Exploring Factors Contributing to Crash Injury Severity at Al-Diwaniyh City Streets: Random Parameter Ordered Probit Model Technique

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Abstract. Traffic crashes are among the problems that affect societies because the losses caused by these crashes directly impact the citizen due to the psychological suffering it leaves. Therefore, care must be taken, and strenuous efforts must be made in order to reduce the percentage of crash victims and losses. Depending on the characteristics of the local transportation environment, the study outcomes of traffic crash data may differ. Therefore, in order to comprehend the factors that contribute to and are involved in traffic crashes in Iraq, it is important to concentrate on the city's unique characteristics. So, the purpose of this study is to pinpoint the contributing factors that substantially impact how serious traffic crashes are in Al-diwaniya City for the years (2017-2022). RStudio was used to examine complex interactions and assess the fundamental elements that influence the severity of the crash by applying the ordered Probit model, the random parameter ordered Probit model and the marginal effect of the significant factors. The results showed a random parameter ordered Probit model well performed over the ordered Probit model. Moreover, many statistically significant variables were found to impact how severe the injury is, like road features, vehicle characteristics, crash cause, crash reason, time distribution, and crash type. Addressing these contributing factors through effective policies and programs promoting safe driving practices can create safer roads for everyone.

Keywords: injury severity; random parameter; ordered Probit model; contribution factors; road crashes.

1. INTRODUCTION

Traffic crashes are one of the prime problems that have attracted the attention of the state and citizens in the recent period, causing huge loss of life and property, and the economic problems caused by them directly affect stability and national security. This is also one of the complex issues that arise due to the overlapping of multiple parties in its creation, whether it is the human side, i.e., the driver, improve or passengers, or the technical side, i.e., the road and any vehicle, or weather, day and night, etc. A party to which natural factors change. Each of these parties plays a role in the occurrence of the collision, which leads to the occurrence of the traffic crash.

A model was chosen to evaluate the risk variables that raise the likelihood of serious injury and death, according to a study [1,2], to evaluate the safety's two primary elements (incidence and severity). Age, alcohol usage, phone use, and weather are a few of these factors, and their severity brought on the rise in pedestrian injuries. Participation in alcohol when a pedestrian is struck by a straight-track vehicle, there is a larger chance of serious injury or death compared to other vehicular motions. Shankar et al. [3] claim that a larger evident injury or death disability is the cause of the rollover crash index variable. The potential to inflict a clear or fatal injury is a bigger problem due to the impact of a single-car rollover and the number of rollovers [3-5].

This study aims to identify the factors contributing to the high number of vehicle crashes in Al-Diwaniyah City and to develop strategies to reduce the frequency and severity of these incidents. By analyzing data on past crashes, examining traffic patterns and infrastructure, and considering driver behavior, this study seeks to provide actionable recommendations for improving road safety in the city. Ultimately, the goal is to create a safer environment for drivers, pedestrians, and cyclists.

2. METHODOLOGICAL APPROACH

Iraq is considered one of the developing countries in the Middle East, with about 40 million people distributed over 18 governorates, with a total number of vehicles of approximately 5.75 million. With a size of 438,000 km^2 and a substantial population, Iraq has a fantastic location in the Arab world and is situated inside the Middle East region of southwest Asia. Latitude 33 North and Longitude 43 East define Iraq. Al- Diwaniyah governorate is located in southern Iraq and is in the middle of the two governorates of Muthanna and Najaf. It is one of the governorates of the Middle Euphrates, and the Euphrates River passes through it. Its area is about 8,507 km^2.

After the process of collecting road crash data from the Al-Diwaniyah Traffic Directorate, the variables were counted, and work was done to typeset this data in the Excel program and a statistical description of these variables using the SPSS program to find out the average and standard deviation (SD). Then, RStudio software is utilized based on the S language. R is a free and open-source program for statistical analysis. The R Foundation for Statistical Computing supports R, a programming language and software environment for statistical computing and graphics. R is an integrated set of tools for calculating, manipulating data, and displaying graphics. The integrated development environment (IDE) for R is called RStudio. Along with a console-based editor with syntax highlighting and direct code execution, it also has features for managing workspaces and graphing, history, debugging, and history.

2.1 Data Description

Table 1 illustrates the variables obtained from the Al-Diwaniyah Traffic Directorate and divides these variables according to time, day, types of crashes, number of lanes, and causes of the crash number of 769 crashes crash for the period (2017-2022) years. In order to arrive at the best decisions for the study group, statistics analysis methods and methods of gathering and analyzing data use a set of procedures and characterizing variables using a set of data. The mean and standard deviation were calculated after entering the variables into the SPSS computer, as shown in Table 1. The mean and standard deviation, the most widely used value among the measurements of central dispersion to gauge the degree of statistical scatter, are statistically described in this Table 1.

Table 1: Statistical description of the significant variables.

Variablel		**Mean**	**Standard Deviation**	**Min**	**Max**
Temporal characteristics	Morning	0.446	0.497	0	1
	weekday	0.715	0.451	0	1
	Winter	0.273	0.445	0	1
	Spring	0.261	0.439	0	1
	Summer	0.302	0.459	0	1
Vehicle characteristics	Passenger	0.339	0.490	0	1
	Hit Motorcycle	0.202	0.402	0	1
Type of crash	Collision	0.731	0.443	0	1
Car damage type	Head on	0.308	0.462	0	1
	Complete smash	0.145	0.352	0	1
	Partial smash	0.096	0.295	0	1
	Minor damage	0.066	0.249	0	1
Crash cause	Wrong pass	0.072	0.260	0	1
	Inattention	0.039	0.190	0	1
	Loss of control	0.252	0.435	0	1
Crash Circumstances	Collision and overturning	0.035	0.184	0	1
Road alignment	Straight	0.856	0.352	0	1

2.2 Statistical Methodology

Road safety is a critical issue that affects millions of people worldwide. Statistical models are essential tools for analyzing and understanding road safety data, identifying risk factors, and developing effective interventions to reduce crashes and fatalities. Various statistical models are available for road safety analysis, including regression models, time-series models, spatial models, and machine learning algorithms. Each model has its strengths and limitations, depending on the type of data and research questions being addressed. This paper uses advanced econometric techniques to help control confounding variables that may affect road safety outcomes. For example, a simple correlation between alcohol consumption and crash rates may be misleading if other factors, such as age or gender, are not considered. Econometric analysis can help to isolate the effect of alcohol consumption on crash rates while controlling for these other factors. For this and because of the current data characteristics, an ordered Probit model has been used to analyze the current data.

2.2.1 Ordered Probit model

A statistical technique is used to analyze the ordinal dependent variables, which have a natural ordering but do not have a fixed numerical distance between categories. The benefit of using an ordered Probit model (fixed-parameter model) is that it estimates the relationship between the independent variables and the ordinal dependent variable while considering the natural ordering of the categories (Weiss, 1997). This model also provides estimates of the probability of each category, which can be useful in predicting outcomes or making decisions based on the dependent variable. According to the National Highway Traffic Safety Administration, the severity of traffic crash injuries is categorized into four types of dependent variables. The categories indicate the dependent variables (y = outcome) and are (fatal, severe, moderate, and no injury). The independent variables stand in for (X) and are comparable to the crash's causes and timing, as described in Table 2. According to Equation 1, ordered models use a latent variable y* to calculate the results for injury severity.

$$y *= f(\beta x + \epsilon) \qquad (1)$$

Where x is a vector of educative elements for the specific injury, β is a vector of the logical factor coefficients, ϵ is a random error term with normal standard deviations, and y is as follows:

$$
\begin{cases}
4 \text{ if } y* \geq \mu2 & \text{No injury} \\
3 \text{ if } \mu1 < y* \leq \mu2 & \text{Minor injury} \\
2 \text{ if } \mu0 < y* \leq \mu1 & \text{Sever} \\
1 \text{ if } y* \leq \mu0 & \text{death}
\end{cases}
$$

Where μ0 = 0, μ1, and μ2 are thresholds that are jointly estimated with β′ parameters.

2.2.2 Random parameter ordered Probit model

A random parameter-ordered Probit model has also been applied for more accurate results, allowing for the estimation of individual-specific parameters. The random parameter-ordered Probit model can account for unobserved heterogeneity across individuals by estimating individual-specific parameters. This can help to better understand how different factors affect road safety outcomes for different groups of people by accounting for unobserved heterogeneity and complex interactions between factors. The random parameter-ordered Probit model may provide more accurate predictions of road safety outcomes than simpler models. The model can capture the correlation between unobserved factors that may affect road safety outcomes, such as driver behavior and vehicle characteristics. This can help better understand the complex interactions between different factors contributing to road crashes [6]. The following equation can represent the random parameter ordered Probit model:

$$y*ij = \beta' xij + \varepsilon ij \quad (2)$$

Where y*ij is the latent variable for individual i and choice j, β is a vector of fixed coefficients, xij is a vector of observed explanatory variables for individual i and choice j, and εij is a normally distributed random error term with mean zero and variance σ^2.

The observed outcome variable yij is obtained by discretizing the latent variable y*ij into ordered categories using cut-off points τ1, τ2... τJ-1. The probability of observing category j given the explanatory variables xij can be expressed as:

$$P\,(yij = j \mid xij) = \Phi\,((\tau j - \beta' xij)/\sigma) - \Phi\,((\tau j - 1 - \beta' xij)/\sigma) \quad (3)$$

Where Φ denotes the standard normal cumulative distribution function.

The model allows for heterogeneity in the coefficients by assuming that each coefficient follows a normal distribution with mean μk and variance σk^2. The parameters μk and σk^2 are estimated from the data using maximum likelihood estimation.

2.2.3 Temporal Instability and Transferability Tests

A likelihood ratio test comparing these models was performed according to Washington (2011) to test the null hypothesis that the fixed-parameter model is statistically equivalent to the random-parameter model, as shown in Equation 4, and the results indicate that with 99% confidence, the null hypothesis can be rejected. As a result, random parameter model outcomes have been selected over the fixed ones in this study.

$$x^2 = -2(LL(\beta)\text{fixed} - LL(\beta)\text{Random}) \quad (4)$$

x^2 can be obtained by using the $LL(\beta)$ from Tables 2 and 3.

$$x^2 = -2[(-972.76 - (-952.78)] = 39.96$$

The ordered Probit model with random parameters is preferable to the ordered Probit model with Xed parameters, according to the Chi-square statistic value of 39.96 and then 99.0% confidence level of the associated degrees of freedom, 5 (number of random parameters). These findings suggest that the theory needs to be disproved.

3. RESULTS

The R language is a programming environment for computer statistics that enables the development of statistical programs and the execution of statistical applications and has been utilized in this study.

3.1 Ordered Probit Model

The assumption behind ordered models like ordered logit and ordered Probit is that the error variance is constant across observations. When this assumption is broken, estimates of marginal effects are often distorted [7]. This package enables the user to provide a model for the variance, allowing the generalization of ordered Probit and ordered logit models. The software also features tools for calculating marginal impacts. In order to estimate the common restricted dependent variable models, wrapper functions are also available. The results outcome for applying the ordered Probit mode are shown in Table 2.

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Table 2: Estimation results of ordered Probit model.

Variable|	**Estimate**	**Standard Error**	**t-stat**
Constant	1.745***	0.205	8.50
Temporal characteristics			
Morning (6-11:59 am)	0.492***	0.158	3.10
Weekday	0.255***	0.085	2.98
Winter (Dec., Jan., Feb.)	0.379***	0.126	3.01
Spring (Mar., Apr., May)	0.261**	0.126	2.46
Summer (June, July, Aug.)	0.309**	0.467	2.38
Vehicle characteristics			
Passenger car	0.356 **	0.196	2.67
Hit Motorcycle	0.532***	0.137	3.88
Type of crash			
Collision	0.721***	0.237	3.15
Car damage type			
Head on	0.278***	0.107	2.61
Complete smash	-0.308**	0.149	-2.06
Partial smash	-0.439***	0.162	-2.70
Minor damage	0.068**	0.240	2.34
Crash cause			
Wrong pass	0.999***	0.196	5.10
Inattention	0.866***	0.218	3.97
Loss of control	-0.254**	0.113	-2.26
Crash Circumstances			
Collision and overturning	0.558**	0.225	2.48
Road alignment			
Straight	0.473***	0.135	3.65
Log-likelihood function at zero LL (0) Log-likelihood function at convergence LL (β) McFadden AIC AIC/N	-985.73 -972.76 1990.5 2.589		

3.2 Random Parameter Model

The conducted results of applying a random parameter-ordered Probit model are shown in Table 3. The outcome indicates that five random parameters are statistically significant and have a normal distribution. These variables are (crashes at Moring (6:00-11:59 am), passenger car type, crashes at straight road alignment, crashes during summer (June, July, Aug.), and collision crash type through the process of statistical description of the variables to find out the normal distribution of the variables that affect the severity of the crash injury in terms of effects under and over the area, the variables that included the type of crash, the roadway characteristics (straight), the type of vehicle, the vehicle damages, and the causes of the crash, where in terms of the rate, the type of crash, which is the collision, has the rate of 0.731 and a standard deviation of 0.443. This means that 75.55% of drivers are more likely to increase no-injury outcomes, whereas 24.45 is the opposite. Among the other influencing variables are the causes of the crash, and among these reasons is the loss of control, as it was found to us through the normal distribution of this variable at a mean of 0.252 and a standard deviation of 0.435 and the results included the probability of the area above zero is 71.88% and below zero 28.12%. This indicates that 71.88% of the driver who loses control during the crash has more probability of having no injury crashes, whereas the others have more probability of getting fatal crashes. The remaining random parameter distribution results are illustrated in Table 4.

3.3 Marginal Effects

A marginal effect measures the association between a change in a regressor and a change in the response variable. A joint effort was made to transfer the margins command to R with the prediction and margins packages. Using these tools, the common quantities of interest can be extracted from regression-type models. Marginality offers "marginal effects" summaries of models, while prediction offers predictions from unit-specific and sample-average models. Average marginal effects are just the mean of these unit-specific partial derivatives over some samples; marginal effects are partial derivatives of the regression equation concerning each variable in the model for each unit in the data. The estimated slope coefficients in ordinary least squares regression without interactions or higher-order factors are marginal effects. The coefficients are not marginal effects in other situations or for extended linear models, at least not on the scale of the response variable. Table 5 illustrates the results of the marginal effect of the significant variables, and Table 6 shows the effect of these variables on the driver injury severity outcomes.

Table 3: Results of random parameter ordered Probit model.

Variable|	Coefficient	Standard Error	z
Non-Random parameter			
Weekday	0.715***	0.082	3.2
Winter (Dec., Jan., Feb.)	0.374***	0.129	3.02
Spring (Mar., Apr., May)	0.300**	0.127	2.41
Hit Motorcycle	0.540***	0.139	3.76
Head on	0.270***	0.105	2.54
Complete smash	-0.317**	0.151	-2.04
Partial smash	-0.418***	0.164	-2.28
Minor damage	0.490***	0.165	3.12
Wrong pass	0.995***	0.192	5.26
Inattention	0.831***	0.232	3.89
Loss of control	-o.252**	0.120	-2.32
Collision and overturning	0.535**	0.231	2.52
Random parameter			
Moring (6:00-11:59 am)	0.222***	0.083	2.66
Standard deviation of parameter, normally distributed	(0.333)		(5.47)
Passenger car	0.498***	0.117	4.23
Standard deviation of parameter, normally distributed	(0.611)		(9.03)
Straight road alignment	0.840***	0.109	7.67
Standard deviation of parameter, normally distributed	(0.426)		(9.25)
Summer (June, July, Aug.)	0.444***	0.121	3.66
Standard deviation of parameter, normally distributed	(0.365)		(4.93)
Collision crash type	0.227**	0.115	1.98
Standard deviation of parameter, normally distributed	(0.209)		(4.42)
Log-likelihood function at zero LL (0)	-962.73		
Log-likelihood function at convergence LL (β)	-952.78		
McFadden AIC	1975.5		
AIC/N	2.569		

Table 4: Statistical description of the significant variables and Percent observations for random parameters.

Variable|		Mean	Standard Deviation	Percent observations above 0	Percent observations below 0
Temporal characteristics	Morning (6:00-11:59 am)	0.222***	0.333	74.75%	25.25%
	Summer (June, July, Aug)	0.444***	0.365	88.81%	11.19%
Vehicle characteristics	Passenger car	0.498***	0.611	79.25%	20.75%
Type of crash	Collision	0.227**	0.209	86.13%	18.87%
Road alignment	Straight	0.840***	0.135	97.57%	2.43%

Table 5: Marginal effects of random parameter Ordered Probit model.

Variable|		Marginal effects of random parameter Ordered Probit model			
		Death [Y =0]	Sever [Y=1]	Minor injury [Y=02]	No injury [Y=03]
Temporal characteristics	Morning (6-11:59 am)	-0.022***	-0.070***	0.080***	0.003**
	Weekday	-0.019***	-0.079***	0.090***	0.002***
	Winter (Dec., Jan., Feb.)	-0.021***	-0.119***	0.138***	0.006**
	Spring (Mar., Apr., May)	-0.018***	-0.097**	0.113**	0.005*
	Summer (June, July, Aug.)	-0.025***	-0.139***	0.162***	0.007***
Vehicle characteristics	Passenger car	-0.031***	-0.156***	0.179** *	0.007***
Type of crash	Collision	-0.016* *	-0.071**	0.080**	0.002**
	Hit Motorcycle	-0.027***	-0.165***	0.194***	0.011**
Car damage type	Head on	-0.01***	-0.088***	0.101***	0.004**
	Complete smash	0.025*	0.095**	-0.106**	-0.003***
	Partial smash	0.041*	0.131***	-0.147***	-0.003**
	Minor damage	-0.017***	-0.019 *	0.011*	0.180***
Crash cause	Wrong pass	-0.032***	-0.274***	0.339***	0.042**
	Inattention	-0.028***	-0.243***	0.300***	0.033*
	Loss of control	0.019*	0.079**	-0.089**	-0.002**
Crash Circumstances	Collision and overturning	-0.023***	-0.168***	0.203***	0.014 **
Road alignment	Straight	-0.099***	-0.226***	0.259***	0.006***

4. DISCUSSION

For each variable contribution effect, the values of the coefficients in the fixed and the random parameter ordered Probit model, the marginal effects ratios, and the odds ratios are shown, as well as the effects of certain key explanatory variables on the severity of injury are discussed in the following section.

4.1 Type of Crash

Where a parameter was found that the type of crash, which is a collision, is statistically capable of being random, with a mean of 0.227 and a standard deviation of 0.209 in Table 3, this indicates that 18.87 % in Table 4 of the collision has a value less than zero, which means that it is also less likely to cause any consequence of the severity of the injury. On the contrary, 86.13% of them have a value greater than zero, which means that this collision is a severe injury type. Table 5 marginal effect of the same indicator shows the type of injury (fatal injury and severe injury) reduces the probability of its impact by (0.13 and 0.532, respectively). It increases the probability of minor injury and no injury by 0.583 and 0.006, respectively. Shankar et al., 1996 found that the chance of injury is higher when two cars collide in the rear than when only property damage occurs. The likelihood of suffering serious or fatal internal injuries increases as the number of participating vehicles decreases since there is a higher impact on each vehicle [8].

4.2 Vehicle Characteristics

Where a parameter was found that the type of vehicle, which is a passenger car, is statistically incapable of random with an average of 0.498 and a standard deviation of 0.611 in Table 3, and this indicates that 20.75 % in Table 4 has a value less than zero, which also means less likely to cause severe injury. On the contrary, 79.25 % of them have a value greater than zero and have A marginal effect on the severity of the injury, where the probability of reducing the severity of the injury (fatal injury and severe injury by 0.023 and 0.114, respectively), and the probability of increasing the severity of the injury in the case of (minor injury and no injury by 0.124 and 0.014, respectively. Kockelman et al. [9] also discovered that drivers of pickups, SUV, and minivans frequently suffer more significant injuries in single-vehicle collisions than do those of passenger cars. The report's findings indicate that the types of cars influence the severity of the damage. Given that the damage typically increases with the size of the vehicle, according to research, several results were initially detected [9].

4.3 Crash causes

Where a parameter was found that one of the types of causes of traffic crashes, which is inattention, is statistically unable, random, at a rate of 0.039 and a standard deviation of 0.190 in Table 3, and this indicates that 41.87% has a value less than zero, which means that it is also less likely to cause any consequence of the severity of the injury. In contrast, 58.13% of which has a value greater than zero, and this indicates that the driver's inattention has a marginal effect on the severity of the injury, as the probability of reducing the severity of the injury (fatal injury and severe injury by -0.028*** and -0.242***) respectively in Table 5, and increases the probability of the severity of the injury (minor injury and no injury). By (0.300*** and 0.033*), respectively, indicate the significance of occupant protection systems. Another indicator of the impacts of increasing collision forces is that higher speed restrictions also made injuries more severe [10-12].

4.4 Temporal characteristics

As it was found that a parameter of a typical time of day, which is morning from 6:00 to 11:59 am, is statistically incapable of being random, with an average of 0.222 and a standard deviation of 0.333 in Table 3, and this indicates that 25.25 % of the road characteristics, which is straight, have a value less than zero, which means that it is less likely to cause injury as well, due to the severity of the injury. On the contrary, 74.75 % of them have a greater value, and this has a marginal effect on the severity of the injury, such as the probability of reducing the severity of the injury (fatal injury and severe injury by -0.022*** and -0.070*** respectively, and increasing the probability of (minor injury and no injury by (0.080*** and 0.003**) respectively in Table 5 [13].

4.5 Road alignment

With its design and planning features, the road plays a significant role in traffic accidents and contributes significantly to the causes of crashes. Intersections influence the severity of the injury, straight lines, bends, curves, and the width of the road, pedestrian walkways, and traffic regulations as it was found that a parameter of a type of road characteristic, which is straight, is statistically incapable of being random, with an average of 0.846 and a standard deviation of 0.426 in Table 3. On the contrary, 97.57 % in Table 4 of them have a greater value, and this has a marginal effect on the severity of the injury, such as the probability of reducing the severity of the injury (fatal injury and severe injury by -0.099*** and -0.226***) respectively, and increasing the probability of (minor injury and no injury by (0.259*** and 0.006***) respectively in Table 5. The variables were analyzed using the ordered response model, and the variables were not dependent on the characteristics of the road, which included straightness. It was found that greater force (both straight and curved) increases the injury's severity [14-16].

5. CONCLUSIONS

Through working on this manuscript, some proposals and recommendations have come up that can be followed to reduce the number of crashes and the severity of injury during the crash and to facilitate the work of specialists in collecting and analyzing data to produce more accurate and effective outputs. Among these recommendations are:

- Carrying out extensive and deep studies on the previously mentioned areas in the research to find out the causes of crashes and their seriousness and to know the current situation by providing:

a) A - Sound streets.
b) B - Traffic signs.
c) C - Determine commitment to a safe speed.

- Establish strict laws for the use of motorcycles on the streets.
- Concerted efforts are an important requirement in reducing severe traffic crashes, through the development of strategic policies aimed at spreading and consolidating traffic safety concepts, based primarily on young people and school students, provided that this strategy includes the inclusion of educational curricula for traffic safety at all stages without exception so that students grow up in an environment that contributes to the promotion of traffic culture.
- Determine the roads with the most significant crashes and develop strategic plans to reduce them.
- Support the security authorities by the citizen and the central government to implement the law against violators.
- Activate the cooperation mechanism between the state departments to develop a comprehensive, scientific, and practical methodological plan to reduce the occurrence of crashes and reduce them.
- An important recommendation that must consider road infrastructure safety is that roads should ideally be designed with the safety of all road users in mind. Safe crossing points and other traffic calming measures are critical in reducing the risk of injury among these road users.

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