IOSR Journal of Environmental Science, Toxicology and Food Technology (IOSR-JESTFT)
e-ISSN: 2319-2402,p- ISSN: 2319-2399.Volume 16, Issue 1 Ser. II (January 2022), PP 14-23
www.iosrjournals.org

Comparative Analysis of Motor Vehicle Traffic Fatality Rate in Metropolitan and Non-Metropolitan Population of Alabama

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Reduction of automobile crash death was ever amongst the best health achievement of the 20th century. However, quite 32,000 are killed and a couple of million are injured annually from automobile crashes. The purpose of this study is to compare and analyse motor vehicle crash fatality rate in both metropolitan and non-metropolitan areas of Alabama. Data obtained from the US Department of Health and Human Services, National Highway Traffic Safety Administration and US Department of Transportation between 2005 to 2018. Regression analysis was used in this study to identify the relationships between MVT fatality rate and various factors like speed driving, blood alcohol concentration (BAC), gender, age, and role of daytime, night-time, weekdays, and weekends. It helps understand the fictional interaction and accuracy between factors or variables. The multivariate linear regression analysis is performed to investigate the effect of individual factors in this study. Descriptive analysis is also used to understand the MVT fatality rate of metropolitan and non-metropolitan populations of Alabama from 2005 to 2019. The result reveals that out of the total motor vehicle fatality which occurred during the period of review, 63% was from non – metropolitan (rural), 36.4% from metropolitan (urban) while 0.23% was unknown. Conclusively, over speeding, driving under influence of alcohol, driver -inexperience, breaking roadway rules and regulations are some of the major causes of high motor vehicle fatality rate in the state. There is need to implement more stringent policy to encourage drivers in enforcing traffic regulation to reduce loss of property and lives.

Key Words – *Metropolitan, nonmetropolitan, exploration, MVC Motor Vehicle Collisions, MVT Motor Vehicle Traffic, Alcohol Positive (AP)*

Date of Submission: 14-01-2022 Date of Acceptance: 29-01-2022

I. Introduction

The lives of numerous individuals and societies have been improved due to the use of automobiles, but the advantages have come at a cost. Although the number of lives lost in motor accidents has decreased in high-income nations in recent years, the burden of motor traffic injury in terms of societal and monetary costs is increasing significantly for most of the global population (Ameratunga et al., 2006). Every year, motor vehicle fatalities result in more than 1.2 million deaths and considerably more non-fatal injuries globally (World Health Organization, 2015), significantly impacting the health and well-being of injured victims and their families (Donaldson et al., 2009).

In the United States, motor vehicle collisions (MVCs) constitute the largest cause of mortality. For decades, road traffic accidents have been a primary cause of unnatural death in the United States. According to the National Highway Traffic Safety Administration (2015), 32,719 persons were killed in motor vehicle accidents in the United States in 2013, the equivalent of one person killed every 16 minutes. The causes of car accidents are diverse, but they are largely determined by the qualities of the drivers. The roadway design components and drivers have been highlighted as the two key factors influencing the occurrence of traffic accidents (Abdel-Aty and Radwan, 2000). The study investigated the influence of driver age groups and gender on the occurrence of accidents, as well as their correlations with AADT (Annual Average Daily Traffic), segment length, median, and lane width. Aside from the geometric elements of the roadway and environmental factors, age, gender, skill level (McGwin & Brown, 1999), level of experience (McCartt et al., 2003), risk-taking behaviours (Rolison et al., 2014), use of alcohol and drugs, drivers' fatigue, drivers' distraction due to use of cell phone are all factors associated with driver's demographic characteristics and behaviours (Kassu and Anderson, 2019). Excessive speed (Gonzales et al., 2005; Lam, 2003), driving carelessly (Lam, 2003), and traffic offences (Gonzales et al., 2005), as well as drugs and alcohol (Bingham et al., 2008), have all been associated to accidents involving young drivers. Lack of respect/concern for other motorists, impatience and negligence, overloading of cars, fatigue, poor vision, and frequent disobedience of road traffic signs by road users are also some of the reasons for motor accidents, according to Afolabi and Gbadamosi (2017). More than 12,000 MVC fatalities comprised motorists with positive blood alcohol concentration (BAC) in 2017. In 2016, 37,461 persons died in motor vehicle accidents, with 10,497 (28%) of them being alcohol-related (NHTSA, 2017). Every year, more than 32,000 people have been killed and (two) 2 million are injured in motor vehicle incidents, according to Naimi et al (2018). For many years, the fatality rate from motor vehicles in the United States has been a serious issue. This study examines motor vehicle fatality rate by month, the number of crashes reported, vehicles involved and the number of persons who lost their lives between 2004 and 2018. It further examines the number of fatalities that are related to high alcohol blood concentration over the same period.

II. Literature Review

As a result of the rising number of fatalities and injuries caused by motor vehicle incidents each year, road safety has become a major global problem. (Adanu et al, 2018). Numerous published studies (Ansari et al., 2000; Odero et al., 2003; Vanlaar and Yannis, 2006; Shaw and Sichel; Afolabi and Gbadamosi, 2017) have concentrated on the causal association between traffic conditions, driver situations such as drunken driving, driver behaviour, age, gender, and atmospheric condition such as precipitation, rain, snow, fog, etc and traffic accident rates in various populations. Some of these studies utilized techniques such as the Bayesian model (Guo et al., 2018), regression analysis (Ashraf et al., 2019), Poisson model (Guo et al., 2018), Cochran's Q test, Analysis of Variance (Rolison et al., 2018), and latent class analysis (Rolison et al., 2018; Adanu et al., 2018).

Clark and Cushing (2004) discussed how alcohol affects people's behaviour, including how it impairs thinking, judgment, and motor coordination, all of which contribute to traffic accidents. Alabama has the fifth (5th) highest rate of drunk driving fatalities, according to Alabama News Network on December 28, 2018. However, it has been observed throughout time that the rate in rural populations is substantially higher than in metropolitan areas. Long periods of travel in rural populations have been related to the likelihood of serious collisions.

Culhane et al. (2019) focused their investigation on drivers, by considering baseline parameters such as alcohol positive (AP) and alcohol negative (AN) individuals and comparing them using logistic regression for categorical data and Student's t-test for continuous data. Their hypothesis was that alcohol makes MVC less survivable, and they concluded that when driving while inebriated, there is larger chance of MVC and lower chance of survival.

In Louisiana, Zhang (2010) investigated and analysed the elements that influence the severity of highway crashes. The severity of the crash was predicted using Ordered Mixed Logit. The gender and age of the driver, vehicle speed, alcohol consumption, seat belt usage, whether the driver was ejected from the vehicle, whether the crash was a head-on collision, whether an airbag was deployed, and whether one of the vehicles was following too closely behind another vehicle were all identified as contributing factors.

Keller (2003) used an ordered probit model to assess the seriousness of an incident and found that accidents involving motorist have the highest risk of serious injury. Left turn, angle, head-on, and rear-end accidents all result in increased injury severity levels in motor vehicle accidents. The projected injury level was found to be lower after the minor road was divided (a median) and the speed limit was increased.

Ratanavaraha and Suangka (2014) investigated the factors that influence the severity of accidents on Thailand's expressways. Average speed on the road section, average traffic volume per day, length of time, environmental conditions, physical characteristics of accident region, and reason of accident are among the independent variables assessed. According to the findings of the study, the speed limit is the only element that influences the severity of expressway accidents.

Li and Tay (2014) developed a scheme for educating drivers and mitigating one possible cause of traffic accidents: drivers' failure to recall highway safety rules and signs, as well as knowledge gained during their written and road test preparation stages. The proposed method employs digital games to inspire targeted drivers to participate in refresher training on safe driving for both young and seasoned drivers.

Usman et al. (2016) investigated the frequency of injury and severity of crashes on 31 roads in Ontario, Canada, between 2001 and 2003, using several logistic regression models and several covariates such as asphalt pavement conditions, geometric variables, vehicle and driver characteristics (age, gender, alcohol use). According to the findings, there is an average rise of 0.297 from no injury to fatality for every percentage change in the driver's age, and a 0.121 increase from no injury to moderate injury for every percentage change in the driver's age. In terms of gender, female drivers are 46 per cent more likely than male drivers to get minor injuries. Alcohol use was also proven to have a greater impact on the likelihood of a crash, with a 0.80 increase in major injury and mortality.

Al-Balbissi (2003) performed a statistical study on variables such as distance covered, environmental conditions, driver's age, and gender from low, middle, and high-income regions to investigate the association between road accidents and driver gender. In typical driving conditions, male drivers are connected with a considerably greater accident rate, according to this study. In changing atmospheric condition circumstances, however, the differences in accident rates between male and female drivers are substantially minimized. However, for a variety of reasons, the conclusions of the aforementioned studies cannot be directly applied to Alabama. There's a decent chance the data gathering isn't clear, complete, or reliable because most of the data is collected by police stations or insurance companies. As a result, numbers from both victims and offenders may be overstated (Cooper 1994; Brayley et al., 2011).

Furthermore, many times when the parties involved strike an agreement, accidents are not recorded. The analysis is carried out on a specific area, such as a city or country, with various demographic characteristics. Accidents can also be influenced by the infrastructure, economy, culture, social norms, and gender discrimination that exist in a certain place. As a result, a single analysis cannot be applied to all sectors. This is why a different statistical analysis is necessary, taking into account Alabama's environmental, Atmospheric conditions, and driving circumstances to better understand the components that contribute to road accidents. However, this study examines motor vehicle fatality rate by year, the number of crashes reported, vehicles involved and the number of persons who lost their lives between 2004 and 2018. It further examines the number of fatalities that are related to high blood alcohol concentration over the same period using comparative analysis.

III. Methodology

3.1 About the Study Area

According to the United States Census Bureau (2020), Alabama has a land area of 50,645.33 square miles and a population of around 4.90 million people in 2019 with 48.3 percent of the population being male while the remaining 51.7 percent of the population is female. The distribution of metropolitan and nonmetropolitan statistical areas is visualized in Figure 1.

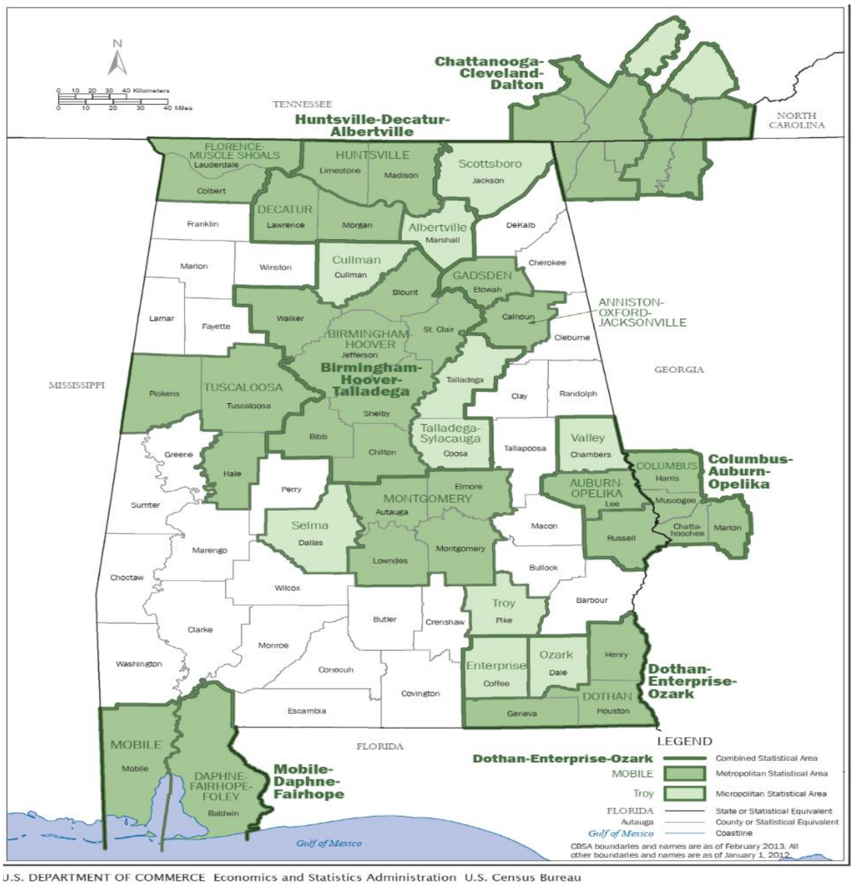

Figure 1: Distribution of metropolitan and nonmetropolitan statistical areas of Alabama
(Source: United States Census Bureau, 2020)

3.2 Data collection

The present study is based on data obtained from the Fatality Analysis Reporting System Database of National Highway Traffic Safety Administration between 2005 and 2019, comprising data on motor traffic fatality happening during weekdays and weekends, daytime, and night-time fatality occurrence due to speed driving, high blood alcohol concentration (BAC), gender involved in the crashes. The number of people who died in such crashes from 2005 to 2019 in metropolitan and non-metropolitan areas of Alabama were included.

3.3 Data Analysis

Regression analysis was used in this study to identify the relationships between MVT fatality rate and various factors like speed driving, blood alcohol concentration (BAC), gender, age, and role of daytime, night-time, weekdays and weekends. Regression analysis is a method used to examine the interaction between groups of factors. It helps understand the fictional interaction and accuracy between factors or variables. The multivariate linear regression analysis is performed to investigate the effect of individual factors in this study.
Descriptive analysis is also performed to understand the MVT fatality rate of metropolitan and non-metropolitan populations of Alabama from 2005 to 2019.
The fatality rate is expressed as:

$$= \frac{Number\ of\ death\ in\ motor\ traffic\ fatality}{Total\ number\ of\ people\ involved\ in\ motor\ traffic\ fatality} \quad (1)$$

As mentioned by Chatterjee and Hadi (2015), multiple regression is considered to examine the impact of two or more factors or variables on the output to draw out meaningful knowledge from the data. For example, studying the effect of Atmospheric conditions, gender, speed driving on the fatalities, which gives a better knowledge of the root problem. Multivariate regression is performed to draw conclusions based on the collective influence of various factors. The regression model is given as,

$$y = constant + \beta_1 x_1 + \beta_2 x_2 +, \dots \dots \dots + \beta_n x_n + \mu \quad (2)$$

where y is a dependent variable, constant is an intercept, β values represent coefficients for regressors x and μ denotes error constant to show the discrepancy or failure of the data model. The dependent parameter y stands for the fatality rate, which is determined by x variables such as BAC, driver gender, speed driving etc. However, μ reflects a part of the accidents that these factors cannot explain.
The p-value and R^2 are utilized to assess the regression precision and interpret the findings. In a model, the - value is used to test the hypothesis. The marginal significance level is another term for it (Davidson and MacKinnon, 1981). It tests the null hypothesis Ho, which states that the predictions and regressors have no meaningful relationship. A low - value indicates that the prediction is accurate and that the null hypothesis can be dismissed. The goodness-of-fit index, often known as R^2, is determined in (Chatterjee and Hadi, 2015) as follows:

$$R^2 = 1 - \frac{SSE}{SST} \quad (3)$$

Where,

$$SSE = \sum \quad (y_i - \underline{y}_i)^2 \quad (4)$$

$$SST = \sum \quad (y_i - \underline{y}_i)^2 \quad (5)$$

where SSE stands for the sum of squared residuals or errors while SST represents a total sum of squared deviations of y from its mean value. The value of R^2 varies between 0 and 1 (Wan, 2013). If R^2 is close to 1 it implies that the variables are perfectly related with perfect goodness of fit. Conversely, if R^2 approaches 0, it then infers that there is no relationship between the given variables and the regressors do not explain the prediction.

IV. Analysis and Results

The fatality rate of several factors considered including blood alcohol concentration (BAC), driving speed, gender, day of the week, time of the day considered in this study was calculated.

4.1 Exploratory data analysis

The objective of this study is to study the motor traffic fatality rate of metropolitan and non-metropolitan populations of Alabama from 2005 to 2019. Table 1 displays the mean fatality rate of metropolitan contributing factors of fatality rate from 2005 to 2019. It was observed that BAC (0.478), speed driving (0.478), male drivers (0.473) contributed highly to the metropolitan fatality rate while female drivers (0.388) had the least contribution over the years. Figure 2 plots the series of metropolitan and non-metropolitan populations of Alabama from 2005 to 2019. The fatality rate for metropolitan was observed to be at its lowest (0.391) in 2007 but had a significant increase to peak (0.430) by a total of 6.9% in 2009 which was caused majorly by factors such as BAC, speed driving, male and female drivers, weekend and nighttime driving. Reduction in fatality rate of female drivers and daytime was one of the factors that caused a significant decrease in metropolitan fatality rate by 5% in 2010 until 2012 while there was a gradual increase in fatality rate by 5% from 2014 to 2017 and a slight decrease by 0.5% from 2018 to 2019.

The mean fatality rate of non-metropolitan contributing factors in Table 1 shows that BAC was the highest contributor to the fatality rate in non-metropolitan populations of Alabama while female drivers were the

least contributor. As displayed in figure 2, the non-metropolitan populations of Alabama had their highest (0.533) fatality rate in 2013 majorly due to the high fatality rate of BAC, speed driving, male drivers and night time driving while the female drivers were the least contributor to the fatality rate. Reduction in fatality rate of these factors also leads to a substantial decrease by a total of 6.5% from 2014 to 2015 where the lowest fatality rate (0.468) was observed but there was a gradual fluctuation of fatality rate from 2016 to 2019.
Table 2 displays the cumulative mean of MVT fatality rate of metropolitan and non-metropolitan populations of Alabama from 2005 to 2019, it can be observed that non-metropolitan populations had a higher fatality rate of 6.5% than metropolitan populations of Alabama over the years.

Table 1: Mean fatality rate of MVT factors of the metropolitan and non-metropolitan population of Alabama from 2005 to 2019

	Mean fatality rate	
Factors	**Metropolitan**	**Non-metropolitan**
BAC	0.478	0.598
Speed	0.478	0.569
Male	0.473	0.528
Female	0.388	0.460
Weekday	0.424	0.488
Weekend	0.424	0.502
Daytime	0.398	0.464
Night-time	0.450	0.531

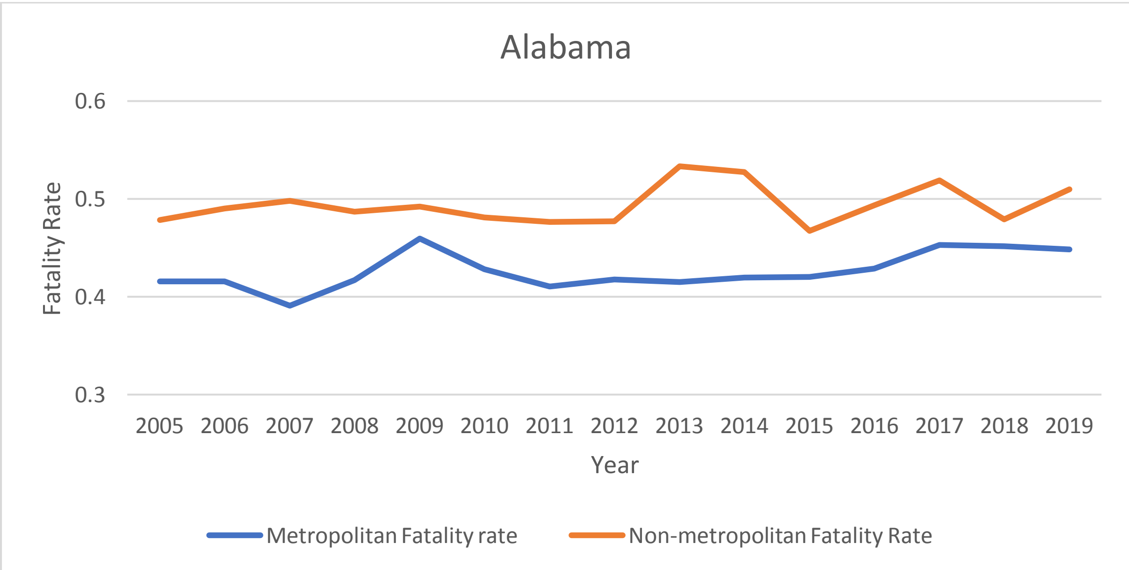

Figure 2: Plot series of MVT Fatality rate of Metropolitan and Non-metropolitan populations of Alabama

Table 2: Fatality rate of Metropolitan and Non-metropolitan populations of Alabama

	Fatality rate			
Years	**Metropolitan**	%Change	**Non-metropolitan**	%Change
2005	0.416		0.479	
2006	0.415	-0.1%	0.490	1.1%
2007	0.391	-2.4%	0.498	0.8%
2008	0.417	2.6%	0.487	-1.1%
2009	0.460	4.3%	0.492	0.5%
2010	0.428	-3.2%	0.481	-1.1%
2011	0.410	-1.8%	0.476	-0.5%

2012	0.417	0.7%	0.477	0.1%
2013	0.415	-0.2%	0.533	5.6%
2014	0.420	0.5%	0.528	-0.5%
2015	0.420	0.0%	0.468	-6.0%
2016	0.429	0.9%	0.493	2.5%
2017	0.453	2.4%	0.519	2.6%
2018	0.452	-0.1%	0.479	-4.0%
2019	0.448	-0.4%	0.510	3.1%
Mean	**0.426**		**0.494**	

4.2 Model development and analysis of relationship

Correlation and regression analysis is performed to investigate the relationship and the effect of the variables on the fatality rate of Alabama. From table 3, the variables were correlated to under the relationship between them. It can be observed that there is a high correlation between the following variable: Night-time and BAC, speed and daytime, male drivers and weekend, male drivers and night-time, daytime and weekend, night-time and weekend. According to table 3, all variables have a strong relationship with metropolitan fatality rate except the female drivers, which had a small relationship.

From the regression statistics in Table 4**,** it can be observed that R^2= 0.9970 which indicates that 99.7% variability of metropolitan fatality rate can be explained by the entire setup of the variables or factors that causes MVT. The model of the regression is statistically significant as can be observed from ANOVA in Table 5. The metropolitan fatality rate predictive model was also obtained from the regression analysis and expressed as follows;

Metropolitan fatality rate = $2.502 - 0.001X_1 - 0.057X_2 - 0.003X_3 + 0.175X_4 + 0.094X_5 + 0.848X_6 + 0.563X_7 + 0.060X_8 + 0.016X_9$

From the analysis in table 6, all variables have a strong relationship with the non-metropolitan fatality rate except the female drivers, which had a medium relationship. The regression statistics in Table 7 showed that R^2= 0.9986 which indicates that 99.8% variability of non-metropolitan fatality rate can be explained by the entire setup of the variables or factors that causes MVT. The model of the regression is statistically significant as can be observed from ANOVA in Table 8. A predictive model was also determined for non-metropolitan fatality rate, expressed as;

Non-metropolitan fatality rate= $-0.43732 - 0.0002X_1 - 0.00223X_2 - 0.00502X_3 + 0.01596X_4 + 0.04071X_5 + 0.5109X_6 + 0.3510X_7 + 0.08798X_8 + 0.09066X_9$

Table 3: correlation analysis of metropolitan fatality rate variables

	BAC	*Speed*	*Male*	*Female*	*Weekday*	*Weekend*	*Daytime*	*Night-time*	*Metro-Fatality rate*
BAC	1.000								
Speed	0.170	1.000							
Male	0.469	0.375	1.000						
Female	0.391	0.026	-0.114	1.000					
Weekday	0.433	0.450	0.323	0.244	1.000				
Weekend	0.489	0.439	0.701	0.008	0.088	1.000			
Daytime	0.064	0.585	0.112	0.170	0.667	0.189	1.000		
Night-time	0.776	0.194	0.746	0.171	0.324	0.736	-0.131	1.000	
Metro-Fatality rate	0.588	0.594	0.647	0.199	0.756	0.709	0.611	0.682	1.000

Table 4: Regression Statistics of metropolitan fatality rate variables

Regression Statistics	
Multiple R	0.9985

R Square	0.9970
Adjusted R Square	0.9917
Standard Error	0.0017
Observations	15

Table 5: Analysis of variance for metropolitan fatality rate

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	0.005067	0.000563	187.3631	8.79E-06
Residual	5	1.5E-05	3E-06		
Total	14	0.005082			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	2.501563	0.855445	2.924281	0.03285
Year	-0.00127	0.000432	-2.94387	0.032112
BAC	-0.05687	0.029219	-1.94622	0.109198
Speed	-0.00319	0.019919	-0.16021	0.878984
Male	-0.17519	0.060974	-2.87326	0.034862
Female	-0.09375	0.043825	-2.13917	0.085407
Weekday	0.848192	0.179509	4.725057	0.005219
Weekend	0.562722	0.131015	4.295105	0.007751
Daytime	0.060119	0.16596	0.36225	0.731973
Night-time	0.015797	0.185298	0.085253	0.935369

Table 6: correlation analysis of non-metropolitan fatality rate variables

	BAC	*Speed*	*Male*	*Female*	*Weekday*	*Weekend*	*Daytime*	*Night-time*	*Non-metro Fatality Rate*
BAC	1.000								
Speed	0.357	1.000							
Male	0.503	0.605	1.000						
Female	0.134	0.018	0.470	1.000					
Weekday	0.580	0.595	0.705	0.052	1.000				
Weekend	0.318	0.572	0.604	0.571	0.100	1.000			
Daytime	0.389	0.931	0.664	0.100	0.638	0.564	1.000		
Night-time	0.389	-0.015	0.557	0.642	0.377	0.406	-0.050	1.000	
Non-metro Fatality Rate	0.593	0.764	0.877	0.447	0.757	0.722	0.789	0.564	1.000

Table 7: Regression Statistics of non-metropolitan fatality rate variables

Regression Statistics	
Multiple R	0.99933
R Square	0.99867
Adjusted R Square	0.99627
Standard Error	0.00122

Observations	15

Table 8: Analysis of non-metropolitan fatality rate variables

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	0.00557	0.000619	416.295	1.2E-06
Residual	5	7.43E-06	1.49E-06		
Total	14	0.005577			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.43732	0.52224	-0.83738	0.44056
Year	0.00020	0.00026	0.77842	0.47153
BAC	0.00223	0.03222	0.06915	0.94755
Speed	-0.00502	0.03777	-0.13299	0.89939
Male	-0.01596	0.05534	-0.28847	0.78456
Female	0.04071	0.05099	0.79850	0.46081
Weekday	0.51090	0.11115	4.59671	0.00586
Weekend	0.35100	0.09145	3.83796	0.01215
Daytime	0.08798	0.10172	0.86488	0.42664
Night-time	0.09066	0.06857	1.32205	0.24340

V. Findings and Conclusions

5.1 Findings

The study revealed that the MVT fatality rate of metropolitan and non-metropolitan populations of Alabama over the period under study had a strong positive correlation with the factors considered except female drivers. The female drivers of metropolitan population had a weak positive correlation, on the other hand, female drivers of non-metropolitan populations had a medium positive correlation with the MVT fatality rate of metropolitan. This indicates that the males are the major victims of MVT fatality in the Alabama population.

Secondly, the period under study revealed in metropolitan populations, BAC (0.478), speed driving (0.478) were the highest contributing factors to MVT fatality rate while the female drivers were the least contributor (0.388). For non-metropolitan populations, BAC (0.598) was the highest contributing factor to MVT fatality rate, speed (0.569) is the second while female drivers with (0.460) is the least contributing factor to MVT fatality rate. This indicates that BAC and speed are the critical factors causing MVT fatality in Alabama.

Moreover, from the overall mean of MVT fatality rate of the period under study, it was observed that the MVT fatality rate of non-metropolitan (0.494) is greater than the MVT fatality rate of metropolitan (0.426) populations by 6.8%.

Furthermore, the independent variables of metropolitan and non-metropolitan populations of Alabama account for 99.7% and 99.8% of the change in MVT fatality rate of metropolitan and non-metropolitan respectively.

Finally, the study revealed that all the regression models are best at explaining and predicting the MVT fatality rate in metropolitan and non-metropolitan populations since they have a very high R^2 and are found to be statistically significant.

5.2 Conclusion

In this paper, several factors which may cause MVT fatality were analysed in the metropolitan and non-metropolitan populations of Alabama. The MVT data was obtained from NHSA to carry out comparative analysis using descriptive analysis and inferential analysis. The study revealed that the MVT fatality rate is higher in the non-metropolitan than metropolitan Alabama while such crashes are related to high blood alcohol contraction (BAC) and speed driving. Continuous education of drivers to adhere to all traffic rules, operate within the posted speed and always drive with full concentration so that both metropolitan and non-metropolitan highways can be made safer to use and travel for everybody. Along the lines of this study, the state government of Alabama needs to review alcohol policy to reduce excess death and loss of property.

Reference

[1]. Abdel-Aty, M., Radwan, A.E., (2000). Modeling traffic accident occurrence and involvement. Accid. Anal. Prev. 32, 633–642

[2]. Adanu, E.K., Penmetsa, P., Jones, S. and Smith, R., (2018). Gendered analysis of fatal crashes among young drivers in Alabama, USA. *Safety*, *4*(3), p.29.

[3]. Afolabi, J. A. - Gbadamosi Kolawole, T., (2017) Road traffic crashes in Nigeria: Causes and consequences. Transport & Logistics: The International Journal, 2017; Volume 17, Issue 42, April 2017, ISSN 2406-1069

[4]. Ameratunga S, Hijar M, Norton R.(2006) Road-traffic injuries: Confronting disparities to address a global-health problem. [Last cited on 2011 June 27];*Lancet.* 2006 367:1533–40. Available from, http://www.thelancet.com/journals/lancet/article/PIIS0140-6736 (06)68654-6/fulltext

[5]. Al-Balbissi, A. H (2003), "Role of gender in road accidents. Traffic injury prevention" 4(1):64–73. https://doi. org/10.1080/15389580309857 PMID: 14522664

[6]. Ansari S, Akhdar F, Mandoorah M, Moutaery K, (2000), "Causes and effects of road traffic accidents in Saudi Arabia. Public health" 114(1):37–39. https://doi.org/10.1038/sj.ph.1900610 PMID: 10787024

[7]. Ashraf I, Hur S, Shafiq M, Park Y (2019) Catastrophic factors involved in road accidents: Underlying causes and descriptive analysis. PLoS ONE 14(10): e0223473. https://doi.org/10.1371/ journal. pone.0223473

[8]. Brayley H, Cockbain E, Laycock G. (2011). The value of crime scripting: Deconstructing internal child sex trafficking. Policing: A Journal of Policy and Practice.; 5(2):132–143. https://doi.org/10.1093/police/ par024

[9]. Bingham, C.R., Shope, J.T., Zhu, J., (2008). Substance-involved driving: predicting driving after using alcohol, marijuana, and other drugs. Traffic Inj. Prev. 9 (6), 515–526.

[10]. Cooper PJ (1994). Estimating overinvolvement of seat belt nonwearers in crashes and the effect of lap/shoulder restraint use on different crash severity consequences. Accident Analysis & Prevention.; 26 (2):263–275. https://doi.org/10.1016/00014575(94)90096-5

[11]. Chatterjee S, Hadi AS. (2015) Regression analysis by example. John Wiley & Sons.

[12]. Culhane, J., Silverglate, B. and Freeman, C., 2019. Alcohol is a predictor of mortality in motor vehicle collisions. *Journal of safety research*, *71*, pp.201-205.

[13]. Clark, D.E. and Cushing, B.M., 2004. Rural and urban traffic fatalities, vehicle miles, and population density. *Accident Analysis & Prevention*, *36*(6), pp.967-972.

[14]. Donaldson, L.H., Brooke, K., Faux, S.G., 2009. Orthopaedic trauma from road crashes: is enough being done? Aust. Health Rev. 33 (1), 72–83

[15]. Davidson R, MacKinnon JG. (1981) Several tests for model specification in the presence of alternative hypotheses. Journal of the Econometric Society.; p. 781–793. https://doi.org/10.2307/ 1911522

[16]. Guo Y, Li Z, Wu Y, Xu C (2018) Evaluating factors affecting electric bike users' registration of license plate in China using Bayesian approach. Transportation research part F: traffic psychology and behaviour. 59:212 221https://doi.org/10.1016/j.trf.2018.09.008

[17]. Guo Y, Osama A, Sayed T. (2018) A cross-comparison of different techniques for modeling macro-level cyclist crashes. Accident Analysis & Prevention.113:38–46. https://doi.org/10.1016/j.aap.2018.01.015

[18]. Gonzales, M.M., Dickinson, L.M., DiGuiseppi, L.M., Lowenstein, S.R., (2005). Student drivers: A study of fatal motor vehicle crashes involving 16-year-old drivers. Ann. Emerg. Med. 45 (2), 140–146

[19]. Hadland SE, Xuan Z, Sarda V, et al (2017). Alcohol policies and alcohol-related motor vehicle crash fatalities among young people in the U.S. Pediatrics. 2017;139(3):e20163037. https://doi.org/10.1542/peds.2016-3037

[20]. Kassu, A. and Anderson, M., 2019. Analysis of severe and non-severe traffic crashes on wet and dry highways. *Transportation research interdisciplinary perspectives*, *2*, p.100043.

[21]. Keller, J.(2003) Analysis of Type and Severity of Traffic Crashes at Signalized Intersections Using Tree-Based

[22]. Li, Q and Tay, R., (2014). Improving drivers' knowledge of road rules using digital games. Accident. Anal. Prev. 65, 8–10.

[23]. Lam, L.T., (2003). Factors associated with young drivers' car crash injury: comparisons among learner, provisional, and full licensees. Accid. Anal. Prev. 35 (6), 913–920

[24]. McGwin, G., Sims, R.V., Pulley, L., Roseman, J.M., (2000). Relations among chronic medical conditions, medications, and automobile crashes in the elderly: A population-based case control study. Am. J. Epidemiol. 152 (5), 424–431

[25]. McCartt, A.T., Shabanova, V.I., Leaf, W.A., (2003). Driving experience, crashes and traffic citations of teenage beginning drivers. Accid. Anal. Prev. 35 (3), 311–320

[26]. McGwin, G., Brown, D.B., (1999). Characteristics of traffic crashes among young, middleaged, and older drivers. Accid. Anal. Prev. 31 (3), 181–198.

[27]. NHTSA's National Center for Statistics and Analysis, (2015), Fatalities of vehicle nonoccupants in wheelchairs struck by motor vehicles. (Traffic Safety Facts Crash Stat. Report No. DOT HS 812 185). Washington, DC: National Highway Traffic Safety Administration

[28]. National Highway Traffic Safety Administration(2017) Traffic Safety Facts: Alcohol Impaired Driving. https://crashstats.nhtsa.dot.gov/Api/ Public/ViewPublication/812630. Published 2018. Accessed January 31, 2019

[29]. Naimi TS, Xuan Z, Sarda V, et al.(2018) Association of state alcohol policies with alcohol-related motor vehicle crash fatalities among U.S. adults. JAMA Intern Med.;178(7):894–901. https://doi.org/10.1001/ jamainternmed.2018.1406.

[30]. Odero W, Khayesi M, Heda P.(2003) Road traffic injuries in Kenya: magnitude, causes and status of intervention. Injury control and safety promotion.; 10(1-2):53–61. https://doi.org/10.1076/icsp.10.1.53. 14103 PMID: 12772486

[31]. Rolison, J.J., Hanoch, Y., Wood, S., Pi-Ju, L., (2014). Risk-taking differences across the adult lifespan: A question of age and domain. J. Gerontol. Ser. B: Psychol. Sci. Soc. Sci. 69, 870–880.

[32]. Rolison, J.J., Regev, S., Moutari, S. and Feeney, A., 2018. What are the factors that contribute to road accidents? An assessment of law enforcement views, ordinary drivers' opinions, and road accident records. *Accident Analysis & Prevention*, *115*, pp.11-24.

[33]. Regression and Ordered Probit Models, (2003), A thesis submitted to the University of Central Florida, Orlando, FL,

[34]. Ratanavaraha, V & Suangka, S. (2014), "Impacts of Accident Severity Factors and Loss Value of Crashes on Expressways in Thailand", International Association of Traffic and Safety Science Research 37, 130-136

[35]. Shaw L & Sichel, H. S. (2013), "Accident proneness: Research in the occurrence, causation, and prevention of road accidents". Elsevier.

[36]. Usman, T, Fu, L & Miranda-Moreno, L.F. (2016). "Injury severity analysis: comparison of multilevel logistic regression models and effects of collision data aggregation", Journal of Modern Transportation 24(1): 73-87

[37]. U. S. Census Bureau (2021). 2020 state-based Metropolitan and Micropolitan statistical Areas Maps. The United States Census Bureau. https://www2.census.gov/programs-surveys/metro-micro/reference-maps/2020/state-maps/01_Alabama_2020.pdf

[38]. Vanlaar W & Yannis G (2006), "Perception of road accident causes. Accident Analysis & Prevention".; 38(1):155–161. https://doi.org/10.1016/j.aap.2005.08.007

[39]. Wan A.(2013) Basic Concepts of Regression Analysis

[40]. World Health Organization, (2015). Global Status Report on Road Safety 2015. Available at: http://www.who.int/violence_injury_prevention/road_safety_status/2015/en/. (Accessed December 20, 2017).

[41]. Zhang H., (2010), Identifying and Quantifying Factors Affecting Traffic Crash Severity in Louisiana, A dissertation submitted to Louisiana State University

Abimbola Babatunde. "Comparative Analysis of Motor Vehicle Traffic Fatality Rate in Metropolitan and Non-Metropolitan Population of Alabama." *IOSR Journal of Environmental Science, Toxicology and Food Technology (IOSR-JESTFT)*, 16(01), (2022): pp 14-23.