

On Maintaining High Levels of Immunization Coverage in Edo State Using Binary Logistic Regression Model

Iduseri A. and Osemwenkhae J. E.

**Department of Mathematics, Faculty of Physical Sciences, University of Benin, P.M.B. 1154,
Benin City, Edo State, 300001, Nigeria.**

Abstract

A target of 90-95% levels of immunization coverage is necessary for the sustained control of vaccine-preventable diseases. In Nigeria, achieving and maintaining a high level of 90-95% immunization coverage which is an indication of the effectiveness of a health care system has remained elusive till date. This paper is therefore aimed at exploring the possibility of maintaining high levels of immunization coverage in Edo state using best subset binary logistic regression model and the chi-square test as validation tool. We found that the obtained logistic model which constitutes only five key predictor variables out of eight potential predictors used had a good predictive performance. In addition, validation of the five key predictor variables using the chi-square test shows that all had significant association in relation to a child completion of immunization schedule.

Keywords: Immunization coverage, best subset, binary logistic regression model, chi-square test, predictive performance

1.0 Introduction

Immunization prevents illness, disability and death from vaccine-preventable diseases including cervical cancer, diphtheria, hepatitis B, measles, mumps, pertussis (whooping cough), pneumonia, polio, rotavirus diarrhea, rubella and tetanus. Immunization currently averts an estimated 2 to 3 million deaths every year [1]. But an estimated 18.7 million infants worldwide are still missing out on basic vaccines [1]. In public health interventions, immunization remains one of the most cost effective strategies to reduce both the morbidity and mortality associated with childhood infectious diseases in developing countries like Nigeria. Immunization is often cited as being one of the greatest public health achievements of 20th century [2], but effective immunization requires population coverage levels of 90 to 95% depending upon the vaccine-preventable disease [3]. Achieving high levels of immunization coverage is, by itself, not a sufficient indication of the effectiveness of a health care system, as deficiencies in other areas could be widespread. However, *lack* of progress in moving towards maintaining high levels of immunization coverage is a strong indication of failure to provide essential services to protect the health of the most vulnerable segment of a population [4, 5]. Immunization coverage refers to information on the proportion of children who have received specific vaccines or are up to date with the recommended vaccine schedule. This information is essential for planning immunization programmes, identifying vulnerable groups or areas that require targeting of increased resources, assessing the acceptability of a programme, and predicting likely vaccine-preventable disease epidemics [3].

In Nigeria, the Expanded Program on Immunization (EPI) target eight diseases namely diphtheria, polio, neonatal tetanus, tuberculosis, hepatitis B, pertussis, yellow fever and measles. Routine immunization of children in Nigeria is carried out using the following vaccines: (1) Bacilli Calmette Guerin (BCG) given at birth or as soon as possible after birth, (2) Oral Polio Vaccine (OPV) given at birth and at 6, 10, and 14 weeks of age, (3) Diphtheria, pertusis, tetanus (OPT) given at 6, 10, and 14 weeks of age, (4) Hepatitis B given at birth, 6 and 14 weeks of age, (5) Measles given at 9 months of age, (6) Yellow Fever given at 9 months of age, and (7) Vitamin A given at 9 months and 15 months of age. All these vaccines should be given to children during the first year of their life, over the course of five visits, including the doses given at birth. Therefore, children are considered fully immunized if they receive one dose of BCG, three doses of DPT and polio vaccine each, and one measles vaccine.

Corresponding author: Iduseri A., E-mail: augustine.iduseri@uniben.edu, Tel.: +2348036698860

Nigeria has a long history of implementation of EPI beginning with pilot efforts in 1975, and the strategy revision which was completed in 1984 with major inputs from United Nations Children Fund (UNICEF). In 1983, the government began increasing their inputs such as funding, logistics, transport, power generators, information, education and communication materials, training packages, as well as organizing series of national immunization days (NIDs) and state immunization days (SIDs). Analysis of recent immunization coverage data reported in [4] reveals that only 4.6% of the total number of children 12–23 months of age had received all of the recommended doses by one year of age, with only 1.1% in the rural areas. UNICEF estimates of coverage per antigen between 1995 and 2011 provide information on only four antigens in Nigeria [4]. Further analysis of the UNICEF coverage data per antigen shows that between 1995 and 2011, BCG average coverage was 52.49%, DPT had an average coverage of 38.06%, polio average coverage was 37.09%, and measles' average coverage was 42.92%. Judging from the UNICEF average coverage data per antigen from 1995 to 2011 as against the required population coverage levels of between 90 and 95 %, this still leaves a considerable proportion of children that should be targeted if deaths from the eight killer diseases are to be prevented.

Numerous studies have been published on immunization coverage and the factors associated with full immunization in Nigeria. Majority have considered social demographic factors, such as gender, age, mother's religion, mother's level of education, place of residence, mother's occupation, source of information, region of residence, illness of the child, unawareness of the need for immunization, being busy with other works, availability of facilities, and delivery by a health staff as predictors of full immunization coverage [6-11]. However, these studies have generally failed to adequately address the *lack* of progress in maintaining high levels of immunization coverage which is a strong indication of failure to provide essential services to protect the health of the most vulnerable segment of a population. According to Tarantola et al [7], out of a total annual cohort of some 29 million infants who survived to their first birthday in African Region, 8.4 million had not received their third dose of DPT compared to 7.4 million in 2010. The majority of these children (more than 80%) were located in only ten of the Africa countries with Nigeria having over 40% [7]. This is of great concern, as Nigeria is regarded as the most populous in Africa. This means that Nigeria will contain a large proportion of Africa's unimmunized children. However, in 2012, among the nine states in the Niger Delta region in Nigeria which consists of Bayelsa, Delta, Rivers, Akwa Ibom, Cross River, Edo, Ondo, Abia and Imo States, the highest proportion of children 12 to 23 months that completed their immunization schedule were in Edo state [6]. All the children in Edo state were either partially or fully immunized. In terms of Immunization coverage for vaccines, Edo state had the highest coverage for all the vaccines. Coverage of DPT3 was estimated to be 75.9% based on card and history, and 68.4% based on card alone for all the States. Measles coverage (card + history) was estimated to be 69.7% across the six States (i.e., Rivers, Bayelsa, Delta, Abia, Akwa Ibom, and Edo States) with the highest coverage of 83.4% in Edo state [6]. There has been a rekindled commitment to immunization coverage in Edo state, larger budget dedicated to this service area, lower cost of basic vaccines and greater focus on logistic and human resources than ever before. Other key strategies adopted to expand immunization coverage include routine immunization services in static health care facilities, National Immunization Days (NID), and mop-up campaigns for oral polio. Despite her enhanced focus on immunization coverage, maintaining her relatively high level of immunization coverage has been a challenge to the Government of Edo state. Hence, these vaccine preventable diseases still remain the most common cause of childhood mortality in Edo state.

Though Edo has perform better than her neighboring states in terms of her relatively high levels of immunization coverage for all the vaccines, yet achieving and maintaining a target of 90-95% levels of immunization coverage is necessary for the sustained control of vaccine-preventable diseases. Even if immunization coverage levels are sufficiently high to block disease transmission, pockets of susceptibility may act as potential reservoirs of infection [4]. Thus achieving and maintaining high levels of immunization coverage must therefore be a priority for all health systems in Edo state. That is, ensuring that all children given BCG at birth also receives three doses of DPT , polio vaccine each, and one measles vaccine at the age of nine months. Therefore the purpose of this study is to obtain numerical estimate in terms of the probability of a child completing his/her vaccination schedules, thereby identifying those children who will likely not complete their immunization schedule from among the children who have received specific vaccines. In other words, such numerical estimate will serve as information criterion for identifying children "vulnerable to partial immunization" with the aim of providing special follow-up programs for their mothers in order to maintain high levels of immunization coverage in Edo state.

2.0 A Brief Overview of Background Theory

Logistic regression model (or simply logistic model) is part of a category of statistical models called generalized linear models. This broad class of models includes ordinary regression and analysis of variance (ANOVA), as well as multivariate statistics such as analysis of covariance (ANCOVA) and loglinear regression. Logistic model is a promising statistical technique that can be used to predict the likelihood of a categorical outcome variable. It has found widespread use in the epidemiological literature, where often the dependent variable is presence or absence of a disease state. The best known variety of logistic model is the Binary logistic model. Generally, the logistic models are appropriate when the response takes

one of only two possible values representing success and failure, or more generally the presence or absence of an attribute of interest. Binary logistic regression models, by design, overcome many of the restrictive assumptions of linear regressions. For example, linearity, normality and equal variances are not assumed, nor is it assumed that the error term variance is normally distributed [12]. To obtain a logistic model, we first define a logistic function, $f(Z)$, given as:

$$f(Z) = \frac{1}{1 + e^{-Z}} \tag{1}$$

The logistic function (1) describes the mathematical form on which the logistic model is based and its range is between 0 and 1, regardless of the value of Z . To obtain the logistic model from the logistic function, we first define Z as:

$$Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k \tag{2}$$

Where X 's are the independent variables of interest, α and β_i are constant terms representing unknown parameters and Z is an index that combines the X 's. Substituting the linear sum expression for Z (2) in the right-hand side of (1), we get

$$\begin{aligned} f(Z) &= \frac{1}{1 + e^Z} \\ &= \frac{1}{1 + e^{-(\alpha + \sum \beta_i X_i)}} \end{aligned} \tag{3}$$

To view this expression as a statistical model, we will first have observed independent variables X_1, X_2, \dots, X_k on a group of subjects, for whom we have also determined a certain condition status as either 1 if “with the condition” or 0 if “without the condition”. This information can be used to describe the probability that the certain condition will develop during a defined study period, say T_0 to T_1 in a condition-free individual with independent variable values X_1, X_2, \dots, X_k

which are measured at T_0 . The probability being modeled can be denoted by the conditional probability statement $P(Y = 1 | X_1, X_2, \dots, X_k)$. If we define

$$P(Y | X_1, X_2, \dots, X_k) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i X_i)}} \tag{4a}$$

and we denote the probability statement $P(Y = 1 | X_1, X_2, \dots, X_k)$ as simply $\pi(\mathbf{X})$, where the bold \mathbf{X} is a shortcut notation for the collection of variables X_1, X_2, \dots, X_k . The logistic model (4) may be written as

$$\pi(\mathbf{X}) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i X_i)}} \tag{4b}$$

Thus, if we knew the parameters α and the β_i and we had determined the values of X_1, X_2, \dots, X_k for a particular condition-free individual, we could use this model to plug in these values and obtain the probability that this individual would develop the condition over some defined follow-up time interval.

Logistic regression model has been a useful statistical tool in public health interventions. In the area of routine immunization, it has proven useful in assessing the determinants of full immunization coverage in Nigeria. To the best of our knowledge, its usefulness in obtaining numerical estimate (in terms of the probability of a child completing his/her vaccination schedules) which will serve as information criterion for identifying children “vulnerable to partial immunization” with the aim of providing special follow-up programs for their mothers in order to maintain high levels of immunization coverage has not been studied by any substantive researcher.

3.0 Materials and Methods

Study area

The study was carried out in Edo state located in Mid-Western Region of Nigeria. With an estimated population of 3,218,332 made up of 1,640,461 males and 1,577,871 females and a growth rate of 2.7% per annum [13], as well as a total landmass of 19,187 square kilometers, the state has a population density of about 168 persons per square kilometers. Edo state could be defined as a collection, gathering or nation of people of united yet diverse identity. It was created on August 27, 1991 with its capital situated in Benin City, and currently made up of eighteen (18) local government areas (LGAs) scattered around three senatorial districts. The main ethnic groups in Edo state are: Edos, Afemais, Esans, Owans and Akoko Edos. Edo state health

system is divided into two, the private and public health sector. The private health sector is made up of private hospitals, clinics, maternity homes, and private individuals. While the public health facilities are owned and run by either the federal, state or local governments. The state primary health care (PHC) encompasses family planning, immunization, prevention and control of health problems and environment for the well being and health of its citizens.

Data collection

The data for this present article was obtained from World Health Organization office, Edo State, Nigeria. The data were collected in 2011 from six of the eighteen local government areas of Edo state, with two LGAs chosen from each of the three senatorial districts. A house-to-house survey using designed questionnaire and examination of vaccination cards was conducted in two wards (1 Urban, 1 Rural) from each of the selected LGAs which include Oredo, Uhunmwode, Esan West, Esan North East, Etsako West and Etsako East. Mothers of child-bearing age who had at least one child was administered a questionnaire by trained interviewers in order to obtain maternal characteristics and child immunization history. Children were considered to have completed their immunization if they had received BCG, three doses of DPT, three doses of OPV, three doses of Hepatitis-B vaccine, one dose of Measles vaccine and one dose of Yellow Fever vaccine. In all, 811 eligible mothers were successfully interviewed about the immunization status of their children 12-23 months of age.

Data Analysis

The sex of respondent’s child, religion, level of education, age, place of residence, occupation, source of information and region of residence are considered as potential predictors in the analysis. The immunization status of the respondent’s child is treated as the response variable, Y. The responses for variable Y are coded as 0 for “children who did not take measles vaccine” indicating incomplete immunization schedule and 1 for “Children who took measles vaccine” indicating completion of immunization schedule. All the predictor variables, Xs are coded according to their number of categories. To determine the key predictors that distinguish between children that completed their immunization schedule and the children who did not complete their immunization schedule, a stepwise discriminant analysis (SDA) was performed using SPSS 16 in Windows. In order to confirm the selected key predictor as the best subsets of the predictor, we then used an “all- possible-subsets” approach which gave the same result [14, 15]. This includes mothers’ religion, level of education, area of residence, source of information and region of residence.

To obtain numerical estimate in terms of the probability of a child completing his/her vaccination schedules, a binary logistic regression model was employed. Given the five key predictors variables $X = \{x_1, x_2, \dots, x_5\}$, and the response variable Y (which is a binary variable indicating whether a child complete immunization schedule ($Y = 1$) or do not complete immunization schedule ($Y = 0$)), the probability of developing Y given the X’s denoted as π is

$$\pi = p(Y = 1 | X = x_1, x_2, \dots, x_5), \quad 1 - \pi = p(Y = 0 | X = x_1, x_2, \dots, x_5)$$

The above expressions or conditional probabilities can be model as follows;

$$\pi(x) = \frac{\exp\{\beta_0 + \beta_1 x_1 + \dots + \beta_5 x_5\}}{1 + \exp\{\beta_0 + \beta_1 x_1 + \dots + \beta_5 x_5\}} \tag{5}$$

$$1 - \pi(x) = \frac{1}{1 + \exp\{\beta_0 + \beta_1 x_1 + \dots + \beta_5 x_5\}} \tag{6}$$

where $\{\beta_0, \beta_1, \dots, \beta_5\}$ are the unknown parameters to be estimated.

If we denote π as the probability that a child complete immunization schedule, the ratio $\pi / (1 - \pi)$ which is called the *odd ratio* for completing immunization schedule is given as

$$\frac{\pi}{(1 - \pi)} = \exp\{\beta_0 + \beta_1 x_1 + \dots + \beta_5 x_5\} \tag{7}$$

Taking the natural logarithm of both sides of (7), we obtain the logit transform of (5) in terms of π as

$$g(x_1, \dots, x_5) = \beta_0 + \beta_1 x_1 + \dots + \beta_5 x_5 \tag{8}$$

To estimate coefficients (β_j) of the predictor variables we apply the maximum likelihood method (MLE). The log-likelihood function for n individuals is given as

$$L(\beta_0, \beta_1, \dots, \beta_5) = \sum_{i=1}^n Y_i (\beta_1 x_1 + \dots + \beta_5 x_5) - \sum_{i=1}^n \ln\{1 + \exp(\beta_1 x_1 + \dots + \beta_5 x_5)\} \tag{9}$$

Differentiating the log-likelihood equation w.r.t. $(5 + 1)\beta_j$ ’s, results in 5+1 likelihood equations, which could be solved simultaneously or with special purpose software. We however used SPSS 16 in Windows for this analysis.

Further Validation of Predictor Variables

To further assess the statistical significance of association between each of the identified predictor variables (discriminate factors) and the binary dependent variable (response variable), the chi-square test (χ^2) of independence was used.

Judging the Fit of the Model

In standard regression, R (Squared R in Particular) gives you an idea of how powerful your model is at predicting the variable of interest. However, Statisticians have come up with several R-like measures for logistic regression model such As Cox and Snell’s R-square, Pseudo-R-square and Hagle and Mitchell’s Pseudo-R-square. These measures are not particularly informative. Base on their common drawback, we therefore consider a simple but efficient approach by counting the number of the fitted probabilities for each observation (or child) that is greater than our 0.5000 cutoff and then compare it with the base level for correct classification. A measure of the base level for correct classification is given as

$$Max\left(\frac{n_1}{n}, \frac{n_2}{n}\right) = (0.56, 0.44) \tag{10}$$

Where n is the sample size, n_1 is the number of cases in Group 1 (children who did not complete their immunization schedule) and n_2 is the number of cases in Group 2 (children who completed their immunization schedule)

4.0 Results and Discussion

The SPSS 16 outputs for the Logistic model (9) using the five key predictor variables, the chi-square test of independence, as well as the confusion matrix for the actual and predicted categories of children immunization status are shown in Tables 1, 2 and 3 respectively.

Table 1: Output from Logistic Model Using the Five Key Predictor Variables

Variable	Coef.	S.E	Z-test	P-Value	Odd	95% C.I		
						Ratio	Lower	Upper
Constant	4.027	0.527	7.64	0.000				
Mother’s Religion(x_1)	-0.638	0.191	-3.35	0.001		0.62	0.36	0.77
Mother’s Education(x_2)	0.535	0.131	4.08	0.000	1.48	1.32	2.21	
Area of Residence(x_3)	1.006	0.223	4.52	0.000		2.38	1.77	4.23
Source of Information(x_4)	0.238	0.075	3.19	0.001	1.31	1.10	1.47	
Region of Residence(x_5)	-2.532	0.182	-13.92	0.000		0.55	0.06	0.11
Log-likelihood=	-323.425	G=464.82	df=5	p<0.000				

In Table 1, the constant and coefficients are shown in column 2. Substituting these values in (9), we obtain the fitted Logit model given by:

$$g(x_1, \dots, x_5) = 4.027 - 0.638x_1 + 0.535x_2 + 1.006x_3 + 0.238x_4 - 2.532x_5 \tag{11}$$

Column 4 headed by Z-test which is sometimes referred to as the *Wald Statistic* is the ratio of the coefficients and the standard errors in columns 2 and 3 respectively, with their corresponding *p-values* in column 5. Considering the results in column 5 of Table 1, we may conclude that all the five key predictors are significant for predicting the logits of the observations at 5% level of significance. The odds ratios and the 95% confidence intervals of the odd ratios are given in columns 6 and 7 respectively. The values of the odds ratios represent a unit change of a particular variable while the others are held constant. For example, the value of the odds ratio for area of residence (which is a binary variable) is 2.38. This value is a measure of the change in the log-odds of a child completion of immunization schedule among urban mothers with respect to rural mothers. Therefore, the interpretation of this value is that child completion of immunization schedule is approximately 2 times as likely among mothers in urban areas compared to mothers in rural areas. Also in Table 1, we observed a *p-value* of 0.000 for the G statistic (which has a chi-square distribution) with a value of 464.82 which is less than our 0.05 cutoff. This indicates that the predictor variables collectively influence the logits.

Table 2: Chi-Square Test of Independence for Distribution of Mothers by Demographic Characteristics and Children Immunization Status

Characteristics	Measles Vaccination		Total	Chi-Square Test
	Yes	No		
Mother's Religion				
Christians	429	261	690	$\chi^2 = 69.630$
Islam	13	66	79	$p < 0.000$
African Tradition	14	28	42	
Mother's Education				
No Education	23	50	73	$\chi^2 = 42.976$
Primary	168	140	308	$p < 0.000$
Secondary	203	154	357	
Higher	62	11	73	
Area of Residence				
Urban	208	110	318	$\chi^2 = 17.919$
Rural	248	245	493	$p < 0.000$
Source of Information				
TV		24	66	90
	$\chi^2 = 89.996$			
Radio		70	6	76
Print Media	7	1	8	$p < 0.000$
Health Worker	239	215	454	
Friends/Neighbors	74	54	128	
Religious Leaders	25	12	37	
Traditional Leaders	17	1	18	
Region of Residence				
Central	222	37	259	$\chi^2 = 3.916$
South		234	103	337
North		0	215	215

In Table 2, we notice that all the predictor variables considered independently using the chi-square test of independence showed a significant association in relation to a child completion of immunization schedule. These results agree reasonably well with the Z-test results (see Table 1) for individual predictors that all the coefficients have significant independent contribution in predicting the response variable. Also in Table 2, looking at the percentage distribution of children completing their immunization, the values showed great differences in the distribution of children 12-23 months completing their immunization schedule by mother's religion, education, area of residence, source of information and region of residence.

Table 3: Confusion Matrix for Actual and Predicted Categories of Children Immunization Status

Group	Predicted Group Membership (Y)		Total
	0	1	
Original Count (Y) 0	277	78	355
1	63	393	456
%	0	21.97	100
1	78.03	86.18	100

Overall Percentage = 82.11 Cutoff value 0.5000

From Table 3, we observed that the fitted model identified correctly 78.03% of the mothers whose children did not complete their immunization schedule and 86.18% percent of the mothers whose children completed their immunization schedule. This amounts to overall correct identification of 82.11%. Since this percentage of correct identification by the fitted logistic model is much higher than the base level rate of 56% (10), this indicates that the obtained model in (11) has a good predictive performance.

5.0 Conclusion

The overall high percentage of correct identification rate achieved by the fitted model in this study as seen in Table 3, shows that the logistic model can be used in identifying those children who will likely not complete their immunization schedule from among the children who have received specific vaccines. This study tends to illustrate the logicity and wisdom in examining related statistical models useful for the purpose of identification. The use of logistic model in this manner that is, obtaining numerical estimate in terms of the probability of a child completing his/her vaccination schedules will enable Health Workers to identify likely defaulters of immunization from among the children who have received specific vaccines (or BCG at birth).

Therefore, to maintain high levels of immunization coverage in Edo state, the Government should ensure strategic communication is established with the mothers of identified children with high probability of defaulting, as well as provide such mothers with targeted information. If for example such mothers are constantly reminded (through text messages and emails) of their children next appointment date, and also constantly provided with adequate health education tailored towards the dangers of partial immunization on every appointment date, will in no doubt significantly reduce the drop-out rate.

6.0 Acknowledgement

The authors of this article would like to thank Faith Ireye of World Health Organization, Edo State, Nigeria for making available the data used in this study.

7.0 References

- [1] WHO (2016). Immunization coverage fact sheets. WHO Review, March 2016.
- [2] CDC (1999). Ten great public health achievement—United States, 1900-1999. *Morbidity and Mortality Weekly Report*, 48(12), 241–243.
- [3] Ministry of Health (2007). The national childhood immunisation coverage survey 2005. Wellington: Ministry of Health, April 2007.
- [4] Endurance, A. O., Musa, Y. T., Azuka, V. A., Rachel O., and Precious E. I. (2014). Current trends of immunization in Nigeria: Prospect and Challenges. *Trop Med Health*, 42(2), 67–75.
- [5] Emmanuelle, R., Michèle, D., and Béatrice, S. (2014). Vaccination coverage for infants: Cross-sectional studies in two regions of Belgium. *BioMed Research International* Accessed on April 10 from <http://dx.doi.org/10.1155/2014/838907>
- [6] Angela, O., Babatunde, F., Akinwumi, F., and Edet, E. (2012). Immunization coverage in selected communities in the Niger Delta, Nigeria. *World Journal of Vaccines*, 2, 21-26.
- [7] Tarantola, D., Hacen, M., Lwanga, S., and Clements, C. J. (2014). Is immunization coverage in Africa slipping? An Evaluation of Regional Progress to 2013. *Ann Vaccines Immunization* 1(2): 1007.
- [8] Odusanya, O. O., Alufohai, E. F., Meurice, F. P., and Ahonkhai, V. I. (2008). Determinants of vaccination coverage in rural Nigeria. *BMC Public Health*, 8: 381.
- [9] Oluwadare, C. (2009). The Social determinant of routine immunization in Ekiti State of Nigeria. *Ethno-Med*, 3(1), 49–56.
- [10] Abdulraheem, I. S., Onajole, A. T., Jimoh, A. A. G., and Oladipo, A. R. (2011). Reasons for incomplete vaccination and factors for missed opportunities among rural Nigerian children. *Journal of Public Health and Epidemiology*, 3(4), 194-203.

- [11] BEN, C. A. (2014). Routine immunization in Nigeria: The Role of Politics, Religion and Cultural Practices. *African Journal of Health Economics*, 3 (1):0002.
- [12] Tabachnick, B. G. & Fidell, L. S. (2012). *Using multivariate statistics* (6th ed.). Boston, MA: Pearson.
- [13] NPC (2006). Population Distribution by Sex. Accessed on April 10 from <http://www.population.gov.ng/index.php/censuses>
- [14] Huberty, C. J. (1989). Problems with Stepwise Methods: Better Alternatives. In B. Thompson (ED), *Advances in Social Science Methodology*, 1, 43-70.
- [15] Thompson, B. (1995). Stepwise regression and stepwise discriminant analysis need not apply here: a guidelines editorial. *Educ Psychol Meas* 55(4), 525–534