International Journal of Advanced and Applied Sciences, 5(10) 2018, Pages: 1-6

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Analysis of the inter-relationship between students' first year results and their final graduating grades

Pelumi E. Oguntunde [1,*], Hilary I. Okagbue [1], Omoleye A. Oguntunde [2], Abiodun A. Opanuga [1], Sola J. Oluwatunde [3]

[1]*Department of Mathematics, Covenant University, Ota, Nigeria*
[2]*Department of Economics and Development Studies, Covenant University, Ota, Nigeria*
[3]*Department of Computer Science, Caleb University, Lagos State, Nigeria*

ARTICLE INFO

Article history:
Received 22 March 2018
Received in revised form
22 July 2018
Accepted 1 August 2018

Keywords:
Academic performance
Students
University
Multiple linear regressions

ABSTRACT

There is a tendency for students to lose focus in tertiary institutions because of change in environment and peer pressure (among several others); hence, a need to monitor and study the trend of students' performance in the tertiary institution. This article, therefore, seeks to know the correlation between the first year results and in particular, the final graduating grade of students in a leading Nigerian University. Test of normality was performed for the final graduating results and multiple linear regression models were fitted to the data; this enables us to predict what a student can graduate with having known a previous result (or first year result). All the analyses were performed using Minitab software. The result established that there are strong linear relationships between the GPAs as a student progresses in his/her academic journey.

© 2018 The Authors. Published by IASE. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

Many variables are often considered as key in the choice of university education. Some of the factors are conducive environment for effective learning, high graduation rates, low attrition rates for tutors, course accreditation by regulatory bodies, feedback from industry, academic ranking, affordable fees for low income families and so on (Odukoya et al., 2018a; 2018b; 2018c; Popoola et al., 2018). This paper however describes in details, the perceived relationship between the final graduating grade of students and their previous results in the university.

In Nigeria, most of the studies in this area have been limited to the use of WASSCE, NECO, UTME/JAMB or post UTME in predicting the final CGPA of students of University students. This can be viewed as the use of cognitive entry characteristics to predict academic performance of students. We refer readers to Obemeata (1974), Ohuche (1974), and Gbore (2013) amongst many authors. Furthermore, Kolawole and Ilugbusi (2007) showed that there was a linear and significant positive relationship between cognitive entry characteristics and CGPA of mathematics students.

* Corresponding Author.
Email Address: pelumi.oguntunde@covenantuniversity.edu.ng (P. E. Oguntunde)
https://doi.org/10.21833/ijaas.2018.10.001
2313-626X/© 2018 The Authors. Published by IASE.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

The link between first year and final year CGPA has rarely been reported in literature in the Nigerian context. The two related works are Bamgboye et al. (2001) but they limited their scope to relationship between entry requirements and pre MBBS clinical examinations while Salahdeen and Murtala (2005) and Afolabi et al., (2007) considered first professional medical examinations.

The same results have also been echoed elsewhere as seen in the works of Jaafar et al. (2016) and Eng et al. (2017). However, a combination of cognitive abilities, demographic factors and entry requirements has been used to predict the final CGPA of students (Alfan and Othman, 2005).

Generally, cognitive abilities such as study skills and learning skills can predict their CGPA without the use of pre-entry characteristics (Halde et al., 2016) as psychological state of the students greatly affect their academic performance irrespective of other studied variables.

Several statistical tools have been applied in this aspect such as regression analysis and artificial neural network (Arsad and Buniyamin, 2014). This present research makes use of the normality tests, correlation analysis and multiple linear regression analysis.

2. Materials and methods

The various methods and data sets used in this research are discussed in the section.

2.1. Test of normality

To know if the dataset come from a normal distribution or not, we performed the test for normality using the Kolmogorov-Smirnov (KS) test. The KS normality test only applies to continuous distributions. Other normality tests that can be used include Anderson Darling (AD) test and Saphiro Wilks test. The hypothesis for such test is: H_0: The data come from a normal population; Vs; H_1: The data does not come from a normal population.

Our judgment on whether to accept or reject the null hypothesis is based on the p-value and we make use of 0.05 as the level of significance. H_0 is rejected if the p-value is less than the level of significance.

2.2. Correlation analysis

Correlation coefficient measures the degree of linear relationship between two variables. Its value ranges from -1 to +1. It is denoted by 'r' and particularly, the formula for the product moment correlation coefficient is:

$$r = \frac{n\sum(xy)-(\sum x)(\sum y)}{\sqrt{(n\sum x^2-(\sum x)^2)}\sqrt{(n\sum y^2-(\sum y)^2)}} \qquad (1)$$

To test for the significance of the correlation coefficient, we use the statistic:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \qquad (2)$$

The corresponding hypothesis is: H_0: The correlation coefficient is not significantly different from zero; Vs; H_1: The correlation coefficient is significantly different from zero.

The H_0 is rejected if the p-value is less than or equal to the level of significance.

2.3. Multiple linear regression analysis

Multiple linear regression analysis is used to show the linear relationship between a dependent (or response) variable and two or more independent (or predictor) variables. The multiple linear regression models are of the form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + e_i \qquad (3)$$

where Y is the dependent variable; X_i are the independent variables; β_i are the regression coefficients; e_i is the random error.

To test if the regression model significantly fits the data, we consider the hypothesis: H_0: The regression model does not significantly fit the data; Vs; H_1: The regression model significantly fits the data.

Also, H_0 is rejected if the p-value is less than or equal to the level of significance.

2.4. The data

The dataset used in this research represents the GPA of engineering students for a period of 5 years and their graduating CGPA. The departments considered are Information Communication Engineering department, Mechanical Engineering department and Petroleum Engineering department. The dataset itself and descriptive analysis of the data were provided by Popoola et al. (2018).

3. Results

3.1. Graphical overview of the students' first GPA and their final CGPA

The plots in Figs. 1 to 3 show the joint plot of the first GPA of the students and their graduating CGPA for the three engineering departments.

3.2. The Kolmogorov Smirnov (KS) test for the students' final CGPA

The values for the KS test for the final CGPA of students from the three departments are indicated in Figs. 4 to 6.

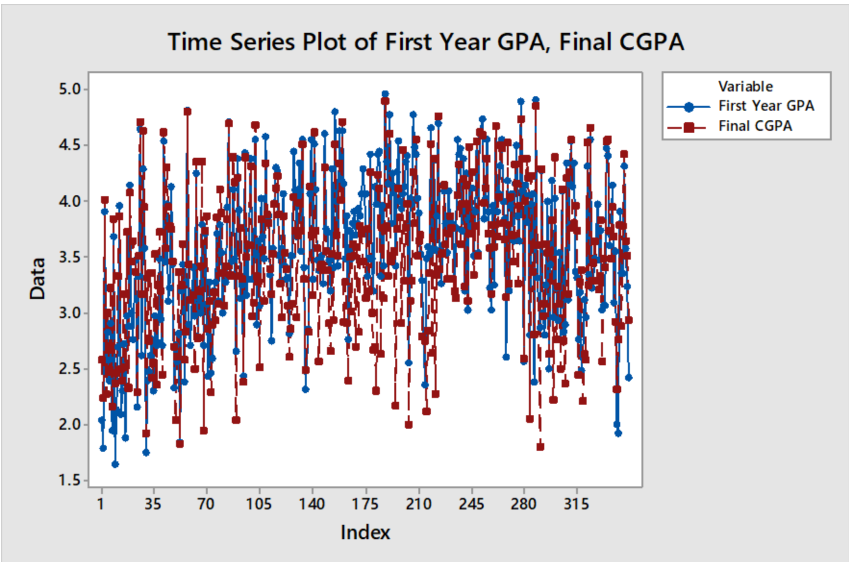

Fig. 1: Plots of first year GPA and final CGPA for ICE department

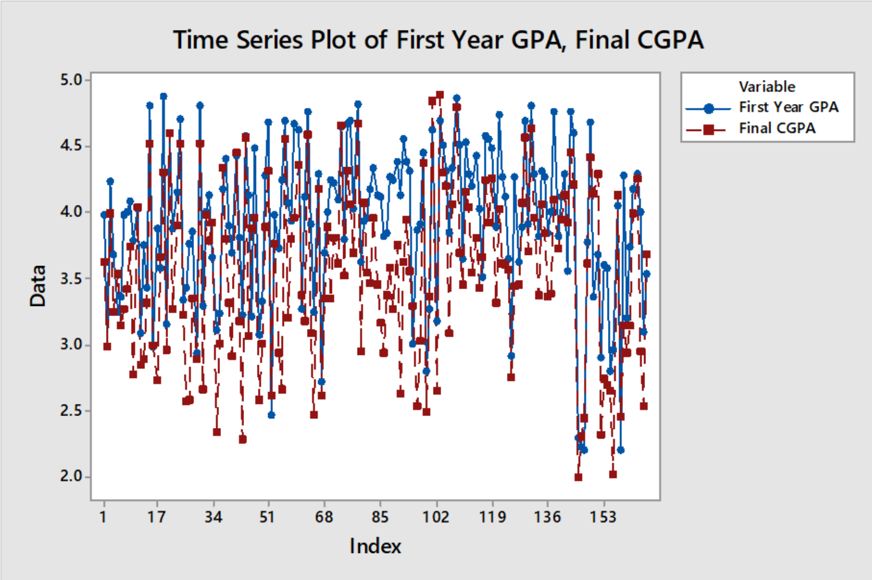

Fig. 2: Plots of first year GPA and final CGPA for mechanical engineering department

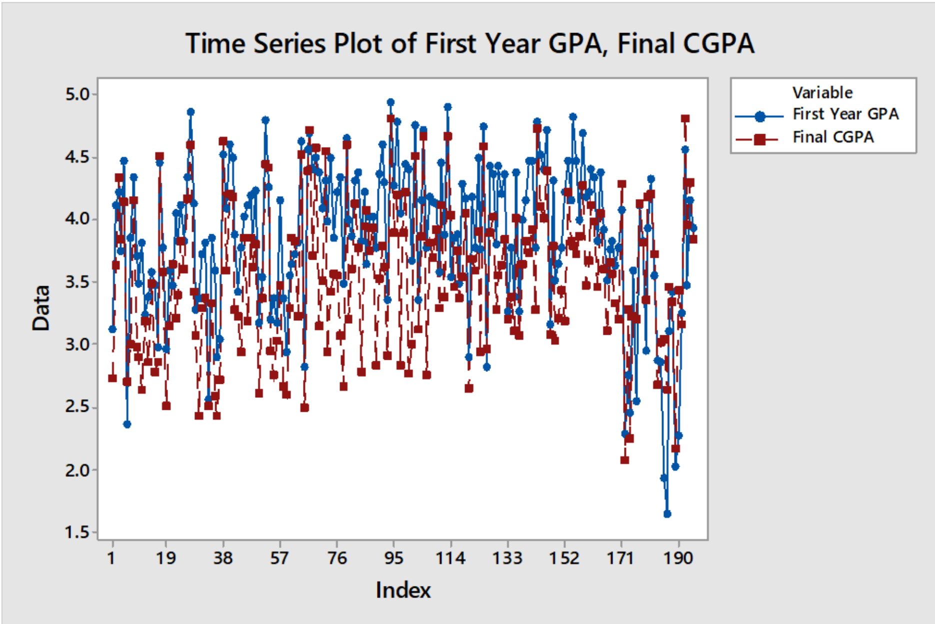

Fig. 3: Plots of first year GPA and final CGPA for petroleum engineering department

The p-values indicated in Figs. 4 to 6 are all greater than the level of significance (0.05). Therefore, we accept the null hypotheses and conclude that the final CGPA of students in all the three departments come from a normal population.

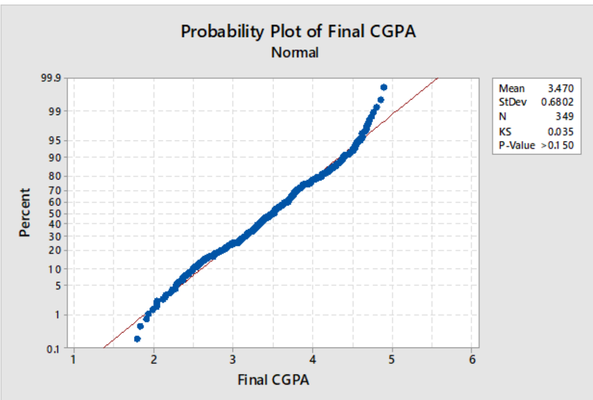

Fig. 4: Normality plot for the final CGPA of ICE students

3.3. Correlation analysis

The correlation coefficients between the GPAs of the students from the first year till the point of graduation for all the three departments are presented in Tables 1 to 3.

The results in Tables 1 to 3 show that there are positive linear relationships among the GPAs across all levels. The linear relationships are also strong except for few occasions where there exist fair relationships.

3.4. Regression analysis

The final CGPA is made to be the dependent variable while the other 5 GPAs are made to be independent variables. The regression line for ICE scores is:

$$Final\ CGPA = 0.0181 + 0.19470\ First\ Year\ GPA + 0.20954\ Second\ Year\ GPA + 0.24185\ Third\ Year\ GPA + 0.14140\ Fourth\ Year\ GPA + 0.21097\ Fifth\ Year\ GPA$$

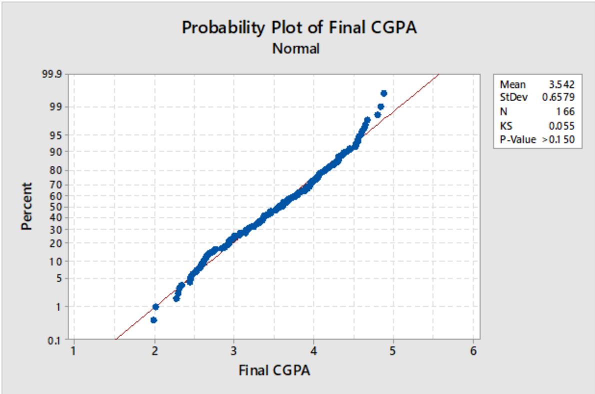

Fig. 5: Normality plot for the final CGPA of students from mechanical engineering department

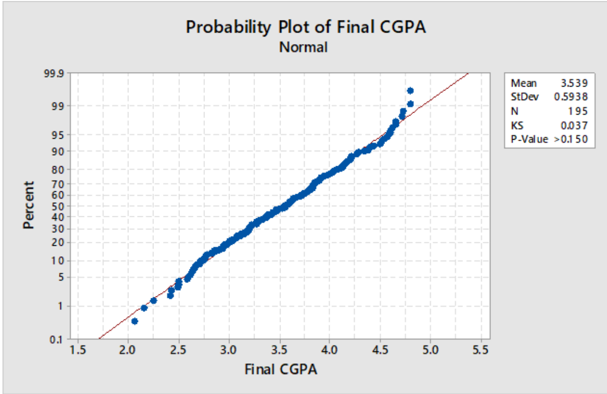

Fig. 6: Normality plot for final CGPA of students from petroleum engineering department

Table 1: Correlation coefficient among the GPAs for ICE students

	First GPA	Second GPA	Third GPA	Fourth GPA	Fifth GPA
Second GPA	0.771				
Third GPA	0.677	0.800			
Fourth GPA	0.587	0.719	0.836		
Fifth GPA	0.584	0.726	0.849	0.801	
Final CGPA	0.808	0.905	0.947	0.874	0.892

Table 2: Correlation coefficient among the GPAs for mechanical engineering students

	First GPA	Second GPA	Third GPA	Fourth GPA	Fifth GPA
Second GPA	0.734				
Third GPA	0.651	0.825			
Fourth GPA	0.548	0.694	0.826		
Fifth GPA	0.626	0.662	0.784	0.749	
Final CGPA	0.798	0.890	0.937	0.863	0.882

Table 3: Correlation coefficient among the GPAs for petroleum engineering students

	First GPA	Second GPA	Third GPA	Fourth GPA	Fifth GPA
Second GPA	0.692				
Third GPA	0.626	0.795			
Fourth GPA	0.505	0.678	0.747		
Fifth GPA	0.597	0.768	0.793	0.725	
Final CGPA	0.773	0.923	0.917	0.818	0.895

Interpretation: For every unit increment in First year GPA of ICE students, there will be an increase of 0.19470 in the Final CGPA provided that all the other variables are held constant. Also, for every unit increment in Second year GPA, there will be an increase of 0.20954 in the Final CGPA provided that all the other variables are held constant and so on. The summary of the model is presented in Table 4.

This implies that about 99.62% of the variability in the final CGPA is being explained by the other GPAs for ICE students.

The Analysis of variance (ANOVA) table testing for the significance of the model is presented in Table 5.

Table 4: Model summary

R^2	Adjusted R^2	Predicted R^2
99.62%	99.61	99.60%

The p-value of 0.000 means that the null hypothesis should be rejected. In other words, we conclude that the regression model significantly fits the data. The test for the individual regression parameters is presented in Table 6.

Table 5: Analysis of variance for the fitted regression model ICE department

Source of Variation	Degree of Freedom	Sum of Square	Mean Square	F-value	P-value
Regression	5	160.403	32.0807	17956.96	0.000
First Year GPA	1	2.497	2.4972	1397.79	0.000
Second Year GPA	1	2.218	2.2179	1241.44	0.000
Third Year GPA	1	2.680	2.6803	1500.27	0.000
Fourth Year GPA	1	1.001	1.0012	560.41	0.000
Fifth Year GPA	1	1.936	1.9357	1083.51	0.000
Error	343	0.613	0.0018		
Total	348	161.016			

Table 6: Test for individual coefficient

Terms	Coefficients	SE	T-value	P-value
Constant	0.0181	0.0154	1.18	0.240
First Year GPA	0.19470	0.00521	37.39	0.000
Second Year GPA	0.20954	0.00595	35.23	0.000
Third Year GPA	0.24185	0.00624	38.73	0.000
Fourth Year GPA	0.14140	0.00597	23.67	0.000
Fifth Year GPA	0.21097	0.00641	32.92	0.000

All the variables used contribute significantly to the fitness of the model. The regression line for Mechanical engineering scores is:

$$Final\ CGPA = -0.0676 + 0.20877\ First\ Year\ GPA + 0.20803\ Second\ Year\ GPA + 0.19902\ Third\ Year\ GPA + 0.15519\ Fourth\ Year\ GPA + 0.24222\ Fifth\ Year\ GPA$$

Interpretation: For every unit increment in First year GPA of mechanical engineering students, there will be an increase of 0.20877 in the Final CGPA provided that all the other variables are held constant. Also, for every unit increment in Second year GPA, there will be an increase of 0.20803 in the Final CGPA provided that all the other variables are held constant and so on. The summary of the model is presented in Table 7.

Table 7: Model summary

R^2	Adjusted R^2	Predicted R^2
99.62%	99.61	99.56%

This implies that about 99.62% of the variability in the final CGPA is being explained by the other GPAs for mechanical engineering students.

The ANOVA table and the F-value for the regression model are presented in Table 8.

Table 8: ANOVA for the fitted regression model of mechanical engineering department

Source of Variation	Degree of Freedom	Sum of Square	Mean Square	F-value	P-value
Regression	5	71.1540	14.2308	8467.83	0.000
First Year GPA	1	1.0974	1.0974	652.98	0.000
Second Year GPA	1	0.9339	0.9339	555.68	0.000
Third Year GPA	1	0.8537	0.8537	507.96	0.000
Fourth Year GPA	1	0.6722	0.6722	400.01	0.000
Fifth Year GPA	1	1.7185	1.7185	1022.54	0.000
Error	160	0.2689	0.0017		
Total	165	71.4229			

The regression model significantly fits the data. The test for the individual regression parameters is presented in Table 9.

Table 9: Test for individual coefficient

Terms	Coefficients	SE	T-value	P-value
Constant	-0.0676	0.0239	-2.83	0.005
First Year GPA	0.20877	0.00817	25.55	0.000
Second Year GPA	0.20803	0.00883	23.57	0.000
Third Year GPA	0.19902	0.00883	22.54	0.000
Fourth Year GPA	0.15519	0.00776	20.00	0.000
Fifth Year GPA	0.24222	0.00757	31.98	0.000

All the variables contribute significantly to the rejection of the null hypothesis.

The regression line for petroleum engineering scores is:

$$Final\ CGPA = 0.0779 + 0.17435\ First\ Year\ GPA + 0.25764\ Second\ Year\ GPA + 0.21027\ Third\ Year\ GPA + 0.13453\ Fourth\ Year\ GPA + 0.21019\ Fifth\ Year\ GPA$$

Interpretation: For every unit increment in First year GPA of petroleum engineering students, there will be an increase of 0.17435 in the Final CGPA provided that all the other variables are held constant. Also, for every unit increment in Second year GPA, there will be an increase of 0.25764 in the Final CGPA provided that all the other variables are held constant and so on.

The summary of the model is presented in Table 10.

Table 10: Model summary

R^2	Adjusted R^2	Predicted R^2
99.67%	99.66	99.64%

This implies that about 99.67% of the variability in the final CGPA is being explained by the other GPAs for petroleum engineering students. The ANOVA table and the F-value for the regression model are presented in Table 11. The regression model significantly fits the data. The test for the individual regression parameters is presented in Table 12.

Table 11: ANOVA for the fitted regression model of petroleum engineering department

Source of Variation	Degree of Freedom	Sum of Square	Mean Square	F-value	P-value
Regression	5	68.1882	13.6376	11505.60	0.000
First Year GPA	1	1.1239	1.1239	948.23	0.000
Second Year GPA	1	1.7619	1.7619	1486.47	0.000
Third Year GPA	1	1.1570	1.1570	976.13	0.000
Fourth Year GPA	1	0.6568	0.6568	554.11	0.000
Fifth Year GPA	1	1.0678	1.0678	900.88	0.000
Error	189	0.2240	0.0012		
Total	194	68.4122			

4. Conclusion

Inferential statistics has been performed on the academic performance of engineering students in a leading Nigerian university. There are strong linear relationships between the GPAs as a student progresses in his/her academic journey. All the regression models significantly fit the dataset used and each of the regression parameters contributes to the significance of the model. We therefore advise that since the first GPA and early GPAs of a student determines their final CGPA, students should take their first year (or early years) very serious, otherwise, they may not be able to significantly amend their errors and negligence in the final year.

Table 12: Test for individual coefficient

Terms	Coefficients	SE	T-value	P-value
Constant	0.0779	0.0178	4.38	0.000
First Year GPA	0.17435	0.00566	30.79	0.000
Second Year GPA	0.25764	0.00668	38.55	0.000
Third Year GPA	0.21027	0.00673	31.24	0.000
Fourth Year GPA	0.13453	0.00571	23.54	0.000
Fifth Year GPA	0.21019	0.00700	30.01	0.000

Definition of terms

UTME Unified Tertiary Matriculation Examination

JAMB Joint Admission and Matriculation Board

CGPA Cumulative Grade Point Average

WASSCE West African Senior School Certificate Examination

NECO National Examination Council

Acknowledgment

The authors are grateful to the anonymous reviewers for their constructive comments and to Covenant University for financial supports.

References

Afolabi AO, Mabayoje VO, Togun VA, Oyadeyi AS, and Raji Y (2007). The effect of mode of entry into medical school on performance in the first two years. Journal of Medical Sciences, 7(6): 1021-1026.

Alfan E and Othman N (2005). Undergraduate students' performance: The case of University of Malaya. Quality Assurance in Education, 13(4): 329-343.

Arsad PM and Buniyamin N (2014). Neural network and linear regression methods for prediction of students' academic achievement. In the IEEE Global Engineering Education Conference, IEEE, Istanbul, Turkey: 916-921.

Bamgboye EA, Ogunnowo BE, Badru OB, and Adewoye EO (2001). Students admission grades and their performance at Ibadan University pre-clinical MBBS examinations. African Journal of Medicine and Medical Sciences, 30(3): 207-211.

Eng TH, Daneil ILA, Kamaruddin SFB, and Rijeng JSA (2017). High school academic performance and academic success in university. Advanced Science Letters, 23(8): 7653-7656.

Gbore LO (2013). Relationship between cognitive entry characteristics and the academic performance of university undergraduates in South West, Nigeria. Nigeria Journal of Educational and Social Research, 3(1): 19-24.

Halde RR, Deshpande A, and Mahajan A (2016). Psychology assisted prediction of academic performance using machine learning. In the IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, IEEE, Bangalore, India: 431-435.

Jaafar R, Bais B, Zaki WMDW, Bukhori MF, Shaarani MFAS, and Huddin AB (2016). Correlation study of student achievement at pre-university level and their corresponding achievement in the year-one undergraduate course of circuit theory at UKM. Pertanika Journal of Social Sciences and Humanities, 24: 87-96.

Kolawole EB and Ilugbusi AA (2007). Cognitive entry grade as predictors of students' academic performance in mathematics in Nigeria universities. Medwell Journal, 2(3): 322-326.

Obemeata JO (1974). The predictive validity of intelligence tests M, ML and MQ. African Journal of Educational Research, 1(2): 205-211.

Odukoya JA, Adekeye O, Igbinoba AO, and Afolabi A (2018a). Item analysis of university-wide multiple choice objective examinations: The experience of a Nigerian private university. Quality and Quantity, 52(3): 983-997.

Odukoya JA, Omole DO, Atayero AA, Badejo J, Popoola S, John M, and Ucheaga E (2018b). Learning attributes of summa cum laude students: Experience of a Nigerian university. Cogent Education, 5(1): 1426675. https://doi.org/10.1080/2331186X.2018.1426675

Odukoya JA, Popoola SI, Atayero AA, Omole DO, Badejo JA, John TM, and Olowo OO (2018c). Learning analytics: Dataset for empirical evaluation of entry requirements into engineering undergraduate programs in a Nigerian university. Data in Brief, 17: 998-1014.

Ohuche RO (1974). Academic achievement of Nigerian undergraduates as a function of previous educational experiences. West African Journal of Education, 18(2): 111-115.

Popoola SI, Atayero AA, Badejo JA, John TM, Odukoya JA, and Omole DO (2018). Learning analytics for smart campus: Data on academic performances of engineering undergraduates in a Nigerian Private University. Data in Brief, 17: 76-94.

Salahdeen HM and Murtala BA (2005). Relationship between admission grades and performances of students in the first professional examination in a new medical school. African Journal of Biomedical Research, 8(1): 51-57.