A STUDY OF UNDERGRADUATE STUDENTS' PERFORMANCE IN NIGEGIA

A. A. AKINREFON, A. O. ADEJUMO
University of Ilorin, NIGERIA

Abstract. This research work was carried out to assess undergraduate students' performance in their first year and their final year in order to ascertain which of them gives the student's true ability in his/her chosen field of study and also to investigate the effect of some variables on their final grade. The Conditional Symmetry model is used in investigating the level of agreement that exist between the students' performance in their entry year and that of their final year in the University while the multinomial logit regression is used in assessing the influence of such variables as Age, Mode of entry, Gender, First, Second, and Third year GPAs on their Final CGPA. The tau estimate from the Conditional Symmetry model showed, in all the various cross classified data, that their first year performance rated the students' performance better than their final year performance while the multinomial logit showed that the estimated odds of the student making a first/second class (upper division) as against a second class (lower division) is higher in their first year than in the final year.

Keywords: undergraduate, performance, conditional symmetry, multinomial logit, Grade Point Average (GPA), Cumulative Grade Point Average (CGPA)

Introduction

Over the years, academic institutions, from primary to tertiary, have employed several methods of evaluating students' academic performance to determine whether or not he/she is displaying adequate knowledge, skill values and attitudes, and is meeting institutional standards for satisfactory academic progress. A grading system is used to indicate how well a student has met the school's expectations for academic performance. The final grades of a student can be used by potential employers or further post secondary or tertiary institutions to assess and compare applicants, hence the importance of such grades.

Some students at entry level start off with excellent grades but by their final year, one observes a decline in their academic program. Since it is still the same student that is still being rated at various intervals, there is need to check whether or not the various ratings for student performance agree , and the extent to which each of them are classified accurately. Also, there is need to check for the influence/contribution of certain variables such as age, mode of entry, gender etc on their overall cumulative grade point average.

The research work covers students' grades for the 2009/2010 academic session for some departments from the Faculty of Science, University of Ilorin, Nigeria. These departments include Physics, Geology, Biochemistry and Statistics.

Methodology

Since the major focus of this research work is to model the structure of agreement that exist between the student's performance at entry level and that at his/her final level in the institution, we present here the method used in achieving this aim. We also present another approach used in estimating the effect of certain variables on the students' final CGPA (Cumulative Grade Point Average).

Conditional symmetry model

The conditional symmetry model is a special case to the symmetry model having an extra parameter for the off-diagonal cells. It is designed for square tables like the one arising from the ratters' result. The model was proposed by McCullagh (1978) and is given as

$$\pi_{ij} = \begin{cases} \theta\phi_{ij} & if \quad i < j \\ \phi_{ij} & if \quad i = j \\ (2-\theta)\phi_{ij} & if \quad i > j \end{cases} \qquad (1)$$

With $\phi_{ij} = \phi_{ji}$ and $\sum_{i=1}^{I}\sum_{i=1}^{I}\phi_{ij} = 1$ for i=j=1,2,…,I

The conditional symmetry model is a palindromic invariant and not a permutation invariant (McCullagh, 1978). However, the reverse permutation applied to conditional symmetry model (Eq. 1) yields

$$\pi_{ij} = \begin{cases} (2-\theta)\phi_{I-i+1,I-j+1} & if \quad i<j \\ \phi_{I-i+1,I-j+1} & if \quad i=j \\ \theta\phi_{I-i+1,I-j+1} & if \quad i>j \end{cases} \tag{2}$$

With $\phi_{I-i+1,I-j+1} = \phi_{I-j+1,I-i+1}$ and $\sum_{i=1}^{I}\sum_{j=1}^{I}\phi_{I-i+1,I-j+1} = 1$ for i=j=1, 2… I

The conditional symmetry model as a log-linear model is given as

$$\log(m_{ij}) = \mu + \lambda_i^{R_1} + \lambda_j^{R_2} + \lambda_{ij}^{R_1R_2} + \tau I(i<j)\text{, i, j =1, 2... I} \tag{3}$$

Where $\lambda_{ij}^{R_1R_2} = \lambda_{ji}^{R_1R_2}$, $\sum_{i=1}^{I}\lambda_i^{R_1} = 0$ and $\sum_{i=1}^{I}\lambda_{ij}^{R_1R_2} = 0$ for j=1, 2... I

And $I(i<j)$ is the indicator function defined as $I(i<j) = \begin{cases} 1 & if \quad i<j \\ 0 & if \quad i \geq j \end{cases}$

Based on this additional parameter, the model is mainly for ordered classification when symmetry may not hold, often either

$$\pi_{ij} > \pi_{ji} \quad \forall i<j \quad \text{Or} \quad \pi_{ij} < \pi_{ji} \; \forall i<j$$

The model (Eq. 1) implies that for all i<j, if R_1 denote the row number and R_2 the column number of an observation made according to distribution then the conditional interpretation of the model (Eq. 3) is

$$P(R_1 = i, R_2 = j / R_1 < R_2) = P(R_1 = j, R_2 = i / R_1 > R_2) = \phi_{ij}$$

This means that the cell probabilities above the main diagonal are mirror image of the cell probabilities below it.

The generalized linear model (GLM) procedure would be used to fit the model (Dobson, 1945, Tanner & Young, 1985). Poisson sampling is mostly assumed when fitting GLM to categorical data with m>2. The log likelihood function is

$$l(\theta,\phi)=\sum_{i=1}^{n}(\frac{y_i\theta_i-b(\theta_i)}{\phi}+c(y_i,\phi)) \quad (4)$$

Where θ subsumes all of θ_i. It could be written as function of β and Φ because (given the x_i), β determines all the θ_i.The main way of maximizing β is by maximizing (Eq. 4), *cf.* Adejumo, 2005; Agresti, 2002; Lawal, 2003; Dobson, 1945; and Liu & Agresti, 2005.

The fact that $G(u_i)=x_i\beta$ suggest a crude approximation estimate: regress $G(y_i)$ on x_i, perhaps modifying y_i in order to avoid violating range restrictions (such as taking log (0)), and accounting for the differing variances of the observations.

The Fisher scoring iteration is the widely used technique for maximizing the GLM likelihood over β. The basic step is

$$\beta^{(k+1)}=\beta^k-(E(\frac{\partial^2 l}{\partial\beta\partial\beta^{/}}))^{-1}\frac{\partial l}{\partial\beta} \quad (5)$$

This can also be written as

$$\beta^{(k+1)}=\beta^k+(-E(l^{//}(\beta^{(k)})))^{-1}l^{/}(\beta^{(k)}) \quad (6)$$

Where l is the log-likelihood function for the entire sample $y_1,y_2...y_N$ and the expectations are taken with $\beta=\beta^{(k)}$. Fisher scoring simplifies to

$$\beta^{(k+1)}=(X^{/}WX)^{/}X^{/}WZ$$

Where w is a diagonal matrix with

$$W_{ii}=(G^{/}(\mu_i)^2 b^{//}(\theta_i))^{-1} \quad (7)$$

and

$$Z_i=(Y_i-\mu_i)G^{/}(\mu_i)+x_i\beta \quad (8)$$

Both equations (2.7) and (2.8) use $\beta = \beta^{(k)}$ and derived values of $\theta_i^{(k)}$ and $\mu_i^{(k)}$.

In describing the structure of variables involved in the modification of the model to obtain their estimates as stated in the model, we create variables that take on a unique value for each diagonal cells and a unique value of each pair of cells, Adejumo, 2005, Adejumo et al., 2005. For example, if I=5, we have

$$
u = \begin{pmatrix}
u_1 & if & i = j = 1 \\
u_2 & if & i = j = 2 \\
u_3 & if & i = j = 3 \\
u_4 & if & i = j = 4 \\
u_5 & if & i = j = 5 \\
u_{12} & if & (i, j) = (1,2)(2,1) \\
u_{13} & if & (i, j) = (1,3)(3,1) \\
. & . & . \\
. & . & . \\
. & . & . \\
'. & . & . \\
u_{45} & if & (i, j) = (4,5)(5,4)
\end{pmatrix}
$$

Multinomial logit regression

Here we present the basic procedures involved in fitting a logit regression when we have a polytomous or multiple response category. Although the response categories for this research work are ordinal, we would be treating them as nominal. Earlier attempt to consider the ordinal nature of response using the proportional/ordered logit model could not be continued with since the effect of the predictors was not the same across the logit models. Hence, the use of multinomial logit regression seems to be reasonable (Agresti, 2002; Liu & Agresti, 2005).

Multinomial logit regression compares multiple groups through a combination of binary logistic regression. The category comparisons are equivalent to the comparisons of binary logistic repression. The category comparisons are equivalent to the comparisons for a dummy-coded dependent variable and the baseline category/group.

The choice of reference/baseline category is arbitrary but most often the group with the highest frequency is chosen for this research work, those who made second class lower division in their Cumulative Grade Point are chosen as the baseline category. Thus, we'd be having two equations, one for each of the category defined by the dependent variables. The equation will be used to compute the probability that an individual belongs to each category associated with the highest probability.

Pseudo R square will be used to compute the correlation (estimate the strength of relationship between the dependent and the independent variables).The pseudo R square reports the proportion of variation explained by the independent variables.

There are two types of statistics used in testing for individual independent variable. They are the likelihood ratio test and the Wald test.

The interpretation for an independent variable focuses on its ability to distinguish between pairs of categories and the contributions which it makes to change the odds of being in one dependent variables rather than the other.

If an independent variable has an overall relationship with the dependent variable, it might not be statistically significant in differentiating between pairs and categories defined by the dependent variables.

Data presentation

Table 1. Summary data for Department of Physics

First Year new	Final Year New				Total
	Pass	3^{rd}	2-2	2-1	
Pass	1	3	1	1	6
3^{rd}	1	4	7	2	14
2-2	0	0	0	1	1
2-1	0	0	0	0	0
Total	2	7	8	4	21

Table 2. Summary data for Department of Biochemistry

year1new	final new					Total
	Pass	3rd class	2-2	2-1	1st class	
Pass	1	7	4	0	0	12
3rd class	1	11	36	6	0	54
2-2	0	7	27	33	0	67
2-1	0	0	2	19	0	21
1st class	0	0	0	0	2	2
Total	2	25	69	58	2	156

Table 3. Summary data for Department of Geology

First Year new	Final Year New				Total
	Pass	3^{rd}	2-2	2-1	
Pass	3	10	8	2	23
3^{rd}	4	11	17	4	36
2-2	0	4	17	5	26
2-1	0	0	1	0	1
Total	7	25	43	11	86

Table 4. Summary data of Department of Statistics

year1new	final new					Total
	Pass	3rd class	2-2	2-1	1st class	
Pass	0	0	0	0	0	0
3rd class	0	2	3	0	0	5
2-2	1	0	5	7	1	14
2-1	0	0	4	7	3	14
1st class	0	0	0	0	2	2
Total	1	2	12	14	6	35

Table 5. Combined data

year1new	final new					Total
	pass	3rd class	2-2	2-1	1st class	
Pass	5	20	13	3	0	41
3rd class	6	28	63	12	0	109
2-2	1	11	49	46	1	108
2-1	0	0	7	26	5	38
1st class	0	0	0	0	2	2
Total	12	59	132	87	8	298

Analysis, results and conclusion

The algorithm written based on the assumptions and properties of the model, fit the model for $i=1, 2, \dots, I$ as described earlier:

$$\log(m_{ij}) = \mu + \lambda_i^{R_1} + \lambda_j^{R_2} + \lambda_{ij}^{R_1 R_2} + \tau I(i < j)$$

$$i, j = 1, 2 \dots I$$

The following results are based on the data 1-5 which contain student totals of 21 (for Physics); 86 (for Geology); 156 (for Biochemistry); 35 (for Statistics); and 298 (for the combined analysis).

Parameters estimate under conditional symmetry model

Table 6. Department of Physics

COEFFICIENTS	VALUE	S.E	Z-VALUE
INTERCEPT	-1.93E+01	9.427E+03	-0.002
λ_1	1.93E+01	9.427E+03	0.002
λ_2	2.069E+01	9.427E+03	0.002
λ_3	1.892E-08	1.333E+04	1.42E-12
λ_{12}	2.062E+01	9.427E+03	0.002
λ_{13}	1.924E+01	9.427E+03	0.002
λ_{14}	1.924E+01	9.427E+03	0.002
λ_{23}	2.118E+01	9.427+03	0.002
λ_{24}	1.993E+01	9.427E+03	0.002
λ_{34}	1.924E+01	9.427E+03	0.002
τ	-2.708	1.033	-2.622
Goodness of Fit Statistics (degree of freedom = 5, no. of iterations = 17)			
G^2	2.9827	X^2	3.200

Table 7. Department of Geology

COEFFICIENTS	VALUES	S.E	Z-VALUE
Intercept	-18.3026	5717.532	-0.002
λ_1	19.4012	5717.532	0.003
λ_2	20.7005	5717.532	0.004

λ_3	21.1358	5717.532	0.004
λ_{12}	20.763	5717.532	0.004
λ_{13}	20.2033	5717.532	0.004
λ_{14}	18.8170	5717.532	0.004
λ_{23}	21.1684	5717.532	0.004
λ_{24}	19.9107	5717.532	0.003
λ_{34}	19.9157	5717.532	0.003
τ	-1.6314	0.3645	-4.476
Goodness of Fit Statistics (degree of Freedom =5, iteration = 16)			
G^2	6.413	X^2	4.375

Table 8. Department of Biochemistry

COEFFICIENTS	VALUE	S.E	Z-VALUE
Intercept	-21.3026	25624.1998	-0.001
λ_1	21.3026	25624.1998	0.001
λ_2	23.7005	25624.1998	0.001
λ_3	24.5984	25624-1998	0.001
λ_4	24.2470	25624.1998	0.001
λ_{12}	23.2470	25624.1998	0.001
λ_{13}	22.5812	25624.1998	0.001
λ_{14}	1.0103	29517.4057	3.24E-05
λ_{15}	1.0103	29517.4057	3.24E-05
λ_{23}	24.9562	25624.1998	0.001

λ_{24}	22.9867	25624.1998	0.001
λ_{25}	1.0103	29517.4057	3.42E-05
λ_{34}	24.7503	25624.1998	0.001
λ_{35}	1.0103	29517.4057	3.42E-05
λ_{45}	21.8881	25624.1998	0.001
τ	-2.1748	0.3337	- 6.517
Goodness of Fit Statistics (degree of Freedom = 9, iteration =19)			
G^2	5.0229	X^2	3.9116

Table 9. Department of Statistics

COEFFICIENTS	VALUES	S.E	Z-VALUE
Intercept	0.6931	0.7071	0.980
λ_1	-21.00	1.554E+04	-0.001
λ_2	3.446E-17	1.000	3.45E-17
λ_3	0.9163	0.8367	1.095
λ_4	1.253	0.8018	1.562
λ_{12}	-20.54	1.061E+04	-0.002
λ_{13}	-0.9985	1.232	-0.810
λ_{14}	-20.54	1.061E+04	-0.002
λ_{23}	0.1001	0.9231	0.108
λ_{24}	-20.54	1.061E+04	-0.002
λ_{25}	-20.54	1.061E+04	-0.002

λ_{34}	1.399	0.7808	1.792
λ_{35}	-0.9985	1.232	-0.810
λ_{45}	0.1001	0.9231	0.108
τ	-1.030	0.5210	-1.976
Goodness of Fit Statistics (degree of freedom = 9, iteration = 18)			
G^2	7.4801	X^2	5.8727

Table 10. Combined data

COEFFICIENTS	VALUES	S.E	Z-VALUE
Intercept	0.6931	0.7071	0.980
λ_1	0.9163	0.8367	1.095
λ_2	2.6391	0.7319	3.606
λ_3	3.1987	0.7214	4.434
λ_4	2.5649	0.7338	3.495
λ_{12}	2.4223	0.7344	3.298
λ_{13}	1.8032	0.7565	2.384
λ_{14}	0.2628	0.9133	0.288
λ_{15}	-19.1028	5616.5365	-0.003
λ_{23}	3.4682	0.7172	4.836
λ_{24}	1.6491	0.7209	4.348
λ_{25}	-19.1028	5616.5365	-0.003
λ_{34}	3.1345	0.7209	4.348
λ_{35}	-0.8358	1.2251	-0.682
λ_{45}	0.7736	0.8371	0.924
τ	-1.8749	0.2148	-8.729
Goodness of Fit Statistics (degree of freedom = 9, iteration =19)			
G^2	8.5141	X^2	5.9954

From the results in the Tables 6-10, based on the Goodness-of-fit statistics and their degrees of freedom, we would observe that the models for Physics, Geology, Biochemistry, Statistics, and the combined data fit well.

The tau values for Physics, Geology, Biochemistry, Statistics and the Combined data are -2.708,-1.6314,-2.1748,-1.030,and -1.8749 whose exponent are 0.0667,0.1957,0.1136,0.357, and 0.1534 respectively which give the odds that their Final year performance rates the students compared to that of their First year performance.

Also, we observe from the fitted (expected) values that the estimated probabilities of being classified into cell (i,j) for $R_1<R_2$ is the same for $R_1>R_2$ where R_1 and R_2 denote the First year Final year respectively. That is,

$$P(R_1 = i, R_2 / R_1 < R_2) = P(R_1 = j, R_2 = i / R_1 > R_2) = \phi_{ij}$$

The independent variables considered in this research work are Age at entry, Gender, Mode of entry, First year GPA, second year GPA and their Final year GPA. For these, Gender, Mode of entry and Age at entry were treated as CATEGORICAL variables while the others as CONTINUOUS variables.

For Age, we have two (2) categories: (i) <20 and (ii) ≥20 (which is the reference category coded 0).

For Gender, we have two categories (i) males (which is the reference category coded 0) and, (ii) females.

For Mode of Entry, we have Remedial, UME and Direct Entry (De) with Remedial being the reference category.

The model to be estimated is:

$$\log\left(\frac{\pi_i}{\pi_2}\right) = \beta_0 + \beta_1 y_1 + \beta_2 y_2 + \beta_3 y_3 + \beta_4 agenew + \beta_5 UME + \beta_6 De + \beta_7\ female$$

Where Y_1 is First year GPA, Y_2 is Second year GPA, Y_3 is Final year GPA, and De is Direct entry.

π_i = Probability of making category i on their CGPA

π_2 = Probability of making a second class lower division (2^2)

$$i = \begin{cases} 1 & if \quad CGPA = pass/3^{rd}\, class \\ 3 & if \quad CGPA = 2^1/1^{st}\, class \end{cases}$$

Log likelihood = -74.001538

Number of observations: 298

Likelihood ratio Chi-square (14) = 479.97

P-value = .0000

Pseudo R^2= 0.7643

Table 11. Summary table for multinomial logit regression

CGPPANEW	$\hat{\beta}$	S.E	Z	P</Z/	95% CONFIDENCE INTERVAL	Exp($\hat{\beta}$)
Pass/3rd class						
Y1 new	-1.3846	0.5153	-2.69	0.007	-2.3945 - 0.3746	0.2504
Y2new	-4.9509	1.0694	-4.63	0.000	-7.0468 - 2.8549	0.0071
Yfinal	-2.0481	0.5929	-3.45	0.001	-3.2101 - 0.8861	0.1290
Agenew	-0.1339	0.5975	-0.22	0.823	-1.3050 1.0373	0.8747
UME	0.363	0.7011	0.52	0.604	-1.0109 1.7374	1.4379
De	-0.3574	1.0357	-0.35	0.730	-2.3873 1.6725	0.6995
Female	0.1798	0.5862	0.31	0.759	-0.9690 1.3287	1.1970
Constant	19.2526	3.4724	5.54	0.000	12.4467 26.0585	
2^1/FIRST CLASS						
Y1new	3.3519	1.0177	3.29	0.001	1.3573 5.3466	28.5577
Y2new	3.1768	0.7344	4.32	0.001	1.7367 4.6168	23.9693
Y finalnew	2.7657	0.7347	4.32	0.000	1.7367 4.3387	15.8896
Agenew	0.5134	0.8052	0.64	0.524	-1.0645 2.0916	1.6710
UME	-0.6258	0.8299	-0.75	0.451	-2.2523 1.0007	0.5348

De	0.7421	1.0629	0.70	0.485	-1.3411 2.8253	2.1000
Female	-1.1551	0.7411	-1.56	0.119	-2.6075 0.2974	0.3150
Constant	-32.2752	5.8890	-5.48	0.000	-43.8174 - 20.7330	

From Table 11, the logit for (i) pass/third class vs. 2^2 is

logit (π_1)= 19.2526 - 1.3846Y1 - 4.9509Y2 - 2.0481Yfinal - 0.1339agenew + 0.3632UME - 0.3574De + 0.1798female

(ii) 2^1/first class vs. 2^2 is

Logit (π_3) = -32.2752 + 3.3519Y1 + 3.1768Y2 + 2.7657Yfinal + 0.5134agenew – 0.6258UME + 0.7421De – 1.1551female

$H_0 : \beta_1 = \beta_2 = \ldots = \beta_k$ vs. H_1: Not H_0 $\alpha = 0.05$

The likelihood Ratio chi-square statistic is reported as 497.97 with 14 degrees of freedom and a p-value of 0.001. So, we conclude that there exist an overall relationship between the response variable and the independent variables. The Pseudo R^2 value is reported as 0.7643 which indicates a strong positive correlation between the response variable and the explanatory variables. It implies also that the proportion of variation in the response variable explained by the independent variables is about 76.43%.

Using the Wald statistic,

$H_0: \beta_i = 0$ vs $H_1: \beta_i \neq 0$ $\alpha = 0.05$ $Z = \hat{\beta} / S.E(\hat{\beta})$

	Y1	Y2	Yfinal	Agenew	UME	De	females
pass/ third class vs 2^2	0.007*	0.001*	0.001*	0.823	0.604	0.730	0.759
2^1 / first class vs 2^2	0.001*	0.001*	0.001*	0.524	0.451	0.485	0.119

*values are significant in distinguishing between logits at α=0.05

Table 12. Inference about estimate of β̂ for different categories

	Category 1: (Pass/ 3rd Class vs 2^2) Exp(β)	Category 2: (2^1/ 1st Class vs 2^2) Exp(β)
1st year (Y_1)	0.250	28.5577
2nd year (Y_2)	0.0071	23.9693
Final year (Y_3)	0.1290	15.8896

.

Category 1indicates that for a one category rise in the students' performances in their first, second and final year, controlling for other factors, the estimated odds of making a pass/ third class multiply by 0.250, 0.0071 and 0.1290 respectively. That is, the odds of making a pass/third class as against a second class lower division reduce respectively by about 75%, 99.29% and 87.1% for every one category rise in their performances.

Also, Category 2 implies that for every one category rise in their first, second and final year performances, controlling for other factors, the estimated odds of making a 2^1 / first class multiply by 28.5577, 23.9693 and 15.8896 respectively. That is, they are respectively about 29, 24 and 16 times more likely to make a 2^1 / first class than a 2^2 for every rise in their first year performances.

Table 13. Inference on the Conditional Symmetry's tau estimate

	Tau (τ)	Exp(τ)
Physics	-2.708	0.0667
Geology	-1.6314	0.1957
Biochemistry	-2.1748	0.1136
Statistics	-1.030	0.357
Overall	-1.8749	0.1534

.

This implies that the estimated probability for each of Physics, Geology, Biochemistry, Statistics and overall is that their final year GPA is more consistent in rating the students' performance better respectively is about 0.0667, 0.1957, 0.1136, 0.357 and 0.1534 times the probability that their first year GPA rates them better.

All these results point to the fact that the students' performance in their first year GPA is more consistent in rating the students' performance better. This can be seen clearly by taking the reciprocal of the various results.

It would be noted that in the First year GPA, the odds of making a Second class upper/ First class is about twenty-nine (29) times that of making a Second class lower; in their Final year, it is only about 16 times.

Drawing from the results obtained from the analysis and their various interpretations, we may come to the conclusion that Students' grades in their First Year gives a better picture of their performance than their Final Year.

REFERENCES

Adejumo A.O. (2005). *Modelling generalized linear (log-linear) models for raters agreement measure with complete and missing cases.* Frankfurt am Main: Peter Lang.

Adejumo, A.O., Heumann, C. & Toutenburg, H. (2005). Conditional symmetry model as a better alternative to symmetry model for rater agreement measure. *J. Nigerian Statistical Asoc., 18,* 77 – 90.

Agresti, A. (2002). *Categorical data analysis*. New York: Wiley & Sons.

Dobson, A.J. (1945). *An introduction to generalized linear models*. New York: CRC Press.

Lawal, B. (2003). *Categorical data analysis with SAS and SPSS application*. London: Lawrence Erlbaum Associates.

Liu, I. & Agresti, A. (2005). The analysis of ordered categorical data: an overview and a survey of recent developments. *TEST, 14,* 1-73.

McCullagh, P. (1978). A class of parametric models in the analysis of square contingency tables with ordered categories. *Biometrika, 65,* 413-418.

Tanner, M.A & Young, M.A. (1985). Modeling agreement among raters. *J. American Statisical Assoc.*, *80*,175-180.

✉ Mr. A.A. Akinrefon
Dr. A.O. Adejumo (corresponding author)
Department of Statistics,
University of Ilorin, Ilorin, NIGERIA
E-Mail: aodejumo@unilorin.edu.ng