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Statistical Study of Under-Five Child Mortality in Nigeria

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ABSTRACT
This study examined the rate and risk factors of child mortality in Nigeria that significantly affects the child mortality. Estimates of mortality rate indicators on the situation of women and children for the 36 states of the federation and the Federal Capital Territory were used for the analysis. The study shows that from 1966 to 1986 there have been a decrease in child mortality by almost 63%, then an increase of about 3% were recorded between 1987 and 1991followed by a decrease from 2003 down to year 2017. For the purpose of robustness, Principal Component Analysis and Multiple Linear Regression (backward elimination) model procedure was used. The backward elimination method and principal component regression procedure shows that maternal and environment risk factors (early marriage, female education, poor sanitation, early child birth, place of delivery, birth registration, solid fuels and birth registration) impacts significantly on child mortality in Nigeria. The study therefore calls for an urgent action and greater national priority on child survival through interventions that will be integrated at community and family levels, targeting pregnant women, under-five children and accessing the hard-to- reach in order to improve child survival in Nigeria.
Keywords: Under-five Child mortality, Principal component Analysis, Multiple linear regression

1.0 INTRODUCTION

Childhood mortality is one of the important indicators of a countries general medical and public health conditions, and consequently it's level of socio-economic development. Its increase is not only undeliverable but also indicative of a decline in general living standard (Anderson et al., 1998). Reducing mortality and improving the health of young children has long been a concern of the international community. Since then, the United Nations has been actively involves with efforts aimed at reducing infant and under five mortality in developing countries. Globally, the number of deaths among children under the age of five has reduced from 12.4 million in 1990 to 8.1 million in 2009 (UNICEF, 2010). Environmental, maternal and socio-economic factors were acknowledged as additional important determinant of child survival. Child mortality rate stills remain unacceptably high in sub-Saharan African countries as approximately half of childhood deaths take place in sub-Saharan Africa despite the region having only one fifth of the words children population (Smith, 2010). For instances, in sub-Sahara Africa, 1 child in 8 dies before the age of five-nearly 20 times the average of 1 in 167 in developed parts of the world. The region's under-five mortality rates was 173 per 1,000 live births compared to the minimum goal of 70 per 1,000 internationally adopted in the 1990 world summit for children. Of the thirty countries with the world highest child mortality rates, twenty seven are in sub-Saharan Africa. It is not known why the infant and child mortality rates are staying higher or even increasing in many sub-Sahara countries despite action plans and interventions. While others areas of the world have experienced declining rates of childhood mortality over the last 30 years, this area, for the most part still maintains relatively high rates. Country estimates of the level and determinants in childhood mortality are needed to help set priorities, shape policies, design programs and monitor progress towards the MDG's at the national level. These estimates are needed at the international level to inform funding decisions for activities directed towards reducing child mortality.

The main objective of the study is to assess the rate of under-five mortality and to determine the impact of socio-economic, maternal and environmental contamination variables on child mortality in Nigeria using Multiple linear regression and Principal component regression models and model performance indicators procedure to determine the variables that significantly affects child mortality in Nigeria and assess the validity of the model

2.0 LITERATURE REVIEW

The literature deals with the collection of other relevant research works that will provide bases for present research the collection, collation and coordination of related literature are of paramount importance in every study. Review of related literatures in statistical research is sometimes very elaborate and very necessary due to its vast areas of applications.

Folashade (2000) in a study to determine the relative significance of environmental and maternal factors on childhood mortality in South Western Nigeria found that child mortality rate continued to be a function of an environmental factor namely source of drinking water and a child care behavior factor. Also Ozumba and Nwogu-Ikojo (2008) applied multiple regressions with autocorrelation adjustment to estimate mortality. Doctor, (2011) used multivariate logistic regression. All these studies find demographic, socio-economic and environmental factors (source of drinking water, sanitation facilities) to be significantly related to infant and child mortality.

Jamal and Zakir (2009) in their study of child mortality in Bangladesh used the cross tabulation and multiple logistic regression techniques to estimates the predictor of child mortality. The cross tabulation analysis shows that parent's education is the vital factor associated with child mortality.

Cornelia (2011) used data from Jordan's 2007 Demographic and Health Survey to assess the main determinant of child mortality in this middles income country. Application of different Logit estimations to allow for different time windows and sets of variable show that behavioral factors have gained importance compared to the household and community factors that were found to be important in earlier studies. He concluded that once a country has passed a certain threshold in household income, education and access to health care and safe drinking water, policies targeting behavioral changes are the most promising for achieving further reductions in mortality rates.

Bello (2014) used Logistic regression method of examine and identifies some important determinant of infant and child mortality in Oyo state. A total of 150 respondents were randomly selected from the entire populace in the metropolis. Findings reveals that out of the major determinant listed, Poverty, Malaria, Postnatal care and Breastfeeding are the major determinants of child mortality in the state while HIV though catalyzes child mortality was not a major determinant.

Aliyu (2015) in a study examined the assessment of rate and risk factors of child mortality in Nigeria to ascertain the risk factors that significantly affects child mortality. Estimates of mortality rate and some number of indicators on the situation of women and children for the 36 states of the federation and the Federal Capital Territory were used for the analysis using the 2011 Nigeria Multiple Indicator Cluster Survey (MICS4) data. He employed factor analysis and multiple regressions (Backward Elimination Procedure and Stepwise Regression Procedure). Finding of the study show that our model is significant and the risk factors (Immunization, Poor Sanitation, Early Child Bearing and the Use of Solid Fuels) perfectly predicts child mortality.

3.0 RESEARCH METHODOLOGY

This section discusses the data sources variables and the methods used in the analysis of the result generated.

3.1 Data Sources

The study uses data from the Nigeria Multiple Indicator Cluster Survey (MICS4). The series of multiple indicator clusters survey is conducted by the National Bureau of Statistics (NBS) with technical assistance and funding assistance from UNICEF. Also National Demographic and Health Survey (NDHS), National Planning Commission (NPC), Survey Reports, Academic Articles, and programme documents were used.

Estimates of mortality rates and some number of indicators on the situation of women and children for the 36 states of the federation and the Federal Capital Territory

3.2 Multiple Regression

Multiple regression is a statistical technique use in exploring the relationship between two or more variables. In the fixed-*x* regression model, we express each y in a sample of n observation as a linear function of the *x*'s plus a random error, ε :

$$y_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \ldots\ldots\beta_q x_{iq} + \varepsilon_1$$

$$y_2 = \beta_0 + \beta_2 x_{21} + \beta_2 x_{22} + \ldots\ldots\beta_q x_{iq} + \varepsilon_2$$

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$$y_n = \beta_0 + \beta_1 x_{n1} + \beta_2 x_{n2} + \ldots\ldots\beta_q x_{nq} + \varepsilon_n$$

The $\beta's$ in the model are called regression coefficient.

Using matrix notation, the models for the n observations can be written much more concisely in the form $y = X\beta + \varepsilon$

$$\begin{pmatrix} y_1 \\ y_2 \\ y_n \end{pmatrix} = \begin{pmatrix} 1x_{11}x_{12}\ldots\ldots\lambda_{1q} \\ 1x_{21}x_{22}\ldots\ldots\lambda_{2q} \\ 1x_{n1}x_{n2}\ldots\ldots\lambda_{nq} \end{pmatrix}\begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_q \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_n \end{pmatrix}$$

3.3 Backward Elimination Procedure and Stepwise Regression Procedure

The backward elimination procedure begins with all *x's* (all variables) included in the model testing the deletion of each variable using a chosen model comparison criterion, and deleting any variable that improves the model the most by being deleted, and repeating this process until no further improvement is possible. The stepwise procedure is an extension of forward selection. Each time a variable enters, all the variable that have entered previously are checked using a model selection procedure to see if the least "significant" one is now redundant and can be deleted from the model.

3.4 Principal Component Analysis

Principal component analysis is used to find a small set of linear combination of the covariates which are uncorrelated with each other. This will avoid the multicollinearity problem. Besides, it can ensure that the linear combinations chosen have maximal variance. Application of principal component analysis (PCA) in regression has long been introduced by Kendall (1957) in his book on Multivariate Analysis. Jeffers (1967) is suggested for regression model to achieve an easier and more stable computation, a whole new set of uncorrelated ordered variables that is the principal components (PCs) be introduced (Lam *et al*., 2010).

Hussain et.al (2011) says that the steps involved in the PCA include the method of getting the data standardized. Calculating the covariance matrix, the eigenvectors and eigenvalues of the covariance matrix and visualizing the results. Algebraically, principal components are particular linear combinations of the p random variables. Geometrically, these linear combinations representing the selection of a new coordinate system obtained by rotating the original system with their development do not require a multivariate normal assumption. On the other hand, principal components derived for multivariate normal populations have useful interpretations in terms of the constant density ellipsoids.

Step 1: Get the data

Consider the linear combinations:

$$Y_1 = a_1 X = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p$$

$$Y_2 = a_2 X = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p$$

$$\vdots \qquad (2)$$

$$Y_p = a_p X = a_{p1}X_1 + a_{p2}X_1 + \cdots + a_{pp}X_p$$

Step 2: Standardize the data

Sometimes it makes sense to compute principal components for raw data. This is appropriate when all the variables are in the same units. Standardizing the data is often preferable when the variables are in different units or when the variance of the different columns is substantial. This can be done by subtracting the mean of each column and dividing by its standard deviation namely:

$$Z = \frac{(X - \mu_i}{\sqrt{\sigma_{1i}}}, \qquad i = 1,2, \ldots, p$$

In matrix notation, it is given by:

$Z = (V^{1/2})$-1 $(X - \mu)$

Where

$V^{1/2}$ is the diagonal standard deviation matrix. From this, we obtain mean of Z equals to zero, E(Z) = 0.

3.5 Keiser Meyer Olkin's and Bartlett's test of Sampling Adequacy and measuring the Homogeneity of variance across variables for Credit scoring.

H_{01}: The sampled data is adequate for the study

H_1: The sampled data is not adequate for the study.

H_{02}: $\delta_1 = \delta_2 = \cdots = \delta_k$

H1: $\delta_i \neq \delta_k \; for \; at \; least \; one \; pair(i,j)$

Test Statistic: KMO

4.0 RESULTS AND DISCUSSIONS

4.1 Descriptive Statistics and Distribution of Variables

Table 1 present's descriptive statistics covers mean values, standard deviation, and a two-sample t-test statistic to compare the means of child mortality and explanatory variables. The null hypothesis (H_0) in this test is that: "there is no statistical difference between the child mortality rate and socio-economic, maternal and environmental contamination variables". It is clear from the table that child mortality rate has significant differences in their mean values in term of some socio-economic, maternal and environmental contamination variables.

Table 1. Profile Analysis of Means and Standard Deviations of mortality level and socio-economic, maternal and environmental contamination variables:

	Child Mortality rate Mean =149.19; Std. Dev. = 54.996				
Variables	Mean	Std. Dev.	Mean Diff.	t-value	p-value
Early marriage	19.468	16.007	7.020	18.478	0.000
Female education	64.605	29.405	13.205	6.405	0.000
Fertility	5.678	1.267	8.908	16.111	0.000
health vaccination	29.592	18.676	11.418	10.474	0.000
Orphanage	9.557	4.1862	9.454	14.769	0.000
solid fuels	75.795	24.039	7.134	10.291	0.000
Water	57.481	17.212	10.449	8.777	0.000
Sanitation	33.159	19.196	9.701	11.960	0.000
Aids	15.268	11.102	8.689	15.413	0.000
breast feeding	32.757	10.112	8.576	13.576	0.000
skilled birth attendant	51.376	30.921	13.182	7.420	0.000
low birth weight	14.695	3.703	8.709	15.442	0.000
Safe Disposal child feaces	48.800	20.039	9.551	10.511	0.000
Early child Birth	16.014	12.472	7.663	17.380	0.000
Antenatal care coverage	67.186	24.818	12.227	6.707	0.000
Early childhood education	50.640	31.033	12.884	7.649	0.000
Place of delivery	49.932	29.107	12.834	7.734	0.000
Inadequate care	43.032	14.7196	9.965	10.653	0.000
Birth registrar	42.503	20.8510	11.793	9.047	0.000

Note: p-values are meant for testing the null hypothesis that there is no statistical difference between the child mortality rate and socio-economic, maternal and environmental contamination variables.

4.2: MULTIPLE REGRESSION ANALYSIS

4.2.1 Backward elimination method

In child mortality rate modeling techniques such as the one employed in this study, predictions and evaluation of models are mainly based only on the function of the significant predictor variables. Therefore, for us to generate a reduced form of the model that contains only the significant variables at a respectable alpha-value, the backward elimination procedure was applied to arrive at the final child mortality rate model. In this project, variables were retained and/or eliminated at the 0.05 significance level. After nineteen backward elimination processes, one statistically significant early marriage was retained in the model. The result of the regression is summarized in Table 2 below. The early marriage was found to be statistically significantly at the 1 percent α-level with p-values of 0.001. The coefficient estimate of the regression model is traditionally interpreted as, a unit increase in the early marriage, as result of increase in child mortality rate by 2.844 holding all else constants.

Table 2 Estimating Results

Regression Model						
Steps	**Variables**	**Coefficients**	**std. Error**	**t-value**	**Sig. value**	**VIF**
	Constant	76.229	115.703	0.659	0.519	
	Early marriage	2.589	1.422	1.821	0.086	18.147
	Female education	-0.788	0.793	-0.993	0.334	19.047
	Fertility	4.548	8.001	0.568	0.577	3.599
	health vaccination	0.471	0.831	0.567	0.578	8.437
	Orphanage	8.152	3.410	2.391	0.029	7.139
1	solid fuels	0.420	0.412	1.018	0.323	3.442
	Water	-0.353	0.562	-0.629	0.538	3.277
	Sanitation	-1.429	0.759	-1.884	0.077	7.432
	Aids	-1.034	0.735	-1.407	0.178	2.334
	breast feeding	1.048	0.872	1.202	0.246	2.723
	skilled birth attendant	0.097	0.945	0.103	0.920	29.895
	low birth weight	-0.542	3.007	-0.180	0.859	4.342
	Safe Disposal child feaces	-0.374	0.651	-0.574	0.573	5.958
	Early child Birth	0.727	1.004	0.724	0.479	5.490
	Antenatal care coverage	0.566	0.726	0.780	0.446	11.370
	Early childhood education	-0.269	0.405	-0.664	0.515	5.531
	Place of delivery	0.817	0.834	0.980	0.341	20.645
	Inadequate care	-0.595	0.551	-1.080	0.295	2.303
	Birth registrar	-1.339	0.873	-1.533	0.144	11.612
2	.	.	.			
3	.					
		.	.			
17	.					
			.			
		.				
18	Constant	56.556	28.456	1.988	0.055	
	Early marriage	3.411	0.525	6.491	0.000	2.664
	Orphanage	2.745	2.009	1.366	0.183	2.664
19	Constant	93.830	8.169	11.486	0.000	
	Early marriage	2.844	0.326	8.726	0.000	1.000
F-statistics: 17.138 on 1 and 35 DF, p-value: 0.000, Multiple R-squared: 0.685, Adjusted R-squared: 0.676, Mean Square Error: 979.717, RMSE: 31.300, Coefficient of variation: 0.2098, Ave. Abs. Pct. Error: 18.083.						

In order to ascertain the fit of the model, the coefficient of Determinant (adj.R-square), Coefficient of variation (C.V), mean square error (MSE), Root mean square error (RMSE) and Ave. Abs pct. Error. A look at the Coefficient of Determinant (adj. R-square), Coefficient of Variation (C.V), mean square error, Root mean square error, and Ave. Abs. pct Error values in Table 2 reveals that the model recorded some values of 0.676, 0.2098, 979.717, 31.3004 and 18.083 respectively.

From the regression result (i.e. Table 2), we can state our regression model for child mortality rate and early marriage from final step (step 19) using back ward elimination as follows:

$$Mortality = 93.830 + 2.844 early\_marriage$$

4.4 Principal Component Analysis

We wish to determine the hidden factors behind the variables (socio-economic, maternal and environmental contamination) in order to determine the natural groupings (factors that are highly correlated with each other and those that are weakly correlated with others) of Child mortality rate. The correlations between the independent variables are in the range of -0.913 to 0.871. Another important test for PCA is the Kaiser-Meyer-Olkin (KMO) of sampling adequacy and Bartlett's test of sphericity. Kaiser (1974) recommends accepting values greater than 0.5 that means the result for this research is acceptant with the value of KMO is 0.825. Bartlett's test is highly significant ($p < 0.001$) and therefore factor analysis is appropriate for this data.

Table 3: KMO Statistics for Sampling Adequate and Bartlett's test for Homogeneity

Test	DF	Approx. Chi-Square	P-value
Keiser-Meyer-Olkin Measure of Sampling Adequate	-	-	0.825
Bartlett's Test of Sphericity	171	677.763	0.000

Table 4: Total Variance Explained

Component	Initial Eigenvalue			Extraction sums of Squared loadings			Rotation sums of Squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	10.041	52.849	52.849	10.041	52.849	52.849	8.946	47.085	47.085
2	2.682	14.114	66.963	2.682	14.114	66.963	2.368	12.463	59.548
3	1.126	5.929	72.891	1.126	5.929	72.891	1.404	7.389	66.937
4	0.993	5.224	78.115	0.993	5.224	78.115	1.245	6.551	73.488
5	0.865	4.551	82.666	0.865	4.551	82.666	1.227	6.456	79.944
6	0.679	3.575	86.242	0.679	3.575	86.242	1.197	6.298	86.242
7	0.594	3.126	89.368						
8	0.439	2.311	91.679						
9	0.353	1.860	93.539						
10	0.292	1.538	95.077						
11	0.239	1.259	96.336						
12	0.182	0.960	97.297						
13	0.138	0.725	98.022						
14	0.119	0.627	98.649						
15	0.088	0.461	99.110						
16	0.062	0.325	99.436						
17	0.054	0.282	99.718						
18	0.037	0.192	99.910						
19	0.017	0.090	100.000						

Table 4 lists the eigenvalues associated with each linear component (factor) before extraction, after extraction and after rotation. Before extraction, it has identified eight (19) linear components within the data set. The eigenvalues associated with each factor represent the variance explained by the particular linear component and also displays their eigenvalue in term of the percentage of variance explained (so, Factor 1 explains 52.849% of total variance). PCA extracts all Factors with eigenvalues greater than 0.6; the cumulative variance explained by six principal components is 86.242%. The eigenvalues associated with these factors are again displayed in the label extraction sums of squared loading. In the final part of the Table 4, the eigenvalues of the factors after rotation are displayed. Rotation has the effect of optimizing the factor structure and one consequence for these data is that the relative importance of the

four factors is equalized. Before rotation, factor 1 accounted for considerably more variance than the remaining other factors (52.849% compare to 14.114%, 5.929%, 5.224%, 4.551% and 3.575%) however after extraction it accounts for only 47.085% compared to 12.463%, 7.389%, 6.551%, 6.456% and 6.298%.
Rotated matrix rotation using varimax rotation with Kaiser Normalization is shown in Table 5. This matrix contains the loading of each variable onto each factor where values less than 0.4 are suppressed from the output.

Table 5: Rotated Component Matrix

Variables	Component					
	1	2	3	4	5	6
Early marriage	-.902					
Female education	.858					
Fertility	-.553		.569			
health vaccination	.837					
Orphanage	.820					
solid fuels	-.658					
Water	.641	0.436				
Sanitation		-0.904				
Aids					.897	
breast feeding				.828		
skilled birth attendant	.936					
low birth weight	-.548		.776			
Safe Disposal child feaces		0.883				
Early child Birth	-.760					
Antenatal care coverage	.852					
Early childhood education	.811					
Place of delivery	.917					
Inadequate care						.947
Birth registrar	.857					

Table 5 shows the factor loading for socio-economic, maternal and environmental contamination on each component. The results are shown below:

- Early marriage (-0.902), Female education (0.858), Fertility (-0.553), health vaccination (0.837), Orphanage (0.820), solid fuels (-0.658), water (0.641), skilled birth attendant (0.936), low birth weight (-0.548), Early child Birth (-0.760), Antenatal care coverage (0.852), Early childhood education (0.811), Place of delivery (0.917), and Birth registrar (0.857) have large positive and negative loadings on component 1, so label as socio economic, maternal and environmental contamination
- Water (0.436), sanitation (-0.904) and safe disposal child feaces (0.883) Length of service (0.782) have large positive and negative loadings on component 2, so label this component as maternal and environmental contamination.
- Fertility (0.569) and low birth weight (0.776) have strong positive loadings on component 3, so label this component as maternal
- Breast Feeding (0.828) have strong positive loadings on component 4, so label this component as maternal
- Aids (0.897) have strong positive loadings on component 5, so label this component as socio-economic
- Inadequate cares (0.947) have strong positive loadings on component 6, so label this component as socio economic and environmental contamination.

Table 6. Component Score Coefficient Matrix

Variables	**Component**					
	1	**2**	**3**	**4**	**5**	**6**
Early marriage	-0.091	0.065	0.038	-0.011	0.069	0.041
Female education	0.065	-0.054	-0.023	-0.203	0.026	0.033
Fertility	0.123	0.147	0.522	0.249	0.215	0.060
health vaccination	0.140	-0.002	0.224	0.123	-0.088	0.221
Orphanage	0.172	-0.131	0.206	-0.087	0.263	-0.025
solid fuels	-0.022	-0.120	0.117	0.183	-0.127	-0.060
Water	0.203	0.198	0.233	0.420	-0.025	-0.278
Sanitation	0.075	-0.418	0.142	0.135	-0.144	-0.150
Aids	0.085	0.078	0.022	0.016	0.832	-0.014
breast feeding	0.030	0.008	-0.103	0.732	-0.007	0.100
skilled birth attendant	0.151	-0.038	0.150	-0.050	0.050	-0.074
low birth weight	0.123	-0.190	0.852	-0.211	-0.144	0.030
Safe Disposal child feaces	-0.024	0.407	-0.113	0.118	0.002	-0.064
Early child Birth	-0.041	0.121	0.148	-0.094	0.186	-0.015
Antenatal care coverage	0.101	-0.020	0.004	0.100	-0.080	0.003
Early childhood education	0.118	0.153	-0.035	0.105	0.271	0.036
Place of delivery	0.151	-0.001	0.120	0.006	0.054	-0.118
Inadequate care	-0.018	0.036	0.073	0.100	0.000	0.832
Birth registrar	0.146	0.031	0.260	0.006	-0.114	0.053

$$PC1 = -.091 Early\_marriage + .065 female\_edu. + .123 Fertility + ... + .146 Birth\_registrar$$

$$PC2 = -.065 Early\_marriage + (-.034) female\_edu. + .147 Fertility + ... + .0.031 Birth\_registrar$$

$$PC3 = .038 Early\_marriage + (-.034) female\_edu. + .522 Fertility + ... + .260 Birth\_registrar$$

$$PC4 = -.011 Early\_marriage + (-.203) female\_edu. + .249 Fertility + ... + .006 Birth\_registrar$$

$$PC5 = .069 Early\_marriage + .026 female\_edu. + .215 Fertility + ... + (-.114) Birth\_registrar$$

$$PC6 = .041 Early\_marriage + .033 female\_edu. + .060 Fertility + ... + (-.053) Birth\_registrar$$

The Principal Component Regression (PCR) model was obtained using six main factors from Principal component Analysis (PCA) as independent variables.

Table 7: Multiple linear Regression based on Principal Component scores Coefficient

Predictor	Coefficient	Std. Error	t	p-value	VIF
Constant	149.189	5.447	27.391	0.000	
PC1	-12.587	1.743	-7.223	0.000	1.000
PC2	2.096	3.372	0.622	0.539	1.000
PC3	14.045	5.204	2.699	0.011	1.000
PC4	10.014	5.541	1.807	0.081	1.000
PC5	12.287	5.937	2.070	0.047	1.000
PC6	-8.985	6.701	-1.341	0.190	1.000
R-squares(R^2) 0.698 Mean Square Error 1097.844 Ave. Abs. Pct. Error 16.609					
Adj. R-Square(R^2) 0.637 Root Mean Square Error 33.134					
F-statistic 11.533 Coefficient of variation 0.222					

Multiple linear regression analysis was repeated by using principal component analysis as inputs. Here coefficient of determination (R^2) and adj. R-squared are 0.698 and 0.637 respectively. This indicated that the model is good. The Value for variance Inflation Factor (VIF) for the independent variables is 1 indicating no multicollinearity problem. Six main factors from PCA were used as independent variables and the following model was obtained. The principal component scores of selected PCs (PC1-PC6) are used as predictor variables for MLR analysis. The results revealed that multicollinearity was removed and PC1, PC3, PC4 and PC5 were found to be statistically significant at 5 percent 10 percent level of significance, as shown in Table 7.
The final model can be written as:-

$$Mortality = 149.189 + (-12.587)*PC1 + 2.096*PC2 + ... + 12.287PC5 + (-8.985)PC6$$

5.0 FINDINGS

In finding, we received several literatures on works and finding of other researchers on child mortality; we noted the gap in literature and approach, and then set our objectives of studying the rate and risk factors of child mortality in Nigeria as a whole by using a factor analysis and multiple linear regression to discover that though there has been decrease in child mortality but the decrease is slower than expected and that maternal and environmental contamination variables significantly affects child mortality.
The results of the multiple regression and principal component regression are comparing using performance indicators such as Adjusted R-squared, Mean square error (MSE), Root mean square error (RMSE), Coefficient of variation (C.V) and Average Absolute Percentage Error (APE).

Table 8 Summary of Comparison of the models performance

Performance indicator	**Models**		**Remark**
	Multiple linear regression (**Backward elimination**)	Principal Component regression **(PCR)**	
Adjusted R-squared	**0.676**	0.637	**MLRB**
Mean square error (MSE)	**979.717**	1097.844	**MLRB**
Root mean square error (RMSE)	**31.300**	33.154	**MLRB**
Coefficient of variation (C.V)	**0.2098**	0.222	**MLRB**
Ave. Abs Pct Error (APE).	18.083	**16.609**	**PCR**

Table 8 shows the various performance indicators of multiple linear regression (backward elimination method) and principal Component regressions Models for child mortality rate. The results shown that multiple linear regression (backward elimination method) model has minimum values of mean square error (MSE) with 979.717, root mean square error (RMSE) with 31.3, coefficient of variation (CV) with 0.2098 and higher value of adjusted R-square with 0.676 respectively compare with principal component regression while principal component regression has minimum value of average absolute percentage error with 16.609 compare with multiple linear regression(backward elimination method). Therefore the multiple linear regression (backward elimination method) model gives better results than principal component regression model.

5.1 CONCLUSION

Based on our finding we make the following conclusion;

i. Nigeria has made great strides over the past decades in lowering under-five mortality. However, the recent rate of progress has been slower than in many other developing countries, and the gap with the developed countries remains large. Additional efforts are therefore required to further improve child survival.

ii. After empirically examining the impact of socio-economic, maternal, environmental contamination risk factor of child mortality in Nigeria, results from the factor analysis and simultaneously multiple regression has shown that maternal and environmental contamination variables (Female Education, Orphan, Solid Fuel, Poor Sanitation, Early Childbirth, Place of Delivery and Birth Registration) have significant effect of child mortality than socio-economic risk factors and the model obtained from the backward elimination procedure and principal component regression procedure is given as:

$$Mortality = 93.830 + 2.844 early\_marriage$$

$$Mortality = 149.189 + (-12.587) * PC1 + 2.096 * PC2 + ... + 12.287 PC5 + (-8.985) PC6$$

iii. Key intervention services identified for curbing these problems include urgent action and greater national priority on child survival through intervention that will be integrated at community and family levels, targeting pregnant women, under-five children and accessing the hand-to-reach in order to improve child survival in Nigeria.

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