Mathematical Theory and Modeling
ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.15, No.1, 2025

Child Abuse and Its Consequences: A Multinominal Logistic Regression Model Approach

[1]Lasisi, T.A, [2]Akomolafe, A. A. and [3]Oladimeji O.A
[1]Department of Statistics, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.

[2]Department of Statistics, School of Physical Sciences, Federal University of Technology, Akure, Nigeria.

[3]Department of Statistics, Federal Polytechnic, Ile-Oluji, Nigeria

Corresponding Author: adedipupo.oladimeji@gmail.com

ABSTRACT

Children are the bedrock of any society and as such needs to be properly brought up and adequately handled. Children are the greatest assurance of the continuity of human race, without children there will be no race tomorrow. In the technology age of today, children are becoming more vulnerable members among adults in the society. This research evaluated the effects and consequences of child abuse in our environment using Oyo state as a case study and also and proffer possible and practicable solutions to the problem from the study. The population of the study comprises of children within a specific age bracket in Oyo State using Ibadan as a case study, in which four public and private schools four secondary schools were selected purposively due to accessibility and readiness to provide necessary information needed for the research work. Moreover to get more valid data source, a secondary data were also collected from the Nigeria Security and Civil Defence Corps through the department of Antihuman Traffic and Child Protection unit which was utilized by fitting a multinomial logistic regression model. The analysis revealed different forms of child abuse melted out on children by parents, teachers and guidance. Some of the abuse and consequences were attributed to poverty, ignorance, parental income, parental occupation and inadequacies in protection of children while others may be seen as deliberate act by the parent/guardians that look like correcting measure but it is still child abuse. Also, domestic violence and child neglect have various forms of consequences such as sexual transmitted diseases, stigmatization, school drop-out, abortion and unwanted pregnancy; all these were significant to the explanatory variables under consideration.

Keyword: Child Abuse, Domestic violence, Multinomial Logistic Regression Model, Stigmatization and Poverty

1. INTRODUCTION

The child is the bedrock of any society and as such needs to be properly brought up and adequately handle. Children are the greatest assurance of the continuity of human society, without children there will be no society of human tomorrow. In the technology age of today, children are becoming more vulnerable members among adults in the society. It was indicated that children more vulnerable to various vices and are therefore exposed to various forms of abuse. (Olok-Ake 2000). Therefore child abuse is all sort of injustices, abnormality and inhuman treatment given to young feeble only by the adult generation. Child abuse is among one of the many other criminal acts involved in, and some criminal acts can also be inflicted by adult to another adult in the advance generation we are child abuse which is one of the criminal acts involved in includes any behavior which neglects the child's survival and development needs, causes physical or emotional injury, harassment or subjects the child to measures, situations and experiences which interfere with the healthy development towards adulthood (Alokan 2010).

Child Abuse is one the most pervasive criminal form of repulsive cases that is disintegrating Nigeria values and moral today. It robs children especially of the childhood they deserve which is their rights and leaves so many homes broken, dashes aspirations and awake misery in children. . Such act may be intentional or unintentional which depend on the view of the suspect (Bromfield, 2005; Cristofel et al., 1992; Gilbert et al., 2009).

Child abuse violates the United Nations declaration on Human Rights, the United Nations Conventions on the Right of the child adopted in 1989 and the African Character on Right and welfare of the African Child. This criminal act is also considered as offensive in our society. Nigerian child like any other child in the world has the right to live and such protects them from people trampling on their rights. Children in Nigeria are exposed vulnerably to engage in highway/street hawking, exploitative labour and domestic help, street begging, child marriage, illiteracy and violence. The Nigeria government and some non-governmental organization are working tirelessly to curtail the menace of child abuse in this country. Nevertheless, child abuse still persists, and various consequences experience in the acts has actually affects the life and future of the so called future generation of tomorrow negatively.

1.1 Forms of Child Abuse

Emotional abuse: is any attitude, behaviour, or failure to act that interferes with a child's mental health or social development. A repeated pattern of parent/guardian behaviour or extreme incident(s) that convey to children that they are worthless, flawed, unloved, unwanted, endangered, or only of value in meeting another's needs. It can range from a simple verbal insult to an extreme form of punishment. Emotional abuse is almost always present when another form of abuse is found.

Physical abuse: is the non-accidental infliction of physical injury to a child characterized by injury, such as bruises, lesions and fractures that result from hitting (hand, stick, strap, or other object), punching, shaking, kicking, beating, choking, burning (with open flame or hot objects – boiling water, cigarettes), throwing, stabbing or otherwise harming a child.

Sexual abuse: Is any sexual behavior with- or sexual exploitation of a child. There are various forms of sexual offenses against children.. A child cannot legally give consent to sexual activity. Child sexual abuse includes a wide range of behaviors, including: Rape which is referring to as vaginal or anal penile penetration or any vaginal or anal intercourse with a child, oral sex by or to any adult, genital contact with no intrusion, indecent exposure, production, distribution or possession of child pornography, sexual exploitation: which is the usage of a child in prostitution, pornography and incest which is perpetrated by a family member or someone the child knows, including those in biological families, adoptive families, and step families.

Child neglect: Neglect is a pattern of failing to provide for a child's basic needs. It is abuse through omission; of not doing something resulting in significant harm or risk of significant harm. There are various form of neglect, which include: physical neglect, medical neglect, educational neglect and emotional neglect.. Physical neglect is the failure to provide food, weather appropriate clothing, and supervision, a safe and clean home for a child. Medical neglect which failure to provide the necessary medical or dental care for a child's condition. Educational neglect which is the failure to enroll a school-age child in school or to provide necessary special education. Emotional neglect which is the failure to provide emotional support, love, and affection to a child, exposure of a child to spousal, pet, or drug and alcohol abuse.

2. LITERATURE REVIEW

Over the years, specialized statistical methods for analyzed categorical data have increased. Among several available statistical tools used for categorical data, regression analysis is one of these statistical tools that utilize the relationship between two or more variables. The regression models can be divided into two groups, the first related to linear relationship models, and the second related to non-linear relationship models. The linear models, considering the assumption of normality test are satisfactory for most regression applications. Nonlinear model is used when the linear model is not suitable. Many researchers believe that the logistic regression model is one of the important models can be applied to analyze a categorical data; this model is a special case of generalized linear models (GLM). The multinomial logistic regression (MLR) model used in generally effective where the response variable is composed of more than two levels or categories. Continuous variables are not used as response variable in logistic regression, and only one response variable can be used. The Multinomial Logistic Regression model can be used to predict a response variable on the basis of continuous and/or categorical explanatory variables to determine the percent of variance in the response variable explained by the explanatory variables, to rank the relative importance of independents, to assess interaction effects, and to understand the impact of covariate control variables. The Multinomial Logistic Regression model allows the simultaneous comparison of more than one contrast, that is, the log odds of three or more contrasts are estimated simultaneously, Garson (2009). The logistic regression model assumes that the categorical response variable has only two values, in general, 1for success and 0 for failure. The logistic regression model can be extended to situations where the response variable has more than two values, and there is no natural ordering of the categories. Natural ordering can be treated as nominal scale, such data can be analyzed by slightly modified methods used in dichotomous outcomes, and this method is called the multinomial logistic. The impact of predictor variables is usually explained in terms of odds ratios. Logistic regression applies maximum likelihood estimation after transforming the dependent into a logit variable (the natural log of the odds of the dependent occurring or not). Logistic regression calculates changes in the log odds of the dependent, not changes in the dependent itself as ordinary least square (OLS) regression does. Logistic regression has many analogies to Ordinary Least Square regression: logit coefficients correspond to $\boldsymbol{\beta}_\mathbf{i}$ coefficients in the logistic regression equation, the standardized logit coefficients correspond to beta weights, and a pseudo R square R^2 statistic is available to summarize the strength of the relationship. Unlike Ordinary Least Square regression, however, logistic regression does not assume linearity of relationship between the independent variables and the dependent, does not require normally distributed variables, does not assume homoscedasticity, and in general has less stringent requirements. It does, however, require that observations be independent and that the independent variables be linearly related to the logit of the dependent. The predictive success of the logistic regression can be assessed by looking at the classification table, showing correct and incorrect classifications of the dichotomous, ordinal, or polytomous dependent. Goodness-of-fit tests such as the likelihood ratio test are available as indicators of mode appropriateness, and also the Wald statistic to test the significance of individual independent variables.

3. METHODOLOGY

Multinomial logistic regression is a classification method that generalizes logistic regression to multiclass problems that is with more than two possible discrete outcomes, it is a model used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variables which may be real-valued, binary-valued, categorical-valued. Logistic regression is used when the dependent variable is nominal that is equivalently categorical , meaning that it falls into any one of a set of categories that cannot be ordered in any meaningful way and for which there are more than two categories used to predict the dependent variable.

Multinomial logistic regression (MLR) model is a fairly straight forward generalization of the binary model, which depend mainly on logit analysis or logistic regression. Logit analysis in many ways is the natural complement of ordinary linear regression whenever the response is categorical variable. When such discrete variables occur among the explanatory variables they are dealt with by the introduction of one or several (0, 1) dummy variables, but when the response variable belongs to this type, the regression model breaks down. Logit analysis provides a ready alternative.

For a response variable Y and explanatory variables X_i, the logistic regression model has linear form for logit of the probability;

$$\log[\pi(x)] = \log\left[\frac{\pi(x)}{1-\pi(x)} = \alpha + \beta_x \quad \text{, where the odds} = \frac{\pi(x)}{1-\pi(x)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The odds = exp $(\alpha + \beta_x)$, and the logarithm of the odds is called logit, so

$$\log[\pi(x)] = \log\left[\frac{\pi(x)}{1-\pi(x)} = \log\left[\exp(\alpha + \beta_x\right) = \alpha + \beta_x \ldots\ldots\ldots \qquad (2)$$

The logit has linear approximation relationship, and logit = logarithm of the odds. The parameter $\boldsymbol{\beta}$ is determined by the rate of increase or decrease of the shaped curve of $\boldsymbol{\pi(x)}$.

The sign of $\boldsymbol{\beta}$ indicates whether curve ascends ($\beta > 0$) or descends ($\beta < 0$), and the rate of change increases as $|\boldsymbol{\beta}|$ increases.

3.1 Logistic regressions

The logistic regression can be extending to models with multinomial explanatory variables. For the dataset, let **k** denotes the seven explanatory variables for a response variable Y which is the consequence of child abuse by $x_1, x_2, x_3, \ldots x_7$, the model for log odds is

$$\log\left[\, p(y = \text{consequences}) = \alpha + \beta_{1_{x_1}} + \beta_{2_{x_2}} + \beta_{3_{x_3}} + \ldots + \beta_{7_{x_7}} \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

And the alternative formula, directly specifying $\pi(x)$, is

$$\pi(x) = \frac{\exp \alpha + \beta_{1_{x_1}} + \beta_{2_{x_2}} + \beta_{3_{x_3}} + \ldots + \beta_{7_{x_7}}}{1 + \exp \alpha + \beta_{1_{x_1}} + \beta_{2_{x_2}} + \beta_{3_{x_3}} + \ldots + \beta_{7_{x_7}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (4)$$

The parameter β_i refers to the effect of x_i on the log odds that Y = consequences of child abuse, controlling other x_j, for instance, exp (β_i) is the multiplicative effect on the odds of a one unit increase in x_i, at fixed levels of other x_j If we have n independent observations with p-explanatory variables, and the qualitative response variable has k categories, to construct the logits in this analysis one of each category in the explanatory variables must be considered the base level and all the logits are constructed relative to it. Any category can be taken as the base level, for this research the last variables are taken as the category baseline level; each of these categories is therefore label k. Let π_j denote the multinomial probability of an observation falling in the j_{th} category, to find the relationship between this probability and the p explanatory variables, $x_1, x_2, x_3, \ldots x_7$, the multiple logistic regression model then is

$$\log\left[\frac{\pi_{j\,(x_i)}}{\pi_k(x_i)}\right] = \alpha_{0i} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{7j}x_{7i} \ldots\ldots\ldots\ldots\ldots \quad ..(5)$$

Where j= 1, 2, …, (k-1), i = 1, 2, … ,7. Since all the π's add to unity, eqn. 4 reduces to:

$$\log[\pi_{j\,(x_i)}] = \frac{\exp(\alpha_{0i} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{7j}x_{7i})}{1 + \sum \exp(\alpha_{0i} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{7j}x_{7i})} \ldots\ldots\ldots\ldots (6)$$

For j = 1, 2, … , (k-1), the model parameters are estimated by the method of Multinomial Logistic regression model. Practically statistical software is use to do this fitting, Chatterjee and Hadi (2006).

3.2.Baseline-Category Logit Model

In Multinomial Logistic Regression model, the estimate for the parameter can be identified compared to a baseline category for both the response and explanatory variables. We defined bold letter as matrix or vector, let $\pi_j(x) = P(Y = j/x)$ at a fixed setting **x** for explanatory variables, with $\sum_j \pi_j(x) = 1$,for observations at that setting, we treat the counts at the J categories of Y as multinomial with probabilities $\pi_1(x), \ldots \pi_5(x)$, logit models pair each response category with a baseline category the baseline for the response variable is unlawful gang/ cultism, often the most common model is: $\log\frac{\pi_{J(x)}}{\pi_j(x)} = \alpha_j + \beta_j x$ where j = 1,…, (J □1), simultaneously describes the effects of **x** on these (J-1) logits, the effects of this analysis depends response paired with the baseline (unlawful gang/ cultism), these (J-1) equations determine parameters for logits with other pairs of response categories, with categorical predictors, Pearson chi-square statistic x^2, the likelihood ratio test, pseudo R^2, model of fitting information and goodness-of-fit statistics provide a model check when data are not sparse. When an explanatory variable is continuous or the data are sparse, such statistics are still valid for comparing nested models differing by relatively few terms, Agresti (2002).

3.3 The Data

Report dataset cases were collected from Nigeria Security and Civil Defence Corps through the department of Antihuman Traffic and Child Protection unit, Nigeria Security and Civil Defence Corps, Oyo Command, Oyo state Nigeria. In this research work, child abuse were classified based on the offence committed, socio demographical factors that influence such abuse and the consequences of it. The age of suspect, religion of suspect and gender of suspect were put into consideration with respect to the victim age as well as their religion. The target population of this research work consist of all reports cases of child abuse within 2017 to 2019..

3.4. Target Population and Sample Size Used

The target population for the research work is one thousand and thirty one (1031) reported cases, in which there is total number of eighty hundred and two (802) female victims, two hundred and twenty three (223) male victims, out of this population four hundred and twelve were Christian while six hundred and thirteen were Muslim. The total number of eight hundred and seven (807) male suspects was recorded while two hundred and eighteen (218) female suspects were recorded, in which five hundred and thirty one (531) are Muslim and four hundred and twelve (412) are Christian. Among the various child abuse express by the victims over the period of years putting into consideration in this research work, we have total number of three hundred and sixty six (366) cases of rape, two hundred and sixty (260) cases of physical assaults, 0ne hundred and twenty seven (127) cases of human trafficking, fifty four (54) cases of incest, two hundred and eighteen (218) cases of child neglect and six (6) missing cases. Amidst various socio demographic factors; the socio demographic factors influencing child abuse recorded is the total number of four hundred and forty seven (447) cases of poverty and unemployment, seventy four (74) cases of peer group, one hundred and eighty one (181) cases of education background influence, one hundred and ninety six (196) of parental influence and sixty eight (68) of religion belief cases. There are various consequences associated with child abuse, but the total number of two hundred and six (206) sexual transmitted diseases cases were recorded, one hundred and eight (108) unwanted pregnancy cases were recorded, three hundred and forty five (345) school dropout and stigmatization cases were recorded, sixty five (65) abortion cases were reported and three hundred and one (301) unlawful gang / cultism cases were recorded.

The below are the descriptive analysis in tabular form illustrating the target population put into consideration in the courses of this research in tables 1 to 4 below:

Table 1: Descriptive table illustrating victim sex and religion

	Victims	Frequency	Percent
Valid	female	802	77.8
	male	223	21.6
	Total	1025	99.4
Missing	System	6	0.6
Total		1031	100
	Christian	412	40
	Muslim	613	60
Total		1031	100

Table 2: Descriptive table illustrating the suspect sex and religion

Suspect		Frequency	Percent
	Female	218	21.1
	Male	807	78.3
Valid	Total	1025	99.4
Missing	System	6	0.6
	Muslim	531	51.5
		494	47.9
Christian			
	Total	1031	100

Table 3: Descriptive statistics tables showing various child abuses committed

Child abuse		Frequency	Percent
	Rape	366	35.5
	Human trafficking	127	12.3
	Incest	54	5.2
		260	25.2
	Physical assaualt		
	Child neglect	218	21.1
	Total	1025	99.4
Missing	System	6	0.6
	Total	1031	100

Table 4: Descriptive statistics table showing socio demographic factors influencing child abuse

Factors		Frequency	Percent
	Poverty/unemployment	447	43.4
	Peer group	74	7.2
	Educational background	181	17.6
	Parental influence	196	19
	Religion belief	68	6.6
	Total	966	93.7
Missing	System	65	6.3
Total		1031	100

4. ANALYSIS AND RESULTS

Various consequences experienced by children who in one way or the other experience child abuse were considered. The consequences highlight from the dataset are categorical in nature, and this include sexual transmitted diseases, unwanted pregnancy, abortion, school drop out, stigmatization and unlawful gang/cultism. The tune of the research does not focus basically on socio demographic factors that influence child abuse only, but also evaluates the consequences of child abuse using the application of multinomial logistic regression model. Consequences of child abuse contain five measures and this serves as the five(5) level of measures for the response variable, as the target population comprises of children within a specific age range (6 months t0 22years) residing in Oyo state, Nigeria. The research focuses more on these five levels of measure for the response variable (consequences). The response variable became as follows ''child abuse consequences" having five categories 1- sexual transmitted diseases, 2-unwanted pregnancy, 3- school dropout/stigmatization, 4-abortion and 5- unlawful gang/cultism. Table 5 below is the frequencies of the response variable according to these categories

Table 5: The frequencies of responses variable categories

Response variable categories	Frequencies	Percent
1- Sexual Transmitted Diseases	206	20
2- Unwanted pregnancy	108	10.5
3-Drop out of school/stigmatization	345	33.5
4-Abortion	65	6.3
5- Unlawful gang/cultism	301	29.2
Total	1025	99.4
Missing value	6	0.6
Total	1031	100

4.1: Baseline category (reference) of the response variable

Any category of response variable can be chosen to be the baseline or reference category, the model will fit equally well, achieving the same likelihood and producing the same fitted values, only the values and interpretation of the parameters will change, Schafer (2006). In course of this research work, the software makes reference default to be used as the baseline category, which is cultism/unlawful gang. This mean the comparison will be against children who find themselves in cultism as their own consequences of their experienced child abuse.

The explanatory variables

This research tried to select a set of explanatory variables, that, we believed it has an effect on the consequences of child abuse against children in the specific age range put into consideration. Some of these explanatory variables gives details about the child abuse experience by each child. The explanatory variables use is as follows: age of the suspect; which indicate various age of those people found in the act of abusing children, religion of the suspect; which serves as an indicator to the suspect belief on child abuse, the suspect gender, the victim gender, the victim age, the victim religion, the form of child abuse committed by the suspect, and the socio demographical factors that influence such act. Each of the explanatory variables put under consideration, in which some are categorical in nature while some are continuous in nature. The continuous variable serves as the covariates for the multinomial logistic regression model. Table 6 below shows the list of the explanatory variables and their frequencies:

Table 6: List of the explanatory variables and their frequencies

Explanatory variable	Forms	Frequencies	Percentage
Suspect sex	0-Female	218	21.1
	1-Male	807	78.3
	Missing value	6	0.6
	Total	1031	100
Suspect religion	1-Muslim	531	51.5
	2-Christian	494	47.9
	Missing value	6	0.6
	Total	1031	100
Victim sex	0-Female	802	78.2
	1-Male	223	21.4
	Missing value	6	0.6
	Total	1031	100
Victim religion	1-Muslim	613	59.8
	2-Christian	412	40.0
	Missing value	6	0.6
	Total	1031	100
Child abuse	1-Rape	366	35.5
	2-Human trafficking	127	12.3
	3-Incest	54	5.2
	4-Physical Assault	260	25.2
	5-Child neglect	218	21.1
	Missing value	6	0.6
	Total	1031	100
Socio demographic influences	1-Poverty/unemployment	447	43.4
	2-Peer group	74	7.2
	3-Educational background	181	17.6
	4-Parental influence	196	19.0
	5-Religion belief	68	6.6
	Missing value	65	6.3
	Total	1031	100

4.2: Baseline category (reference) of the explanatory variable

Any category of explanatory variable can be chosen to be the baseline or reference category, the model will fit equally well, achieving the same likelihood and producing the same fitted values, only the values and interpretation of the parameters will change, Schafer (2006). In course of this research work, the software makes reference default to be used as the baseline category for each explanatory variables considered. The reference base category for sex of the suspect was “male”, while that of suspect religion was ”Christian”, the reference categories for sex of the victim was “male”, while that of victim religion was ”Christian”. The explanatory variable baseline reference for form child abuse is “child neglect”, while that of the socio demographic factors that influence child abuse is “religion belief”.

Missing

Missing indicates the number of cases in the dataset where data are missing of the response variable or any of explanatory variables. In the dataset collected we found out that are 0.6% missing values generally in both explanatory and response variables excluding the age of the suspect and victim and also the socio demographical factors influencing child abuse acts. Brannon et al (2007) suggests that we can calculate scales with missing items if at least two thirds of the items were completed and others were dropped. However, despite the missing values, this model stills it into consideration while performing the analysis. The missing values will be considered as missing system as this procedure will not affect the final result, Moorman and Carr (2008).the table below indicate the missing system in the dataset.

Table 7: Missing system for the response and explanatory variables

		Age of victim	Victim sex	Age of suspect	victim religion	offence	suspect gender	influence	Suspect religion	consequences
N	Valid	991	1025	1025	1025	1025	1025	966	1025	1025
	Missing	40	6	6	6	6	6	65	6	6
Sum		12080.5	223	39613	1437	2912	807	2262	1519	3222

Building of Multinomial Logistics Regression model

The response variables y which is the consequences of child abuse and the various explanatory variables such as age of the suspect, religion of the suspect, the sex of the suspect, age of the victim, religion of the victim, sex of the victim, child abuse and the socio demographical factors influencing child abuse are believed to have lead to the consequence experienced by children in each acts. We tried to explore the Socio demographical factors influencing child abuse in related to its consequences by building Multinomial Logistic Regression model and then examined of the results, cross tabulation will as well be perform on the actual response variable and the predicted response variable so as to check the relationship between them. To achieve this goal, we used SPSS software, analysis Multinomial Logistic Regression model with response variable and all explanatory variables to make the primary model while validating the assumption if multicolinearity must be put to check which is one the assumption of multinomial logistic regression model.

4.3: Validating the assumption of multinomial logistic regression model

There various enlisted assumptions for multinomial logistic regression analysis in which one of it dictates that there shouldn't be multicolinearity in the explanatory variables of the dataset. Multicolinearity is therefore a statistical phenomenon in which two or more variables in a regression model are dependent upon the other variables in such a way that one can be linearly predicted from the other with a high degree of accuracy. It occurs when two or more explanatory variables are highly correlated with one another in a regression model. It can cause a problem in regression model because we would not be able to distinguish between the individual effects of the dependent variable. Therefore to detect multicolinearity in a giving dataset, there are various statistical tools to be used such as: variance inflation factors, prominent changes in the estimated regression coefficient by adding or deleting a predictor, correlation analysis of the predictors e.t.c. among all the listed tools correlation analysis for the explanatory variable to be used for the multinomial logistic regression model.

Table 8: Correlation analysis for the explanatory variables to check for Multicolinearity

Correlation	Age of victim	Age of suspect	Victim sex	Victim religion	Child abuse	Suspect gender	Suspect religion	Socio demographic factors
Age of victim	1	.133**	-.040	-.060	-.079*	-.043	-.024	.069*
Age of suspect	.133**	1	-.129**	.182**	-.306**	.048	-.148**	-.054
Victim sex	-.040	-.129**	1	-.022	.275**	-.084**	.073*	.000
Victim religion	-.060	.182**	-.022	1	-.131**	-.031	-.078*	-.195**
Child abuse	-.079*	-.306**	.275**	-.131**	1	-.139**	-.044	.010
Suspect gender	-.043	.048	-.084**	-.031	-.139**	1	.110**	-.200**
Suspect religion	-.024	-.148**	.073*	-.078*	-.044	.110**	1	.151**
Socio demographic factors	.069*	-.054	.000	-.195**	.010	-.200**	.151**	1

Correlation is a statistical measure that indicates the degree of relationship between two or more variable. A positive correlation indicate that the variables increase or decrease together, while a negative correlation indicate that if one variable increase , the other decreases and vice versa Collinearity is a linear association between two or more predictors, multicolinearity occurs in correlation analysis when there two or more predictors that are highly linearly related . in general, an absolute correlation coefficient of > 0.7 among two or more predictors indicates the presence of multicolinearity. From the correlation table below, the results indicate that there is no multicolinearity problem in the explanatory variable of the dataset, because the correlation coefficients is less than 0.7 and the negative coefficient indicate that as one variable increase the other variable increase and vice versa, this therefore lead to the multinomial regression model analysis

4.4. Multinomial logistic regression model output

The likelihood ratio test table 9 below validates the explanatory variables of the dataset for the consequences of child abuse indicated in the dataset.

Table 9: Likelihood Ratio Test

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	1416.293[a]	0.000	0	
ageofvictim	1481.702	65.409	4	.000
ageofsuspect	1431.743	15.450	4	.004
victimsex	1446.271	29.978	4	.000
victimreligion	1443.037	26.744	4	.000
offences	2242.506	826.213	16	.000
suspectgender	1471.953	55.660	4	.000
suspectreligion	1419.358	3.065	4	.547
influence	1522.375	106.082	16	.000

In the likelihood model, the various explanatory variables considered are; age of the victims, age of the suspects, sex of the victim, victim religion, and the child abuse highlighted the gender of the suspect, the suspect religion and the child abuse influence. The likelihood ratio tests the significant of the explanatory variables against the consequences of child abuse. A statistically significant result (that is $\text{pvalue} < 0.05$) indicates that the explanatory variables is statistically significant to the consequences of child abuse recorded. From the table above there is all indication that majority of the explanatory variables put under consideration (age of the victims, age of the suspects, sex of the victim, victim religion, the child abuse highlighted, the gender of the suspect, and the child abuse influence) row, are statistically significant to the consequences of child abuse highlighted since the p-value is 0.00 (that is $\text{pvalue} < 0.05$) (from the significant column) ,meanwhile the religion suspect is not statistically significant that is $\text{pvalue} > 0.05$) which mean the suspect religion might not be a stronh indicator to the consequence of child abuse highlighted. Generally, the table indicates that the model as a whole fit significantly better than an empty model (that is a model with no predictor).

The model indicates the relationship between the actual recorded report of the various forms of consequence of child abuse highlighted and the predicted variables as shown below.

Table 10: The actual recorded report of the various forms of consequence of Child Abuse

		Predicted Response Category					Total
		STD	Unwanted Pregnancy	Drop out of school/stigmatization	Abortion	cultism	
consequences	STD	144	20	23	10	0	197
	Unwanted Pregnancy	31	70	6	0	0	107
	Drop out of school/stigmatization	26	15	197	7	76	321
	Abortion	17	26	8	12	0	63
	cultism	1	0	59	2	182	244
Total		219	131	293	31	258	932

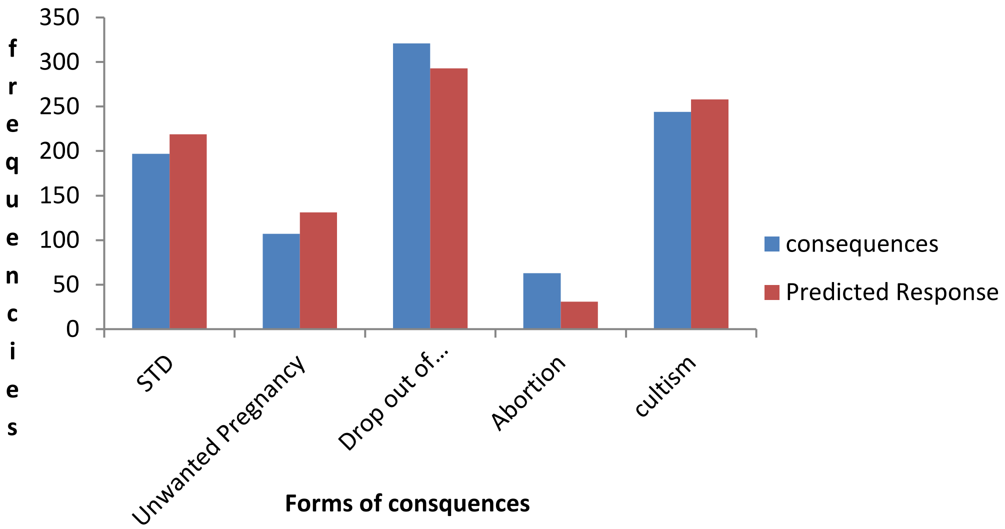

Figure 1: Chart showing the relationship between the predicted response variable and actual response variable

Goodness of fit test

The goodness of fit table provides two measures that can be used to access how well the model fits the data; as shown below:

	Chi-Square	df	Sig.
Pearson	5723.121	844	0.000
Deviance	1353.873	844	.000

The first row, labeled "pearson" present the pearson x^2 statistic. Large chi-square values indicate a good fit for the model. A statistically significant result (that is $pvalue < 0.05$) indicates that the model fit the data set. Generally, from the table above, the pearson values is 5723.121 which indicated a good fit for the model, the p-value is 0.00 (that is $pvalue < 0.05$) (from the significant column) and it is therefore statistically significant. The second row , labeled "Deviance" also indicate that the model fit the data, therefore the two measures of goodness- of- fit test gives the same statistical significant level for the model.

Model fitting information

Table: the table showing the model fitting information for the response and explanatory variable.

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2595.835			
Final	1416.293	1179.542	56	.000

Model: this indicates the parameters of the model for which the model fit is calculated. "Intercept only" describes a model that does not control for any explanatory variables and simply fits an intercept to predict the response variable. "Final" describes a model that includes the specified explanatory variables and has been arrived through an iterative process that maximizes the log likelihood of the outcomes seen in the response variable. By including the predictor variables and maximize the log likelihood of the outcomes seen in the dataset, the "Final" model should improve upon the "intercept only" model, which can be seen in the difference in the -2(Log Likehood0 values associated with the models.

-2 (Log Likelihood) : this is the product of -2 and the log likelihood of the null model and the fitted "final" model. The likelihood of the model is used to test of whether all predictors' regression coefficients in the model are simultaneously zero and in tests of the nested models.

Chi-square : this is the likelihood ratio chi square test that at least one of the predictors' regression coefficient id not equal to zero in the model, which can be calculated by -2L(nulled model) – (-2L(fitted model)) = 2595.835 – 1416.293=1179.542.

Degree of freedom (df): this indicates the degree of freedom of the chi-square distribution used to test the likelihood ratio chi-square statistic and it is defined by the number of explanatory variables in the model. Generally, the final row present information on whether al the coefficients of the model are zero (that is whether any of the coefficients are statistically significant) and also shows whether variables added statistically significantly improve the model compared to the intercept alone (that is with no variable added), we deduce that from the significant column that $p = 0.000$, which indicates that the full model statistically significantly predicts the explanatory variables better than the "intercept only" model.

Parameter Estimates

The multinomial logistic regression model output

Table 11: Showing the output for the multinomial logistic regression model

Consequences		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
STD	Intercept	-22.737	2360.196	.000	1	.992			
	Age of victim	-.046	.038	2.254	1	.133	.945	.878	1.017
	Age of suspect	.027	.016	3.060	1	.080	1.027	.997	1.059
	[victim religion=Muslim]	.557	.358	1.636	1	.201	1.580	.784	3.185
	[victim religion=Christian]	0[b]	.	.	0	.	.	.	.
	Rape	40.810	2360.195	.000	1	.986	52917338023	.000	.[c]
	Human Trafficking	18.905	2360.195	.000	1	.994	162247565.4	.000	.[c]
	Incest	39.845	2360.195	.000	1	.987	20167908882	.000	.[c]
	Physical assault	-.021	3323.388	.000	1	1.000	.980	.000	.[c]
	Child neglect	0[b]	.	.	0	.	.	.	.
	[victim sex=Female]	.559	.526	.091	1	.763	1.172	.418	3.290
	[victim sex=Male]	0[b]	.	.	0	.	.	.	.
	[suspect gender=Female]	2.233	.069	22.658	1	.000	9.332	3.720	23.409
	[suspect gender=male]	0[b]	.	.	0	.	.	.	.
	[suspect religion=Muslim]	.004	.402	.000	1	.992	1.004	.457	2.207
	[suspect religion=Christian]	0[b]	.	.	0	.	.	.	.
	Poverty/unemployment	1.356	.970	1.953	1	.162	3.881	.579	25.994
	Peer group	.044	1.130	3.339	1	.068	7.881	.861	72.150
	Educational background	.023	1.002	.675	1	.411	2.277	.320	16.224
	Parental influence	.015	1.034	.478	1	.489	2.044	.270	15.497
	Religion belief	0[b]	.	.	0	.	.	.	.
Unwanted Pregnancy	Intercept	-21.796	3081.338	.000	1	.994			
	Age of victim	.097	.041	5.547	1	.019	1.102	1.016	1.195
	Age of suspect	.017	.017	.988	1	.320	1.017	.983	1.053
	[victim religion=Muslim]	-1.057	.401	6.935	1	.008	.348	.158	.763
	[victim religion=Christian]	0[b]	.	.	0	.	.	.	.
	Rape	39.923	3081.338	.000	1	.990	21804415136	.000	.[c]
	Human Trafficking	18.731	3081.338	.000	1	.995	136400204.9	.000	.[c]
	Incest	20.284	6990.365	.000	1	.998	644785649.2	.000	.[c]
	Physical assault	-1.408	4244.602	.000	1	1.000	.245	.000	.[c]
	Child neglect	0[b]	.	.	0	.	.	.	.
	[victim sex=Female]	.483	.690	.489	1	.484	1.620	.419	6.264

	[victim sex=Male]	0b	.	.	0	.	.	.	.
	[suspect gender=Female]	1.745	.522	11.167	1	.001	5.724	2.057	15.927
	[suspect gender=male]	0b	.	.	0	.	.	.	.
	[suspect religion=Muslim]	-.040	.458	.008	1	.930	.961	.391	2.359
	[suspect religion=Christian]	0b	.	.	0	.	.	.	.
	Poverty/unemployment	-.607	.965	.395	1	.530	.545	.082	3.612
	Peer group	-19.228	4575.813	.000	1	.997	4.461E-009	.000	.c
	Educational background	-1.038	1.006	1.066	1	.302	.354	.049	2.541
	Parental influence	.385	.993	.150	1	.698	1.469	.210	10.279
	Religion belief	0b	.	.	0	.	.	.	.
Drop out of school/stigmatization	Intercept	-1.647	.745	4.890	1	.027			
	Age of victim	.000	.023	.000	1	.985	1.000	.956	1.045
	Age of suspect	.030	.011	6.702	1	.010	1.030	1.007	1.053
	[victim religion=Muslim]	-.189	.224	.713	1	.398	.828	.534	1.284
	[victim religion=Christian]	0b	.	.	0	.	.	.	.
	Rape	18.669	.547	1164.0	1	.000	128143792.6	43846	3745041
	Human Trafficking	-.585	.339	2.981	1	.084	.557	.287	1.082
	Incest	19.742	.000	.	1	.	374792572.1	37479	3747925
	Physical assault	-1.063	.287	13.684	1	.000	.346	.197	.607
	Child neglect	0b	.	.	0	.	.	.	.
	[victim sex=Female]	-.916	.226	16.381	1	.000	.400	.257	.624
	[victim sex=Male]	0b	.	.	0	.	.	.	.
	[suspect gender=Female]	1.103	.288	14.659	1	.000	3.014	1.713	5.302
	[suspect gender=male]	0b	.	.	0	.	.	.	.
	[suspect religion=Muslim]	-.285	.238	1.439	1	.230	.752	.472	1.198
	[suspect religion=Christian]	0b	.	.	0	.	.	.	.
	Poverty/unemployment	1.784	.597	8.921	1	.003	5.952	1.846	19.187
	Peer group	1.654	.663	6.227	1	.013	5.227	1.426	19.158
	Educational background	2.126	.615	11.950	1	.001	8.381	2.511	27.977
	Parental influence	2.460	.594	17.136	1	.000	11.709	3.653	37.533
	Religion belief	0b	.	.	0	.	.	.	.
Abortion	Intercept	-6.640	1.552	18.309	1	.000			
	Age of victim	.354	.068	27.257	1	.000	1.425	1.247	1.627
	Age of suspect	.064	.018	12.647	1	.000	1.066	1.029	1.104
	[victim religion=Muslim]	.591	.459	1.663	1	.197	1.807	.735	4.439
	[victim religion=Christian]	0b	.	.	0	.	.	.	.
	Rape	19.005	.000	.	1	.	179417626.1	17941	1794176
	Human Trafficking	-22.235	3949.133	.000	1	.996	2.207E-010	.000	.c
	Incest	.340	6884.611	.000	1	1.000	1.405	.000	.c

Physical assault	-22.605	3193.513	.000	1	.994	1.524E-010	.000	.[c]
Child neglect	0^b	.	.	0	.	.	.	.
[victim sex=Female]	-2.403	.700	11.789	1	.001	.090	.023	.357
[victim sex=Male]	0^b	.	.	0	.	.	.	.
[suspect gender=Female]	-1.892	.834	5.147	1	.023	.151	.029	.773
[suspect gender=male]	0^b	.	.	0	.	.	.	.
[suspect religion=Muslim]	.188	.501	.140	1	.708	1.206	.451	3.224
[suspect religion=Christian]	0^b	.	.	0	.	.	.	.
Poverty/unemployment	.250	.966	.067	1	.796	1.284	.193	8.520
Peer group	-2.475	1.604	2.381	1	.123	.084	.004	1.953
Educational background	.730	1.015	.518	1	.472	2.075	.284	15.159
Parental influence	1.505	1.011	2.218	1	.136	4.505	.622	32.652
Religion belief	0^b	.	.	0	.	.	.	.

From the table above, the first block is treating the consequence (stigmatization) against all other selected dependent variables: β is the estimated multinomial logistic regression coefficients for the model. An important feature of the multinomial logistic regression model is the estimates $n - 1$ models, where n is the number of levels of the outcome variables which in this case are age of the victims, victim religion, suspects religion, victim gender, forms of child abuse, and causes of child abuse, for each of this independent variables, the last variables are treated as the referent group and therefore estimated a model for stigmatization relative to each of the independent variables. Therefore , since the parameter estimates are relative to the referent groups, it indicate that for a unit change in the dependent variable (stigmatization) , the logit of the outcome relative to the reference group is expected to change by its respective parameter (which is in log- odds units) given that the variables in the model are held constant.

Intercept: this is the multinomial logistic estmate for stigmatization relative to the independent variables, where the referent variables in the model are evaluated at zero.

The multinomial log-odds of stigmatization against age of the victims are expected to increase by 0.056 while holding other variables in the model constant. The multinomial log-odds of stigmatization against age of the suspects are expected to increase by 0.67 while holding other variables in the model constant. The multinomial log-odds of stigmatization against victim religion [Muslim] are expected to increase by 0.557 while holding other variables in the model constant. The multinomial log-odds of stigmatization against age human trafficking is expected to increase by 18.905 while holding other variables in the model constant. The multinomial log-odds of stigmatization against incest is expected to increase by 39.845 while holding other variables in the model constant. The multinomial log-odds of stigmatization against victim sex are expected to increase by 0.59 while holding other variables in the model constant.

The multinomial log-odds of stigmatization against suspect gender [female] is expected to increase by 2.233 while holding other variables in the model constant. The multinomial log-odds of stigmatization against poverty/unemployment is expected to increase by 1.356 while holding other variables in the model constant. Standard error; these are error of each regression coeffients for the model estimated with is the consequences of child abuse against each dependent variables. Significant difference; these are the p-values of the coeffients that is within a given model, the null hypothesis that a particular predictors regression model is zero given that the

rest of the dependent variables are in the model, which is based on wald test statistics of the predictors, which can be calculated by dividing the square of the predictor's estimate by the square of its standard error.
The consequence of child abuse relative to age of the victim, the wald test statistic for the predictor stigmatization is 2.254 with the associated p-value of 0.038. if the $\alpha = 0.05$.
For the consequence of child abuse relative to age of the suspect, the wald test statistic for the predictor stigmatization is 3.060 with the associated p-value of 0.016. if the $\alpha = 0.05$, the age of the suspect has been found to be significantly influence stigmatization which is one of the child abuse consequence.
For the consequence of child abuse relative to victims who are muslim or Christian as a referent group, the wald test statistic for the predictor is 1.636 with the associated p-value of 0.358. if the $\alpha = 0.05$ we fail to reject the null hypothesis and conclude that for stigmatization relative to victim religion, victim religion does not have any statistically influence on stigmatization.
For the consequence of child abuse relative to victims gender who are female holding male as a referent group, the wald test statistic for the predictor is 1.636 with the associated p-value of 0.526. if the $\alpha = 0.05$ we fail to reject the null hypothesis and conclude that for stigmatization relative to victims gender, victim gender does not have any statistically influence on stigmatization.
For the consequence of child abuse relative to gender of the suspect, the wald test statistic for the predictor stigmatization is 22.656 with the associated p-value of 0.046. if the $\alpha = 0.05$ we would reject the null hypothesis and conclude that for stigmatization relative to gender of the suspect, the gender of the suspect has been found to statistically influence stigmatization
Compared to the low victimisation class, participants in the domestic violence class, emotional abuse and neglect class and especially the maltreatment and domestic violence class, reported higher symptoms of anxiety and depression and an increased likelihood of non-suicidal self-injury, suicide ideation and suicide attempt.

5. CONCLUSION

This research provides an overview of the possible consequences that are associated with child abuse using a Multinomial Logistic Regression [MLR] model approach, various categories of abuse was discovered and the most prevalence was determined, and, also comparative analysis between the consequences of child abuse and other related crimes with the suspect age and religion. The review reveals different forms of child abuse melted out on children and other related crimes. Some of the abuse and consequences are attributed to poverty/unemployment, family size, educational background, peer group, religion belief, and parental influence.
Model had been tested through a set of statistical tests to ensure its appropriateness for the data. Also the model had been tested by selecting randomly of two observations of the data used to predict the position of each observation in any classified group it can be as shown in table 11, by knowing the values of the explanatory variables used. It was concluded that using the multinomial logistic regression model that was able to define accurately the relationship between the group of explanatory variables and the response variable, identify the effect of each of the variables, and predict the classification of any individual case.
The model ability of prediction had been checked by choosing two cases of the data ran domly and applying the model to predict in any of the response variable's group can be classified of these cases. The model has been successful in one classification. The crucial conclusion can be presented by several important points:
1). The usage of the MLR model gives us the opportunity to deal with a response categorical variable with more than two levels and variety of explanatory variables.
2). MLR indicates the effect of each of explanatory variables as well as its additive effect by used in the analysis simultaneously which we are aiming of the study of this model.
3). MLR enables building a statistical model showing those complex and interrelated relationships,

particularly as we are dealing with a qualitative response variable has more than two categories. These equations could measure accurately the effect of each of explanatory variables and excluded those variables which did not have statistical significant.

4). MLR model, also has proved its ability to predict, and has reached the precision with which exhibited 80.7% in our model.

5). The model will help researcher who will try to study the subject of physical violence by gave him an idea about variables importance and effects, of course it can be made comparisons between the effects that are calculated from models if used the similar variables.

6). The logistic regression model is a suitable model to many types of data when the response variable with more than two categories. MLR has no any restrictions about the explanatory variables; this model is most common in the categorical data analysis. MLR can be used in many areas of social, educational, health, behavioral and even scientific experiments

The findings carry important implications for understanding patterns of child maltreatment, and the implications for preventative strategies and support services.

REFERENCES

Agresti, A. (2007). An Introduction to Categorical Data Analysis. John Wiley & Sons, Inc.

Agresti, A. (2002). Categorical Data Analysis. John Wiley & Sons, Inc.

Bellis, M. A., Hughes, K., Leckenby, N., Hardcastle, K. A., Perkins, C., & Lowey, H. (2015). Measuring mortality and the burden of adult disease associated with adverse childhood experiences in England: A national survey. Journal of Public Health, 37(3), 445–454. https://doi.org/10.1093/pubmed/fdu065

Bentley, H., Fellowes, A., Glenister, S., Mussen, N., Ruschen, H., Slater, B., Turnbull, M., Vine, T., Wilson, P., & Witcombe Hayes, S. (2020). How safe are our children? An overview of data on adolescent abuse. NSPCC

Black, D. A., Heyman, R. E., & Slep, A. M. S. (2001). Risk factors for child physical abuse. Aggression and Violent Behavior, 6(2–3), 121–188. https://doi.org/10. 1016/s1359-1789(00)00021-5

Buffarini, R., Coll, C. V., Moffitt, T., da Silveira, M. F., Barros, F., & Murray, J. (2021). Intimate partner violence against women and child maltreatment in a Brazilian birth cohort study: Co-occurrence and shared risk factors. BMJ Global Health, 6(4), e004306. https://doi.org/10.1136/bmjgh-2020- 004306 18 Journal of Interpersonal Violence 0(0)

Button, D. M., & Gealt, R. (2010). High risk behaviors among victims of sibling violence. Journal of Family Violence, 25(2), 131–140. https://doi.org/10.1007/ s10896-009-9276-x

Choo, W. Y., Dunne, M. P., Marret, M. J., Fleming, M., & Wong, Y. L. (2011). Victimization experiences of adolescents in Malaysia. Journal of Adolescent Health, 49(6), 627–634. https://doi.org/10.1016/j.jadohealth.2011.04.020

Dantchev, S., & Wolke, D. (2019). Trouble in the nest: Antecedents of sibling bullying victimization and perpetration. Developmental Psychology, 55(5), 1059–1071. https://doi.org/10.1037/dev0000700

Debowska, A., Willmott, D., Boduszek, D., & Jones, A. D. (2017). What do we know about child abuse and neglect patterns of co-occurrence? A systematic review of profiling studies and recommendations for future research. Child Abuse & Neglect, 70(2017), 100–111. https://doi.org/10.1016/j.chiabu.2017.06.014

Brannon, D., Barry, T., Kemper, P., Schreiner, A., and Vasey, J.(2007). Job Perception and Intent to Leave Among Direct Care Workers: Evidence from the Better Jobs Better Care Demonstrations. The Gerontologist 47:820-829, The Geronotological Society of America.

Chatterjee, S., and Hadi, A. (2006). Regression Analysis by Example. John Wiley & Sons.

Garson, D. (2009). Logistic Regression with SPSS. North Carolina StateUniversity, Public administration Program.

Moorman, S.M., and Carr, D. (2008).Spouses Effectiveness as End-of-Life Health Care Surrogates: Accuracy, Uncertainty, and Errors of Overtreatment or Undertreatment. The Gerontologist 48:811, The Gerontological Society of America.

Schafer J.L. (2006). Multinomial logistic regression models. STAT 544- Lecture 19.

Schwab J., (2007). Multinomial Logistic Regression Basic Relationships.www.utexas.edu/courses/schwab/sw388r7/SolvingProblems/Analyzi.

Takagi, E., Silverstein, M., and Crimmins, E. (2007). Intergenerational Coresidence of Older Adults in Japan: Conditions for Cultural Plasticity . The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 62:S330-S339, The Gerontological Society of America