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Research Paper

# Rural Crash Severity Modelling at Marginal Areas around Cities in Iran Using Ordinal Logistic Regression and Partial Proportional Odds Modelling Approaches

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## Abstract

Proof from earlier investigations indicates that many rural crashes happen in marginal areas around cities. Therefore, Exclusive crash severity models should be developed to pinpoint the factors linked to the increased likelihood of injury and fatality in these segments of rural roads. For this purpose, a partial Proportional Odds (PPO) model alongside the traditional ones including ordered logit (OL) and multinomial logit (MNL) models was utilized in this study to develop crash severity models for these segments of roads. The authors applied rural crash data gathered from highways that lead to Isfahan for modelling. The PPO model outperforms the traditional models, as demonstrated by comparing developed models. Also, the results indicate that rural crashes are more likely to be severe when the average speed exceeds 95 km/h, in multi-vehicle type crashes, in overturn-type crashes, when the at-fault vehicle is a truck/trailer, and when the at-fault or not-at-fault vehicle is a motorcycle. On the other hand, severe crashes in marginal areas around cities tend to decrease when a foreign vehicle is at fault and when the driver of the at-fault vehicle is 30 to 40 years old.

**Keywords:** Rural Highway; Crash severity; Partial Proportional Odds model; Ordered Logit Model; Multinomial Logit Model

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# 1. Introduction

In 2016, more than 1.35 million individuals died globally as a result of traffic-related crashes, according to a report by the World Health Organization (WHO, 2018). This report also indicated that traffic injuries are the eighth major cause of death across different age ranges and the primary cause of death for individuals aged 5 to 29.

Iran, a country with a population of over 85 million (Statistical Center of Iran, 2024), has a traffic mortality rate of 20.5 per 100,000 people, according to the World Health Organization in 2018. The Road Maintenance and Transportation Organization of Iran (RMTO, 2023) stated that 66 percent of crash fatalities in the past decade were associated with rural crashes. Previous research on the spatial distribution of rural crashes demonstrates that a significant number occur in marginal areas around cities (Sajed et al., 2019; Shafabakhsh et al., 2016; Effati et al., 2014; Mohaymany et al., 2013; Hosseinlou & Sohrabi, 2009).

Marginal rural roads near cities are sections of roads situated outside cities. Due to the different land uses, including commercial, residential, agricultural, and industrial, driving conditions in these regions differ from rural roads' basic segments.

Various studies on road safety have highlighted that approximately 60 to 70 percent of crashes in the rural areas of Iran occur on the outskirts of cities (Shamanian Esfahani et al., 2024; Ehsani Sohi et al., 2019; Dashtestaninejad et al., 2018; Davoodi & Ahmadi, 2015; Ahmadi Resketi, 2014; Afandizadeh & Golshan Khavas, 2006; Shafabakhsh and Mousavi, 2006). Hence, pinpointing parameters linked to severe crashes by developing models specifically for predicting crash severity can assist in devising effective strategies to reduce rural crash fatalities.

The Ordinal Logit/Probit (OL/OP) and Multinomial Logit (MNL) models are the most conventional methods used to predict crash severity. MNL models posit that the independent variables have identical impacts across all crash observations. However, this assumption is not accepted when unobserved heterogeneities in the data are considered (Li & Fan, 2020). On the other hand, the mixed logit (ML) model overcomes this limitation by permitting the estimated parameters to alter across observations, thus addressing the Independence of Irrelevant Alternatives (IIA) property (Sasidharan & Menéndez, 2014; McFadden & Train, 2000). The ML and MNL models do not take into account the hierarchical essence of crash injury severities. In fact, they treat all severity levels as unordered. In contrast, OL/OP models follow the proportional odds (PO) assumption, positing the same parameter estimations across various severity levels (Savolainen et al., 2011). However, specific parameters may raise the probability of certain crash severity levels while diminishing the possibilities of others. Thus, it is essential to reconsider this impractical assumption when modelling the severity of crash injuries.

Traditional discrete choice models have constraints, so there is a demand for more sophisticated models that identify the innate ordered essence of traffic crash severity. The models should enable forecasters to have varying effects on different levels of crash injury severity. In these situations, the partial Proportional Odds (PPO) model, introduced by Peterson and Harrell (1990), can be utilized.

Existing literature reviews demonstrate that in developing countries, most investigations have used traditional methods to develop crash severity models (Nguyen et al., 2021; Asare & Mensah, 2020; Amoh-Gyimah et al., 2017; Barua & Tay, 2010). Conversely, the failure to develop specific severity models for these areas could be seen as a shortcoming of earlier studies, given the significant proportion of rural crashes occurring in marginal areas around cities. The study's goal is to create enhanced models, in addition to conventional ones, to predict crash severity in marginal areas around cities. By comprehending the factors that impact crash severity in marginal areas around cities and putting in place suitable safety measures, it is possible to decrease fatalities of rural crashes substantially. Further, it could aid in minimizing road safety costs, particularly in light of the substantial economic constraints and challenges faced by developing nations.

The following sections of this paper are organized as follows. Firstly, a concise summary of the relevant literature is presented. Following this, an explanation of the research methodology is provided. Next, the procedure of gathering and organizing data for modelling is explained. Afterward, the models are estimated, and the results are compared and discussed. Lastly, the final section summarizes the conclusions.

## 2. Literature Review

### 2.1. Factors Affecting Crash Severity

Considerable investigations have assessed the factors related to crash severity and formed an association between different factors and crash severity. The factors include road user characteristics, features of the vehicles, travel speed, type of collision, conditions of the road, and temporal factors like the season and time of day, and location of crashes.

Xie et al. (2012) conducted a study on the severity of driver injuries in single-vehicle crashes on rural highways. The study emphasized influential factors, including the age of drivers, environmental lighting conditions, seatbelt use, alcohol impairment, and the primary point of effect on the vehicle.

Yasmin et al. (2014b) carried out an investigation that studied the Australian crash database spanning from 2006 to 2010 to investigate the variables that impact the severity of driver injuries. A number of important factors contributing to severe driver injuries were identified in the study. They include drivers who were 65 years old or above, crashes that took place in areas with high-speed limits, and not wearing seat belts.

In addition, research conducted by Dashtestaninejadet al. (2018) found that important factors such as the age and level of education of the at-fault driver, the time of the crash, the type of collision, and the number of heavy vehicles involved in the crash significantly influence the severity of rural crashes within 30 kilometers of city entrances. This research implied that a head-on crash, a rise in the participation of heavy vehicles, and the at-fault driver being under the age of 30 elevated the chances of more serious outcomes. In contrast, lateral collisions and daytime crashes heightened the probability of collisions, which led to damage to properties.

Bachani et al. (2017) discovered that a 1% rise in the average speed of vehicles led to a 4% increase in the likelihood of fatal crashes and a 3% increase in the likelihood of severe injury crashes. On the other hand, the World Health Organization (2018) stated that a potential 30% reduction in road crash fatalities could be achieved by lowering the average speed limit by 5%.

Asare and Mensah (2020) researched traffic crashes in Ghana. Their findings indicated that different parameters, including the kind of involved vehicles, speed limits, and the location of the incident, impact the severity of the crashes. The research showed that there is a higher probability of severe or fatal injuries in motorcycles and passenger cars than in commercial vehicles. Further, crashes on rural roads are more prone to result in severe injuries or fatalities than on urban roads. The association between speed and crash severity has been confirmed not only in the research by Asare and Mensah (2020) but also in other studies.

Sun and Xiaoduan (2020) created models for predicting pedestrian-vehicle collisions in rural regions of Louisiana. Their study, based on pedestrian rural crash data from 2006 to 2015, revealed a strong correlation between fatal and severe crashes in these regions and factors such as drug or alcohol use, dark and unlighted conditions, pedestrians crossing roads away from intersections, speed limits exceeding 60 mph, and the pedestrians' elderly age.

Kamboozia et al. (2020) performed research aimed at developing predictive models for determining the severity of pedestrian-vehicle crashes on the rural highways of Gilan in Iran. They analyzed rural crash data from March 2014 to March 2019 to assess the likelihood of the occurrence of various types of crashes. The study focused on various levels of crash severity as the dependent variable, dividing them into two groups: injury and fatal crashes. The research determined several substantial factors related to serious pedestrian-vehicle crash injuries, such as female pedestrians, the autumn and spring seasons, heavy trucks, pedestrians aged 30-45 and 45-60, and crashes happening midweek. Furthermore, crashes occurring between 12:00 and 18:00 are less likely to result in fatalities.

Liu and Fan (2021) determined 14 essential parameters that impact the severity of head-on crashes. Significant factors that raised the probability of more head-on severe crashes comprised driving under the influence, elderly drivers, rural roads, winding roads, straight and flat roads, speed limitations ranging from 30 to 50 mph, speed limitations surpassing 50 mph, and the presence of motorcycles.

Adanu et al. conducted a study on rural highways in 2022, where they classified crash severity into three groups: no injury, minor injury (non-incapacitating or potential injury), and severe injury (fatal or incapacitating). The research determined several factors that impact crash severity in rural roads. The study revealed that driver behaviors such as aggressive driving, driving under the influence, and speeding were associated with an increased probability of more serious rural crashes. In addition, the research also found that in rural regions, level and straight roads were related to a higher likelihood of no-injury crashes. Insignificant injuries were prevalent in rear-endings, while crashes involving animals raised the risk of severe injuries. At-fault female drivers were more likely to cause severe injuries, and minor injuries were common among younger drivers. An expired license diminished the chance of severe injury but raised the likelihood of minor injuries. Crashes that happened in dark conditions were more prone to causing injury. Winter was a significant factor that diminished the probability of any injury on rural highways. The research particularly concentrated on analyzing motorcycle crashes due to their susceptibility to multi-vehicle crashes, and the results indicated that motorcycle involvement heightened the chances of severe and minor injuries on rural highways.

## 2.2. Crash Severity Analysis Approaches

Various statistical methods have been commonly utilized for the analysis of the severity of crashes. They include MNL models (Quddus et al., 2009; Aziz et al., 2013; Zhou et al., 2013; Chen and Fan, 2019b), binary logit models (Sze and Wong, 2007; Moudon et al., 2011), ML models (Milton et al., 2008; Malyshkina and Mannering, 2010; Chen and Chen, 2011; Haleem et al., 2015; Chen and Fan, 2019a), PPO models (Wang and Abdel-Aty, 2008; Rifaat et al., 2012; Li and Fan, 2019), and OL/OP models (Lee and Abdel-Aty, 2005; Yasmin et al., 2014a, b). The MNL model is frequently utilized, but its reliability might be affected when unobserved data heterogeneities are present. The reason is that it posits consistent impacts of descriptive variables across observations. In practice, the problem is tackled using an ML model that includes haphazardly dispersed parameters. However, neither the MNL nor ML models account for the ordered essence of crash injury severity. In fact, they consider all levels of severity to be disordered. Likewise, the OL/OP models posit that parameter estimates stay the same across each level of severity. This might be unrealistic. Thus, it is necessary to analyze this assumption in crash injury severity modelling. In practice, to overcome the limitations of traditional models, this investigation utilizes the PPO model to explore the influence of various factors on crash severity in marginal areas around cities. The PPO model merges the hierarchical essence of ordinal models with the adaptability of the MNL model, allowing specific independent variables to impact various levels of the dependent variable distinctly. PPO models relax the assumption of PO for independent variables that affect different levels of injury severity in various ways (Mooradian et al., 2013; Peterson & Harrell, 1990).

In earlier research on modelling crash severity, various models were assessed, and their predictive accuracy was compared using model fit measures. The findings indicated the superior performance of enhanced models like the PPO model compared to traditional ones, such as OL/OP and MNL models (Li & Fan, 2020; Sasidharan & Menéndez, 2014).

# 3. Methodology

This section contains a summary of the three models (MNL, OL, and PPO) that were utilized to explore the crash severity data in this study. The severity of crash injuries is divided into three categories: property damage only (PDO), injury, and fatal.

In all the models developed, variables that do not show statistical significance at the 0.05 level will be removed based on the correlation analysis results derived from the Spearman coefficient and a backward stepwise regression method. Also, it is necessary to check the correlation of independent explanatory variables for all developed models.

## 3.1. Multinomial Logit Model (MNL)

The multinomial logit model is employed for situations where the dependent variable encompasses three or more values. The MNL model utilizes a linear utility function, $U_{ij}$, to convey the association between injury severity levels (j = 0, 1, 2, …, J) and contributing factors, as demonstrated in Equation 1:

$$U_{ij} = \beta_j X_{ij} + \varepsilon_{ij} \tag{1}$$

Where $X_{ij}$ signifies the observable variable vector for i$^{th}$ individual with j$^{th}$ injury severity level, $\beta_j$ denotes the estimated coefficient vector, and $\varepsilon_{ij}$ represents the error term, which includes the unobserved factors and is posited to be autonomously and identically dispersed. Therefore, the MNL model can be demonstrated as in Equation 2:

$$P_{ij} = \frac{\exp(\beta_j X_{ij})}{\sum_{j=1}^{J} \exp(\beta_j X_{ij})} \tag{2}$$

Where $P_{ij}$ denotes the probability of i$^{th}$ crash with j$^{th}$ injury severity level result.

The MNL model is developed by assuming that the unobserved factors are uncorrelated across the different choices or results. This is also referred to as the assumption of Independence of Irrelevant Alternatives (IIA). This assumption is the most substantial limitation of the ML model because it is very probable that some results share unobserved factors. The assumption can be tested by the analyst utilizing the Hausman and the small Hsiao tests (Abdel-Aty, 2003). One way to relax this limitation is by employing the ML model (Chen et al., 2018). The MNL fails to account for the innate ordinal features of various injury severity levels. For all injury severity levels, the estimated coefficients vary.

## 3.2. Ordered Logit Model (OL)

A basic assumption of OL models is that the data satisfies the PO assumption. That is to say, the relationship between any two levels of the dependent variable group is identical. Thus, the slope coefficients remain constant across various choices. (Wang & Abdel-Aty, 2008). The assumption of parallel lines may not hold true in various scenarios, and it must be assessed for each individual variable. Therefore, the infringement of the parallel-lines assumption is evaluated for each descriptive variable utilizing the Brant test (Brant, 1990).

The crash injury severity level in crash i is denoted by $Y_i$, and $Y^*_n$ represents the latent crash injury severity measure. X signifies the matrix of independent variables, j denotes the crash injury severity level, and J is the number of severity levels. The latent injury severity measure $Y^*_n$ can be calculated as follows:

$$Y_i^* = \beta X_i + \varepsilon \quad (3)$$

Where the regression coefficient for X is denoted as β, and the error term is represented as ε. The thresholds for injury severity are signified by $\mu_k$, where k = 1, 2, …, J-1. It should be noted that level k=1 corresponds to the minimum threshold, PDO. The various values of Y are outlined below:

$$Y = 1\ (PDO\ crash)\ if\ \ Y^* \leq \mu_1$$
$$Y = 2\ (injury\ crash)\ if\ \ \mu_1 \leq Y^* \leq \mu_2$$
$$Y = 3\ (fatal\ crash\ crash)\ if\ \ Y^* > \mu_2$$

The probability of crash injury severity level j for a provided crash i can be determined as:

$$P(Y_i > j) = P_{ij} = \frac{exp(\alpha_j + \beta X_j)}{1 + exp(\alpha_j + \beta X_j)} \quad (4)$$

Where the regression coefficient for X is represented by β, $\alpha_j$ denotes the intercept for the $j^{th}$ logit. It is important to emphasize that β remains consistent for all levels of crash injury severity.

### 3.3. Partial Proportional Odds Model (PPO)

The PPO model holds the ordered essence of the dependent variable while easing the assumption of parallel lines in ordered models. According to this premise, the influence of an independent variable is consistent across different levels of crash injury severity, indicating that the coefficients for all independent variables are identical across various levels of the dependent variable. Wald Chi-square tests are employed to compare various levels of crash injury severity for each independent descriptive variable. The Brant test's null assumption indicates that a single coefficient is applicable to all levels of dependent variables for each independent factor. Independent descriptive variables that do not pass Brant's test may refute the assumption and can be eased by employing the PPO model. The variables exhibit distinct coefficients for each level of crash injury severity. Thus, the likelihood of crash i resulting in injury severity level j (where j = 1, 2, 3) is depicted as follows (Williams, 2006):

$$(Y_i > j) = \frac{exp\left(X_{1i}\beta_1 + X_{2i}\beta_2 - \Phi_j\right)}{1 + exp\left(X_{1i}\beta_1 + X_{2i}\beta_2 - \Phi_j\right)} \quad (5)$$

In the provided equation, $\beta_1$ denotes a parameter vector linked to a subset $X_{1i}$ of descriptive variables that did not infringe the Brant test. $\beta_2$ signifies a parameter vector associated with a subset $X_{2i}$ of descriptive variables that did infringe the Brant test. $\Phi_j$ represents the threshold cut-off points for the ordered model. The parameters in the vectors $\beta_1$ and $\beta_2$ and the cut-off points, $\Phi_j$, are calculated by maximizing the log-likelihood function LL (Williams, 2006):

$$LL = \sum_{i=1}^{N}\sum_{j=1}^{3} y_{ij} lnP(\mathrm{Y_i > j}) \quad (6)$$

here crash i resulted in severity level j is denoted by $y_{ij}$, and N represents the total number of crashes. The model development utilizes gologit2 software in Stata 17. It is crucial to carefully analyze the outcomes of the PPO model, as the sign of β may not dependably show the trend of the intermediate outcomes (Washington et al., 2003; Wooldridge, 2002).

One of the key advantages of the PPO model is taking into account unobserved heterogeneity in crash data. Previous studies have also confirmed this (Yasmin et al., 2014a; Eluru, 2013; Quddus et al., 20110).

### 3.4. Comparison of Models

The goodness-of-fit of the models is evaluated using the Pseudo $\rho^2$, Akaike's Information Criterion (AIC), and Bayesian information criterion (BIC).

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \quad (7)$$

$$AIC = -2\ LL(\beta) + 2k \quad (8)$$

$$BIC = -2LL(\beta) + kln(n) \quad (9)$$

Where the log-likelihood at convergence is denoted as LL(β), while the log-likelihood with the steady term is represented as LL(0). The number of variables is signified as k, and that of observations is denoted as n. In fact, the models with the lowest AIC, lowest BIC, and highest log-likelihood values at convergence are the most preferred.

The likelihood ratio test is utilized to assess if the specification is statistically superior to the others:

$$\chi^2 = -2[LL(\beta_1) - LL(\beta_2)] \quad (10)$$

Where the two competitive models' log-likelihoods at convergence are denoted by $LL(\beta_1)$ and $LL(\beta_2)$, further, the $\chi^2$ statistic is a representation of the chi-square distribution, with the freedom degree being the difference between the variable numbers in models 1 and 2 (Washington et al., 2020).

According to the evaluated parameters, the average marginal effect values can be used to analyze the effects of the descriptive independent variables on crash severity. The evaluated marginal impacts illustrate the influence of changes in an independent variable on the dependent variable. The marginal impact of each independent variable is computed as an alteration in probability rather than a derivative since all variables are binary in this investigation. The following equation gives the marginal effect of explanatory variable l:

$$ME_{X_{il}}^{y_i} = \frac{\partial y_i}{\partial X_{il}} = \beta_l EXP(\beta x) \quad (11)$$

where x and β are the vectors of explanatory variables and corresponding parameter estimates, respectively.

# 4. Data

This research seeks to develop models to predict the severity of crashes in marginal areas around cities. In practice, data for crashes on rural highways leading to Isfahan is used to achieve this. Given Isfahan's central location in Iran, the traffic volume and frequency of crashes on the rural roads leading to this city are significant. The highways selected are those that have Isfahan as the starting point or destination for trips. An evaluation of the rural road network shows six highways that lead to Isfahan: Isfahan-Shahrza, Isfahan-Zarinshahr, Isfahan-Naein, Isfahan-Shahinshahr, Isfahan-Morchehkhort, and Isfahan-Airport.

Research carried out by Shamanian Esfahani et al. (2022) introduced the idea of the boundary of the influence area (BIA) for rural road crashes near cities. This research delineates the BIA as the distance from a city where there is a significant difference in the number of rural crashes before and after that point. The influence boundary of the highways leading to Isfahan can be ascertained by utilizing the models introduced in the research performed by Shamanian Esfahani et al. (2022). The BIA values computed for these highways vary from 10 to 20 km.

A database of rural crashes in the marginal areas around Isfahan was collected by calculating the BIA for each investigated highway. The crashes in this database totaled 2,613 and took place over three years, from March 20, 2016 to March 20, 2019. The Isfahan Provincial Traffic Police was the source of the rural crash data.

The crash injury severity is the dependent variable in the models. Indeed, it is depicted as the most severe injury resulting from the crash. Within the Isfahan province highway police database, three distinct levels of crash severity are identified for inclusion in the model: PDO, injury (I), and fatal (F) crashes. Table 1 provides a comprehensive summary of each variable and the number of observed crash records for each severity level. The independent variables consist of roadway/geometrical, collision, traffic, vehicle, driver, and environmental/temporal features. The Road and Urban Development Bureau of Isfahan Province and the Road Maintenance and Transportation Organization of Isfahan Province provided the highways' roadway/geometrical features. In this respect, traffic features, including average speed, volume, the proportion of speed-limit violations, the proportion of longitudinal distance-limit violations, and the proportion of heavy vehicles, were gathered utilizing road loop detectors. Traffic detectors have limitations in their accuracy and may include errors. The detectors' accuracy is one of this research's foundational assumptions. Further data was obtained from the crash database.

Dummy variables are determined for each categorical variable, as described in the table. Furthermore, to reveal potential relationships, correlation studies were conducted on all independent variables before the modelling.

**Table 1. Descriptive statistics of the variables**

| Variable | Description | No. of crashes | Injury severity | | |
|---|---|---|---|---|---|
| | | | F[a] | I[b] | PDO[c] |
| Severity | Crash severity | 2613 | 78 | 1437 | 1098 |
| | Collision characteristics | | | | |
| Collision type | Sideswipe | 233 | 2 | 82 | 149 |
| | Right angle | 435 | 11 | 225 | 199 |
| | Rear end | 506 | 19 | 181 | 306 |
| | Multi-vehicle | 192 | 14 | 123 | 55 |
| | Run-off-road | 76 | 1 | 51 | 24 |
| | Overturn | 383 | 14 | 316 | 53 |
| | Hit object | 402 | 14 | 267 | 121 |
| | Hit Pedestrian | 85 | 13 | 72 | 0 |
| | Other | 302 | 0 | 115 | 187 |
| Pedestrian-vehicle crash | 1 | 85 | 13 | 72 | 0 |
| | 0 | 2528 | 75 | 1359 | 1094 |
| Motorcycle | 1 | 335 | 28 | 300 | 7 |
| | 0 | 2278 | 60 | 1131 | 1087 |
| Number of vehicles | 1 | 964 | 42 | 716 | 206 |
| | 2 | 1457 | 32 | 592 | 833 |
| | 3 or more | 192 | 14 | 123 | 55 |
| Number of heavy vehicles | 0 | 2064 | 58 | 1147 | 859 |
| | 1 | 504 | 28 | 264 | 212 |
| | 2 or more | 45 | 2 | 20 | 23 |
| | Roadway/geometrical characteristics | | | | |
| Road type | Freeway | 1223 | 47 | 695 | 481 |
| | Expressway | 1390 | 41 | 736 | 613 |
| Number of lanes | 2 | 439 | 8 | 210 | 221 |
| | 3 | 2174 | 80 | 1221 | 873 |
| Shoulder type | Paved | 1562 | 55 | 878 | 629 |
| | Unpaved | 1051 | 33 | 553 | 465 |
| Shoulder width (m) | <=2.5 | 141 | 25 | 81 | 35 |
| | 2.5-3.5 | 1224 | 34 | 798 | 392 |
| | >=3.5 | 1248 | 29 | 552 | 667 |
| Crash location | Straight | 2495 | 86 | 1353 | 1056 |
| | Curve | 30 | 1 | 19 | 10 |
| | Intersection | 27 | 0 | 16 | 11 |
| | Other | 61 | 1 | 43 | 17 |
| | Traffic characteristics | | | | |
| Speed limit (km/h) | 110 | 1390 | 41 | 736 | 613 |
| | 120 | 1223 | 47 | 695 | 481 |

| Variable | Description | No. of crashes | Injury severity | | |
|---|---|---|---|---|---|
| | | | F[a] | I[b] | PDO[c] |
| Traffic volume (1000 vehicle per month) | <=500 | 868 | 28 | 421 | 419 |
| | 5000-1000 | 293 | 6 | 154 | 133 |
| | 1000-1500 | 1117 | 38 | 648 | 431 |
| | >=1500 | 335 | 16 | 208 | 111 |
| Proportion of heavy vehicles (%) | <=5 | 935 | 34 | 560 | 341 |
| | 5-10 | 542 | 21 | 314 | 207 |
| | 10-20 | 833 | 21 | 409 | 403 |
| | >=20 | 303 | 12 | 148 | 143 |
| Average speed (km/h) | <=85 | 665 | 21 | 341 | 303 |
| | 85-90 | 601 | 14 | 279 | 308 |
| | 90-95 | 562 | 19 | 251 | 292 |
| | >=95 | 785 | 34 | 560 | 191 |
| Proportion of speed-limit violation (%) | <=5 | 929 | 33 | 509 | 387 |
| | 5-10 | 812 | 26 | 493 | 293 |
| | 10-15 | 545 | 15 | 274 | 256 |
| | >=15 | 327 | 14 | 155 | 158 |
| Proportion of longitudinal distance-limit violation (%) | <=5 | 94 | 1 | 45 | 48 |
| | 5-10 | 521 | 13 | 246 | 262 |
| | 10-15 | 412 | 18 | 211 | 183 |
| | 15-20 | 651 | 22 | 369 | 260 |
| | >=20 | 935 | 34 | 560 | 341 |
| Environmental/temporal characteristics | | | | | |
| Season | Spring | 628 | 25 | 358 | 245 |
| | Summer | 713 | 29 | 413 | 271 |
| | Fall | 620 | 19 | 341 | 260 |
| | Winter | 652 | 15 | 312 | 325 |
| Time of crash | Day | 1418 | 29 | 647 | 742 |
| | Night | 1093 | 52 | 735 | 306 |
| | Rise | 56 | 4 | 25 | 27 |
| | Sunset | 46 | 3 | 24 | 19 |
| Weather condition | Clear | 2482 | 84 | 1384 | 1014 |
| | Other | 131 | 4 | 47 | 80 |
| Pavement condition | Dry | 2517 | 84 | 1399 | 1034 |
| | Wet | 96 | 4 | 32 | 60 |
| Vehicle characteristics | | | | | |
| At-fault vehicle type | Passenger car | 1880 | 37 | 992 | 851 |
| | Truck/Trailer | 278 | 17 | 172 | 89 |
| | Bus | 21 | 1 | 9 | 11 |
| | Single-unit truck/Minibus | 17 | 0 | 6 | 11 |
| | Pickup/Van | 224 | 8 | 87 | 129 |
| | Motorcycle | 166 | 19 | 146 | 1 |
| | Other | 27 | 6 | 19 | 2 |
| At-fault vehicle manufacture | Domestic | 2048 | 74 | 1197 | 777 |
| | Foreign | 565 | 14 | 234 | 317 |
| Not-at-fault vehicle type | Passenger car | 1121 | 21 | 422 | 678 |

| Variable | Description | No. of crashes | Injury severity | | |
|---|---|---|---|---|---|
| | | | F[a] | I[b] | PDO[c] |
| | Truck/Trailer | 193 | 11 | 83 | 99 |
| | Bus | 27 | 0 | 9 | 18 |
| | Single-unit truck/Minibus | 24 | 0 | 5 | 19 |
| | Pickup/Van | 132 | 3 | 65 | 64 |
| | Motorcycle | 143 | 9 | 128 | 6 |
| | Other | 15 | 2 | 9 | 4 |
| | Single-vehicle crash | 958 | 42 | 710 | 206 |
| Not-at-fault vehicle manufacture | Domestic | 1298 | 35 | 584 | 679 |
| | Foreign | 357 | 11 | 137 | 209 |
| | Single-vehicle crash | 958 | 42 | 710 | 206 |
| Driver characteristics | | | | | |
| At-fault vehicle driver age | <=30 | 642 | 31 | 409 | 202 |
| | 30-40 | 836 | 17 | 360 | 459 |
| | 40-50 | 484 | 10 | 270 | 204 |
| | >=50 | 480 | 14 | 277 | 189 |
| | N/A[d] | 171 | 16 | 115 | 40 |
| At-fault vehicle driver gender | Male | 2313 | 73 | 1240 | 1000 |
| | Female | 241 | 7 | 147 | 87 |
| | N/A | 59 | 8 | 44 | 7 |
| Not-at-fault vehicle driver age | <=30 | 400 | 14 | 191 | 195 |
| | 30-40 | 551 | 12 | 226 | 313 |
| | 40-50 | 325 | 8 | 136 | 181 |
| | >=50 | 286 | 7 | 115 | 164 |
| | N/A | 93 | 5 | 53 | 35 |
| | Single-vehicle crash | 958 | 42 | 710 | 206 |
| Not-at-fault vehicle driver gender | Male | 1532 | 41 | 664 | 827 |
| | Female | 95 | 2 | 38 | 55 |
| | N/A | 28 | 3 | 19 | 6 |
| | Single-vehicle crash | 958 | 42 | 710 | 206 |

[a] Fatal crash
[b] Injury crash
[c] Property damage only crash
[d] Not applicable

## 5. Modelling Results

This section contains the findings of the three distinct crash severity models employed in this research. In addition, it features a comparison between the OL, MNL, and PPO models employing criteria such as BIC, pseudo-$R^2$, and AIC. Further, this section encompasses the marginal effects of the PPO model for interpretation of results. All the models in this study were developed using the STATA software.

### 5.1. Multinomial Logit Model (MNL)

The Hausman and Small-Hsiao tests were utilized to assess the IIA assumption. The findings from both tests indicated that the IIA assumption was not infringed. Thus, an MNL model was employed in this investigation. Table 2 displays the standard errors and coefficients for the predictors in the MNL model developed for various levels of injury severity. As PDO crashes were deemed to be the base level, no outcomes for PDO crashes are included in Table 2.

According to the MNL model, various factors influencing the increase in accident severity include average vehicle speeds exceeding 95 km per hour, multi-vehicle type crashes, overturn type crashes, the at-fault vehicle being a truck or trailer, the at-fault vehicle being a motorcycle, the at-fault vehicle being foreign-made, the driver's age of the at-fault vehicle between 30 to 40 years old, and the not-at-fault vehicle being a motorcycle.

The impact of distinct variables on varying degrees of severity can be evaluated and contrasted by applying the MNL model. For instance, the odds ratios for the "multi-vehicle crash" variable were 3.14 ($e^{1.146}$) for fatal crashes and 1.86 ($e^{0.623}$) for injury crashes using PDO crashes as the base. The finding indicates that the probability of a multi-vehicle crash being fatal is 214 percent higher than that of a PDO crash. Additionally, the probability of a multi-vehicle crash resulting in injury and being classified as an injury crash is 86 percent higher than that of PDO.

**Table 2. The results of the MNL model for predicting rural crash severity at marginal areas around cities**

| **Variable** | | **F[a]** | | **I[b]** | |
|---|---|---|---|---|---|
| | | **Coef.** | **S.E.** | **Coef.** | **S.E.** |
| Intercept | | -3.180 | 0.208** | -0.200 | 0.072* |
| Average speed (km/h) | >=95 | 1.065 | 0.246** | 1.056 | 0.107** |
| Collision type | Overturn | 1.617 | 0.338** | 1.959 | 0.165** |
| | Multi-vehicle | 1.146 | 0.345** | 0.623 | 0.186** |
| At-fault vehicle type | Truck/Trailer | 2.003 | 0.353** | 1.172 | 0.170** |
| | Motorcycle | 5.698 | 1.040** | 4.728 | 1.007** |
| At-fault vehicle manufacture | Foreign | -1.130 | 0.357* | -0.909 | 0.125** |
| At-fault vehicle driver age | 30-40 | -0.961 | 0.285** | -0.714 | 0.099** |
| Not-at-fault vehicle type | Motorcycle | 3.250 | 0.545** | 3.230 | 0.427** |

[a] Fatal crash

[b] Injury crash

Number of observations: 2613

Log-likelihood at convergence: -1708.324

Log-likelihood (constant only): -2112.542

Pseudo $\rho^2$: 0.191

*Level of significance>95%. **Level of significance>99%

## 5.2. Ordered Logit Model (OL)

The MNL model does not account for the hierarchical essence of crash injury severities. The model treats all severity levels as unordered. However, the OL model recognizes the ordered essence of the different levels of crash severity. Table 3 demonstrates the OL model designed for various levels of crash injury severity.

Table 3 represents the increasing effect of variables such as average vehicle speeds over 95 km per hour, multi-vehicle type crashes, overturn type crashes, the at-fault vehicle being a truck or trailer, the at-fault vehicle being a motorcycle, and the not-at-fault vehicle being a motorcycle on the severity of rural crashes in suburban areas. In contrast, variables such as the at-fault vehicle being foreign-made and the driver's age of the at-fault vehicle being 30 to 40 years old have a diminishing effect on the severity of crashes in these areas.

The Brant test results, reported in Table 4, indicate a violation of the basic assumption of ordinal models (APO) for the variables "average vehicle speeds over 95 km per hour," "overturn type crashes," "the at-fault vehicle being a motorcycle," and "the at-fault vehicle being a motorcycle." Consequently, the same coefficients for all descriptive variables at different levels of severity invalid.

**Table 3. The results of the OL model for predicting rural crash severity at marginal areas around cities**

| Variable | | Coef. | S.E. |
|---|---|---|---|
| Average speed (km/h) | >=95 | 0.892 | 0.096** |
| Collision type | Overturn | 1.456 | 0.129** |
| | Multi-vehicle | 0.690 | 0.166** |
| At-fault vehicle type | Truck/Trailer | 1.177 | 0.154** |
| | Motorcycle | 2.230 | 0.208** |
| At-fault vehicle manufacture | Foreign | -0.842 | 0.116** |
| At-fault vehicle driver age | 30-40 | -0.665 | 0.092** |
| Not-at-fault vehicle type | Motorcycle | 1.815 | 0.191** |
| Cut 1 | | 0.067 | 0.069 |
| Cut 2 | | 4.740 | 0.161 |

Number of observations: 2613

Log-likelihood at convergence: -1767.552

Log-likelihood (constant only): -2112.542

Pseudo $\rho^2$: 0.163

*Level of significance>95%. **Level of significance>99%

**Table 4. The results of Brant test for individual independent variables in OL model**

| Variable | | Wald chi-square | P-value |
|---|---|---|---|
| Average speed (km/h) | >=95 | 9.89 | < 0.01 |
| Collision type | Overturn | 30.93 | < 0.01 |
| | Multi-vehicle | 0.01 | 0.943 |
| At-fault vehicle type | Truck/Trailer | 0.01 | 0.937 |
| | Motorcycle | 10.14 | < 0.01 |
| At-fault vehicle manufacture | Foreign | 1.18 | 0.278 |
| At-fault vehicle driver age | 30-40 | 0.70 | 0.404 |
| Not-at-fault vehicle type | Motorcycle | 25.46 | < 0.01 |

## 5.3. Partial Proportional Odds Model (PPO)

Table 5 presents the outcomes of the PPO modeling using maximum likelihood estimation techniques for all descriptive variables. Any variable that was found to be not statistically significant at the 0.05 level according to the correlation analysis outcomes was excluded. The findings of the model, which are shown in Table 5, indicate that numerous variables correlate with the severity of crashes in marginal areas around cities. These variables include the width of the shoulder, average speed, type of collision, involvement of pedestrians in crashes, type of at-fault vehicle, manufacturer of the at-fault vehicle, and age of the at-fault vehicle driver.

The Brant test is used to verify the assumption of PO for the PPO model. The null hypothesis of this test suggests that every variable has a single coefficient across all levels of severity. Variables that infringe on the PO assumption hold various coefficients across the levels of injury severity, while variables that comply with the assumption maintain identical impacts. The results indicate that certain independent variables, such as shoulder width greater than or equal to 3.5, average speed greater than or equal to 95 km per hour, and overturn collision, do not meet the proportional odds assumption. As a result, they will be eased and contain various coefficients for the diverse levels of crash severity. The assumption is followed by the other variables, and they have the same coefficient at every level.

**Table 5. The results of the PPO model for predicting rural crash severity at marginal areas around cities**

| Variable | | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
|---|---|---|---|---|---|---|---|
| | | All levels | | F[a] | | I[b] | |
| Intercept | | | | -3.751** | 0.185 | 0.327** | 0.084 |
| Shoulder width (m) | >=3.5 | | | -0.519* | 0.244 | -1.330** | 0.102 |
| Average speed (km/h) | >=95 | | | 0.358* | 0.177 | 1.603** | 0.117 |
| Collision type | Overturn | | | 0.653* | 0.310 | 2.172** | 0.169 |
| | Multi-vehicle | 0.907** | 0.175 | | | | |
| | Hit object | 0.942** | 0.124 | | | | |
| Pedestrian-vehicle crash | 1 | 2.676** | 0.258 | | | | |
| At-fault vehicle type | Truck/Trailer | 1.076** | 0.161 | | | | |
| At-fault vehicle manufacture | Foreign | -0.903** | 0.121 | | | | |
| At-fault vehicle driver age | 30-40 | -0.662** | 0.096 | | | | |

[a] Fatal crash

[b] Injury crash

Number of observations: 2613

Log-likelihood at convergence: -1681.671

Log-likelihood (constant only): -2112.542

Pseudo $\rho^2$: 0.204

*Level of significance>95%. **Level of significance>99%

## 5.4. Comparison of Models

The log-likelihood values at convergence, along with AIC and BIC values, were utilized to compare the performance of the various models employed in this research. The outcomes of the model comparison are detailed in Table 6. The table indicates that the PPO model demonstrates lower AIC and BIC values than the OL and MNL models. Therefore, the PPO model surpassed the other two models. In this regard, it is a feasible approach for modeling crash severity in marginal areas around cities. Furthermore, the PPO model produced reasonable signs for all predictors, and its overall model fit outperformed that of the other two models. The log-likelihood at zero (-2112.542) and convergence (-1681.671) result in a pseudo ρ2 value of 0.204, which is significant for the PPO model. The log-likelihood at convergence for the same data was -1767.552 when using the OL model. When the MNL model was used, the log-likelihood improved to -1708.324. The MNL model's performance was superior to the OL model according to the BIC, AIC, and LL. However, the PPO model outperformed both the MNL and OL models when analyzing crash severity data. The outcomes of the likelihood ratio test show that the $\chi^2$ value obtained from comparing the OL and models is 118.46 with eight degrees of freedom. This demonstrates the significant supremacy of the MNL model over the OL model within the 0.05 confidence interval (the crucial chi-square value was 15.51). Further, comparing the MNL and PPO models revealed the supremacy of the PPO model over the MNL model within the 0.05 confidence interval. In fact, the significant difference in the performance of the two models was determined based on comparing the calculated value for χ2 (53.31 with four degrees of freedom) and the crucial chi-square value (9.49).

**Table 6. Comparison of developed models**

| Description | MNL | OL | PPO |
|---|---|---|---|
| **Goodness-of-fit-measures** | | | |
| Log-likelihood at convergence | -1585.078 | 1566.113 | -1560.427 |
| Log-likelihood with constant only | -1708.324 | -1767.552 | -1681.671 |
| pseudo $\rho^2$ | 0.191 | 0.163 | 0.204 |
| AIC | 3542.648 | 3555.104 | 3391.343 |
| BIC | 3558.276 | 3613.787 | 3473.498 |
| **Likelihood ratio test** | | | |
| Competing models | MLN vs. OL | | MNL vs. PPO |
| Degree of freedom | 8 | | 4 |
| Level of confidence | 95% | | 95% |
| Computed chi-square | 118.46 | | 53.31 |
| Critical chi-square | 15.51 | | 9.49 |
| Statistically superior model | MNL | | PPO |

## 6. Discussion

The marginal impacts are calculated for each variable to facilitate interpretation. This shows how significant factors impact the levels of injury severity. These impacts estimate discrete alterations for categorical independent variables. In this research, the marginal impacts of all independent variables represent the changes in expected probability when a binary descriptive variable shifts from 0 to 1. Table 7 details the marginal impacts for all descriptive variables.

Notably, the width of roads exceeding 3.5 meters on the shoulder reduces the probability of fatal or severe injury crashes in marginal city areas. Haghighi et al. (2018) provided evidence supporting the relationship between road shoulder features and crash severity.

Extreme driving speed, especially over 95 km per hour, notably amplifies the crash severity in marginal areas around cities. As expected, vehicles' average speed directly impacts the severity of collisions, resulting in an increased probability of fatal or injurious consequences. The relationship between driving speed and the severity of crashes has been extensively studied in earlier research (Adanu et al., 2022; Liu & Fan, 2021; Asare & Mensah, 2020; Sun & Xiaoduan, 2020; Bachani et al., 2017; Yasmin et al., 2014b).

The results of modeling show that the type of crash collision has a significant impact on the degree of injuries and fatalities. Therefore, crashes involving overturns, multiple vehicles, and collisions with objects elevate the likelihood of severe injury or death to occupants. It is clear that multi-vehicle crashes, because of the great number of involved vehicles, pose an increased risk of fatalities or injuries. Likewise, turnovers or hit object crashes can have a significant influence on the vehicle and its passengers, resulting in more serious injuries. In this respect, previous investigations have verified the correlation between the type of collision and the severity of crashes (Adanu et al., 2022; Dashtestaninejad et al., 2018; Feng et al., 2016; Celik & Oktay, 2014).

**Table 7. Marginal effects of independent variables in the PPO model for predicting rural crash severity at marginal areas around cities**

| Variable | | Crash injury severity | | |
|---|---|---|---|---|
| | | F | I | PDO |
| Shoulder width (m) | >=3.5 | -0.0112 | -0.2942 | 0.3054 |
| Average speed (km/h) | >=95 | 0.0083 | 0.3223 | -0.3306 |

| Variable | | Crash injury severity | | |
|---|---|---|---|---|
| | | F | I | PDO |
| Collision type | Overturn | 0.0179 | 0.3504 | -0.3683 |
| | Multi-vehicle | 0.0290 | 0.1569 | -0.1860 |
| | Hit object | 0.0286 | 0.1691 | -0.1977 |
| Pedestrian-vehicle crash | 1 | 0.2111 | 0.1440 | -0.3551 |
| At-fault vehicle type | Truck/Trailer | 0.0361 | 0.1807 | -0.2168 |
| At-fault vehicle manufacture | Foreign | -0.0157 | -0.2032 | 0.2189 |
| At-fault vehicle driver age | 30-40 | -0.0130 | -0.1455 | 0.1585 |

Pedestrian involvement in crashes is another significant parameter that raises the likelihood of more serious outcomes. This is because pedestrians are especially vulnerable, especially in rural crash settings. This result is consistent with previous discoveries. (Celik & Oktay, 2014).

When a trailer or truck is the at-fault vehicle, modeling results indicate that the risk of an injurious or fatal crash increases. The larger size of these vehicles compared to standard passenger cars frequently results in damage and more severe injuries.

The outcomes regarding the correlation between the involvement of foreign (non-Iranian) at-fault vehicles in crashes and the severity of the incident are significant. As per the model, at-fault vehicles from foreign countries are related to decreased crash severity. This could be due to the improved performance of the suspension and control systems in foreign vehicles, which allow drivers to react more efficiently to dangerous circumstances, thus reducing the likelihood of more severe crashes. Moreover, the vehicles maintain strict safety standards, which are more stringent than those for domestic vehicles. This helps lessen the severity of probable influences on passengers, thereby reducing the outcomes of crashes.

Driver age has a notable impact on the severity of crashes. Modeling data indicates that when the at-fault driver is between 30 and 40 years old, there is a decreased likelihood of injuries or fatalities. This may be indicative of their considerable experience and ability to react promptly in dangerous scenarios. However, research offers conflicting findings regarding the effect of driver age on the severity of crashes. Recent research conducted by Adanu et al. (2022) affirms a direct association between young drivers and a reduced probability of being involved in fatal or injurious crashes. In contrast, Dashtestaninejad et al. (2018) found that drivers below the age of 30 elevate the likelihood of such crashes.

square value (9.49).

# 7. Conclusion

The substantial parameters impacting the severity of rural crashes in marginal areas around cities in Iran were explored using MNL, OL, and PPO models in this investigation. The current research was performed based on a three-year crash dataset of six highways leading to Isfahan. In this regard, the study classified the crashes into three levels according to the severity of injuries. The developed models were compared based on their log-likelihood values at convergence, as well as their AIC and BIC values. The comparison showed that the PPO model surpassed the other two models. In addition, the log-likelihood ratio test affirmed the superior performance of the PPO model compared to the other two models.

The PPO model was used to estimate the marginal impacts of descriptive variables to reveal the important factors that impact the levels of injury severity in rural crashes in marginal areas around cities. The results of this research indicate that wider road shoulders (3.5 meters or more) on rural roads decrease the probability of serious crashes in comparison to narrower ones. Another significant discovery from this study is the direct correlation between the speed of vehicles and the crash severity in marginal areas around cities. If the average speed on peripheral rural roads surpasses 95 km per hour, the likelihood of serious crashes rises. The severity of a collision is greatly affected by its type. Overturns, multiple vehicles, and collisions with stationary objects considerably raise the likelihood of passenger injuries or fatalities. Moreover, pedestrian participation in a rural crash in marginal areas around cities exponentially intensifies the probability of serious consequences due to their vulnerability. The severity of a collision is likely to be higher if an at-fault vehicle is a trailer or truck. It is worth noting that the safety standards of Iranian domestically manufactured cars are a cause for concern. Indeed, these standards are generally lower than those of foreign cars. Crashes, where the at-fault parties are foreign vehicles, tend to result in less serious consequences.

In marginal areas around cities, the age of the driver is an influential factor that affects the severity of rural crashes. The probability of serious crashes is lower when an at-fault driver is rather young, aged between 30 and 40 years old.

This investigation focuses on understanding the factors that impact the severity of rural crashes in marginal areas around cities. In fact, this study aims to develop suitable safety measures according to their features. Executing effective safety measures in these regions helps lower the number of casualties resulting from crashes. This is vital for both safety and cost-effectiveness, avoiding unnecessary expenses on road safety, especially in economically struggling developing countries such as Iran.

As a suggestion for future studies, it is recommended to model the severity of accidents in base segments of roads and compare the influencing variables on accident severity in the vicinity of cities with those in base segments. Additionally, given the significant share of motorcycle accidents in the outskirts of major cities, separate models can be developed for this type of accident around cities and compared with the models presented in this research.

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