A Comparison on Impact of HIV/AIDS Patients Characteristics on their Blood Pressure in Nigeria

Ezeokeke C. Anthonia, and Okoli C. Nchedo

Abstract—The study focused on comparison on impact of HIV/AIDS patient’s characteristics on their blood pressure in Nigeria: a case of NAUTH, COOUTH and Onitsha general hospital in Anambra State. The blood pressure being the response variables are systolic blood pressure & diastolic blood pressure, while the predictor variables being the HIV/AIDS patient’s characteristics are age, baseline count, initial weight, present weight and CD4 count of HIV/AIDS patients. The R software package was employed to facilitate the data analysis. The Multivariate Regression Model of the two response variables (Systolic PB and Diastolic PB) was first fitted with the coefficient of determination of 31.88% and 46.80% respectively for NAUTH data, 27.9% and 37.98% respectively for COOUTH data and 97.35% and 57.15% respectively for general hospital, Onitsha data. The test on the significance of the parameters for the multivariate regression for NAUTH data revealed that age and baseline count of HIV/AIDS patients have significant relationship with systolic BP at 5% level of significance, whereas other predictor variables (initial weight, present weight and CD4 count of HIV/AIDS patients) are not significant, while in the second model, only age has a significant relationship with diastolic BP, whereas initial weight, present weight, baseline count and CD4 count of HIV/AIDS patients do not have significant relationship with diastolic BP at 5% level of significance. The test on the significance of the parameters for the multivariate regression also revealed that only age has significant relationship with systolic and diastolic BP at 5% level of significance, whereas other predictor variables are not significant for both COOUTH and general hospital Onitsha data. It was further revealed that the data collected from the general hospital Onitsha has the highest coefficient of determination (0.9735) with the lowest AIC (1348.944), BIC (1374.462) and residual standard error (2.587) for systolic blood pressure model which makes the data used in this study the most suitable for the model employed under the stipulated year of study. Also observed that the same data collected from the general hospital Onitsha has the highest coefficient of determination (0.5715) with the lowest AIC (1825.917), BIC (1851.435) and residual standard error (6.008) for diastolic blood pressure model which equally makes the data used in this study the most suitable. It is clear from the result obtained in this study that the data set collected from general hospital, Onitsha from 2003 to 2017 is most appropriate for the multivariate multiple linear regression models.

Index Terms—Akaike Information Criterion, Bayesian Information Criterion, Blood Pressure, HIV/AIDS Patients, Multivariate Multiple Regression, Residual Standard Error.

I. INTRODUCTION

The Human Immune Virus and Acquired Immune Deficiency Syndrome epidemics are both global phenomena threatening the health of various peoples, culture and population in the world. The Sub-Saharan Africa (SSA) with about 10% of the world’s population has over two third of the people living with HIV [1]. HIV means Human Immune Virus. It is a virus that attacks, destroys and continues to deplete human immune system. The acronym AIDS means Acquired Immune Deficiency Syndrome. This suggests that the condition or illness is not inherited but acquired from possible environment factors such as virus infections. Similarly, immune deficiency means that the viruses have gradually caused deficient immunity as clearly manifested in poor nutrition and low resistance to opportunistic infections [2].

The threat of HIV has continued to be one of the most dreaded health challenges in the world since 1980s. The global AIDS response revealed that the national meridian HIV prevalence infection in Nigeria as 4.1% [3]. HIV/AIDS affects both the old, young, men and women in the society and in fact affect the productivity of every nation. From its inception this disease has destroyed lives, families and societies. HIV and AIDS deplete human immune system which kills the white blood cells resulting to death of its victims. The epidemic has become a serious issue globally. It is no longer only a health issue but a substantial threat to blood pressure, imposing a heavy burden, first on families, communities and eventually on the economy.

It is obvious that some characteristics of HIV/AIDS patients may be influenced by their blood pressure. Blood pressure measures cardiovascular function by measuring the force of blood exerted on peripheral arteries during the cardiac cycle or heartbeat. The measurement consists of two components [4]. The first is the force exerted on the arterial walls during cardiac contraction and is called systole. The second is the force exerted during cardiac relaxation and is called diastole. They represent the highest (systole) and lowest (diastole) amount of pressure exerted during the cardiac cycle. Blood pressure is recorded as fraction, with the systolic measurement written, followed by a slash and then the diastolic measurement [5]. Blood pressure may be affected by many factors, including blood volume, peripheral resistance, age, condition of the muscle of the heart genetics, diet and weight, activity, and emotional state [6]. In this paper, we used the R software for estimating the parameters of Multiple Linear Regression Model for blood pressure; examine whether there is any significant relationship between HIV/AIDS patients’ characteristics and their blood pressure; and to ascertain among the hospitals

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C. A. Ezeokeke, Department of Statistics, Faculty of Physical Sciences, Chukwuemeka Odumegwu Ojukwu University, Uli, Anambra State, Nigeria.
(e-mail: author@boulder.nist.gov)

C. N. Okoli, Department of Statistics, Faculty of Physical Sciences, Chukwuemeka Odumegwu Ojukwu University, Uli, Anambra State, Nigeria.

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the best that adequately fit the multivariate multiple linear regression model.

II. REVIEW OF RELATED LITERATURE

Zakari and Abdullahi [7] examined economic impact of HIV/AIDS and stigmatization on women in Nigeria as a challenge for the actualization of Millennium Development Goals (MDGs). The study was carried out using primary data among groups of Nigerian women. The data were analyzed using simple percentage method. The results of the study revealed that negative presentation by some medical personnel and the sensational captions by the Nigerian mass media on the so-called dead sentence nature of HIV/AIDS epidemic made it so scary that people found it difficult to accept its presence and so stigmatize people especially women with the disease. However, the study recommends that religious organizations, government and non-governmental organizations intensify sensitization efforts towards combating the epidemic.

Obansa et al. [8] examined the burden of HIV/AIDS on income groups (upper and lower income earners) in Nigeria, its impacts on human capital development and economic growth. Income differential, the relative difference in income per capita of the quintile group, life expectancy, out-of-pocket health expenditure, direct health expenditure, gross per capita formation was estimated, using data for the period 1986-2010. The study employed a panel data analysis procedure in order to capture the relative incidence (burden) of the epidemic between these income groups in Nigeria. Stationarity test was conducted on the variables used in the estimation. It was found that all the variables with an exception of health expenditure were stationary at first difference. Similarly, the long-run variability test of the incidence (burden) of HIV/AIDS on differential income earners and economic growth in Nigerian was also carried out and the residuals were found parsimonious over the period. Findings showed that the epidemic is already putting pressure on the income earners in Nigeria, especially those in the lower income group.

Sunday et al. [9] in their study evaluated the impact of HIV/AIDS on the Performance of the Nigerian Economy using annual time series data sourced from the World Bank Database, and Central Bank of Nigeria statistical bulletin. The variables considered in their study includes: gross domestic product which was used as proxy for economic growth, hence the dependent variable while HIV/AIDS and government expenditure on health were considered as independent variables respectively. The findings of their study indicated that all the variables defined in the model were stationary and there exists a unique long run relationship between the dependent and independent variables in the model. Hence, it was revealed that HIV/AIDS had a significant negative impact on productivity and by implication economic growth. Similarly, findings showed that government spending on health had a significant positive impact on economic growth in Nigeria during the period studied.

Ekezie et al [10] researched on application of multivariate multiple linear regression model on vital signs and social characteristics of patients. The result revealed that the multivariate multiple linear regression model was adequate for the relationship between the variables: Systolic Blood Pressure, Temperature and Height of patients on one hand, and the two social characteristics: Age and Sex on the other. A test of significance revealed that Age and Sex have influence on the Vital Signs. Following the result, they recommended that researchers should carry out a similar research work, making the predictor variables up to four to compare result.

The study shall examine the comparison on impact of HIV/AIDS patient’s characteristics on their blood pressure in Nigeria: a case of NAUTH, COOUTH and Onitsha general hospital, having reviewed past works.

III. METHODOLOGY

The multiple linear regression with n independent observations on Y and the associated values of Z, is the complete model of

\[
Y_1 = \beta_0 + \beta_1 Z_{11} + \beta_2 Z_{12} + \beta_3 Z_{13} + \cdots + \beta_r Z_{1r} + \epsilon_1
\]

\[
Y_2 = \beta_0 + \beta_1 Z_{21} + \beta_2 Z_{22} + \beta_3 Z_{23} + \cdots + \beta_r Z_{2r} + \epsilon_2
\]

\[
Y_3 = \beta_0 + \beta_1 Z_{31} + \beta_2 Z_{32} + \beta_3 Z_{33} + \cdots + \beta_r Z_{3r} + \epsilon_3
\]

\[
\vdots
\]

\[
Y_n = \beta_0 + \beta_1 Z_{n1} + \beta_2 Z_{n2} + \beta_3 Z_{n3} + \cdots + \beta_r Z_{nr} + \epsilon_n
\]

where the error terms are assumed to have the properties:

1. \( E(\epsilon_j) = 0; \)
2. \( \text{Var}(\epsilon_j) = \sigma^2 \) (constant); and
3. \( \text{Cov}(\epsilon_j, \epsilon_k) = 0, j \neq k \)

Representing equations (2) in matrix form, we have

\[
\begin{bmatrix}
Y_1 \\
Y_2 \\
Y_3 \\
\vdots \\
Y_n
\end{bmatrix} =
\begin{bmatrix}
Z_{11} & Z_{12} & Z_{13} & \cdots & Z_{1r} \\
Z_{21} & Z_{22} & Z_{23} & \cdots & Z_{2r} \\
Z_{31} & Z_{32} & Z_{33} & \cdots & Z_{3r} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
Z_{n1} & Z_{n2} & Z_{n3} & \cdots & Z_{nr}
\end{bmatrix}
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_r
\end{bmatrix} +
\begin{bmatrix}
\epsilon_1 \\
\epsilon_2 \\
\epsilon_3 \\
\vdots \\
\epsilon_n
\end{bmatrix}
\]

or

\[
Y = Z \beta + \epsilon
\]

and the specifications in (1) become:

1. \( E(\epsilon) = 0; \)
2. \( \text{Cov}(\epsilon) = \text{E}(\epsilon \epsilon') = \sigma^2 I \)

A one in the first column of the design matrix Z is the multiplier of the constant term \( \beta_0 \). It is customary to introduce the artificial variable \( Z_0 = 1 \) so

\[
\beta_0 + \beta_1 Z_{11} + \cdots + \beta_r Z_{r1} = \beta_0 Z_0 + \beta_1 Z_{11} + \cdots + \beta_r Z_{r1}
\]

Each column of Z consists of the n values of the corresponding predictor variable, while the jth row of Z contains the values for all predictor variables on the jth trial.
Classical Linear Regression Model

\[
Y = (\begin{pmatrix} Y_1 \\ \vdots \end{pmatrix}) = (\begin{pmatrix} Z_1 \\ \vdots \end{pmatrix})(\begin{pmatrix} \beta_1 \\ \vdots \end{pmatrix}) + \epsilon
\]

\[
E(\epsilon) = 0 \quad \text{and} \quad \text{Cov}(\epsilon) = \sigma^2 I
\]

where \( \beta \) and \( \sigma^2 \) are unknown parameters and the design matrix \( Z \) has \( j \)th row \([Z_{j0}, Z_{j1}, \ldots, Z_{jn}]\).

IV. LEAST SQUARES ESTIMATION

One of the objectives of regression analysis is to develop an equation that will allow the investigator to predict the response for given values of the predictor variables. Thus, it is necessary to “fit” the model in (3) to the observed \( y_j \) corresponding to the known values \( b_0 + b_1Z_{j1} + \cdots + b_jZ_{jn} \). That is, we must determine the values for the regression coefficients \( \hat{\beta} \) and the error variance \( \sigma^2 \) consistent with the available data. Let \( b \) be the trial values for \( \hat{\beta} \). Consider the difference \( y_j - b_0 - b_1Z_{j1} - \cdots - b_jZ_{jn} \) between the observed responses, \( y_j \), and the value \( b_0 + b_1Z_{j1} + \cdots + b_jZ_{jn} \) that would be expected if \( b \) were the “true” parameter vector [11]. The method of least squares selects \( b \) to minimize the sum of squared differences.

\[
S(b) = \sum_{j=1}^{n} (y_j - b_0 - b_1Z_{j1} - \cdots - b_jZ_{jn})^2 = (y - Zb)'(y - Zb)
\]

The coefficient \( b \) chosen by the least squares criterion is called least squares estimates of the regression parameters. They will henceforth be denoted by \( \hat{\beta} \) to emphasize their role as estimates of \( \beta \). The coefficients \( \hat{\beta} \) are consistent with the data in the sense that they produce estimated (fitted) mean responses, \( \hat{\beta}_0 + \hat{\beta}_1Z_{j1} + \cdots + \hat{\beta}_jZ_{jn} \), whose sum of squared differences from the observed \( y_j \) is as small as possible. The deviations

\[
et = y_j - \hat{y}_j = y_j - (b_0 + b_1Z_{j1} + \cdots + b_jZ_{jn}) \quad j = 1, 2, \ldots, n
\]

are called residuals. The vector of residuals \( \hat{\epsilon} = y - Z\hat{\beta} \) contains the information about the remaining unknown parameter \( \sigma^2 \).

V. MULTIVARIATE MULTIPLE REGRESSION

Let us consider the problem of modeling the relationship between \( m \) responses, \( Y_1, Y_2, \ldots, Y_m \), and a single set of predictor variables, \( Z_1, Z_2, \ldots, Z_n \). Each response is assumed to follow its own regression model so that

\[
Y_1 = \beta_{01} + \beta_{11}Z_{11} + \beta_{21}Z_{21} + \cdots + \beta_{r1}Z_{r1} + \epsilon_1
\]

\[
Y_2 = \beta_{02} + \beta_{12}Z_{12} + \beta_{22}Z_{22} + \cdots + \beta_{r2}Z_{r2} + \epsilon_2
\]

\[
Y_m = \beta_{0m} + \beta_{1m}Z_{1m} + \beta_{2m}Z_{2m} + \cdots + \beta_{rm}Z_{rm} + \epsilon_m
\]

The error term \( \epsilon = [\epsilon_1, \epsilon_2, \epsilon_3, \ldots, \epsilon_m]' \) has \( E(\epsilon) = 0 \) and \( \text{Var}(\epsilon) = \sigma^2 I \). Thus, the error terms associated with different responses may be correlated [11].

To establish notation conforming to the classical linear regression model, let \([Z_{j0}, Z_{j1}, \ldots, Z_{jn}]\) denote the values of the predictor variables for the \( j \)th trial, let \( Y_j = [Y_{j1}, Y_{j2}, \ldots, Y_{jm}]' \) be the responses, and let \( \epsilon_j = [\epsilon_{j1}, \epsilon_{j2}, \epsilon_{j3}, \ldots, \epsilon_{jm}]' \) be the errors. In matrix notation, the design matrix

\[
Z = \begin{pmatrix} Z_{10} & Z_{11} & Z_{12} & \cdots & Z_{1r} \\ Z_{20} & Z_{21} & Z_{22} & \cdots & Z_{2r} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Z_{n0} & Z_{n1} & Z_{n2} & \cdots & Z_{nr} \end{pmatrix}
\]

is the same as that for the single response regression model in (4). The other matrix quantities have multivariate counterparts. Set

\[
Y = \begin{pmatrix} y_{11} & y_{12} & y_{13} & \cdots & y_{1m} \\ y_{21} & y_{22} & y_{23} & \cdots & y_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & y_{n3} & \cdots & y_{nm} \end{pmatrix}
\]

\[
\beta = \begin{pmatrix} \beta_{01} \beta_{02} \beta_{03} \cdots \beta_{0m} \\ \beta_{11} \beta_{12} \beta_{13} \cdots \beta_{1m} \\ \vdots \vdots \vdots \ddots \vdots \\ \beta_{r1} \beta_{r2} \beta_{r3} \cdots \beta_{rm} \end{pmatrix}
\]

\[
\epsilon = \begin{pmatrix} \epsilon_{11} \epsilon_{12} \epsilon_{13} \cdots \epsilon_{1m} \\ \epsilon_{21} \epsilon_{22} \epsilon_{23} \cdots \epsilon_{2m} \\ \epsilon_{31} \epsilon_{32} \epsilon_{33} \cdots \epsilon_{3m} \\ \vdots \vdots \vdots \ddots \vdots \\ \epsilon_{n1} \epsilon_{n2} \epsilon_{n3} \cdots \epsilon_{nm} \end{pmatrix}
\]
The multivariate linear regression model is

$$Y = Z\beta + \epsilon$$

with $E(\epsilon) = 0$, $\text{Cov}(\epsilon_{i}, \epsilon_{k}) = \sigma_{ik} I$, $i, k = 1, 2, 3, \ldots, m$

The $m$ observations on the $jth$ trial have covariance matrix $\Sigma = \{\sigma_{ik}\}$, but observations from different trials are uncorrelated. Here $\beta$ and $\sigma_{ik}$ are unknown parameters; the design matrix $Z$ has $jth$ row $[Z_{pi}, Z_{j}, Z_{k}, \ldots, Z_{m}]$.

The $ith$ response $Y_{(i)}$ follows the linear regression model

$$Y_{(i)} = Z\beta_{(i)} + \epsilon_{(i)}, \quad i = 1, 2, 3, \ldots, m$$

with $\text{Cov}(\epsilon_{(i)}) = \sigma_{ii} I$. However, the errors for different responses on the same trial can be correlated.

Given the outcomes $Y$ and the values of the predictor variables $Z$ with full column rank, we determine the least squares estimates $\hat{\beta}_{(i)}$ exclusively from the observations, $Y_{(i)}$, on the $ith$ response. Conforming to the single-response solution, we take

$$\hat{\beta}_{(i)} = (ZZ)^{-1}ZY_{(i)}$$

Collecting these univariate least squares estimates produces

$$\hat{\beta} = \left[\begin{array}{c} \hat{\beta}_{(1)} \\ \hat{\beta}_{(2)} \\ \vdots \\ \hat{\beta}_{(m)} \end{array}\right] = (ZZ)^{-1}Z'Y$$

or

$$\hat{\beta} = (ZZ)^{-1}ZY$$

For any choice of parameters say

$$B = \left[\begin{array}{c} b_{(1)} \\ b_{(2)} \\ \vdots \\ b_{(m)} \end{array}\right],$$

the matrix of errors is

$$Y = ZB + \epsilon.$$
For the least squares estimator

\[
\hat{\beta} = \begin{bmatrix}
\hat{\beta}_1 \\
\hat{\beta}_2 \\
\vdots \\
\hat{\beta}_m 
\end{bmatrix}
\]

determined under the multivariate multiple regression model (3–9) with full rank (Z) = r + 1 < n

\[
E(\hat{\beta}_i) = \beta_i \quad \text{or} \quad E(\hat{\beta}) = \beta
\]

and

\[
\text{Cov}(\hat{\beta}_i, \hat{\beta}_k) = \sigma_{ik}(ZZ)^{-1}, \quad i, k = 1, 2, \ldots, r + 1
\]

The residuals

\[
\hat{e} = \begin{bmatrix}
\hat{e}_1 \\
\hat{e}_2 \\
\vdots \\
\hat{e}_m 
\end{bmatrix}
\]

Satisfy

\[
E(\hat{e}_i) = 0 \quad \text{and} \quad E\left(\frac{\hat{e}_i}{n - r - 1}\right) = \Sigma
\]

The mean of the ith response variable is

\[
Z'_0\hat{\beta}_i, \quad \text{the ith component of the fitted regression relationship, collectively,}
\]

\[
\hat{z}_0\hat{\beta} = \begin{bmatrix}
\hat{z}_0\hat{\beta}_1 \\
\hat{z}_0\hat{\beta}_2 \\
\vdots \\
\hat{z}_0\hat{\beta}_m 
\end{bmatrix}
\]

is an unbiased estimator of

\[
Z'_0\hat{\beta}
\]

This means that the fitted multivariate regression models of Systolic and Diastolic blood pressure models for NAUTH, COOUTH and general hospital, Onitsha Anambra State are respectively:

\[
\hat{Y}_1 = 98.43653 + 1.36890Z_1 - 0.00222Z_2 - 0.07536Z_3 - 0.01933Z_4 - 0.00122Z_5
\]

\[
\hat{Y}_2 = 59.34723 + 0.52057Z_1 + 0.05620Z_2 - 0.02324Z_3 - 0.00206Z_4 + 0.00073Z_5
\]

\[
\hat{Y}_3 = 0.01096 + 1.89089Z_1 - 0.07900Z_2 - 0.09568Z_3 - 0.02115Z_4 - 0.00018Z_5
\]

\[
\hat{Y}_4 = 56.32919 + 0.73208Z_1 - 0.03857Z_2 - 0.03693Z_3 - 0.00492Z_4 + 0.00277Z_5
\]

And

\[
\hat{Y}_5 = 47.26746 + 0.75757Z_1 + 0.03913Z_2 + 0.00084Z_3 - 0.00338Z_4 - 0.00134Z_5
\]

B. Test of Significance for the Multivariate Regression Parameters

The test of significance for the multivariate regression parameters of Systolic and Diastolic blood pressure models for NAUTH, COOUTH and general hospital, Onitsha Anambra State are discussed. Outputs 1 & 2, Outputs 3 & 4 and Outputs 5 & 6 are for Systolic and Diastolic blood pressure models for NAUTH, COOUTH and general hospital, Onitsha Anambra State data respectively.

![Fig. 1. Coefficients of the Parameters for Systolic Blood Pressure Coefficients](image-url)
It can be observed from Output 1 that age and baseline count of HIV/AIDS patients have significant relationship with systolic BP at 5% level of significance, whereas other predictor variables (initial weight, present weight and CD4 count of HIV/AIDS patients) are not significant. In the second model (See Output 2), only age has a significant relationship with diastolic BP, whereas initial weight, present weight, baseline count and CD4 count of HIV/AIDS patients do not have significant relationship with diastolic BP at 5% level of significance. Only age of HIV/AIDS patients has a significant relationship with systolic BP at 5% level of significance. From Output 5, only age of HIV/AIDS patients has a significant relationship with systolic BP at 5% level of significance, whereas other predictor variables (baseline count, initial weight, present weight and CD4 count of HIV/AIDS patients) are not significant. In the second model also (See Output 4), only age has a significant relationship with diastolic BP, whereas initial weight, present weight, baseline count and CD4 count of HIV/AIDS patients do not have significant relationship with diastolic BP at 5% level of significance.

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Fig. 2. Coefficients of the Parameters for Diastolic Blood Pressure Coefficients

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|----------|
| (Intercept) | 59.3472336 | 3.8111808 | 15.572 | <2e-16 |
| Z1 | 0.5205733 | 0.0619276 | 8.406 | 8.55e-16 |

Fig. 3. Coefficients of the Parameters for Systolic Blood Pressure Coefficients

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|----------|
| (Intercept) | 1.262e+02 | 1.033e+00 | 122.114 | <2e-16 |
| Z1 | 1.798e+00 | 1.815e-02 | 99.086 | <2e-16 |

Fig. 4. Coefficients of the Parameters for Diastolic Blood Pressure Coefficients

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|----------|
| (Intercept) | 56.329185 | 3.390184 | 16.615 | <2e-16 |
| Z1 | 0.732083 | 0.037340 | 19.323 | <2e-16 |

Fig. 5. Coefficients of the Parameters for Systolic Blood Pressure Coefficients

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|----------|
| (Intercept) | 47.2674594 | 2.400121 | 19.691 | <2e-16 |
| Z1 | 0.7757670 | 0.0421478 | 18.406 | <2e-16 |

Fig. 6. Coefficients of the Parameters for Diastolic Blood Pressure Coefficients

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|----------|
| (Intercept) | 38.21 | 3.215 | 11.921 | <2e-16 |

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CD4 count of HIV/AIDS patients do not have significant relationship with diastolic BP at 5% level of significance.

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Systolic BP</th>
<th>Diastolic BP</th>
<th>R²</th>
<th>RSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAUTH</td>
<td>3371.215</td>
<td>3398.924</td>
<td>0.3188</td>
<td>18.66</td>
</tr>
<tr>
<td>COOUTH</td>
<td>2951.416</td>
<td>2979.125</td>
<td>0.478</td>
<td>10.85</td>
</tr>
<tr>
<td>General</td>
<td>3003.902</td>
<td>3030.237</td>
<td>0.3798</td>
<td>26.89</td>
</tr>
<tr>
<td>Hospital</td>
<td>1825.917</td>
<td>1851.435</td>
<td>0.5715</td>
<td>6.008</td>
</tr>
</tbody>
</table>

C. Source: R software output

R² is the coefficient of determination, while RSE is the residual standard error. Looking at the summarized results in Table I, it can be observed that the data collected from the general hospital Onitsha has the highest coefficient of determination (0.9735) with the lowest AIC (1348,944), BIC (1374,462) and residual standard error (2.587) for systolic blood pressure model, which makes the data used in this study the most suitable. Also, it can be observed that the same data collected from the general hospital Onitsha has the highest coefficient of determination (0.5715) with the lowest AIC (1825.917), BIC (1851.435) and residual standard error (6.008) for diastolic blood pressure model, which makes the data used in this study the most suitable. It is clear from the result obtained in this study that the data set collected from general hospital, Onitsha from 2003 to 2017 is most appropriate for the multivariate multiple linear regression models.

VII. CONCLUSION

From the whole study within the data collected for this study, the following conclusions are drawn from both our preliminary results and the results from our model in achieving our objectives; only age has a significant and positive relationship with both systolic and diastolic BP at 5% level of significance for the three hospitals employed in this study, while baseline count of HIV/AIDS patients has significant and negative relationship with systolic BP for NAUTH data. Again, the data collected from general hospital, Onitsha from 2003 to 2017 is suitably adequate for the multivariate multiple regression models.

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