Applying Log-Linear Regression Models to analyse effect of Remedial Education on Students' Academic Performance : A case study of the Federal University of Technology, Akure, Nigeria

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ABSTRACT

Admission into undergraduate studies in universities all over the world have majorly been through qualifying examinations, most of which are conducted centrally by the appropriate government agencies. In Nigeria, like in some other countries of the world, competing modes of admission have sprang up over the years in many universities, most of which require additional learning known as remedial education, arranged by these universities for intending fresh intakes who were not originally found admissible into their courses of choice through the central examinations. In this paper, hierarchical loglinear analysis was applied to study the effect of mode of admission (with remedial education or not) on students performance using a Federal University of Technology in Nigeria as a case study. The performance of 1584 students in their year of entry and their cumulative performance in their graduating year were considered in this work using their grade point average (g.p.a) scores as the measure of performance. Four models were found to be significantly fit for each of five faculties/schools considered, out of which the saturated models were selected as the best fits using the Likelihood ratio technique. The odd ratio analysis revealed that students who went through remedial education performed significantly better than those who did not, in four of the five Schools considered. The comparative analysis of the change in interaction effect of mode of admission on performance between entry and graduating level also revealed significant changes at p< 0.01. Faculties with low admission scores were found to witness significantly higher percentage increase in the impact of remedial education on performance between the entry level and graduation level.

Keywords: Remedial, Log-linear model, Likelihood ratio, Odds Ratio, Interaction effect.

1.0 INTRODUCTION

Educationists and other stakeholders have always showed much interest in the academic performance of students at all levels of education. In higher education, academic success has a great influence on a student’s self-esteem, motivation and perseverance. Poor academic performance or high failure rate may result in unacceptable levels of attrition, reduced graduate throughput and increased cost of education (Jayanthi, 2014). Apart from this, several scientific breakthroughs have been discovered to be as a result of outstanding academic performance (Mautaugh et al., 1999).The need to identify and understand the variables that contribute to academic excellence has therefore been rigorously pursued over the years. A lot of factors have been discovered to contribute positively to performance, but one notable factor which effect on performance is dynamic, directly measurable and its extent determinable is remedial education. All over the world, including Nigeria, very few researches have been carried out in this area and most of these have only addressed the effect of remedial education on students’ performance either in the first year of entry into higher institution or at the graduation point and only its effect on single courses have been considered (Calcug et al, 2010; Oyekan, 2013 and Oduro-Ofori et al 2014). It was observed from literature that hardly has much work been done on the behaviour (magnitude and direction of movement) of effect of remedial education on performance between first year (short term effect) and final year (long term effect), especially with the Log-linear approach, which are the objectives of this work. In addition, the behaviour of the effect shall be considered for five different areas of discipline using the Federal University of Technology, Akure, Nigeria as a case study. This enabled us investigate the variability of the effect of remedial education on different disciplines and over the entire five-years course of study. The schools/faculties considered were Sciences, Engineering, Environmental, Earth and Mineral Sciences and Agriculture. The idea behind this investigation is to help higher institutions in Nigeria determine if offering remedial programs does improve performance of students.

Remedial education is defined as the education designed to help people with learning difficulties to improve their skills or knowledge. Popularly called Pre-degree in Nigerian Universities, remedial education was introduced by universities to assist in selecting the best students for admission into the various undergraduate programmes (Afenikhe, 2005). However, the majority of those who enrol for the remedial programme are those who are denied admission due to poor performance in the University and Tertiary Matriculation Examination (UTME) conducted centrally by the appropriate government agency called Joint Admission and Matriculation Board

(JAMB). This set of students are made to go through a rigorous one academic session of re-learning the basic educational pre-requisites for secondary school certificate holders and a little advanced knowledge required for freshmen in the universities. At the end of the Pre-degree programme, the students write a university qualifying examination conducted by the Senate of the University. This is in addition to the UTME which they must sit for and pass. Either of the results of these examinations may qualify them for admission into the university.

The performance of these two groups of students who gained admission into the Federal University of Technology, Akure, Nigeria were monitored from their entry level to their graduation level using their cumulative grade point averages (cgpa). The first group numbering 808 gained admission without going through remedial classes while the second group numbering 776 are students who went through a one year remedial classes organised by the University Senate before gaining admission because their first attempt at UTME was not good enough to be admitted.

Performance rating in Nigerian Universities range from cgpa of 0 to 5 and is categorised as follows: 0-1.4(fail); 1.5-1.9(pass); 2.0-2.4(Third class); 2.5-3.4(second class lower); 3.5-4.4(second class upper) and First class(4.5-5.0). For the purpose of this work however, performance is categorised into Good performance (cgpa>2.4) and Poor performance (cgpa<=2.4). This dichotomy helps to simplify the process of comparison and meaningful interpretation of the results of analysis as much as possible.

2.0 LITERATURE REVIEW

In their work on the study of some pneumonia patients, (Sonam and Montip , 2018) applied log-linear method to model the association between pneumonia variables of some pneumonia patients. However, the variability of the magnitude and direction of the interaction effects over a period of time was not considered. This could have given a deeper insight into the behaviour of the factors at different times. Zamalia, Siti and Saperi (2012) used log-linear approach to confound the effects of some variables on different stages of cervical cancer among women in Malaysia, but did not utilise the capability of the approach to do a comparison since it was an homogenous study. A performance study conducted in Nigeria by Oyekan (2013) involved applying two different strategies on teaching Biology to some undergraduate students, Conventional Teaching Method (CTM) and Diagnostic Remedial Teaching (DRT) strategy.

Using first-year retention rates as a measure of performance, he was able to show that the use of Diagnostic Remedial Teaching (DRT) was more effective in improving the students' achievement and retention than CTM in Biology classroom practices.

Using retention and graduation rates as measures of performance in first-year and final year respectively, Kjera (2008) was able to show in a similar work that in America, remedial education worked only for schools with low academic profile and that specifically, schools were not found to benefit from remediation if their average SAT scores were high (above 990). She also found out that though remediation does show a positive impact on graduation rates for certain schools, it does not show any impact on first-year retention rates.

[11] considered the effect of remedial education on the performance of poor performing secondary school graduates, school dropouts as well as continuing secondary school students preparing for examinations outside normal school setting in Ghana and noted the high percentage success of the scheme

The main essence of remedial teaching is to remove the effect of poor learning or lack of learning, which will invariably lead to good performance or at least improve performance. This research is therefore geared towards investigating the effect of remedial education on the performance of university students, using data from the Federal University of Technology, Akure, a university located in South Western Nigeria. The paper is structured as follows. The next section presents the methodology, followed by a description of data and log-linear modeling, and then by an outline of the model constructed. The analysis results are thereafter presented and discussed.

3.0 METHODOLOGY

3.1 Log Linear Analysis

Log-linear analysis is a technique used in statistics to examine the relationship between two or more categorical variables. The technique is used for both hypothesis testing and model building. In both these uses, models are tested to find the most parsimonious (i.e, least complex) model that best accounts for the variance in the observed frequencies (Agresti, 1996). According to Christensen, (1997), the log linear model is one of the specialized cases of generalized linear models for Poisson-distributed data. Log linear analysis is an extension of the two-way contingency table where the conditional relationship between two or more discrete, categorical variables is analysed by taking the natural logarithm of the cell frequencies within a contingency table. The variables investigated with loglinear models are all treated as response variables and, therefore, loglinear models demonstrate association between variables. According to Mustafa, Seyhan & Erhan (2014), Hierarchical loglinear models express the logarithm of cell probabilities as a sum of effects. The fullest loglinear model includes a constant, the main effects of each variable and all second- and higher-order inter actions. This model is known as the saturated model. Once expected frequencies are obtained, we then compare models that are hierarchical to one another and choose a preferred model, which is the most parsimonious model that fits the data.

3.2. Saturated Models

The loglinear models used in this study are constructed from three-way contingency tables of the schools, mode of admission and performance. Following after Christensen (1997), the models are generally specified by the following equation:

$$Ln(Fij) = \mu + \lambda i^{MOA} + \lambda j^{P} + \lambda k^{S} + (\lambda ij)^{MOA*P} + (\lambda ik)^{MOA*S} + (\lambda jk)^{PS} + (\lambda ijk)^{MOA*P*S} \quad \ldots (1)$$

Where

$Ln(Fij)$ = is the log of the expected cell frequency of the cases for cell ijk in the contingency table.

μ = is the overall mean of the natural log of the expected frequencies with Mode of Admission (MOA), Performance (j), School (S)

Λ = terms each represent “effects” which the variables have on the cell frequencies MOA, P and S

λi^{MOA} , λj^{P} , λk^{S} are the main effects, $(\lambda ij)^{MOA*P}$, $(\lambda ik)^{MOA*S}$,$(\lambda jk)^{PS}$ are the interaction effects of two factors, and $\lambda ijk^{MOA*P*S}$ is the interaction effect of three factors, with $1+(I-1)+(J-1)+(K-1)+(I-1)(J-1)+(I-1)(K-1)+(J-1)(K-1)+(I-1)(J-1)(K-1)$ degrees of freedom.

The above model is considered a saturated model because it includes all possible one-way, two-way and three-way effects. However, the saturated model above did not have the same amount of cells in the contingency table as it did effects, therefore the expected cell frequencies did not match the observed frequencies, with 12 degrees of freedom remaining.

Further analysis revealed that the School factor is the culprit as it showed complete independence from mode of entry and performance respectively. A new saturated model with all possible effects involving Performance and Mode of Admission was then sought for each of the schools as:

$$Ln(Fij) = \mu + \lambda i^{MOA} + \lambda j^{P} + (\lambda ij)^{MOA*P} \quad (2)$$

Which is a saturated model involving two factors. There are four effects, μ, λi^{MOA}, λj^{P}, $(\lambda ij)^{MOA*P}$, therefore the expected cell frequencies exactly match the observed frequencies.

The terms on the right-hand side of the equation represent the parameters to be estimated. The constant term represents the fitted log-frequency for the cell where the two variables are on the first level.

3.3 Likelihood Ratio Statistic

Although some authors use the Pearson Chi-square statistic to test for model fitness, the likelihood ratio statistic (L^2), was utilised in this work because it is the statistic that is minimized in maximum likelihood estimation and can be partitioned uniquely for more powerful test of conditional independence in multi-way tables. The formula for the L^2 statistic is as follows:

$$L^2 = 2\sum fij.\ln\left(\frac{fij}{Fij}\right) \quad (3)$$

L^2 follows a chi-square distribution with the degrees of freedom (df) equal to the number of lambda terms set equal to zero. Therefore, the L^2 statistic tests the residual frequency that is not accounted for by the effects in the model (the λ parameters set equal to zero). The larger the L^2 relative to the available degrees of freedom, the more the expected frequencies depart from the actual cell entries. Therefore, the larger L^2 values indicate that the model does not fit the data well and thus, the model should be rejected.

3.4 Odds Ratio

According to [14], as in the case of the logistic regression model, the log-linear model is operationalized in terms of odds ratios. The odds value is defined as $\pi / (1 - \pi)$, which is the ratio of an event occurring (π) to that of it not occurring ($1 - \pi$).The odds ratio approach was explored in order to estimate which of the mode of admission has stronger association with good performance (cgpa>=2.4) than poor performance (cgpa<2.4) and at what magnitude. To test for such a difference, the odds ratio estimate (or more precisely the natural log of the odds ratio estimate and the standard error of the log odds ratio were computed. Odds ratio is one of the three main ways to quantify how strongly the presence or absence of property A is associated with the presence and absence of property B in a given population

Assumption of Odds Ratio

- An odds ratio above l indicates a positive association among variables
- An odds ratio small than l indicate a negative association among variables.
- Odds ratio equalling l demonstrate that there is no association among variables.

3.5 Comparison of Interaction Effects

The null hypothesis of no significant difference between the interaction effects of mode of admission on performance for first year (gpa) and that of final year(cumulative cgpa) were carried out using the test statistic below,

$$Z_{cal} = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{\frac{\hat{p}\hat{q}}{n_1} + \frac{\hat{p}\hat{q}}{n_2}}}, where\ (p_1 - p_2) = 0 \qquad ...(4)$$

$\hat{p}$, the estimator of proportion in the combined sample is given by

$$\hat{p} = \frac{n_1 \hat{p}_1}{n_1 + n_2} + \frac{n_2 \hat{p}_2}{n_1 + n_2} \qquad ...(5)$$

Where $n_1 and\ n_2 =$ sizes of samples, x_1 =number of success in the samples . So, that

$$\hat{p} = \frac{x_1}{n_1}$$

The decision rule is given as

Reject H_0 if $Z_{cal} < -Z_{\frac{\alpha}{2}}\ or\ Z_{cal} > -Z_{\frac{\alpha}{2}} (Two - tailed)$

$$Z_{cal} < -Z_\alpha (H_1 : p_1 - p_2 < 0) \quad (One - tailed)$$

$$Z_{cal} > Z_\alpha (H_1 : p_1 - p_2 > 0) \quad (One - tailed)$$

4.0 DATA PRESENTATION AND RESULTS

4.1 Data Description

The data used for this research was extracted from the Senate approved undergraduate students' results in custody of the Examinations and Records office of the Federal University of Technology, Akure, Nigeria. It comprises the undergraduates' Cumulative Grade Point Average (CGPA) for 1584 students of the five major schools/faculties in FUTA, from entry level (100 level) to their respective graduating level (500 level) CGPA, a period of five(5) years and their mode of entry into the University.

Table 1: Distribution of Students' Overall Performance by Mode of Entry

	OVERALL PERFORMANCE

	Mode of Entry (MOE)	CGPA≥ 2.40	CGPA≤ 2.40	TOTAL
100 Level	UME	363(39.54%)	555(60.46%)	918
	PDS	413(62.01%)	253(37.99%)	666
	TOTAL	**776**	**808**	**1584**
500 Level	UME	428 (67.51%)	206 (32.49%)	634
	PDS	312 (83.20%)	63 (16.80%)	375
	TOTAL	**740**	**209**	**1009**

It can be seen from Table 1 that 363 undergraduates representing 39.54% of UME entrants had CGPA of 2.40 and above, while 413 undergraduates representing 62.01% of PDS entrants had CGPA of 2.40 and above. These results suggested that students who were admitted through PDS performed better than their counterparts in their first year examinations. Similarly, considering the cumulative performance at final year, 428 students representing 67.51% of UME entrants had CGPA of 2.40 and above, while 312 students representing 83.2% of PDS entrants had CGPA of 2.40 and above. These results suggested that students who were admitted through PDS performed better than their counterparts in their final year cumulative grade point average.

Table 2: Distribution of Students' Entry (100) level Examination performance (CGPA) by School and Mode of Entry

	SAAT			SEET			SET			SOS			SEMS		
MOE	CGPA ?2.40	CGPA <2.40	TOTAL	CGPA ?2.40	CGPA ?2.40	TOTAL	CGPA ?2.40	CGPA ?2.40	TOTAL	CGPA ?2.40	CGPA ?2.40	TOTAL	CGPA ?2.40	CGPA ?2.40	TOTAL
UME	47	83	130	94	131	225	52	121	173	108	142	251	62	77	139
PDS	60	53	113	135	62	197	39	72	111	114	51	165	65	16	81
TOTAL	107	136	243	229	193	422	91	193	284	222	193	416	127	93	220

Table 3: Distribution of Final Year (500 level) Student's Performance by CGPA, School and Mode of Entry.

	SAAT			SEET			SET			SOS			SEMS		
MOE	CGPA ≥ 2.40	CGPA ≤ 2.40	TOTAL	CGPA ≥ 2.40	CGPA ≤ 2.40	TOTAL	CGPA ≥ 2.40	CGPA ≤ 2.40	TOTAL	CGPA ≥ 2.40	CGPA ≤ 2.40	TOTAL	CGPA ≥ 2.40	CGPA ≤ 2.40	TOTAL
UME	89	44	133	47	12	59	116	36	152	143	72	215	33	42	75
PDS	82	13	95	42	7	49	57	13	70	98	24	122	33	6	39
TOTAL	171	57	228	89	19	108	173	49	222	241	96	1584	66	48	114

4.2 Results of Analysis

ISSN 2229-5518

This section presents results of analysis for performance and mode of admission of students in their first year and final year respectively. The various models and tests of fit are also presented.

Table 4: Log-linear Models with their Estimated Parameters and their Test of Fit for the whole University

Model	Fitted Marginal	Constant	MOA	Performance	MOA and Performance	Likelihood Ratio	df	Sig
A	{MP}	5.330	-1.179	0.730	0.864	0.00	0	0.000
B	{M}{P}	5.130	-0.525	1.012	0	31.105	1	0.000
C	M	5.759	-0.525	0	0	259.742	2	0.000
D	P	4.902	0	1.012	0	98.337	2	0.000

All the models are found to fit the data with P=0.000. However, the L^2 for the saturated model gives the smallest value, and therefore is the best fitting model. It is presented as below:

$$Fij = 5.330^* -1.179^{MOE} * 0.730^{P} * 0.864^{(MOE)(P)}$$

4.2.1 Model fitting for first year (Entry level) performance

Table 5: Log-linear Models with their Estimated Parameters and their Test of Fit for the Five Schools

	Models	Fitted Marginal	Constant	Model of Entry	Performance	Mode of Entry and Performance	Likelihood Ratio	Df	Sig.
SAAT	A	{MP}	4.425	-0.445	-0.564	0.687	0	0	0
	B	{M}{P}	4.287	-0.14	-0.24	0	7.065	1	0.008
	C	M	4.174	-0.14	0	0	10.535	2	0.005
	D	P	4.22	0	-0.24	0	8.256	2	0.016
SEET	A	{MP}	4.879	-0.744	-0.33	1.104	0	0	0
	B	{M}{P}	4.634	-0.133	0.171	0	30.744	1	0
	C	M	4.723	-0.133	0	0	33.819	2	0
	D	P	4.57	0	0.171	0	32.009	2	0
SET	A	{MP}	4.8	-0.516	-0.839	0.232	0	0	0
	B	{M}{P}	4.767	-0.444	-0.752	0	0.796	1	0.372
	C	M	4.46	-0.444	0	0	38.261	2	0
	D	P	4.57	0	-0.752	0	14.441	2	0.001
	A	{MP}	4.966	-1.025	-0.28	1.079	0	0	0

SOS	B	{M}{P}	4.763	-0.42	-0.135	0	27.686	1	0
	C	M	4.832	-0.42	0	0	29.572	2	0
	D	P	4.575	0	-0.135	0	45.594	2	0
SEMS	A	{MP}	4.35	-1.547	-0.215	1.594	0	0	0
	B	{M}{P}	4.073	-0.54	-0.312	0	28.128	1	0
	C	M	4.241	-0.54	0	0	33.404	2	0
	D	P	3.839	0	-0.312	0	43.602	2	0

From the table above, the L^2 for saturated models give the smallest values and their p-values are significant ($p<0.05$), therefore we cannot eliminate the interaction effect terms MODE OF ENTRY*PERFORMANCE from the models. Thus, the best fitting models for all the schools are the saturated models. Furthermore, the interaction effect of mode of admission on performance are seen to vary among the schools ranging from the lowest 0.232 in SET to 1.594 in SEMS. This shows that the effect of remedial education on students academic performance is most prominent in SEMS, followed by SEET, SOS, SAAT and is only marginal in SET in the 100 level examinations..

4.2.2 Model fitting for final year performance

Table 6: Analysis Showing the Test of Fit of the Models for individual School

SCHOOLS	Model	Fitted Marginal	Constant	Mode of Admission	Performance	Mode of Admission and Performance	Likelihood Ratio	Df	Sig.
SAAT	A	{MP}	3.795	-1.193	0.699	1.111	0	0	0
	B	{M}{P}	3.504	-0.336	1.099	0	11.732	1	0.001
	C	M	4.197	-0.336	0	0	71.382	2	0
	D	P	3.35	0	1.099	0	18.095	2	0
SEET	A	{MP}	2.526	-0.511	1.335	0.4	0	0	0
	B	{M}{P}	2.34	-0.186	1.544	0	0.685	1	0.408
	C	M	3.384	-0.186	0	0	49.931	2	0
	D	P	2.251	0	1.544	0	1.612	2	0.447
SET	A	{MP}	2.597	-0.995	-1.161	0.289	0	0	0
	B	{M}{P}	3.513	-0.775	1.261	0	0.745	1	0.388
	C	M	4.331	-0.775	0	0	74.151	2	0
	D	P	3.199	0	1.261	0	31.763	2	0
SOS	A	{MP}	4.284	-1.085	-0.683	0.709	0	0	0
	B	{M}{P}	4.115	-0.567	0.92	0	7.567	1	0.006

	C	M	4.677	-0.567	0	0	72.039	2	0
	D	P	3.871	0	0.92	0	33.568	2	0
SEMS	A	{MP}	3.75	-1.878	-0.238	1.878	0	0	0
	B	{M}{P}	3.452	-0.654	0.318	0	18.807	1	0
	C	M	3.624	-0.654	0	0	21.661	2	0
	D	P	3.178	0	0.318	0	30.372	2	0

From Table 6 above, the L^2 for saturated models give the smallest values and their p-values are significant ($p<0.05$), therefore the interaction effect terms MODE OF ADMISSION*PERFORMANCE are retained in the models. Thus, the best fitting models for all the schools are the saturated models. Similar to the result of the effect of mode of admission on the students performance at the 100 level examinations, the interaction effect of mode of admission on performance cumulated over the duration of study (5 years) are seen to vary among the schools and with noticeable changes in pattern. The students' performance in SEMS still remains the most affected by mode of admission, with interaction effect even increasing as high as 1.878, but now followed by SAAT(1.111), SOS(0.709),SEET(0.4), and lastly SET(0.289) respectively.

Table 9: Table of comparisons in interaction effects between the two levels in each school

		Entry Year Examinations			Final Year Examinations						
School	Fitted Model	Co-efficient (Interaction effect)	Odds Ratio	Std Error	Co-efficient (Interaction effect)	Odds Ratio	Std Error	Absolute. change in odd ratio	95% Confidence Interval		P-value
SAAT	Saturated Model	0.687	1.99	0.2624	1.111	3.04	0.3508	1.05*	3.3283	1.1898	0.017
SEET	Saturated Model	1.104	3.02	0.2045	0.4	1.49	0.5208	1.53*	4.5088	2.0228	0.006
SET	Saturated Model	0.232	1.26	0.2589	0.289	1.34	0.3618	0.08	2.0929	0.7586	0.857
SOS	Saturated Model	1.079	2.94	0.1916	0.709	2.03	0.2697	0.91*	4.2810	2.0197	0.006
SEMS	Saturated Model	1.594	4.92	0.3271	1.878	6.54	0.5011	1.62*	9.3413	2.5913	0.007

$\alpha=0.05$

5.0 Discussion of results

1. In SAAT, the interaction effect of mode of entry on performance increased significantly from 0.687 in the first year to 1.111 in the final year, a whopping 61% increase in the effect of mode of admission on performance. The odds ratio consequently increased

from 1.99 to 3.04, showing a 52.8% significant increase (p=0.017) in the odds of remediated students having better performance than UTME admitted students in SAAT.

2. In SEET, the interaction effect of mode of entry on performance decreased significantly from 1.104 in the first year to 0.400 in the final year showing that the effect of mode of admission on performance had greatly reduced by 64% in the final year. The odds ratio decreased significantly (p=0.006) between the first and final year from 3.02 to 1.40 showing a 53% decrease in the odds of remediated students performing better than the UTME admitted students.
3. In SET, although the interaction effect of mode of entry on performance increased from 0.258 in the first year to 0.289 in the final year, the interaction effects were not significant as shown earlier. The odds ratio increased between first and final year from 1.26 to 1.34 but not significantly(p=0.857), showing a 6.4% non-significant increase in the odds of remediated students having better performance than UTME admitted students.
4. In SOS, the interaction effect of mode of entry on performance reduced significantly from 1.079 in the first year to 0.709 in the final year showing that the effect of mode of admission on performance in the first year has reduced by 34% in the final year. The odds ratio decreased significantly (p=0.006) between first to final year from 2.94 to 2.03, showing a 31% decrease in the odds of remediated students having better performance than the UTME admitted students.
5. In SEMS, the interaction effect of mode of entry on performance increased significantly from 1.594 in the first year to 1.878 in the final year showing that the effect of mode of admission in the first year has become stronger by 17.8% in the final year, the odds ratio significantly increased (p=0.007) between the first and final year from 4.92 to 6.54, showing a 32.9% increase in the odds of PDS entrants having better performance than UTME admitted students.

In general, it could be seen from the table that the interaction effect of MOA on performance in SEMS turned out to be the highest among all the schools both at entry level and graduation level examinations respectively. On the other hand, the interaction effect of MOA on performance in SEET was the second highest at the entry level, but this effect reduced considerably to the lowest at the final examination. On the average, the admission score for SEET is always the highest. SAAT (which always have the lowest admission score), happens to have the lowest significant effect of MOA on Performance at the entry level examination but this greatly increased to the second highest interaction effect by the final year. These trend tend to show that schools with low admission scores benefit most from remedial education in the long run than schools with high or average admission scores (where the effect is high at entry level but wears off considerably.in the long run).This is in consonance with the findings of Kjera (2008). The non-significance of the interaction effects in SET may not actually denote that remedial education does not have effect on students in environmental studies but rather it could be a deficiency in the contents of the remedial education which may not favour SET students.

5.1 Summary and Conclusion

This research work has revealed that using Likelihood ratio technique, saturated models have the best fit among all significant log-linear models in explaining relationships between MOA and Performance. The three variable model of School, MOA and Performance was found not to be significant with School found to be culprit and so could not be used. Using FUTA as a case study, it is discovered that while there were significant increase in the effects of mode of admission on performance in SAAT and SEMS between first year and final year, the effects of MOA reduced in SEET and SOS. It should be noted that on the average, admission scores into SAAT and SEMS are always lower than those of SEET and SOS in FUTA since majority of intending freshmen always prefer pure sciences and engineering courses to others.

The percentage difference in odds were also computed and used to compare the individual increase or decrease in the odds of types of admission on performance between first and final years. It was shown that the percentage change in the odds of students admitted through PDS performing better than non-PDS students increased considerably for students in SEMS, followed by SAAT, while it decreased in SEET and SOS. It hardly made any change in SET.

CONFLICT OF INTEREST

I, the author, hereby state that there is no conflict of interest

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