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Analyzing the Factors Influencing Road Traffic Accident Severity in Bauchi State

Ali Muhammed Gambo[1], A. Abdulkadir[1,2]* and K. E. Lasisi[1]

[1,2]Department of Mathematical Sciences, Faculty of Sciences, Abubakar Tafawa Balewa University Bauchi. PMB 0248, Bauchi, Nigeria

[2]Department of Mathematical Science, Faculty of Science, Gombe State University, PMB 127 Gombe, Nigeria

Corresponding Author: kadow1992@gsu.edu.ng

ABSTRACT

Road traffic accidents are a complex global issue due to their impact on both financial and public health sectors. Bauchi State, with approximately 1334 kilometers of roadways, experiences a significant number of accidents. To mitigate accident severity, it is crucial to analyze the factors influencing road traffic accident severity in Bauchi State. This study employs multinomial logistic regression to predict accident severity—fatal, serious, and minor—from 422 accidents recorded between January 2021 and December 2022 by the RTC unit of FRSC. Significant factors identified include accident location, cause, route, vehicle class, presence of at least one female passenger, vehicle type, accident timing, and driver's gender. The findings of this study and its recommendations will inform the development and implementation of future road safety policies and measures.

Keywords: Road Traffic, Accident , Multinomial Logistic Regression, Bauchi State.

INTRODUCTION

Road traffic collisions and accidents pose significant global challenges due to their profound impact on both financial and public health sectors. Road safety remains a crucial area of scientific research, with particular emphasis on understanding and mitigating the consequences of road accidents. These incidents often result in tragic loss of life or permanent disability, placing substantial economic burdens on societies through the costs associated with property damage and medical expenses (Eboli and Mazzulla, 2008; de Ona et al., 2014).

Globally, road accidents claim the lives of over 1.2 million people annually, with an additional 20 to 50 million sustaining non-fatal injuries (WHO, 2015). Notably, emerging countries bear a disproportionate burden of these incidents (Agrawal, 2012; Oginni et al., 2009), where more than two-thirds of all global injuries occur (Fatmi et al., 2007). These accidents also account for approximately 85% of deaths and 90% of disability-adjusted life years lost in these nations each year (WHO, 2004).

In Nigeria, the Federal Road Safety Commission has reported the country as having the highest fatality rate from automobile accidents in Africa, surpassing 43 other nations in terms of deaths per 10,000 vehicle accidents (FRSC, 2006; Obinna, 2007). Recent studies have highlighted higher reported cases of road casualties in the North-Central, South-West, and North-West geopolitical zones (Musa et al., 2022). Over the years, road accidents in Nigeria have resulted in damages amounting to approximately 80 billion Naira. Among those involved in these accidents, 29.1% suffer disabilities and 13.5% are unable to return to work (Labinjo et al., 2010).

This paper proposes a multinomial logistic regression model to assess the impact of various factors on accident severity, including vehicle class, route, and the presence of at least one female passenger. The model specifically categorizes accidents by severity—fatal, serious, and minor—and aims to provide a detailed analysis of how specific factors influence the severity of accidents across different vehicle classes (private or commercial), routes, and passenger demographics.

The structure of the paper is as follows: first, a description and statistical analysis of the data used in this study will be presented. Subsequently, results from the statistical models employed will be discussed, followed by a concluding section where the main findings will be summarized and discussed.

LITERATURE REVIEW

There have been numerous studies connected on the use of multinomial logistic regression model for investigating the influence of number of injuries and accidents.Here is a brief literature review of some ofsome studies :

1. (Al-Ghamidi, 2002). Al-Ghamidi (2002) used logistic regression to estimate accident severity and influence of accident factors. As his response variable was binary, he selected the logistic regression model. He showed that logistic regression could be a promising tool for predicting probability, used for future safety improvement or policy making.
2. Champahom et al, (2020) also used the logistic regression model, where the probable outcome was to show the reason behind rear-end crashes through explanatory variables. However, when the response variable has two categories, one can use the binary or binomial logit model.
3. Chen and Fan (2019) used multinomial logistic regression to assess the crash severity of pedestrian versus vehicles to identify significant factors that determine the pedestrian-vehicle crash severity.

Overall these studies suggest that multinomial logistic regression can be useful tool in predicting the outcome of severinity, However, its important to note that not only multinomial logistic regression model for investigating the influence of severity but other statistical factors.

MATERIALS AND METHODS

Multinomial Logistic Regression Model

In the present study, to apply multinomial logistic regression model for predicting crash severity, dependent variables are followed as Y, which has i degrees, sequence with values from low to high which include the crash severity (fatal, serious and minor) when given values i =1 to 3 and k indexes the observation. This is accommodated within the multinomial analysis by designing one of the groups (in the analysis setup) as the reference group. Each of the other groups serves as target group and its compared to this reference group. Thus, with three outcome categories, two separates (binary logistics regression) set of parameter estimate (the raw score coefficients and the odds ratios) are generated, one contrasting one of the outcomes to the reference category and another contrasting the other of the outcomes to the reference category. However, in the classification portion of the analysis, all outcomes categories are considered together in that classification coefficient are generated for and applied to all group, with the group achieving the highest score for each case determining the group to which that case is predicted to belong. The multinomial logistic regression is also known as the polytomous or multiclass regression model.

Let $X_{i1}, X_{i2}, \ldots, X_{ij}$ be a set k predictor, which may be continuous, nominal or ordinal, then the multinomial logistic regression model be presented as:

$$\text{Logit}(P_k(Y_{ij} \leq i | X_j)) = \text{Ln}\left(\frac{P_k(Y_{ij} \leq i|X_j)}{P_k(Y_{ij} > i|X_j)}\right) = \alpha_i + \beta_{i1}X_{i1} + \beta_{i2}X_{i2} + \ldots + \beta_{ij}X_{ij} = \alpha_i + \sum_{j=1}^{J} \beta_{ij}X_{ij}$$

(1)(Gholamreza et al., 2021)

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Where α_i, and β_{ij} , represents the constant for the crash severity level i, and the regression coefficient, respectively. $P_k(Y_{ij} \leq i/X_j)$ is the cumulative probability Y_{ij} under the conditional from of $i|/X$ regarding the crash severity level i (Y=1(fatal); Y=2(serious); Y=3(minor)) and $\sum_{i=1}^{I} P_k/X = 1$.

Thus, multinomial logistic probability model can be express as equation (2)

$$P_k(Y_{ij} \leq i|X_j) = \frac{\exp(\alpha_i + \sum_{i=1}^{I} \beta_{ij} X_{ij})}{1+\exp((\alpha_i + \sum_{i=1}^{I} \beta_{ij} X_{ij})} \quad i = 1,2,3;\ j = 1,2,\dots j \qquad (2)$$

(Gholamreza et al., 2021)

Parameters β_{ij}(j =1, 2,…j ; I = 1,2,3) are estimated using the maximum likelihood estimate (Kaplan, R.M and Saccuzo, D.P 2012). The likelihood function dependent observation can be as:

$$L(\beta) = \prod_{i=1}^{n} \prod_{j=1}^{j} P(Y = 1)\, d_{ij} \text{ where } d_{ij} = \begin{cases} 1 \text{ if } Yi = j \\ 0 \text{ if } Yi \neq j \end{cases}$$

So d_{ij} =1 if ith case belong to jth category. The parameters of a multinomial logistic regression model were determined in several ways. It is possible to take the logarithm of the function L(β) and then calculate the first partial derivatives of lnL(β) with respect to each of the estimated β_{ij} coefficient. These equations should be equated to zero and solved. Testing for statistical significance of individual regression coefficient was performed the statistics based on Wald coefficients: Wald (Z) = $\frac{\beta_k}{SSE(\beta)}$.

A multinomial logistic regression (or multinomial regression for short) is used when outcome variable being predicted is nominal and has more than two categories that do not have a given rank or order. This model can be used with many number of independent variables that are categorical or continuous. In addition to the two assumption mentioned, independence of observation, mutually exclusive and exhaustive categories of outcome variable, no multi-collinearity between independent variables, linear relationship between continuous variable and the logit transformation of the outcome variable and absent of outliers or highly influential points.

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To confirm the appropriateness of the model using multinomial logistic regression model, the likelihood ratio chi-square was performed. Test statistics was based on the difference of the logarithms of the likelihood function of the reduced model with intercept only (L_0) and the fitted model (L_1), in which p =K (J – 1) parameters were considered: LR = -2($\ln L_0$ - $\ln L_1$) χ^2_p

RESULTS AND DISCUSSION

Analysis and Interpretations

According to registered data collected from the RTC unit of FRSC Bauchi state command, 422 accidents occurred in Bauchi state from January 2021 to December 2022. Most of the accident occurred in outskirts/villages along the highways mainly on Bauchi-Jos route, followed by Bauchi-Maiduguri route. The route that accident occurred less was Bauchi-Gombe route

Table 1: Summary Statistics of Road Traffic Accident Data

		Severity	Location	Accident cause	Route	License	Vehicle Class	Presence of a female passenger	Number of injuries	Number of deaths	Vehicle type	Accident time	Accident season	Drivers gender
N	Valid	422	422	422	422	422	422	422	422	422	422	422	422	422
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		.7559	1.5166	1.1730	3.0095	1.7773	1.7227	1.5545	3.5972	.6706	2.2725	1.2109	1.5142	1.1209
Median		1.0000	2.0000	1.0000	4.0000	2.0000	2.0000	2.0000	2.0000	.0000	2.0000	1.0000	2.0000	1.0000
Minimum		.00	1.00	1.00	1.00	1.00	1.00	1.00	.00	.00	1.00	1.00	1.00	1.00
Maximum		2.00	2.00	2.00	5.00	2.00	2.00	2.00	26.00	20.00	4.00	2.00	2.00	2.00
Percentiles	25	.0000	1.0000	1.0000	1.0000	2.0000	1.0000	1.0000	1.0000	.0000	1.0000	1.0000	1.0000	1.0000
	50	1.0000	2.0000	1.0000	4.0000	2.0000	2.0000	2.0000	2.0000	.0000	2.0000	1.0000	2.0000	1.0000
	75	1.0000	2.0000	1.0000	4.0000	2.0000	2.0000	2.0000	4.2500	1.0000	3.0000	1.0000	2.0000	1.0000

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Table 2: Statistics

Variables	Frequency
Accident severity	Fatal (31.3%); serious (61.8%); minor (6.9%)
Location	Township/urban areas (48.3%); villages/outskirts (51.7%)
Accident cause	Speed (82.7%); others (17.3%)
Route	Bauchi-Jos (33.4%); Bauchi-Gombe (6.2%); Bauchi-Kano (8.8%); Bauchi-Maiduguri (29.4%); others (22.3%)
License	Valid (22.3%); not valid (77.7%)
Vehicle class	Private (27.7%); commercial (72.3%)
Presence of at least one female passenger	Yes (44.5%); No (55.5%)
Vehicle type	Car (29.9%); bus (29.6%); motorcycle (23.9%); others (16.6%)
Accident time	Daytime (78.9%); nighttime (21.1%)
Accident season	Dry season (48.6%) wet season (51.4%)
Drivers gender	Male (87.9%) female (12.1%)

Statistics: This table presents descriptive statistics for various variables related to road traffic accidents. Each row represents a different statistical measure, and each column represents a different variable.

Variables: The variables include accident severity (e.g., fatal, serious, minor), location (township/urban areas, villages/outskirts), accident cause (e.g., speed, others), route (e.g., Bauchi-Jos, Bauchi-Gombe), license validity (valid, not valid), vehicle class (private, commercial), presence of at least one female passenger (yes, no), vehicle type (e.g., car, bus, motorcycle), accident time (daytime, nighttime), accident season (dry season, wet season), and driver's gender (male, female).

Measures: For each variable, the table shows the number of valid cases (N), any missing data, the mean (average value), median (middle value), minimum and maximum values observed, and percentile values (25th, 50th, and 75th percentiles).

Table 2: Breakdown of Accident Characteristics by Percentage

Overview: This table provides a breakdown of various characteristics related to road traffic accidents in Bauchi State, presented as percentages of the total dataset.

Variables: It includes accident severity (fatal, serious, minor), location (township/urban areas, villages/outskirts), accident cause (speed, others), route (specific routes and others), license validity, vehicle class (private, commercial), presence of at least one female passenger, vehicle type (car, bus, motorcycle, others), accident time (daytime, nighttime), accident season (dry season, wet season), and driver's gender (male, female).

Percentage Breakdown: Each category within the variables is expressed as a percentage, providing insight into the distribution and prevalence of these factors within the dataset.

The summary provides an overview of descriptive statistics for the variables under investigation, offering a comprehensive understanding of our dataset's characteristics. These statistics encompass frequencies, distributions, central tendencies, quartiles, as well as maximum and minimum values. They form the foundation for interpreting and gaining insights into the determinants of accident severity in Bauchi State.

Table 3 shows the collinearity statistics of independent variables, and for every variable, the VIF is less than five (5), or the tolerance is more significant than 0.2. So, according to

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tolerance, there is no any problem with collinearity for any variable. So, variables can be used for regression models if needed.

Table 3: Collinearity statistics.

Model	Collinearity Statistics	
	Tolerance	VIF
Location	.879	1.138
Accident cause	.867	1.153
Route	.875	1.143
License	.913	1.095
Vehicle Class	.822	1.217
Presence of a female passenger	.884	1.132
Number of injuries	.878	1.139
Number of deaths	.928	1.077
Vehicle type	.823	1.216
Accident time	.944	1.059
Accident season	.882	1.134
Drivers gender	.939	1.065

Hassien Matrix Error/ Complete or Quasi-Complete Separation

The predictors number of injuries, number of fatalities and categories within the route variable were found to be exhibiting the feature. The predictor number of injuries and number of fatalities were removed and categories within the route predictor were corrected by combining them to form five (5) larger categories rather than initial eight (8) to have a complete or quasi-complete separation. The categories became the following: Bauchi-Jos, Bauchi-Gombe, Bauchi-Kano, Bauchi-Maiduguri and Others for route with low frequencies.

Likelihood Ratio Test and "p" Value

For this research, the null hypothesis states that the risk of severity of road accidents does not relate to the selected independent variables. The alternative hypothesis is the hypothesis of significance. Table 3 displays the likelihood ratio test for the selected independent variables for the dependent variables accident severity. For indicating risk or severity of road traffic accident severity by the independent variables, the p- value would be less than 0.05 to predict the dependent variable significantly.

Table 4.4 shows that all the variables are significant except license status and accident season. So, the license status and accident season have been rejected.

Table 4: Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	528.554[a]	.000	0	.
Location	540.929	12.375	2	.002
Accident cause	545.442	16.888	2	.000
Route	568.966	40.412	8	.000
License status	529.743	1.189	2	.552
Vehicle class	541.201	12.647	2	.002
Presence of at least one female passenger	537.290	8.737	2	.013
Vehicle type	545.127	16.573	6	.011
Accident time	535.791	7.238	2	.027
Accident season	530.760	2.207	2	.332
Drivers gender	538.504	9.950	2	.007

Modeling the Risk Factors Affecting Accident Severity

Table 5: Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	594.996			
Final	468.448	126.548	26	.000

Table 6: Pseudo R-Square

Cox and Snell	.259
Nagelkerke	.318
McFadden	.178

Model Interpretation

According to the likelihood ratio test, the last model is significant at 95% confidence interval. So, this model is appropriate for multinomial logistic regression, and the independent variables influence accident severity. On the model fit information from Table 4, the final model has a -2 log likelihood value of 468.448, which is statistically significant ($p < 0.05$) this implies that an individual can predict at a better than chance level using set of predictors. According to McFadden (1977), a good value of pseudo R-square for a suitable model fit ranges between 0.2 and 0.4. Table 5 shows the Nagelkerke pseudo R-square value of 0.318. It indicates that approximately 31% of the variance associated with accident severity for each of the three levels is being explained by the model. According to McFadden's referred value of R-square, the model fits the data well. Table 6 shows the parameter estimates for the multinomial logistic model.

Table 7 shows the parameter estimates which use the model to predict accident severity category. It needs emphasizing that the reference accident severity category was minor. Each of the major rows report the results of contrast between one of the other categories (fatal or serious) and the minor category. The column β provides the raw score coefficients (adjusted for the presence of the other predictors in the model) associated with each of the predictors, and the standard error (Std. Error) of these statistics is shown next to the coefficients. These partial regression coefficients are tested for statistical

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significance using the Wald test, and the outcome of these tests is shown in Sig. column. The odds ratio, which is primary part of the output is shown as Exp (β).

Table 7: Parameter estimates for the multinomial logistic model for accident severity.

Severity	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	95% Confidence Interval for Exp(B) Upper Bound
Intercept	4.562	2.196	4.316	1	.038			
Location	1.850	.580	10.158	1	.001	6.357	2.038	19.823
Drivers gender	-.258	.595	.188	1	.664	.773	.241	2.478
Accident time	.616	.567	1.180	1	.277	1.851	.610	5.621
Presence of at least one female passenger	-1.419	.549	6.679	1	.010	.242	.082	.710
Vehicle class	-1.702	.622	7.484	1	.006	.182	.054	.617
Accident cause	-.878	.707	1.542	1	.214	.416	.104	1.662
[Route=1.00]	1.704	.707	5.809	1	.016	5.496	1.375	21.971
[Route=2.00]	.901	.913	.975	1	.324	2.462	.412	14.727
[Route=3.00]	.875	.789	1.228	1	.268	2.398	.511	11.262
[Route=4.00]	1.722	.702	6.010	1	.014	5.596	1.412	22.172
[Route=5.00]	0b	.	.	0	.	.	.	.
[Vehicle type=1.00]	-.802	.895	.803	1	.370	.449	.078	2.591
[Vehicle type=2.00]	-.434	.819	.280	1	.596	.648	.130	3.227
[Vehicle type=3.00]	-1.509	.806	3.506	1	.061	.221	.046	1.073
[Vehicle type=4.00]	0b	.	.	0	.	.	.	.
Intercept	5.020	2.093	5.753	1	.016			
Location	1.389	.561	6.135	1	.013	4.010	1.336	12.035
Drivers gender	-1.272	.588	4.686	1	.030	.280	.089	.887
Accident time	-.194	.543	.128	1	.720	.823	.284	2.387
Presence of at least one female passenger	-1.465	.534	7.521	1	.006	.231	.081	.658
Vehicle class	-.760	.579	1.722	1	.189	.467	.150	1.455
Accident cause	.713	.631	1.279	1	.258	2.041	.593	7.024
[Route=1.00]	2.066	.651	10.078	1	.002	7.890	2.204	28.246
[Route=2.00]	-.252	.847	.088	1	.766	.777	.148	4.092
[Route=3.00]	-.847	.774	1.198	1	.274	.429	.094	1.954
[Route=4.00]	1.401	.656	4.564	1	.033	4.059	1.123	14.678
[Route=5.00]	0b	.	.	0	.	.	.	.
[Vehicle type=1.00]	-.622	.842	.546	1	.460	.537	.103	2.795
[Vehicle type=2.00]	-1.133	.790	2.058	1	.151	.322	.069	1.514
[Vehicle type=3.00]	-.892	.738	1.463	1	.226	.410	.097	1.739
[Vehicle type=4.00]	0b	.	.	0	.	.	.	.

The first major row labelled as Fatal contrast with Minor. The raw score coefficients associated with route (coded 1=Bauchi-Jos and 4=Bauchi-Maiduguri) and location were positive and significant, while that of presence of at least one female passenger and vehicle class were negative and significant. The odds ratio, adjusted for the other predictor variable in the model, yielded an interpretation of the dynamics of the predictor variables. For example, the categorical predictor location, the odds ratio is 0.773. This means that the odds of town being in fatal category as compared to village/outskirts, increased by 0.773 of being in minor category, controlling for other predictors. For the predictor presence of at least a female passenger, the odds ratio is 0.242. this means that the odds of female passenger in the vehicle being in fatal category as compared to not in the vehicle is reduced by 0.242 of being in minor category. For the predictor vehicle class, the odds ratio is 0.182. this means that the odds of private vehicle being in fatal category as compared to commercial is reduced by 0.182 being in minor category. Similarly, for the categorical predictor route, (coded 1=Bauchi-Jos; 2=Bauchi-Gombe; 3=Bauchi-Kano; 4=Bauchi-Maiduguri; 5=Others), the reference category is Route 5 (Others). The odd ratio of route 1 (Bauchi-Jos) is 5.496. This means that the odds of Bauchi to Jos route being in fatal category compared to Others increased by 5.496 the odds in being in minor category controlling for other predictors. In the same vein, the odds of route 4 (Bauchi-Maiduguri) is 5.596. This means that the odds of Bauchi to Maiduguri being in fatal category compared to Other increased by 5.596 the odds of being in minor category, controlling for other predictors.

The second major row labelled serious contrast with minor. The raw score coefficient associated with route, (coded 1=Bauchi-Jos and 4 = Bauchi-Maiduguri) and location was positive and significant, while that of presence of at least one female passenger and gender were negative and significant. The odds ratio, adjusted for the other predictor variable in the model, yielded an interpretation of the dynamics of the predictor variables. For example, the categorical predictor location, the odds ratio is 4.010. This means that the odds of town being in serious category as compared to village/outskirts, increased by 4.010 of being in minor category, controlling for other predictors. For the predictor presence of at least a female passenger, the odds ratio is 0.231. this means that the odds of female passenger in the vehicle being in serious category as compared to not in the vehicle is reduced by 0.231 of being in minor category. For the predictor driver's gender, the odds ratio is 0.280. this means that the odds of male driver being in serious category as compared to female driver is reduced by 0.280 being in minor category. Similarly, for the categorical predictor route, (coded 1=Bauchi-Jos; 2=Bauchi-Gombe; 3=Bauchi-Kano; 4=Bauchi-Maiduguri; 5=Others), the reference category is Route 5 (Others). The odd ratio of route 1 (Bauchi-Jos) is 7.890. This means that the odds of Bauchi to Jos route being in serious category compared to Others increased by 7.890 the odds of being in minor category controlling for other predictors. In the same vein, the odds of route 4 (Bauchi-Maiduguri) is 4.059. This means that the odds of Bauchi to Maiduguri being in serious category compared to Other increased by 4.059 the odds of being in minor category, controlling for other predictors. Table 7 shows the classification.

Table 8: Classification

Observed	Predicted			
	Fatal	Serious	Minor	Percent Correct
Fatal	55	77	0	41.7%
Serious	27	231	3	88.5%
Minor	3	22	4	13.8%
Overall Percentage	20.1%	78.2%	1.7%	68.7%

Table 8 shows the classification. It displays how well the model classifies cases into the three categories of the outcome variable. Overall predictive accuracy is 68.7%. Those

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falling in the serious category were most accurately predicted (88.8%), then those falling in the fatal category were the next most accurately predicted (41.7%), while those in minor category were the least accurately predicted.

CONCLUSION

This study in Bauchi state employed logistic regression to analyze factors influencing road traffic accident severity, identifying eight variables—accident cause, route, vehicle type, location, presence of at least one female passenger, accident time, vehicle class, and driver's gender—as significantly impacting accident severity across fatal, serious, and minor categories. These factors encompass environmental-related (accident time), road-related (route, location), driver-related (driver's gender), vehicle-related (vehicle type, vehicle class, presence of female passenger), and accident-related factors (accident cause). The findings underscore the model's efficacy in predicting accident severity, offering insights for targeted interventions to enhance road safety and mitigate the impact of these factors on accident outcomes.

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