Traffic Crashes in Jordan. *Jordanian Int. J. Civ. Eng.* **2009**, *3*, 331–343.
28. Al-Omari, B.; Ghuzlan, K.; Hassan, H. Traffic Crashes Trends and Characteristics in Jordan. *Int. J. Civ. Environ. Eng.* **2013**, *13*, 9–16.
29. Al-Omari, A.; Shatnawi, N.; Khedawi, T.; Miqdady, T. Prediction of traffic accidents hot spots using fuzzy logic and GIS. *Appl. Geomat.* **2019**, *12*, 149–161. [CrossRef]
30. Chang, L.Y.; Mannering, F. Analysis of injury severity and vehicle occupancy in truck- and non-truck-involved crashes. *Accid. Anal. Prev.* **1999**, *31*, 579–592. [CrossRef]
31. Garber, N.J.; Hoel, L.A. *Traffic and Highway Engineering Book*, 4th ed.; CENGAGE learning University of Virginia: Charlottesville, VA, USA, 2009; pp. 104–115.
32. Homburger, W.S.; Hall, J.W.; Loutzenheiser, R.C.; Reilly, W.R. *In Fundamentals of Traffic Engineering: Spot Speed Studies*; University of California: Berkeley, CA, USA, 1996.
33. James, A.B. *Highway Safety Manual: Part A/Chapter 3 (Fundamentals)*; American Association of State Highway and Transportation Officials: Washington, DC, USA, 2010; pp. 8–9.
34. American Association of State Highway and Transportation Officials (AASHTO). *Roadside Design Guide, Chapter 7, Urban Arterials*; AASHTO: Washington, DC, USA, 2001; pp. 485–486.
35. Steiner, F.R.; Butler, K. *Planning and Urban Design Standards*; American Planning Association: Chicago, IL, USA, 2017; pp. 16–20.
36. Long, J.S. *Advanced Quantitative Techniques in the Social Sciences Series, Volume 7: Regression Models for Categorical and Limited Dependent Variables*; Sage Publications: Thousand Oaks, CA, USA, 1997.
37. Savolainen, P.; Mannering, F.; Lord, D.; Quddus, M. The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. *Accid. Anal. Prev.* **2011**, *43*, 1666–1676. [CrossRef]

38. Quddus, M.A.; Wang, C.; Ison, S.G. Road traffic congestion and crash severity: An econometric analysis using ordered response models. *J. Transp. Eng.* **2009**, *136*, 424–435. [CrossRef]
39. Liu, C.; Chen, C.L. *An Analysis of Speeding-Related Crashes: Definitions and the Effects of Road Environments*; NHTSA Technical Report; National Center for Statistics and Analysis, NHTSA: Washington, DC, USA, 2009.
40. Dumbaugh, E.; Gattis, J.L. Safe streets, livable streets. *Am. Plan. Assoc.* **2005**, *71*, 283–300. [CrossRef]
41. Peprah, C.; Oduro, C.Y.; Ocloo, K.A. On-street parking and pedestrian safety in the Kumasi metropolis: Issues of culture and attitude. *Dev. Ctry. Stud.* **2014**, *4*, 85–95.
42. Zein, S.; Geddes, E.; Hemsing, S.; Johnson, M. Safety benefits of traffic calming. *Transp. Res. Rec.* **1997**, *1578*, 3–10. [CrossRef]
43. Eboli, L.; Forciniti, C. The Severity of Traffic Crashes in Italy: An Explorative Analysis among Different Driving Circumstances. *Sustainability* **2020**, *12*, 856. [CrossRef]
44. Boufous, S.; Finch, C.; Hayen, A.; Williamson, A. The impact of environmental, vehicle and driver characteristics on injury severity in older drivers hospitalized as a result of a traffic crash. *J. Saf. Res.* **2008**, *39*, 65–72. [CrossRef]
45. Lee, C.; Abdel-Aty, M. Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida. *Accid. Anal. Prev.* **2005**, *37*, 775–786. [CrossRef]
46. Pai, C.W. Motorcyclist injury severity in angle crashes at t-junctions: Identifying significant factors and analysing what made motorists fail to yield to motorcycles. *Saf. Sci.* **2009**, *47*, 1097–1106. [CrossRef]
47. Zajac, S.S.; Ivan, J.N. Factors influencing injury severity of motorvehicle crossing pedestrian crashes in rural Connecticut. *Accid. Anal. Prev.* **2003**, *35*, 369–379. [CrossRef]