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MULTIVARIATE ANALYSIS OF VARIANCE ON ACADEMIC PERFORMANCE OF STUDENTS VIA UTME AND POST-UTME SCORES

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ABSTRACT

This research work is on the academic performance of Imo State University students in UTME and Post-UTME via multivariate analysis of variance using three faculties and five academic sessions as factor 1 and factor 2 respectively. The faculties were Science, Business Administration and Social Sciences, while the academic sessions were 2017/2018, 2018/2019, 2019/2020, 2020/2021 and 2021/2022. The results of 750 students were randomly selected from the faculties and thereafter, 50 students were randomly selected in the faculties of study.

INTRODUCTION

As time passes, more people get concerned about the declining educational standards and the quality of graduates graduating from Nigerian higher institutions (Ikiroma, 2016). Some firms reported that graduates failed to achieve their corporate expectations, particularly in terms of skills and competence. To support this claim, a research sponsored by the National Universities Commission and the Education Tax Fund (NUC, 2004) discovered a mismatch between university graduates and the needs of businesses in a variety of fields. According to Sheyin et al. (2021), the decline in academic achievement among students at all levels of school has been widely observed and accepted in Nigeria.

To obtain a glimpse of evidence of the dramatic drop in the standard of performance in Nigeria according to Adekunle (2012), university education in Nigeria is at a crossroads, with none of them ranking among the top 30 in Africa or among the top 1000 globally. The researcher believes that the quality of students admitted and the admissions process can be linked to academic success. Several universities are already searching for ways to get the best out of admission hopefuls, which has led to the implementation of post-UTME (Ayuba, 2015). Proponents of the Post-UTME screening test claimed that it would ensure quality and that admitting the top students would improve results (Okobia, 2016). It is also anticipated that quality admittance will result in higher-quality graduates, more

The same procedure was adopted for the other academic sessions and the study's dataset was summarized for data analysis. The IBM SPSS software package was used for the data analysis. The results of the analysis revealed the following; there was no interaction between the academic sessions and the faculties based on the academic performance of the students enrolled in Imo State University, Owerri via their UTME and Post-UTME scores; the vector means performed the same in the five academic sessions, that is the academic sessions do not affect the performance of students in UTME and Post UTME scores; while the vector means performed differently in the three faculties, that is the faculties one is admitted into do affect the performance of students in UTME and Post UTME scores.

Keywords: UTME, Post-UTME, Two-way MANOVA, Interaction Effect, Academic Performance.

engaged students, and a lower frequency of examination misconduct and sex for marks.

The scores from the UTME alone cannot be relied upon to provide the basis for admitting students into higher institutions (Aina, 2017). One needs to observe the environmental concomitants during JAMB examination in some areas, such as high rate of infiltration on school compound including swift vehicular movement through which malpractice is aided and abated (Emaikwu, 2012). Some examiners are bribed into allowing unauthorized materials into the hall. Some of them are even used as organ of dissemination of worked answers. In this milieu, the school environment which is supposed to be characterized with calmness is infested with noise, rowdiness, disturbance and misdemeanor. JAMB has tried so much to avert this ugly situation through the help of security agents (Uhunmwuangho & Ogunbadeniyi, 2014). JAMB has also used different numbering systems and codes for different subject combinations to discourage mass cheating. A lot of cancellation of results has been made to no avail. For example, in the 2005/2006 JAMB exercise, the results of the whole Nsukka zone, which included around eight major towns in Enugu state, were annulled, effectively barring the affected centers from taking the examination for up to five years. The impact of these seemingly unreliable UTME scores on undergraduates cannot be overstated.

Despite the Nigerian government's extensive methods and plans to ensure that educational standards are maintained at the university level, it appears that students who have passed all of these rigorous examinations continue to perform significantly below expectations (Imasuen & Ebuwa, 2020). This high rate of poor academic accomplishment among undergraduates is not unrelated to how they entered the university system. It has been observed that using JAMB as a yardstick for admitting students to Nigerian universities has resulted in the intake of poor caliber candidates, as evidenced by a high failure rate, an increase in examination malpractices, high spillovers, and the production of poor quality output that is neither self-reliant nor capable of contributing effectively in the workplace (Babatunde, 2017).

Ironically, while the demand for university education has never been stronger, the quality of students admitted and graduates produced in Nigerian universities today is in steep decline. With the introduction of Post-UTME as a means of improving the quality of students admitted into the University system which will also improve the quality of graduates produced, this study therefore grew out of curiosity to examine the academic performance of Imo State University students in UTME and Post-UTME via multivariate analysis of variance using three faculties and five academic sessions as factor 1 and factor 2 respectively. Thus, the research sought to study if there was interaction between the academic sessions and the faculties based on the academic performance of the students enrolled in Imo State University, Owerri via their UTME and Post-UTME scores.

Materials and Methods

Data Collection

The collection of relevant data is imperative and unavoidable before one could carry out a statistical research. Thus, the method adopted in this study was secondary data. The data consisted of UTME and Post-UTME scores of students enrolled into three different faculties of Imo State University, Owerri Nigeria for five different academic sessions. The faculties are Science, Business Administration and Social Sciences, while the academic sessions are 2017/2018, 2018/2019, 2019/2020, 2020/2021 and 2021/2022. The results of 750 students were randomly selected from the faculties and thereafter, 50 students were randomly selected in the faculties of study. The same procedure was adopted for the other academic sessions and the study dataset was summarized for data analysis.

Method of Analysis

This section discussed the statistical technique used in this research. Based on the nature of data collected, the study was restricted to Two-way Multivariate Analysis of Variance (MANOVA) with interaction.

Two-Way Multivariate Analysis of Variance

We assume that measurements are recorded at various levels of two factors. In some cases, these experimental conditions represent levels of a single treatment arranged within several blocks. The researchers shall, however, assume that observations at different combinations of experimental conditions are independent of one another.

Let the two sets of experiment conditions be the levels of, for instance, factor 1 and factor 2 respectively. Suppose there are r levels of factor 1, c levels of factor 2, and n independent observations at each level. Denoting the kth observation at level i of factor 1 and level j of factor 2 by Z_{ijk}, the univariate two-way model is

$$Z_{ijk} = \mu + \alpha_i + \beta_j + \lambda_{ij} + e_{ijk} \quad \dots \qquad (1)$$

$$i = 1, 2, \dots, r; \qquad j = 1, 2, \dots, c; \qquad k = 1, 2, \dots, n$$

where $\sum_{i=1}^{r}\alpha_i = \sum_{j=1}^{c}\beta_j = \sum_{i=1}^{r}\sum_{j=1}^{c}\lambda_{ij} = 0$ and e_{ijk} are independent $N(0, \sigma^2)$ random variables.

Here, μ represents an overall level, α_i represents the fixed effects of factor 1(A), β_j represents the fixed effect of factor 2(B), and λ_{ij} is the interaction between factor 1 and factor 2. The expected response at the i^{th} level of factor 1 and the j^{th} level of factor 2 is thus

$$E(Z_{ijk}) = \mu + \alpha_i + \beta_j + \lambda_{ij}$$

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$$(mean\ response) = \begin{pmatrix} overall \\ level \end{pmatrix} + \begin{pmatrix} effect\ of \\ factor\ 1 \end{pmatrix} + \begin{pmatrix} effect\ of \\ factor\ 2 \end{pmatrix} + \begin{pmatrix} factor\ 1 - factor\ 2 \\ \text{int}\ eraction \end{pmatrix} \cdots \quad (2)$$

i = 1, 2, … , r ***j*** = 1, 2, … , c

The presence of interaction, λ_{ij}, implies the factor effects are not additive

Table 1: Data Layout for the Design

	Treatment (factor 2) (j)					
Treatment (factor 1) i		1	2	3	⋯	c
	1	Z_{111}	Z_{121}	Z_{131}	⋯	Z_{1c1}
		Z_{112}	Z_{122}	Z_{132}	⋯	Z_{1c2}
		⋮	⋮	⋮	⋮	⋮
		Z_{11n}	Z_{12n}	Z_{13n}	⋯	Z_{1cn}
	2	Z_{211}	Z_{221}	Z_{231}	⋯	Z_{2c1}
		Z_{212}	Z_{222}	Z_{232}	⋯	Z_{2c2}
		⋮	⋮	⋮	⋮	⋮
		Z_{21n}	Z_{22n}	Z_{23n}	⋯	Z_{2cn}
	3	Z_{311}	Z_{321}	Z_{331}	⋯	Z_{3c1}
		Z_{312}	Z_{322}	Z_{332}	⋯	Z_{3c2}
		⋮	⋮	⋮	⋮	⋮
		Z_{31n}	Z_{32n}	Z_{33n}	⋯	Z_{3cn}
	⋮	⋮	⋮	⋮	⋮	⋮
	r	Z_{r11}	Z_{r12}	Z_{r13}	⋯	Z_{rc1}
		Z_{r12}	Z_{r22}	Z_{r23}	⋯	Z_{rc2}
		⋮	⋮	⋮	⋮	⋮
		Z_{r1n}	Z_{r2n}	Z_{r3n}	⋯	Z_{rcn}

Thus, we can estimate the parameters of (1) using the least squares method

$$e_{ijk} = Z_{ijk} - \hat{Z}_{ijk}$$

where $\hat{Z}_{ijk} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\lambda}_{ij}$

$$\therefore \quad e_{ijk} = Z_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\lambda}_{ij}$$

Taking the sum of squares to get

$$\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n} e_{ijk}^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n} (Z_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\lambda}_{ij})^2$$

Let $\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n} e_{ijk}^2 = W$

Equations (3), (4), (5), (6) and (7) were obtained by solving for the estimate of μ, α_i, β_j, λ_{ij}, and e_{ijk} respectively.

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$$\hat{\mu} = \frac{Z_{\dots}}{rcn} = \bar{Z}_{\dots} \quad \dots \quad (3)$$

$$\hat{\alpha}_i = \frac{Z_{i\cdot\cdot}}{cn} - \hat{\mu} = \bar{Z}_{i\cdot\cdot} - \bar{Z}_{\dots} \quad \dots \quad (4)$$

$$\hat{\beta}_j = \frac{Z_{\cdot j\cdot}}{rn} - \hat{\mu} = \bar{Z}_{\cdot j\cdot} - \bar{Z}\dots \quad \dots \quad (5)$$

$$\hat{\lambda}_{ij} = \bar{Z}_{ij\cdot} - \bar{Z}_{i\cdot\cdot} - \bar{Z}_{\cdot j\cdot} + \bar{Z}_{\dots} \quad \dots \quad (6)$$

$$\hat{e}_{ijk} = Z_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\lambda}_{ij} = Z_{ijk} - \bar{Z}_{ij\cdot} \quad \dots \quad (7)$$

In a manner analogous to (1), each observation can be decomposed as

$$Z_{ijk} = \bar{Z}_{\dots} + (\bar{Z}_{i\cdot\cdot} - \bar{Z}_{\dots}) + (\bar{Z}_{\cdot j\cdot} - \bar{Z}_{\dots}) + (\bar{Z}_{ij\cdot} - \bar{Z}_{i\cdot\cdot} - \bar{Z}_{\cdot j\cdot} + \bar{Z}_{\dots}) + (Z_{ijk} - \bar{Z}_{ij\cdot}) \quad \dots \quad (8)$$

where $\bar{Z}_{\dots}$ is the overall average, $\bar{Z}_{i\cdot\cdot}$ is the average for the ith level of factor 1, $\bar{Z}_{\cdot j\cdot}$ is the average for the jth level of factor 2, and $\bar{Z}_{ij\cdot}$ is the average for the ith level of factor 1 and the jth level of factor 2. Squaring and summing the deviations ($Z_{ijk} - \bar{Z}_{\dots}$) gives:

$$\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk} - \bar{Z}_{\dots})^2 = cn\sum_{i=1}^{r}(\bar{Z}_{i\cdot\cdot} - \bar{Z}_{\dots})^2 + rn\sum_{j=1}^{c}(\bar{Z}_{\cdot j\cdot} - \bar{Z}_{\dots})^2 +$$
$$n\sum_{i=1}^{r}\sum_{j=1}^{c}(\bar{Z}_{ij\cdot} - \bar{Z}_{i\cdot\cdot} - \bar{Z}_{\cdot j\cdot} + \bar{Z}_{\dots})^2 + \sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk} - \bar{Z}_{ij\cdot})^2 \quad \dots \quad (9)$$

or

$SS_{cor.} = SS_{foc1} + SS_{fac2} + SS_{int.} + SS_{res.}$

The corresponding degrees of freedom associated with the sums of squares in the breakup in (9) are

rcn – 1 = (r – 1) + (c – 1) + (r – 1)(c – 1) + rc(n – 1) … (10)

The ANOVA table takes the following form as displayed in Table 2.

Table 2: ANOVA Table for Comparing Effects of Two Factors and their Interaction

SV	Sum of Squares (SS)	Degrees of freedom (df)
Factor 1	$SS_{fac1} = cn\sum_{i=1}^{r}(\bar{Z}_{i\cdot\cdot} - \bar{Z}_{\dots})^2$	**r – 1**
Factor 2	$SS_{fac2} = rn\sum_{j=1}^{c}(\bar{Z}_{\cdot j\cdot} - \bar{Z}_{\dots})^2$	**c – 1**
Interaction	$SS_{int} = n\sum_{i=1}^{r}\sum_{j=1}^{c}(\bar{Z}_{ij\cdot} - \bar{Z}_{i\cdot\cdot} - \bar{Z}_{\cdot j\cdot} + \bar{Z}_{\dots})^2$	**(r – 1)(c – 1)**

Residual (error)	$SS_{res} = \sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk} - \bar{Z}_{ij.})^2$	**rc(n – 1)**
Total (corrected)	$SS_{cor} = \sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk} - \bar{Z}_{...})^2$	**rcn – 1**

The F-ratios of the mean squares, $SS_{fac1}/(r-1)$, $SS_{fac2}/(c-1)$ and $SS_{int.}/(r-1)(c-1)$ to the mean square, $SS_{res}/[rc(n-1)]$ can be used to test for the effects of factor 1, factor 2 and factor 1 – factor 2 interaction respectively.

Multivariate Two-Way Fixed-Effects Model with Interaction

Proceeding by analogy, the two-way fixed effects model for a vector response consisting of p components is [see (1)].

$$\mathbf{Z}_{ijk} = \mu + \alpha_i + \beta_j + \lambda_{ij} + \mathbf{e}_{ijk} \quad \ldots \quad (11)$$

i = 1, 2, … , r

j = 1, 2, … , c

k = 1, 2, … , n

where $\sum_{i=1}^{r}\boldsymbol{\alpha}_i = \sum_{j=1}^{c}\boldsymbol{\beta}_j = \sum_{i=1}^{r}\sum_{j=1}^{c}\boldsymbol{\lambda}_{ij} = \mathbf{0}$. The vectors are all of order p ×1 and e_{ijk} is assumed to be an $N_p(0, \varepsilon)$ random vector. Thus, the responses consist of p measurements replicates n times at each of the possible combinations of levels of factors 1 and 2.

Following (8), the observation vectors $\mathbf{Z}_{ijk}$ can be decomposed as

$$\mathbf{Z}_{ijk} = \bar{\mathbf{Z}}_{...} + (\bar{\mathbf{Z}}_{i..} - \bar{\mathbf{Z}}_{...}) + (\bar{\mathbf{Z}}_{.j.} - \bar{\mathbf{Z}}_{...}) + (\bar{\mathbf{Z}}_{ij.} - \bar{\mathbf{Z}}_{i..} - \bar{\mathbf{Z}}_{.j.} + \bar{\mathbf{Z}}_{...}) + (\mathbf{Z}_{ijk} - \bar{\mathbf{Z}}_{ij.}) \ldots \quad (12)$$

where $\bar{Z}_{...}$ is the overall average of the observation vectors, $\bar{\mathbf{Z}}_{i..}$ is the average of observation vectors at the ith level of factor $\bar{Z}_{.j.}$ is the average of the observation vectors at the jth level of factor 2, and $\bar{Z}_{ij.}$ is the average of the observation vectors at the ith level of factor 1 and the jth level of factor 2.

Straight forward generalizations of (9) and (10) give the breakups of the sum of squares cross-products and degrees of freedom.

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$$\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk}-\bar{Z}_{...})(Z_{ijk}-\bar{Z}_{...})'=cn\sum_{i=1}^{r}(\bar{Z}_{i..}-\bar{Z}_{...})(\bar{Z}_{i..}-\bar{Z}_{...})'+rn\sum_{j=1}^{c}(\bar{Z}_{.j.}-\bar{Z}_{...})(\bar{Z}_{.j.}-\bar{Z}_{...})'+$$

$$n\sum_{i=1}^{r}\sum_{j=1}^{c}(\bar{Z}_{ij.}-\bar{Z}_{i..}-\bar{Z}_{.j.}+\bar{Z}_{...})(\bar{Z}_{ij.}-\bar{Z}_{i..}-\bar{Z}_{.j.}+\bar{Z}_{...})'+\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk}-\bar{Z}_{ij.})(Z_{ijk}-\bar{Z}_{ij.})'$$

(13)

rcn – 1 = (r – 1) + (c – 1) + (r – 1)(c – 1) + rc(n – 1) … (14)

Again, the generalization from the univariate to the multivariate analysis consists simply of replacing a scalar such as $(\bar{Z}_{i..}-\bar{Z}_{...})^2$ with the corresponding matrix $(\bar{Z}_{i..}-\bar{Z}_{...})(\bar{Z}_{i..}-\bar{Z}_{...})'$.

The MANOVA table is the following.

Table 2: MANOVA Table for Comparing Effects of Two Factors and their Interaction

SV	Matrix of Sum of Squares and cross-product (SSP)	Degrees of freedom (df)
Factor 1	$SSP_{fac1}=cn\sum_{i=1}^{r}(\bar{Z}_{i..}-\bar{Z}_{...})(\bar{Z}_{i..}-\bar{Z}_{...})'$	**r – 1**
Factor 2	$SSP_{fac2}=rn\sum_{j=1}^{c}(\bar{Z}_{.j.}-\bar{Z}_{...})(\bar{Z}_{.j.}-\bar{Z}_{...})'$	**c – 1**
Interaction	$SSP_{int}=n\sum_{i=1}^{r}\sum_{j=1}^{c}(\bar{Z}_{ij.}-\bar{Z}_{i..}-\bar{Z}_{.j.}+\bar{Z}_{...})(\bar{Z}_{ij.}-\bar{Z}_{i..}-\bar{Z}_{.j.}+\bar{Z}_{...})'$	**(r – 1)(c – 1)**
Residual (error)	$SSP_{res}=\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk}-\bar{Z}_{ij.})(Z_{ijk}-\bar{Z}_{ij.})'$	**rc(n – 1)**
Total (corrected)	$SSP_{cor}=\sum_{i=1}^{r}\sum_{j=1}^{c}\sum_{k=1}^{n}(Z_{ijk}-\bar{Z}_{...})(Z_{ijk}-\bar{Z}_{...})'$	**rcn – 1**

Test Statistic and Hypotheses

A test (the likelihood ratio test) of

H_1 : $\lambda_{11}=\lambda_{12}=\cdots=\lambda_{rc}=0$ (no interaction effect) … (14)

Versus

H_1 : At least one $\lambda_{ij}\neq 0$ is conducted by rejecting H_0 for small values of the ratio

$$\Lambda^*=\frac{|SSP_{res}|}{|SSP_{int}+SSP_{res}|} \quad \ldots \quad (15)$$

For large samples, Wilks Lambda Λ^*, can be referred to a chi-square percentile. Using Bartlett's multiplier to improve the chi-square approximation: Reject H_0 : $\lambda_{11}=\lambda_{12}=\cdots=\lambda_{rc}=0$ at α level if

$$-\left[rc(n-1)-\frac{(p+1)-(r-1)(c-1)}{2}\right]\ln\Lambda^*>\chi^2_{(r-1)(c-1)p(\alpha)} \quad \ldots$$

(16)

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where Λ^* is given by (15) and $\chi^2_{(r-1)(c-1)p(\alpha)}$ is the upper (100α)th percentile of a chi-square distribution with (r – 1)(c – 1)p d.f.

Ordinarily, the test for interaction is carried out before the tests for main factor effects. If interaction effects exist, the factor effects do not have a clear interpretation. From a practical standpoint, it is not advisable to proceed with the additional multivariate tests. Instead, p univariate two-way analyses of variance (one for each variable) are often conducted to see if the interaction appears in some responses but not others. Those responses without interaction may be interpreted in terms of additive factor 1 and 2 effects, provided the latter effects exist.

In multivariate model, we test for factor 1 and factor 2 main effects as following first, consider the hypotheses.

H_0 : $\alpha_1 = \alpha_2 = \cdots = \alpha_r = 0$ and

H_1: at least one $\alpha_i \neq 0$. The hypotheses specify no factor 1 effects and some factor 1 effects respectively. Let

$$\Lambda^* = \frac{|SSP_{res}|}{|SSP_{fac1} + SSP_{res}|} \quad \cdots \quad (17)$$

So that small values of Λ^*, are consistent with H_1. Using Bartlett's correction, the likelihood ratio test is : Reject H_0 : $\alpha_1 = \alpha_2 = \cdots = \alpha_r = 0$ (no factor 1 effect) at level α if.

$$-\left[rc(n-1) - \frac{(p+1)-(r-1)}{2}\right]\ln \Lambda^* > \chi^2_{(r-1)p(\alpha)} \quad \cdots \quad (18)$$

where Λ^* is given by (17) and $\chi^2_{(r-1)p(\alpha)}$ is the upper (100α)th percentile of a chi-square distribution with (r – 1)p d.f.

In a similar manner, factor 2 effects are tested by considering

H_0 : $\beta_1 = \beta_2 = \cdots = \beta_c = 0$ and H_1 : at least one $\beta_j \neq 0$. Small values of

$$\Lambda^* = \frac{|SSP_{res}|}{|SSP_{fac2} + SSP_{res}|} \quad \cdots \quad (19)$$

are consistent with H_1. Once again, for large samples and using Bartlett's correction: Reject H_0 : $\beta_1 = \beta_2 = \cdots = \beta_c = 0$ (no factor 2 effect) at level α if.

$$-\left[rc(n-1) - \frac{(p+1)-(c-1)}{2}\right]\ln \Lambda^* > \chi^2_{(c-1)p(\alpha)} \quad \cdots \quad (20)$$

where Λ^* is given by (19) and $\chi^2_{(c-1)p(\alpha)}$ is the upper (100α)th percentile of a chi-square distribution with (c – 1)p d.f.

Results

Statement of Hypotheses

The following hypotheses shall be tested in this thesis work;

1. H_0: $\lambda_{11} = \lambda_{12} = \cdots = \lambda_{53}$ (There is no interaction over the five levels in factor 1 and three levels in factor two)

H_1: H_0 is false

2. H_0: $\alpha_i = 0$; for all i, i = 1, … , 5. (There is no significant difference in the students' performance over the years)

H_1: not all α_i's are equal to 0

3. H_0: $\beta_j = 0$; for all j, j = 1, 2, 3. (There is no significant difference in the students' performance over the faculties)

H_1: not all β_j's are equal to 0

The statistical methods discussed in this study were implemented for the analysis. The matrices of the appropriate sum of squares and cross-products were calculated using SPSS Statistical software leading to the matrices below as well as the MANOVA table:

$$SSP_{fac1} = \begin{pmatrix} 6371.223 & 4550.048 \\ 4550.048 & 6022.308 \end{pmatrix}$$

$$SSP_{fac2} = \begin{pmatrix} 752.151 & -1340.935 \\ -1340.935 & 5074.903 \end{pmatrix}$$

$$SSP_{\text{int}} = \begin{pmatrix} 15984.025 & 4640.028 \\ 4640.028 & 5410.061 \end{pmatrix}$$

$$SSP_{res} = \begin{pmatrix} 764948.788 & 68433.995 \\ 68433.995 & 944950.242 \end{pmatrix}$$

Table 3: MANOVA Table

Source of variation	SSP	d.f
Factor 1: Academic Sessions	$\begin{pmatrix} 6371.223 & 4550.048 \\ 4550.048 & 6022.308 \end{pmatrix}$	**4**
Factor 2: Faculties	$\begin{pmatrix} 752.151 & -1340.935 \\ -1340.935 & 5074.903 \end{pmatrix}$	**2**
Interaction	$\begin{pmatrix} 15984.025 & 4640.028 \\ 4640.028 & 5410.061 \end{pmatrix}$	**8**
Residual	$\begin{pmatrix} 764948.788 & 68433.995 \\ 68433.995 & 944950.242 \end{pmatrix}$	**735**
Total (corrected)	$\begin{pmatrix} 788056.187 & 76283.136 \\ 76283.136 & 961457.513 \end{pmatrix}$	**749**

To test for interaction, we compute

$$\Lambda^* = \frac{|SSP_{res}|}{|SSP_{\text{int}} + SSP_{res}|} = 0.9747$$

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For (r – 1) (c – 1) = 8

Since we have large samples, we then use the Wilks'lambda, Λ^*

Using (16), we have

$$-\left[5(3)(49)-\frac{2+1-(4)(2)}{2}\right]\ln(0.9747)=18.90$$

$$\chi^2_{(r-1)(c-1)p(\alpha)}=\chi^2_{4(2)(3)\alpha}=\chi^2_{16,0.05}=26.30$$

Since $-\left[rc(n-1)-\frac{(p+1)-(r-1)(c-1)}{2}\right]\ln\Lambda^*=18.90 < \chi^2_{16,0.05}=26.30$, we do not reject the hypothesis $H_0 : \lambda_{11} = \lambda_{12} = \lambda_{13} = \lambda_{21} = \lambda_{22} = \lambda_{23} = \lambda_{31} = \lambda_{32} = \lambda_{33} = \lambda_{41} = \lambda_{42} = \lambda_{43} = \lambda_{51} = \lambda_{52} = \lambda_{53} = 0$ (no interaction effects).

To test for factor 1 and factor 2 effects, we require

$$\Lambda^*=\frac{|SSP_{res}|}{|SSP_{fac1}+SSP_{res}|}=0.986$$

and

$$\Lambda^*=\frac{|SSP_{res}|}{|SSP_{fac2}+SSP_{res}|}=0.976$$

Using (18), we have

$$-\left[5(3)(49)-\frac{2+1-(4)}{2}\right]\ln 0.986=10.37$$

$$\chi^2_{(r-1)p(\alpha)}=\chi^2_{4(2)\alpha}=\chi^2_{8,0.05}=15.51$$

Using (20), we have

$$\left[5(3)(49)-\frac{2+1-(2)}{2}\right]\ln 0.976=17.84$$

$$\chi^2_{(c-1)p(\alpha)}=\chi^2_{2(2)\alpha}=\chi^2_{4,0.05}=9.49$$

From above, $-\left[rc(n-1)-\frac{(p+1)-(r-1)}{2}\right]\ln\Lambda_1^*=10.37 < \chi^2_{(r-1)p(\alpha)}=15.51$, we do not reject the hypothesis $H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = 0$ (no factor 1 effects) at the 5% level. On the other hand, $-\left[rc(n-1)-\frac{(p+1)-(c-1)}{2}\right]\ln\Lambda_2^*=17.84 > \chi^2_{(c-1)p(\alpha)}=9.49$, we do reject $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ (no factor 2 effect) at the 5% level.

Summary and Conclusion

This study work is on the multivariate analysis of variance on the academic performance of students enrolled into Imo State University via their UTME and Post- UTME scores using three faculties of the university and five academic sessions. The statistical techniques for data analysis were explicitly explained prior to analysis of the data in details. The statistical software package used in this research work for data analysis is the IBM SPSS. Thus, the results were well interpreted. The following conclusions were made as;

i. There was no interaction between the academic sessions and the faculties on the academic performance of the students enrolled in Imo State University, Owerri Nigeria via their UTME and Post UTME scores.
ii. The vector means performed the same in the five academic sessions; that is the academic sessions do not affect the performance of students in UTME and Post UTME scores.
iii. The vector means performed differently in the three faculties; that is faculties one is admitted into do affect the performance of students in UTME and Post UTME scores.

Recommendations

Having carried out this study, the following recommendations were made:

i. Future researchers should use other sophisticated statistical software packages, such as R-Studio, SAS, Python, MATLAB etc., for data analysis to enable the researcher get all the components needed.
ii. Future researchers should adopt some other multivariate methods on the similar research work, like Hotellings T^2 distribution, principal component analysis, discriminant analysis etc. to compare results.
iii. Future researchers should carry out a similar research with more than two interaction effects to compare the results.

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