

MULTIVARIATE ANALYSIS OF VARIANCE OF UNIVERSITY STUDENTS' ACADEMIC PERFORMANCE

Okeke, Evelyn Nkiruka¹, Okeke, Joseph Uchenna² & Adashu Daniel³

¹Associate Professor, Federal University, Wukari, Taraba, Nigeria

²Senior Lecturer, Federal University, Wukari, Taraba, Nigeria

³Research Scholar, Federal University, Wukari, Taraba, Nigeria

ABSTRACT

The presented research study was designed to compare the academic performance of 300 level students of Federal University Wukari for the second semester 2015/2016 academic session. The groups we considered were the Faculties of Agriculture and Life Sciences, Pure and Applied Sciences and Humanities, Management and Social Sciences and the random sample of five (5) departments each were selected from the Faculties. The data collected were the CGPA of 300 level students from five (5) departments in each faculty, accessed from the University academic records. For analysis, Multivariate Analysis of variance (MANOVA) and descriptive statistics were used. The findings revealed that there exists no significant difference in the academic performance of the students in the three (3) Faculties. Recommendation that will help to improve the general academic performance of students at University level was also given in the main work.

KEYWORDS: *Academic Performance, Multivariate Analysis of Variance, and Wilks Lambda*

Article History

Received: 24 Dec 2017 | Revised: 03 Jan 2018 | Accepted: 18 Jan 2018

INTRODUCTION

In Nigeria, education is emerging to be one of the biggest and largest industries, and the government continues to ensure that funds, instructional material and teaching personnel are made available for the sector. Despite all the effort put in by the government and stakeholders of educational industry in Nigeria, the academic performance of Nigerian university students is still below expectation. Academic performance of a student is the extent to which he achieves specific academic goals. This is commonly measured by examinations or continuous assessment, but there is no general agreement on how it is best tested or which aspects are most important (Wikipedia 2017).

University education is mostly suited for providing the socioeconomic development that Nigeria yearns for. This is because, it is the development of the human capital that invariably leads to the development of other sectors of the economy. For this, effort has been on how to improve the qualities of the university education to ensure sustainable growth and development. In our effort to add to what other researchers have done toward ensuring quality university training, we decided to study the academic performance of students through numerical calculations. In this study,

we had to apply multivariate analysis of variance MANOVA on the academic performance of university students. The utility of the study lies in the need to undertake corrective measures that improve the academic performance of students, especially in public institutions.

Multivariate analysis of variance is a statistical technique used to determine if the categorical independent variable(s) with two or more levels affect the continuous independent variables (Ying Li et al., 2012). Aykut, Esra and Alperen (2014) carried out a research on the relationship between the academic achievement and performance assignment achievement scores of students in science courses with regard to different variables using MANOVA and correlation analysis and observed no significant difference between the grade levels and the students' academic achievement scores and performance scores whereas a significant difference was found between the gender variable and performance scores, which was in favour of females. Hussein, Gabriel and Adamu (2017) studied the influence of students' sex, age, and course of study on the performance of Senior High School students on mathematic course using MANOVA and discovered no significant difference in the performance of student across sex and age but significant difference across course of study. In this paper, we compared the performance of university students across the faculties using their cumulative grade point average (CGPA).

2.0. Students Academics

2.1. Academic Performance of Students

Academic performance of students may be adversely affected by many factors, some of which include poor location of the school, incessant changes in government policies, closure of schools, teachers strike action, home-school distance, inadequate supervision, monitoring, and evaluation machinery, lack of good textbooks, poor content and context of instructional materials, poor and non-conducive learning environment (Adepoju 1995 and Adepoju, 2003).

Chansarkar and Mishaeloudis (2001) studied the effects of age, qualification, and distance from learning place etc. on student performance. According to them the performance of students on the module is not affected by the factors like age, sex and place of residence, but is associated with qualification in quantitative subjects. They also found that those who live near the University perform better than other students. Yvonne and Kola, (1998) elaborated that the student performance is very much dependent on SEB (socio economic background). High school students' variation in the levels of the performance is linked to their gender, grade level, school location, school type, student type and socioeconomic background (SEB) they later commented.

2.2. Students' Learning Preferences

Learning preferences is the way by which an individual prefers to acquire and process different forms of information. In the account of Omrod (2008), some students seem to learn better when information is presented through words (verbal learners), whereas others seem to learn better when it is presented in the form of pictures (visual learners). According to him, in a class where only one instructional method is employed, there is a strong possibility that a number of students will find the learning environment less optimal and this could affect their academic performance. Felder (1993) established that alignment between students' learning preferences and an instructor's teaching style leads to better recall and understanding. The learning preferences approach, according to him has gained significant mileage despite the lack of experimental evidence to support the utility of this approach. He stated further that there are a number of methods used to assess the learning preferences/styles of students but they all typically ask students to evaluate the kind of information presentation they are most at ease with. One of these approaches being used widely is the

Visual/Aural/Read and Write/Kinesthetic (VARK) questionnaire, pioneered by Neil Flemming in 1987, which categorized learners into a minimum of four major learning preference classes which includes:

Visual learners: These are learners who process information better when it is visually displayed. They prefer information to be presented on the whiteboard or screen, with charts, graphs, diagrams, maps, plans and colour.

Aural (or oral)/auditory learners: These are learners who process information better when it is presented through discussions, stories, guest speakers, and chats. They do not like making a lot of notes and may prefer to record lectures for later playbacks and reference.

Read/write learners: These are learners who prefer information better when it is written down and are made available for reading. They write a lot of notes and text.

Kinesthetic (or tactile) learners: These are learners who prefer practical exercises, examples, cases, trial and errors and use of senses in learning. They prefer to be actively involved in their learning and thus would benefit from active learning strategies in class.

(Flemming 2011)

2.3. Class Attendance and Academic Performance

A number of studies have found positive effects of class attendance on academic performance of student. Lukkarinen, Koivukangas and Seppala (2016) investigated the relationship between university students' class attendance and learning performance using cluster and regression analyses and discovered that attendance is positively and significantly related to performance of students. Durden and Ellis, (1995) in their study reported a nonlinear effect of attendance on learning. According to them a few absences to class do not lead to poor grades but excessive absenteeism does. Newman-Ford, Lloyd & Thomas (2009) expressed a contrary view when they remarked that by the use of information technology, information that used to be obtained through lectures can be obtained at the click of a mouse. According to them web-based learning approaches have become the order of the day.

2.4. Other Determinants of Academic Performance

Other determinants of academics performance such as age and gender had been studied by Haist, et al (2000), who observed that men perform better than women in certain settings while women outperform men in other settings. Borde (1998), on the other hand, found no evidence of academic performance being influenced by gender. Woodfield and Earl-Novell (2006) in study involving a close to two million graduating students found that female students outperformed male students and attributed this partly to female students being more conscientious and thus less likely to miss lectures. La Paro and Pianta (2000) and Crosser (1991) presented evidence that older children fare better academically than their younger age appropriate peers.

3.0. METHOD AND MATERIAL

The data for this study is a real life data collected from the Academic Records Unit of Federal University Wukari by method of two stage cluster sampling and it's on the cumulative grade point average of 300 level students for the 2015/2016 academic session. Data were obtained from the three faculties of the university through the randomly selected

five departments from each faculty. In each of the selected department all the 300 level students were chosen for the study.

3.1. Multivariate Analysis of Variance

When we measure several dependent variables on each experimental units instead of just one variable as in the case of ANOVA we have what we called Multivariate analysis of variance (MANOVA). In multivariate analysis of variance, we assume that k independent random samples of size n are obtained from p -variate normal populations with equal covariance matrices. Analysis of variance tests for the difference in means between two or more groups, while MANOVA tests for the difference in two or more mean vectors.

The model for each observation in a one way MANOVA is

$$X_{ij} = \mu + \alpha_i + \varepsilon_{ij}$$

where

$$i = 1, 2, \dots, k \text{ and } j = 1, 2, \dots, n$$

μ is the overall mean vector

α_i is the i th treatment effect

ε_{ij} are independent normal random errors with mean vector 0 and variance-covariance matrix Σ , that is, $\varepsilon_{ij} \sim N(0, \Sigma)$

Assumptions

The dependent variable should be normally distributed within groups. Overall, the F test is robust to non-normality (Okonkwo, Okeke and Obodozie 2010, and Aaron et. al. 2017), if the non-normality is caused by skewness rather than by outlier. Test for outliers should be run before performing a MANOVA, and outliers should be transformed or removed

MANOVA assumes that there are linear relationship among all pairs of dependent variables, all pairs of covariates, and all dependent variable-covariate pairs in each cell. This is to say that when the relationship deviates from linearity, the power of the analysis will be compromised.

MANOVA is performed under the assumption of homogeneity of variances. Since there are multiple dependent variables in multivariate designs, it is required that their intercorrelations (covariances) are homogeneous across the cells of the design.

When there is multicollinearity and singularity problem, that is, there is high correlation between dependent variables; one dependent variable becomes a near-linear combination of the other dependent variable MANOVA will be limited.

In MANOVA the null hypothesis that is usually tested is that the groups mean vectors are all equal to one another against the alternative that at least one of the group mean differs in only one variable. Mathematically this is written as

$$H_0: \mu_1 = \mu_2 \dots = \mu_g \text{ vs } H_1: \mu_{i\kappa} = \mu_{j\kappa} \text{ for one } i \neq j$$

In multivariate Analysis of variance all the scalar quantities used in calculating the test statistics are replaced by vectors and $p \times p$ matrices. For instance the sample mean for the group i , \bar{x}_i is replaced by sample mean vector

$$\bar{x}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} X_{ij} = \begin{pmatrix} \bar{x}_{i,1} \\ \vdots \\ \bar{x}_{i,p} \end{pmatrix} \text{ for the variables } 1, 2, \dots, p$$

The sum of the n_i 's over the entire group g will give the total sample size, that is,

$$n = \sum_{i=1}^g n_i = n_1 + n_2 + \dots + n_g$$

The overall mean

$$\bar{x}_{..k} = \frac{1}{n} \sum_{i=1}^g \sum_{j=1}^{n_i} X_{ij} \text{ for variable } k$$

The total sum of squares in MANOVA is a cross products matrix defined by the expression

$$T = \sum_{i=1}^g \sum_{j=1}^{n_i} (X_{ijk} - \bar{x}_{..k})(X_{ijk} - \bar{x}_{..l})'$$

When $k = l$ we have total sum of squares for the variable k , but when $k \neq l$ we have the measure of dependence between the variables k and l . It is good to note that

$$\sum_{i=1}^g \sum_{j=1}^{n_i} (X_{ijk} - \bar{x}_{..k})(X_{ijk} - \bar{x}_{..l})' = \sum_{i=1}^g n_i (\bar{x}_{i,k} - \bar{x}_{..k})(\bar{x}_{i,l} - \bar{x}_{..l}) + \sum_{i=1}^g \sum_{j=1}^{n_i} (X_{ijk} - \bar{x}_{i,k})(X_{ijk} - \bar{x}_{i,l})$$

The “between” and “within” sums of squares in univariate ANOVA are replaced by the “between” and “within” matrices B and H respectively. The “between” matrix or Treatment Sum of Squares and Cross Product is denoted as

$$B = \sum_{i=1}^g n_i (\bar{x}_{i,k} - \bar{x}_{..k})(\bar{x}_{i,l} - \bar{x}_{..l})$$

$$= \begin{pmatrix} SSB_{11} & SSB_{12} & \dots & SSB_{1p} \\ \vdots & \vdots & & \vdots \\ SSB_{p1} & SSB_{p2} & & SSB_{pp} \end{pmatrix}$$

when $k = l$ we have treatment sum of squares for the variable k and this measures the between treatment variation for the k th variable. When $k \neq l$, we have a measure of the dependence between variable k and l across treatment.

$$\text{Illustratively, } SSB_{11} = \sum_{i=1}^g n_i (\bar{x}_{i,1} - \bar{x}_{..1})^2 \text{ and } SSB_{12} = \sum_{i=1}^g n_i (\bar{x}_{i,1} - \bar{x}_{..1})(\bar{x}_{i,2} - \bar{x}_{..2})$$

The “within” matrix or Error Sum of squares and Cross Product is denoted as

$$W = \sum_{i=1}^g \sum_{j=1}^{n_i} (X_{ijk} - \bar{x}_{i,k})(X_{ijk} - \bar{x}_{i,l})'$$

$$= \begin{pmatrix} SSW_{11} & SSW_{12} & \dots & SSW_{1p} \\ \vdots & \vdots & & \vdots \\ SSW_{p1} & SSW_{p2} & & SSW_{pp} \end{pmatrix}$$

when $k = l$ we have error sum of squares for the variable k and this measures the within treatment variation for

the k th variable. When $k \neq l$, we have a measure of the dependence between variable k and l after taking into account the treatment. As illustration also $SSW_{11} = \sum_{i=1}^g \sum_{j=1}^{n_i} (X_{ij1} - \bar{x}_{l,1})^2$ and $SSW_{12} = \sum_{i=1}^g \sum_{j=1}^{n_i} (X_{ij1} - \bar{x}_{l,1})(X_{ij2} - \bar{x}_{l,2})$

Wilks' λ is the test statistic preferred for MANOVA, and is found through a ratio of the determinants of the variances

$$\lambda = \frac{|W|}{|B + W|}$$

Since Wilks' λ is equal to the variance not accounted for by the combined dependent variables, then $(1 - \lambda)$ is the variance that is accounted for by the best linear combination of dependent variables and such is the measure of the strength of the association of the test. The null hypothesis is rejected if $\lambda \leq A_{\alpha, p, V_B, V_W}$

where α is the given level of significance, p the number of variable, V_B the treatment degrees of freedom and V_W the error degrees of freedom.

When MANOVA test indicated that there is a statistically significant difference between the groups of independent variable, it is possible to determine which specific groups were significantly different from each other using post hoc tests. This post hoc test is important because MANOVA test cannot tell you which specific groups were significantly different from each other; it only tells you that difference exists.

4.0. RESULT AND DISCUSSIONS

The data for the analysis were first tested for normality and equality of variance to see if they are suitable for analysis of variance test. The Doornik-Hansen test gave a p-value that is greater than 0.05 which indicates that the data were approximately normal. The Box M test of equality of covariance matrices gave a p-value that is greater than 0.05 which indicated that all the covariance matrices are equal across the groups.

The Wilks Lambda test of Table 1 below showed that we have a p-value of 0.306, which is greater than the level of significance ($\alpha = 0.05$). The result indicated that the performance of 300 level students of Federal University Wukari do not significantly depend on the faculty in which they belong.

5.0. CONCLUSIONS

In the light of the result of data analysis carried out and the review of relevant literature, the study concludes that students' performance across the three Faculties does not significantly differ. However, that does not mean that their performances are all up to expectation in the various departments across Faculties. Other measures can still be employed to enhance general academic performance of students.

Table 1: Multivariate Tests^a

| Effect | Value | F | Hypothesis df | Error df | Sig. | Partial Eta Squared | Noncent. Parameter | Observed Power ^d | |
|--|--------------------|--------|----------------------|----------|---------|---------------------|--------------------|-----------------------------|-------|
| Intercept | Pillai's Trace | .978 | 751.266 ^b | 5.000 | 86.000 | .000 | .978 | 3756.328 | 1.000 |
| | Wilks' Lambda | .022 | 751.266 ^b | 5.000 | 86.000 | .000 | .978 | 3756.328 | 1.000 |
| | Hotelling's Trace | 43.678 | 751.266 ^b | 5.000 | 86.000 | .000 | .978 | 3756.328 | 1.000 |
| | Roy's Largest Root | 43.678 | 751.266 ^b | 5.000 | 86.000 | .000 | .978 | 3756.328 | 1.000 |
| Faculties | Pillai's Trace | .126 | 1.173 | 10.000 | 174.000 | .312 | .063 | 11.729 | .599 |
| | Wilks' Lambda | .875 | 1.182 ^b | 10.000 | 172.000 | .306 | .064 | 11.824 | .603 |
| | Hotelling's Trace | .140 | 1.191 | 10.000 | 170.000 | .300 | .065 | 11.913 | .607 |
| | Roy's Largest Root | .124 | 2.149 ^c | 5.000 | 87.000 | .067 | .110 | 10.746 | .682 |
| a. Design: Intercept + Faculties | | | | | | | | | |
| b. Exact statistic | | | | | | | | | |
| c. The statistic is an upper bound on F that yields a lower bound on the significance level. | | | | | | | | | |
| d. Computed using alpha =.05 | | | | | | | | | |

REFERENCES

1. Aron F., Marcelo M. John P., Tyler W. and Yu, A. (2008). *Multivariate Analysis of variance*, userwww.sfsu.edu/efc/classes/biol710/manova/manovanewest.htm
2. Aykut, E.B., Esra G., and Alperen (2004). *An example of secondary school students' academic achievement in science course and achievement scores in performance assignment with regard to different variables: A boarding school example*, *Participatory Education Research*, 1(2): 95-105.
3. Borde, S. F. (1998). *Predictors of student academic performance in the introductory marketing course*. *Journal of Education for Business*, 73 (5), 302 – 307.
4. Chansarkar B. A. and Michaeloudis, A. (2001) *Student profiles and factors affecting performance* *Int. j. math. educ. sci. technol.*, 2001, vol. 32, no. 1, 97–104, Pp 103-104.
5. Pankaj Sharma & Sunil K Sharma, *Internet Addiction, Loneliness and Academic Performance Among the Secondary School Students*, *International Journal of Humanities and Social Sciences (IJHSS)*, Volume 6, Issue 5, August-September 2017, pp. 19-24
6. Crosser, S. L. (1991). *Summer birth date of children, Kindergarten entrance age and academic achievement*, *Journal of Educational Research*, 84(3):140-146
7. Durden, G. C., & Ellis, L. V. (1995). *The effects of attendance on student Learning in principles of economics*. *American Economic Review*, 85(2), 343–346.

8. Felder, R. M. (1993). *Reaching the second tier: Learning and teaching styles in college science education*. *Journal of College Science Teaching*, 23(5), 286 – 290.
9. Flemming, N. (2011) *Vark a guide to learning styles*. Accessed on November 02, 2011 from <http://www.vark-learn.com/english/page.asp?p=categories>.
10. Haist, S. A., Wilson, J. F., Elam, C. L., Blue, A. V., & Fosson, S. E. (2000). *The effect of gender and age on medical school performance: An important interaction*. *Advances in Health Sciences Education*, 5(3), 197 – 205.
11. Hussein S., Gabriel, N., and Adam I. (2017), *Effect of some performance indicator of mathematics in the Nalerigu senior High School.*, *European Scientific Journal*, 13(3):429-437
12. La Paro, K. M. and Pianta, R. C. (2010). *Predicting children's competence in the early school years: A meta-analysis review*, *Review of Educational Research*, 70(4):443-484
13. Lukkarinen, Koivukangas, and Seppala (2016). *Relationship between class attendance and student performance*, *Procedia-Social and Behavioral Sciences* 228:341-347
14. Newman-Ford, L., Lloyd, S., & Thomas, S. (2009). *An investigation in the effects of gender, prior academic achievement, place of residence, age and attendance on first-year undergraduate attainment*. *Journal of Applied Research in Higher Education*, 1(1),13.
15. Magda Abd El-Hamid Abd El-Fattah, *Usage of Smartphones Technology in Learning Environment and its Effect on Academic Performance amongst Nursing Students*, *IMPACT: International Journal of Research in Humanities, Arts and Literature (IMPACT: IJRHAL)*, Volume 5, Issue 2, February 2017, pp. 1-22
16. Okonkwo, E.N, Okeke, J.U., and Obodozie (2010) *Robust Analysis of Variance and Chi-squared tests: A comparative analysis in testing k independent dichotomous Populations*, *Ikogho Journal*. P. 25-36. UNIPORT Nigeria www.ikogho.org.
17. Omrod, J. E. (2008). *Educational psychology: developing learners*. Sixth Edition. Upper Saddle River, New Jersey: Pearson Education. Wikipedia, <http://en.m.wikipedia.org>
18. Woodfield, R., & Earl-Novell, S. (2006). *An assessment of the extent to which subject variation in relation to the award of first class degree between the arts and sciences can explain the 'gender gap'*. *British Journal of Sociology of Education*, 27(3), 355.
19. Ying Li (2012) *Multivariate Analysis of Variance (MANOVA)*. Stockholm University. page 3.
20. Yvonne B., and Kola S. (1998) "An Analysis of High School Students' Performance on Five Integrated Science Process Skills" *Research in Science & Technical Education*, Volume 19, Number 2 / November 1, 2001Pp 133 – 145