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Analysis of Criminal Cases in Adamawa State, Nigeria

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ABSTRACT

The Occurrence of Criminal act worldwide is on the increase, curbing the menace of Crime effect to humanity has been a thing of concern, Adamawa state-Nigeria not excluded. The results show that Crime rate is on the increase and that the Age group that most involved in criminal act is between the Ages 16 – 35. Crime incidence in the state varies over the years given the age-group (i.e. Crime depends on year of occurrence, so also the criminals' age group). Further analysis show that the all possible two-way interactions between crime, year of occurrence and gender (CY.CG.YG) in the first case is most appropriate for assessing crime cases in the state since it has the least AIC value for the first analysis while the model of association between crime cases and age-group independent of gender (CA.G) has the least AIC, and thus, is accepted to be the best model.

Keywords: Crime rates, Log-linear, Criminal cases, Akaike Information criterion (AIC),Crime incidence.

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1. INTRODUCTION

Nigeria has one of the alarming crime rates in the world (Financial, 2011). In Yola, Adamawa state, crime is challenging social vice. Crimes like armed robbery, breaking of homes and industries, rapping, arson, killing, and so on, are the events of the now. Others also include; burglary, pick pocket, destruction of properties, looting, assassination, examination malpractices and mostly recently, the insurgence of bombing and kidnapping by Boko Haram in North-Eastern parts of Nigeria of which Adamawa state is inclusive. The negative effect of these include death of the inhabitants of Adamawa state, increase in the rate of internally displaced persons, living in serious tension, loss of businesses and investment opportunities, and farm products etc. The question is: why is crime getting worse on a daily basis?

Crime is committed by persons when both psychological and social reasoning combine to create such intense feeling as to throw away any hope they have left and release their anger in a devastating way. Some causes of crime are; lack of parental care or neglect, needs, social environment, peer group influence, spiritual undertone etc. But the reason behind crime varies on the background of the mental disorder, traumatic events, individual or group interest etc. Every individual differs in looks, minds, personality and ideas. And this makes it impossible to detect any two or more persons, and also difficult to know who is a criminal. Other reasons may include high levels of unemployment, low labor utilization, high level income and asset inequality, high levels of poverty, immigration etc.

There are evidences, according to Farrington (2007) that children from broken homes may not get proper monitoring and that those from poor homes may not get proper feeding and get necessary provisions for day to day living including school needs and hence they tend to find alternative means to provide these necessities, as the result, the alternative means to them are to involve in criminal offences. Ahmed (2000) observed that crime results from economic structure of the society, he also opined that the gap between the rich and the poor in any society creates crime mostly against property. By this, one needs to re-orientate the society against the syndrome of materialism.

Adamawa State has witnessed a substantial increase on crime rate in recent times. Crime has affected humanity and properties greatly; such as murder, robbery, kidnapping, arson, rape, killing, fraud and what have you. Incessant murdering and bombing by Boko Haram in Adamawa state and its environs is an important issues to monitor because unlike other crimes, the number of reported murders is in a very high rate compared to other crimes in Adamawa state.

This study thus seeks to understand the prevalence of crime cases in Adamawa state via gender distribution, year of incidence, and age dependencies of criminals; and to fit a model that best describes association of these factors with crime statistics.

2. METHODOLOGY

Data for this research work covered crime situations in Adamawa state from 2010 to 2014 and the data used are data from Yola prison. These are secondary data extracted from the records of the Nigerian Prison, Yola, Adamawa state on criminal cases. A total number of 1672 criminal cases were recorded. The analysis were carried out using R package. The variables considered are Crime, Year and Gender, and Crime, Age group and Gender.

Ratio: A ratio is another statistical analysis method used to show any numerator-denominator relationship between two numbers e.g.

Ratio of male to female = $\frac{number\ of\ females}{number\ of\ males} \times 100$

= number of female per 100 males

The ratio is used to explain crime by the years of occurrence (2010-2014), the gender, and the classified age groups.

Rates: A rate is also one of the methods of analysis of social and economic statistics that is regarded as special cases of ratios. Rates measure the likelihood of occurrence of a phenomenon within a given population that is defined by its characteristics.

Therefore, a rate is given by;

Crime rate = $\frac{number\ of\ crime\ committed}{total\ population\ of\ the\ state} \times 1000$

Crude Rates: The crude rates are obtained by dividing the number of events (i.e. criminal cases) of a specified type occurring within an interval (which is usually a year) by the size of the population within which the events occurred.

The mid-interval population is often taken as the best estimate for calculating crude rates, which involves calculating crude crime rate in a given area (i.e. Adamawa) in a given year by the ratio of crimes committed during a 12^{th} month period to the population of the area within the same 12^{th} month.

Specific Rates: Specific rates are similar to crude rates but are computed on the basis of events (i.e. criminal offences) in or to a particular sub-population (i.e. age).

Therefore,

Crude rate = $\frac{number\ of\ criminal\ cases\ in\ a\ given\ year}{the\ total\ popultion\ within\ which\ the\ events\ occur} \times 1000$

Specific rate = $\frac{number\ of\ criminal\ cases\ in\ a\ given\ year}{the\ number\ of\ the\ sub-population\ (age)} \times 1000$

The rate also is used to determine the crime by crime and the years (2010-2014), the gender and the age groups.

2.1. Log-Linear Models

Log-linear models are used to determine whether there are any significant relationships in multi-way contingency tables that have three or more categories variables and/ or to determine if the distribution of the counts among the cells of a table can be explained by a sampler underlying structure. The models specify how the expected count depends on levels of the categorical variables for that cell as well as associations and interactions among those variables. The purpose of log-linear modeling is the analysis of association and interaction patterns. The log-linear analysis assume that the response observations are counts having Poisson distributions (Lawal, 2003). The log-linear model is one of the specialized cases of generalized linear models (GLMs) for Poisson and multinomial distributed data. The variables investigated by log-linear models are all treated as "response variables". In other words, no distinction is made between independent and dependent variables. If one or more variables are treated as explicitly dependent, others as independent, then logit or logistic regression should be used instead. Also, if the variables being investigated are continuous and cannot be broken down into discrete categories, logit or logistic regression would again be the appropriate analysis.

Let us now consider a 2×2 contingency table, its expected frequencies can be expressed by taking the natural logarithms as:

$$E_{ij} = \frac{n_{i.} \times n_{.j}}{N}$$

$$\log E_{ij} = \log n_{i.} + \log n_{.j} - \log \mathrm{N}$$

But our expected frequencies will be expressed as:

$$\log E_{ij} = \log E_{i.} + \log E_{.j} - \log \mathrm{N}$$

Summing over i we have:

$$\sum_{i=1}^{r} \log \mathrm{E_{ij}} = \sum_{\mathrm{i=1}}^{\mathrm{r}} \log_e \mathrm{E_{i.}} + \mathrm{r}\log_e \mathrm{E_{.j}} - \mathrm{r}\log_e \mathrm{N}$$

Summing over j:

$$\sum_{j=1}^{c} \log_e \mathrm{E_{ij}} = \mathrm{c}\log_e \mathrm{E_{i.}} + \sum_{\mathrm{j=1}}^{\mathrm{c}} \log_e \mathrm{E_{.j}} - \mathrm{c}\log_e \mathrm{N}$$

And over i and j we have:

$$\sum_{i}^{r} . \sum_{j}^{c} log_e E_{ij} = c \sum_{i}^{r} log_e E_{i.} + r \sum_{j}^{c} log_e E_{.j} - rclog_e N$$

It is now a matter of simple algebra in a form reminiscent to the models:

$$\log(\mathrm{E_{ij}}) = \mu + \mu_i^a + \mu_j^b \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (*)$$

The model above is unsaturated log-linear model for 2×2 contingency table. The saturated log-linear model will be described below.

Where

$$\mu = \frac{\sum_{i=1}^{r}\sum_{j=1}^{c} log_e E_{ij}}{rc} \; ; \; \mu_{a(i)} = \frac{\sum_{j=1}^{c} log_e E_{ij}}{c} - \frac{\sum_{i=1}^{r}\sum_{j=1}^{c} log_e E_{ij}}{rc} \; ; \; \mu_{b(j)} = \frac{\sum_{i=1}^{r} log_e E_{ij}}{r} - \frac{\sum_{i=1}^{r}\sum_{j=1}^{c} E_{ij}}{rc}$$

Where

μ = overall mean of the natural log of the expected frequencies

$\mu_{a(i)}$ = main effect of the i^{th} category of variable A (row)

$\mu_{b(j)}$ = main effect of the j^{th} category of variable B (column).

We now see that the model is in additive form. Thus, (*) specifies a linear model for the logarithms of the frequencies or, in other words, what is generally known as unsaturated log-linear model.

Consequently:

$$\sum_{i=1}^{r} \mu_{a(i)} = 0. \qquad \sum_{j=1}^{c} \mu_{b(j)} = 0$$

Or using an obvious dot notation:

$\mu_{a(.)} = 0,$ $\mu_{b(.)} = 0$

Statistically dependent variables satisfy a more complex log-linear model

$$\log(\mathrm{E_{ij}}) = \mu + \mu_i^a + \mu_j^b + \mu_{ij}^{ab} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .**$$

$\log(E_{ij})$ = the log of the expected cell frequency of the cases for cell ij in the contingency table.

μ, μ_i^a, μ_j^b, are the overall and marginal effect terms as defined earlier and

μ_{ij}^{ab} represents the association or interaction between variable A and variable B.

i and j = the categories within the variables

Therefore:

μ_i^a = the main effect for variable A

μ_j^b = the main effect for variable B

μ_{ij}^{ab} = the interaction effect for variable A and variable B

The above model (**) resembles the formula for cells means in a two-way ANOVA allowing interaction. The equation is considered a Saturated Model because it includes all possible one-way and two-way effects. Given that the saturated model has the same amount of cells in the contingency table as it does effects, the expected cell frequencies will always exactly match the observed frequencies, with no degrees of freedom remaining, Knoke and Burke (1980). For example, in a 2 x 2 table there are four cells and in a saturated model involving two variables there are four effects, $\mu, \mu_i^a, \mu_j^b, \mu_{ij}^{ab}$, therefore the expected cell frequencies will exactly match the observed frequencies. Thus, in order to find a more parsimonious model that will isolate the effects best demonstrating the data patterns, a non-saturated model must be sought.

This can be achieved by setting some of the effect parameters to zero. For instance, if we set the effects parameter μ_{ij}^{ab} to zero (i.e. we assume that variable A has no effect on variable B, or vice versa) we are left with the unsaturated model. $\log(\mathrm{E_{ij}}) = \mu + \mu_i^a + \mu_j^b$

Thus,

$$\sum_{i=1}^{r} \mu_{a(i)} = 0, \quad \sum_{j=1}^{c} \mu_{b(j)} = 0 \ and \ \sum_{i=1}^{r} \mu_{ij}^{ab} = \sum_{j=1}^{c} \mu_{ij}^{ab} = 0$$

From the above constraints, the model that include the interaction terms, fits the data perfectly, such that fitted values are exactly equal to observed values and has many unique parameters as there are number of cells in the table. That model is called "saturated model". This has independence as a special feature when the interaction effect is zero, that is

$$\mu_{ij}^{ab} = 0 \ \forall \ i \ and \ j$$

2.2. Statistical Independence

The statistical independence between row and column variables means that the joint probabilities $\{\pi_{ij}\}$ of the observed falling into a cell are equal to the product of the marginal probabilities.

Mathematically, it is expressed as

$$\pi_{ij} = \pi_{i.}\pi_{.j} \quad \forall \ i = 1,2,\dots,r \ and \ j = 1,2,\dots,c$$

So in terms of expected frequencies (cell counts)

$$\mu_{ij} = n\pi_{ij} \ \forall \ i,j$$

The probability $\{\pi_{ij}\}$ and the expected frequencies are $\{(\mu_{ij}) = E_{ij} = n\pi_{ij}\}$. Log-linear formulas use $\{\mu_{ij}\}$ as their response variable rather than the cell probabilities $\{\pi_{ij}\}$, (Agresti, 2002; Adejumo, 2005).

For the definition of statistical independence, the model for the expected number of counts in multiplicative

$$\mu_{ij} = n\pi_{ij} = n\pi_{i.}\pi_{.j} \quad \forall \ i = 1,2,\dots,r \ and \ j = 1,2,\dots,c$$

and taking the logarithms gives us

$$\log(\mu_{ij}) = \log(n) + \log(\pi_{i.}) + \log(\pi_{.j})$$

Which can be further expressed as

$$\log(\mathrm{E_{ij}}) = \mu + \mu_i^a + \mu_j^b$$

It is known as the "log-linear model of independence" for 2-ways contingency tables where μ represents an "overall" effect or a constant. This term ensures

$$\sum_{i} . \sum_{j} E_{ij} = n$$

μ_i^a represents the "main" or marginal effect of the row variable A. It represents the effect of classification in row i. $\mu_i^{a}{'s}$ ensure that

$$\sum_{j} E_{ij} = \mu_{i.} = n_{i.}$$

μ_j^b represents the main of marginal effect of the column variable B. It represents the effect of classification in column j.

This term ensures that

$$\sum_{i} E_{ij} = \mu_{.j} = n_{.j} \qquad \text{Also,} \qquad \sum_{i=1}^{r} \mu_i^a = 0, \sum_{j=1}^{c} \mu_j^b = 0$$

Statistical independence also implies that the odds ratios of every sub-table must equal 1.

The odds are defined as the ratio of the probability of response in relation to the probability of non-response, within one category of *X*.

For a 2×2 tables, the odds in row 1 equal

$$\Omega_1 = \frac{\pi_{1|1}}{\pi_{2|1}}$$

Within row 2, the corresponding odds equal

$$\Omega_2 = \frac{\pi_{1|2}}{\pi_{2|2}}$$

The *within-row conditional distributions* are independent when $\Omega_1 = \Omega_2$. This implies that the two variables are independent

i.e., if a_{11}, a_{12}, a_{21}, and a_{22} are the expected values in a 2×2 contingency table given by $\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$

Thus, it means that if independency exist then $(a_{11} \times a_{22})/(a_{12} \times a_{21}) = 1$

The odds ratios are functions of model parameters:

Log (odds ratio) = log ($\theta_{12,12}$) = $log \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$

$$= (\mu + \mu_1^a + \mu_1^b) + (\mu + \mu_2^a + \mu_2^b) - (\mu + \mu_1^a + \mu_2^b) - (\mu + \mu_2^a + \mu_1^b) = 0$$

So the odds ratio, $\theta = \exp(0) = e^0 = 1$

2.3. Independence Model

Under statistical independence, we noted that the $\{\mu_{ij}\}$ have the structure

$$\mu_{ij} = \mu\alpha_i\beta_j$$

For multinomial sampling, for instance, $\mu_{ij} = \mu\pi_{i+}\,\pi_{+j}$ denote the row variable by A and the column variable by B. The formula expressing independence is multiplicative.

Thus, log μ_{ij} has additive form

$$\log(E_{ij}) = \mu + \mu_i^a + \mu_j^b \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (***)$$

For a row effect μ_i^a and a column effect μ_j^b. This is the log-linear model of independence. As usual, identifiability requires constraints such as

$$\mu_i^a + \mu_j^b = 0$$

The ML fitted values are $\{\hat{u}_{ij} = {n_{i+}n_{+j}}/{n}\}$, the estimated expected frequencies for chi-squared tests of independence. The tests using X^2 and G^2 are also goodness-of-fit tests of this log-linear model.

2.4. Interpretation of Parameters

Log-linear models for contingency tables are GLMs that treat the *N* cell counts as independent observations of a Poisson random component. Log-linear GLMs identify the data as the *N* cell counts rather than the individual classifications of the *n* subjects. The expected cell counts link to the explanatory terms using the log link. As equation (***) illustrates, of the cross-classified variables, the model does not distinguish between response and explanatory variables. It treats both jointly as responses, modeling $\{\mu_{ij}\}$

for combinations of their levels. To interpret parameters, however, it is helpful to treat the variables asymmetrically.

We illustrate with the independence model for *1×2* tables. In row *i*,

$$Logit[P(B=1/A=i]=log\frac{P(B=1/A=i)}{P(B=2/A=i)} \quad = \quad log\frac{\mu_{i1}}{\mu_{i2}}=log\mu_{i1}-log\mu_{i2}$$

$$=(\mu+\mu_i^a+\mu_1^b)-(\mu+\mu_i^a+\mu_2^b)=\mu_1^a-\mu_2^b.$$

The final term does not depend on *i*; that is, $logit[P(B=1/A=i)]$ is identical at each level of *A*. Thus, independence implies a model of form, $logit[P(B=1/A=i)]$.

In each row, the odds of response in column 1 equal $\exp(\alpha)=\exp(\mu_1^a-\mu_2^b)$.

An analogous property holds when $J > 2$. Differences between two parameters for a given variable relate to the log odds of making one response, relative to the other, on that variable. Of course, with a single response variable, logit models apply directly and log-linear models are not needed.

2.5. Model Selection in Categorical Data Analysis

In itself, the value of the Akaike's Information Criterion (AIC), for a given data set has no meaning. It becomes interesting when it is compared to the AIC of a series of models specified *a priori*, the model with the lowest AIC being the (best) model among all models specified for the data at hand. After having specified the set of plausible models to explain the data and before conducting the analyses (e.g., log-linear model), one should assess the fit of the global model, defined as the most complex model of the set. AIC judges a model by how close its fitted values tend to be to the true values, in terms of a certain expected value. Even though a simple model is farther from the true model than a more complex model, it may be preferred because it tends to provide better estimates of certain characteristics of the true model, such as cell probabilities. Thus, the optimal model is the one that tends to have fit close to reality.

AIC= -2(Maximum Likelihood – number of parameter in the model).

This penalizes model for having many parameter. We generally assume that if the global model fits, simpler models also fit because they originate from the global model (Cooch and White, 2001; Anderson *et al.*, 2002).

AIC = -2 log(L) + 2p

Where

L = the likelihood under the fitted model

P = the number of estimated parameters included in the model (i.e. number of variables and the intercept).

The Likelihood ratio test (G^2)

$$H_0: \pi_{ij} = \pi_{i.}\pi_{.j} \quad VS \quad H_1: \pi_{ij} \neq \pi_{i.}\pi_{.j}$$

$$A = \frac{\prod_{i=1}^{I}\prod_{j=1}^{J}(n_{i.}n_{.j})^{n_{ij}}}{n^n\prod_{i=1}^{I}\prod_{j=1}^{J}(n_{ij})^{n_{ij}}}$$

It follows that Wilk's G^2 is given by

$$G^2 = -2\log_{10}A$$

$$G^2 = 2\sum_{i=1}^{I}\sum_{j=1}^{J} n_{ij}\log_{10}(\frac{n_{ij}}{m_{ij}})$$

$$with \ m_{ij} = \frac{n_{i.}n_{.j}}{n} \ (estimated\ under\ H_0)$$

If H_0 holds, A will be large (i.e. near 1) and G^2 will be small. Thus, this means that H_0 will be rejected for large G^2.

2.6. Chi-Square Test (χ²)

The chi-square test is usually applied when considering qualitative or count data. It is also used to test independence of two variables. In this case, comparison is made between a set of observed frequencies and a set of expected frequencies.. The row (r) is the cases of criminal offences committed and the column (c) is the five years duration (i.e. 2010-2014).

Test statistic,

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(O_{ij} - E_{ij})^2}{E_{ij}} \sim \chi^2_{(r-1)(c-1),1-\alpha}$$

The expected frequencies, $E_{ij} = \frac{n_{i.} \times n_{.j}}{N}$

3. RESULTS

Table-1. frequency of Criminal Offences by Years (percentages are in parenthesis)

CRIME	YEARS 2010	2011	2012	2013	2014
Murder	3(5.000)	4(6.667)	16(26.667)	15(25.000)	22(36.667)
Rape/assault	15(6.849)	15(6.849)	75(34.247)	55(25.114)	59(26.941)
Robbery	57(10.160)	62(11.052)	85(15.152)	202(36.007)	155(27.629)
Drugs	42(10.500)	77(19.250)	127(31.750)	42(10.500)	112(28.000)
Other crimes	28(6.481)	14(3.241)	52(12.037)	138(31.944)	200(46.296)

Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

In table 1, it is seen that the highest and the lowest percentages of Murder offence was 36.667% in the year 2014 and 5.000% in the year 2010 respectively. The highest and the lowest percentages of Rape/assault was 34.247% in the year 2012 and 6.849% in both 2010, 2011 respectively. The highest and the lowest percentages of Robbery was 36.007% in the year 2013 and 10.160% in the year 2010 respectively.

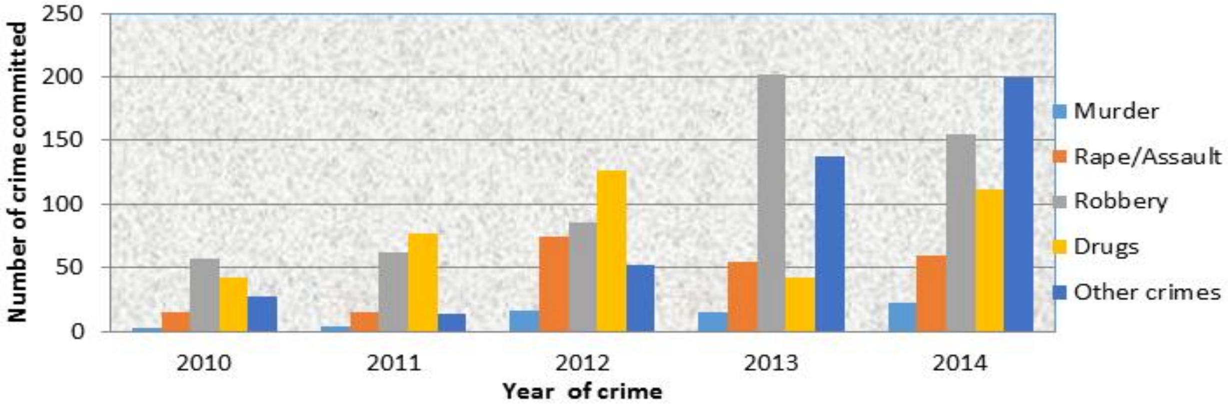

Fig-1. Component Bar Chart Showing Years with various Crimes

Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

The highest and the lowest percentages of Drugs was 31.750% in the year 2012 and 10.500% in both 2010, 2013 respectively. The highest and the lowest that falls in the category of "Other crimes" was 46.296% in the year 2014 and 3.241% in the year 2011 respectively, these are as shown in Fig I Above:

Table-2. Table of Crime Cases by Age Groups in Percentage

Age Group	Total Cases Of Crime	Percentage (%)	Degree (^{0})
16 – 20	346	20.69	74.50
21-25	437	26.14	94.09
26-30	424	25.36	91.29
31-35	260	15.55	55.98
36-40	123	7.36	26.48
41 +	82	4.90	17.66
Total	1672	100	360

Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

From the above table, it is seen that age-groups 16-20, 21-25 26-30 and 31-35 have high counts. People within these age groups may be graduates, and may be involved in crime because of unemployment, thus, they may think that crime becomes the only option in the absence of job opportunities. This is illustrated in Fig. II below:

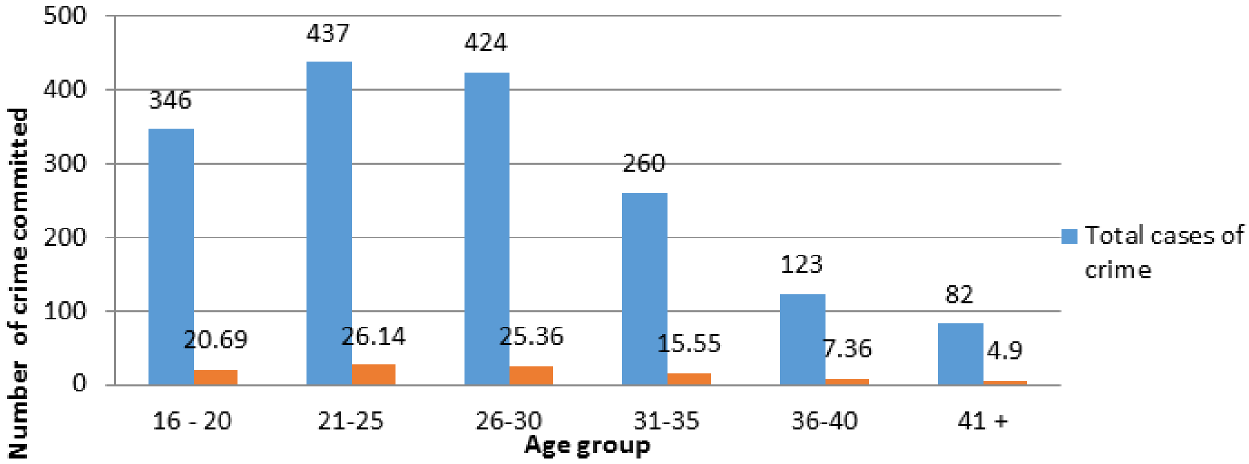

Fig-2. Percentage Bar Chart showing the Age Group that Committed the Highest Crime
Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

Table-3. Table of Crime Cases and the Years in Percentages and Degrees

YEARS	TOTAL CASES OF CRIME	PERCENTAGE (%)	Degree (^{0})
2010	145	8.67	31.22
2011	172	10.29	37.03
2012	355	21.23	76.44
2013	452	27.03	97.32
2014	548	32.78	117.99
TOTAL	1672	100%	360^0

Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

The table above shows the crime cases in proportion by year of occurrence. 2014 has the highest number of crime cases with about 33% of the total.

Table-4. A Table of Ratios of number of Females per 100 Males

CRIME	GENDER				TOTAL	RATIO
	MALE	FEMALE	MALE (%)	FEMALE (%)		
Murder	58	2	3.47	0.12	60	3.45
Rape/assault	210	9	12.56	0.54	219	4.29
Robbery	545	16	32.60	0.96	561	2.94
Drugs	388	12	23.21	0.72	400	3.10
Other crimes	408	24	24.40	1.44	432	5.88
Total	1609	63	96.24	3.76	1672	19.70

Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

Table 4 shows that crime categorized under Other Crimes case with ratio (5.88) has the highest number of ratio, but it cannot be regarded as the highest because it is the accumulation of crimes like illegal arms, environmental sanitation, kidnapping, forgery etc. Rape/assault has the highest number of ratio of 4.29. This means that about 4 females per 100 males were involved in the Rape/assault cases. Next is murder cases with 3.45. Robbery has the lowest ratio with 2.94. This also means that about 3 of females per 100 of males were involved in Robbery within the years (2010-2014).

Table-5. Table of Crime Rate for the years 2010 – 2014

Year	Total crime committed	Crime rate
2010	145	0.046
2011	172	0.054
2012	355	0.112
2013	452	0.143
2014	548	0.173
TOTAL	1672	0.528

Source: Records of the Nigerian Prison, Yola, Adamawa state on criminal cases, 2010-2014.

From table 5, it is evident that crime rate in the state is on the increase.

Crime rate = $\frac{number\ of\ crime\ committed}{total\ population\ of\ the\ state} \times 1000$

NOTE: The total population of Adamawa state as at 2006 population census is 3,168,101.

Crude rate = $\frac{number\ of\ criminal\ cases\ in\ a\ given\ year}{the\ total\ population\ within\ which\ the\ events\ occur} \times\ 1000$

Thus, Crude crime rate for Adamawa state (2010-2014) = $\frac{1672}{3{,}168{,}101} \times\ 1000\ = 0.528$

3.1. Results on Log-Linear Analysis

An algorithm was written in R program to evaluate the models with its respective likelihood ratio statistic (G^2) as well as the Akaike Information Criteria (AIC) for each log-linear model stated above. The results are summarized below.

Case-I. Summary Result for Model Selection on Crime-type, Year and Gender

The saturated model is:

$\log(E_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y + \mu_{ij}^{cg} + \mu_{ik}^{cy} + \mu_{jk}^{gy} + \mu_{ijk}^{cgy}$ Where (C) denotes Crime-type with five levels, factor (Y) denotes year with which crime was committed with five levels and factor (G) denotes the gender of the criminals with two levels. The following models are considered;

$$\text{Model 6 } \{(CG.CY.GY.CGY)\}: \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y + \mu_{ij}^{cg} + \mu_{ik}^{cy} + \mu_{jk}^{gy} + \mu_{ijk}^{cgy}$$

$$\text{Model 5 } (CY.CG.GY): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y + \mu_{ij}^{cg} + \mu_{ik}^{cy} + \mu_{jk}^{yg}$$

$$\text{Model 4 } (CY.GC): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y + \mu_{ij}^{cg} + \mu_{ik}^{cy}$$

$$\text{Model 3 } (CY.G): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y + \mu_{ij}^{cy}$$

$$\text{Model 2 } (CG.Y): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y + \mu_{ij}^{cg}$$

$$\text{Model 1 } (C.G.Y): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^y$$

3.2. Chi-square Test of Independence

Table-6ai. Partial Associations for Crime cases vs Year vs Gender

Effect	df	Partial Chi-Square	χ^2(tab)	Sig.
CRIME*YEAR	16	226.416**	26.296	.000
CRIME*GENDER	4	5.789	9.488	.072
YEAR*GENDER	4	13.842**	9.488	.008
CRIME	4	553.515**	9.488	.000
YEAR	4	385.183**	9.488	.000
GENDER	1	1781.179**	3.842	.000

Source: Result output using R statistical package

Table-6aii. Summarized results for table 6ai (*C.Y.G*)

Model	G^2	AIC	df	Pearson χ^2
1	287.330	499.29	40	273.137
2	281.780	501.74	36	272.762
3	53.964	297.93	24	64.481
4	48.416	300.38	20	56.286
5	34.573	294.53	16	33.817
6 (saturated)	0	291.96	0	0

Source: Result output using R statistical package

Table 6aii shows, based on the results obtained, model 6 which is the saturated model has the least AIC as expected but we select the next model with the least AIC which is model 5 with AIC of (294.53) -the all two way interactions, as the best model on the basis of parsimony.

Case II: Summary Result for Model Selection on Crime-type, Age group and Gender

The saturated model is:

$$\log(E_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a + \mu_{ij}^{cg} + \mu_{ik}^{ca} + \mu_{jk}^{ga} + \mu_{ijk}^{cga}$$

Where (C) denotes Crime-type with five levels, factor (A) denotes the Age group of criminals with 6 levels and factor (G) denotes the gender of the criminals with two levels. The following log-linear models are considered;

$$\text{Model 6 } (CGA): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a + \mu_{ij}^{cg} + \mu_{ik}^{ca} + \mu_{jk}^{ga} + \mu_{ijk}^{cga}$$

$$\text{Model 5 } (CA.CG.GA): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a + \mu_{ij}^{cg} + \mu_{ik}^{ca} + \mu_{jk}^{ag}$$

$$\text{Model 4 } (CA.CG): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a + \mu_{ij}^{cg} + \mu_{ik}^{ca}$$

$$\text{Model 3 } (CA.G): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a + \mu_{ij}^{ca}$$

Model 2 $\quad (CG.A): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a + \mu_{ij}^{cg}$

Model 1 $\quad (C.G.A): \log(\mu_{ijk}) = \mu + \mu_i^c + \mu_j^g + \mu_k^a$

3.2. Chi-Square Test of Independence

Table-6bi. Partial Associations on Crime cases vs Gender vs Agegroup

Effect	df	Partial Chi-Square	χ^2(tab)	Sig.
CRIME*AGE-GROUP	20	137.251**	31.410	.000
CRIME*GENDER	4	5.889	9.488	.208
AGEGROUP*GENDER	5	9.264	11.070	.099
CRIME	4	553.515**	9.488	.000
AGEGROUP	5	461.051**	11.070	.000
GENDER	1	1781.179**	3.842	.000

Source: Result output using R statistical package

Table-6bii. Summarized results for table crime, Age group and gender

Model	G^2	AIC	df	Pearson χ^2
1	169.350	413.21	49	164.387
2	163.800	415.67	45	155.688
3	32.437	316.30	29	31.5962
4	26.888	318.75	25	24.3742
5	17.624	319.49	20	15.192
6 (saturated)	0	341.87	0	0

Source: Result output using R statistical package

Table 6bii shows the values of AIC for each model. Comparing the values of AIC for each model on the results obtained, model 3, (CA.G) when considering association between Crime-type and Age group independent of Gender with AIC (316.30) as the best model.

4. SUMMARY AND CONCLUSION

From the various analyses conducted, crime incidence differs and is on the increase over the years. The year 2014 has the highest criminal cases with robbery being the highest crime committed throughout the interval of five years. The results also show that persons within the age-group 16-20, 21-25, and 26-30 were mostly involved in crime while those that are 41+ years committed the least crime. The analyses showed also that males (about 96%) are more involved in crime offences than the females (4%).

The results show also that in understanding the pattern of criminal cases committed in Adamawa state, the year of occurrence and the criminals' age group (especially youths between 16 -35 years) should be considered. When considering Crime type vs. Year vs. Gender, it is seen that model 5, *the all two way interactions* is considered as the best model for the first analysis based on the results on the likelihood ratio G^2 and Akaike Information Criteria (AIC). Also model 3 when considering Crime type vs. Age group vs. Gender, *association between Crime-type and Age-group independent of Gender* is considered as the best model.

Also the year 2014 recorded the highest crime rate of (0.173) and that crime rates from 2010 to 2014 is on the increase. A total crime rate of 0.528 for the five years interval with crude crime rate of 0.528 is observed.

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