STATISTICAL STUDY OF ACADEMIC PERFORMANCE OF STUDENTS OF FEDERAL UNIVERSITY KASHERE, GOMBE STATE, NIGERIA

M. B. Mohammed[1], B.Nata'ala[2], A.U. Kinafa[3]
[1]Department of Mathematics and Computer science, Federal University Kashere,
P.M.B 0182,Gombe, Nigeria.
[2,3]Department of Mathematics, Gombe State University, Gombe.
e-mail: [1]muhdb1@gmail.com, [2]nataalabako@gmail.com, [3]aukinafa@yahoo.com

Abstract

The aim of this research is to perform some statistical analysis on first year and final year results of Students of Faculty of Science, Federal University Kashere. Some descriptive statistics were computed and Cohen'sKappa Statistic was used to investigate whether the final-year result can be predicted using the first year result of the students. The proposed reliability index gave a value of 0.49 which is considered to be a moderate agreement coefficient. This means that the first year results of the students can be used to predict their final year results fairly accurately. Sixty eight percent (68%) of students retained their first year academic classification on completion of their studies in the University; twenty three percent (23%) improved their first year result on completion while nine percent (9%) regressed.

Key words: Agreement coefficient, First year result, Final year result, Kappa Statistic.

Introduction

Academic institutions (such as Polytechnics, colleges, universitiesetc) have no worth without students. Students are the most essential asset of any educational setting. The social and economic development of the country is directly linked with student academic performance. The students' performance (academic achievement) plays an important role in producing the best quality graduates who will become great leader and manpower for the country thus responsible for the country's economic and social development (Ali et.al, 2009). Student academic performance measurement has received considerable attention in previous research, it is challenging aspects of academic literature, and science student performance are affected due to social, psychological, economic, environmental and personal factors. These factors strongly influence the student performance, but vary from person to person and country to country.

Individual differences in academic performance have been linked to differences in intelligence and personality. Students with higher mental ability as demonstrated by IQ tests and those who are higher in conscientiousness (linked to effort and achievement motivation) tend to achieve highly in academic settings. A recent meta-analysis suggested that mental curiosity (as measured by typical intellectual engagement) has an important influence on academic achievement in addition to intelligence and conscientiousness.vonStumm et al (2011) Children's semi-structured home learning environment transitions into a more structured learning environment when children start first grade. Early academic achievement enhances later academic achievement. Bossaert G. *et al* (2011).

Parent's academic socialization is a term describing the way parents influence students' academic achievement by shaping students' skills, behaviors and attitudes towards school. Parents influence students through the environment. Academic socialization can be influenced by parents' Socio-economic status. Highly educated parents tend to have more stimulating learning environments.Magnuson K. (2007).

Children's first few years of life are crucial to the development of language and social skills. School preparedness in these areas help students adjust to academic expectancies, Lassiter K (1995).

Another very important enhancer of academic achievement is the presence of physical activity. Studies have shown that physical activity can increase neural activity in the brain. Exercise specifically increases executive brain functions such as attention span and working memory.Tomporowski, P. (2008)

Agreement between observers (inter-rater agreement) can be measured in differentways, and some methods may be regarded as more accurate than other. Depending on whichmethod one uses, one can obtain quite different values. The Kappa coefficient hastraditionally been used to evaluate inter-rater reliability between observers of the samephenomenon, and was originally proposed to measure agreement by classifying subjects innominal scales, but it has since been extended to the classification of ordinal data as well.

Other measures such as percentage agreement (also called exact agreement) and weightedKappa coefficient are also used in various studies.

This research considers only 43 pioneer students of Faculty of science, Federal University Kashere. Cohen's Kappa Statistic is applied to see whether their first year class can be used to know their graduating class of degree which will be infer to the whole students of the University and to further compute some descriptive statistics on the academic data.

Literature Review

Academic achievement or academic performance is the outcome of education, the extent to which a student, teacher or institution has achieved their educational goals. Academic achievement 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, procedural knowledge such as skills or declarative knowledge such as facts.

Adebayo and Jolayemi (1998, 1999), applied the Kappa statistic to investigate how predictable the final-year result would be using the first year result or Grade Point Average (GPA) of some selected University of Ilorin graduates, they obtained a Kappa value 0.57 which is a moderate agreement index, that is the final-year result can be using the first year result.Galiher (2006) and Darling (2005), used GPA to measure student performance, they focused on the student performance a particular semester. Usoro (2006) carried out a study on classification of students into various departments on the basis of their cumulative results for a one year Foundation Programme otherwise known as Pre-National Diploma (PRE-ND) in Polytechnics system. Charles and June (1970) carried out a study to determine if a differentiation or separation among students graduating, withdrawing or failing could be identified.

Some other researchers used test results or previous year result since they are studying performance for the specific subject or year (Hijazi and Naqvi, 2006 and Hake, 1998).

In many researches, different factors that affect the student academic performance have been discussed. There are two factors that strongly affect the students' academic performance. These are the internal and external classroom factors. Internal classroom factors includes students competence in English, class schedules, class size, class test results, learning facilities, homework, environment of the class, complexity of the course material, teachers role in the class, technology used in the class and exams systems. External classroom factors include extracurricular activities, family problems, work, financial, social and other problems. Research studies shows that students' performance depends on many factors such as learning facilities, gender and age differences, etc. that can affect student performance (Hansen, Joe B., 2000). Harb and El-Shaarawi (2006) found that the most important factor with positive effect on students' performance is student's competence in English. If the students have strong communication skills and have strong grip on English, it increases the performance of the students. The performance of the student is affected by communication skills; it is possible to see communication as a variable which may be positively related to performance of the student in open learning. A major distinction of this study from previous studies is that it focuses on open learning (Abdullah AL-Mutairi, 2011).

Karemera (2003) found that students' performance is significantly correlated with satisfaction with academic environment and the facilities of library, computer lab and etc. in the institution. With regard to background variables, he found a positive effect of high school performance and school achievement he found no statistical evidence of significant association between family income level and academic performance of the student.

Robert & Sampson (2011), found that the member of educational board will be educated and their impact on school is positive, for professional development it is essential for student learning.

The students who are actively engage in the learning process are observed to have a positive correlation with the CGP.A Study effort from student and the proper use of the facilities provided by the institution to the student, a good match between students' learning style and are positively affect the student's performance (Norhidayah Ali, et. al., 2009).

Young (1999), held the view that student performances are linked with use of library and level of their parental education. The use of the library positively affected the student performance.

The academic environment is the effective-variable for students and has positive relationship with fathers' education and grade level (Kirmani&Siddiquah, 2008).

H2: There is a positive relationship between learning facilities and student performance Noble (2006), students' academic accomplishments and activities, perceptions of their coping strategies and positive attributions, and background characteristics (i.e., family income, parents' level of education, guidance from parents and number of negative situations in the home) were indirectly related to their composite scores, through academic achievement in high school.

The students face a lot of problems in developing positive study attitudes and study habits. Guidance is of the factor through which a student can improve his/her study attitudes and study habits and is directly proportional to academic achievement. The students who are properly guided by their parents have performed well in the exams. The guidance from the teacher also affects the student performance. The guidance from the parents and the teachers indirectly affect the performance of the students (Hussain, 2006).

Methodology

Measures of Agreement

Agreement is a special case of association which reflects the extent to whichobservers classifies a given subject identically into the same category. In orderto assess the psychometric integrity of different ratings we compute inter-ratersreliability and/or inter-rater agreement.Inter-raterreliability coefficients reveal the similarity or consistency of the patternof responses, or the rank-ordering of responses between two or more raters (or two or more rating sources), independent of the level or magnitude of thoseratings.

Cohen's Kappa coefficient

Cohen (1960) proposed a standardized coefficient of raw agreement for nominalscales in terms of the proportion of the subjects classified into the same categoryby the two observers, which is estimated as

$\pi_0 = \sum_{i=1}^{I} \pi_{ii}$

and under the baseline constraints of complete independence between ratingsby the two observers,which is the expected agreement proportion estimated as

$\pi_e = \sum_{i=1}^{I} \pi_{i.} \pi_{.i}$

The Kappa statistic can now be estimated by

$\widehat{K_c} = \frac{\widehat{\pi_0} - \widehat{\pi_e}}{1 - \widehat{\pi_e}}$

Where$\widehat{\pi_0}$ and $\widehat{\pi_e}$are as defined above.Early approaches to this problem have focused on the observed proportion ofagreement (Goodman and Kruskal 1954), thus suggesting that chance agreementcan be ignored. Later Cohen's kappa was introduced for measuring nominalscale chance-corrected agreement. Scott (1955) defined $\widehat{\pi_e}$using the underlyingassumption that the distribution of proportions over the i categories for thepopulation is known, and is equal for the two raters. Therefore if the two ratersare interchangeable, in the sense that the marginal distributions are identical, then Cohen's and Scott's measures are equivalent because Cohen's kappa is anextension of Scott's index of chance-corrected measure. To determine whether $\widehat{K}$differs significantly from zero, one could use the asymptotic variance formulaegiven by Fleiss et al. (1969) for the general I×I tables. For large n, Fleiss etal.'s formulae is practically equivalent to the exact variance derived by Everitt(1968) based on the central hypergeometric distribution. Under the hypothesisof only chance agreement, the estimated large-sample variance of $\widehat{K}$is given by

$$\widehat{Var_0}\left(\widehat{K_c}\right)=\frac{\pi_e+\pi_e^2-\sum_{i=1}^{I}\pi_{i.}\pi_{.i}(\pi_{i.}+\pi_{.i})}{n(1-\pi_e)^2}$$

Assuming that

$$\frac{\widehat{K}}{\sqrt{\widehat{Var_0}\left(\widehat{K_c}\right)}}$$

follows a normal distribution, one can test the hypothesis of chance agreementby reference to the standard normal distribution. In the context of reliabilitystudies, however, this test of hypothesis is of little interest, since generally theraters are trained tobe reliable. In this case, a lower bound on kappa is moreappropriate. This requires estimating the nonnull variance of_k, for which Fleisset al. provided an approximate asymptotic expression, given by:

$$\widehat{Var}(\widehat{K}) = \frac{1}{n(1-\pi_e)^2}\left(\sum_{i=1}^{I}\pi_{ii}\left\{1-(\pi_{i.}+\pi_{.i})(1-\widehat{K})\right\}^2\left(1-\widehat{K}\right)^2\right)\right)\times$$

$$\left(\sum_{i=1}^{I}\pi_{ii'}(\pi_{i.}+\pi_{.i'})^2\left\{\widehat{K}-\pi_e\left(1-\widehat{K}\right)\right\}^2\right)$$

Fleiss (1971) proposed a generalization of Cohen's kappa statistic to the measurementof agreement among a constant number of raters (say, *K*). Each ofthe *n* subjects are related by *K* (>2) raters independently into one of *m*mutuallyexclusive and exhaustive nominal categories. This formulation appliesto the case of different sets of raters (that is random ratings) for each subject.

The motivated example is a study in which each of 30 patients was rated by psychiatrists (selected randomly from a total pool of 43 psychiatrists) into oneof five categories.

Let *kij*be the number of raters who assigned the *ith*subject to the *jth*category *i*= 1, 2, ..., *n*, *j* = 1, 2, ...,*m* and define

$$\pi_j=\frac{1}{Kn}\sum_{i=1}^{n}K_{ij}$$

$\pi_j$is the proportion of all assignments which were to the jthcategory. Thechance corrected measure of overall agreement proposed by Fleiss (1971) isgiven by

$$\widehat{K}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}K_{ij}^2-Kn\left\{1+(K-1)\sum_{j=1}^{m}\pi_j^2\right\}}{Kn(K-1)(1-\sum_{j=1}^{m}\pi_j^2)}$$

Under the null hypothesis of no agreement beyond chance, the *K* assignmentson one subject are multinomial variables with probabilities$\pi_1,\pi_2,...,\pi_m$. Usingthis Fleiss (1971) obtained an approximate asymptotic variance of$\widehat{K}$under thehypothesis of no agreement beyond chance:

$Var_0\hat{K}=$

$$A\left\{\frac{\sum_{j=1}^{m}\pi_j^2-(2K-3)\left(\sum_{j=1}^{m}\pi_j^2\right)^2+2(K-2)\sum_{j=1}^{m}\pi_j^3}{\left(1-\sum_{j=1}^{m}\pi_j^2\right)^2}\right\}$$

Where $A=\frac{2}{nK(K-1)}$

Apart from k statistic for measuring overall agreement, Fleiss (1971) also proposeda statistic to measure the extent of agreement in assigning a subject to aparticular category. A measure of the beyond chance agreement in assignmentto category given by

$$\widehat{K_j}=\frac{\sum_{i=1}^{n}K_{ij}^2-Kn\pi_j\{1+(K-1)\pi_j\}}{nK(K-1)\pi_j(1-\pi_j)}$$

The measure of overall agreement $\widehat{K}$is a weighted average of$\widehat{K_j}$'s, with the corresponding weights π_j $(1-\pi_j)$. The approximate asymptotic variance of $\widehat{K_j}$under the null hypothesis of no agreement beyond chance is

$$Var_0\widehat{K_j}=\frac{\{1+2(K-1)\pi_j\}^2+2(K-1)\pi_j(1-\pi_j)}{nK(K-1)^2\pi_j(1-\pi_j)}$$

Landis and Koch (1977a) have characterized different ranges of arbitrary valuesfor kappa with respect to the degree of agreement they suggest and thesehave become a standard in all the literatures, see below the ranges of kappastatistic with the respective strength of agreement:

Table 1: Range of kappa statistic with the respective strength of agreement

Kappa Statistic	Strength of agreement
< 0.00	Poor
0.00 – 0.20	Slight
0.21 − 0.40	Fair
0.41 − 0.60	Moderate
0.61 − 0.80	Substantial
0.81 − 1.00	Almost perfect

One can distinguish between two possible uses of kappa (Thompson and Walter 1988a and 1988b, Kraemer and Bloch 1988, Guggenmoos-Holzmann 1993),

(i) as a way to test rater independence, that is, as a test statistics, which involves testing the null hypothesis that there is no more agreement than might occur by chance given random guessing; that is, one makes a qualitative, "yes or no" decision about whether raters are independent or not. Kappa is appropriate for this purpose, although to know that raters are not independent is not very informative; raters are dependent by definition, inasmuch as they are rating the same cases.

(ii) as a way to quantify the level of agreement, that is, as an effect-size measure, which is the source of concern. Kappa's calculation uses a term called theproportion of chance (or expected) agreement. This is interpreted as the proportion of times raters would agree by chance alone. However, the term is relevant only under the conditions of statistical independent of raters. Since raters are clearly not independent, the relevance of this term, and its appropriateness as a correction to actual agreement levels, is very questionable.

Thus, the common statement that kappa is a chance-corrected measure of agreement" (Landis and Koch 1977b; Davies and Fleish 1982; Banerjee et al. 1999) is misleading. As a test statistic, kappa can verify that agreement exceeds chance levels. But as a measure of the level of agreement, kappa is not "chance-corrected"; indeed, in the absence of some explicit model of rater decision making, it is by no means clear how chance affects the decisions of actual raters and how one might correct for it. A better case for using kappa to qualify rater agreement is that, under certain conditions, it approximates the intra-class correlation. But this too is problematic in that these conditions are not always met, and one could instead directly calculate the intra-class correlation.

Weighted Kappa coefficient:

Cohen (1968) proposed a modified form of kappa called weighted kappa which allows for scales disagreement or partial credit. Often situations arise when certain disagreements between two raters are more serious than others. For example, in an agreement study of psychiatric diagnosis in the categories personality disorder, neurosis and psychosis, a clinician would likely consider a diagnostic disagreement between neurosis and psychosis to be more serious than between neurosis and personality disorder. However, k makes no such distinction, implicitly treating all disagreements equally. Weighted Kappa is defined as

$$\widehat{K_w}= \frac{\pi_0^*-\pi_e^*}{1-\pi_e^*}$$

Where $\pi_0^*= \sum_{i=1}^{I}\sum_{i'=1}^{I} w_{ii'}\pi_{ii'}$

And

$$\pi_e^*=\sum_{i=1}^{I}\sum_{i'=1}^{I} w_{ii'}\pi_{i.}\pi_{.i'}$$

where $\{w_{ii'}\}$is the weights, which in most cases $0 \leq w_{ii'} \leq 1$ for all i, i' so that $\pi_0^*$is a weighted observed proportion of agreement, and $\pi_e^*$is the correspondingweighted proportion of agreement expected under the constraints of total independence. Note that the Unweighted kappa is a special case of $\widehat{K_w}$ with $w_{ii'}$ =1 for $i = i'$and $w_{ii'}$ =0for$\neq i'$. Also if the I categories form an ordinal scale, with the categories assigned the numerical values 1, 2, . . .I,and

$$w_{ii'}= 1 - \frac{(i-i')^2}{(I-1)^2}$$

Then$\widehat{K_w}$can be interpreted as an intra-class correlation coefficient for a two-way ANOVA computed under the assumption that the n subjects and the two raters are random samples from populations of subjects and raters, respectively (Fleiss and Cohen, 1973).

Fleiss et al.(1969) calculated the unconditional large sample variance of weighted kappa as

$$\widehat{Var}\left(\widehat{K_w}\right)= \frac{1}{n(1-\pi_e^*)^4}\left(\sum_{i=1}^{I}\sum_{i'=1}^{I}\pi_{ii'}[w_{ii'}(1-\pi_e^*) - (\overline{w_{i.}} + \overline{w_{.i'}})(1-\pi_e^*)]^2\right)$$

$$-(\pi_0^*\,\pi_e^* - 2\,\pi_e^* + \pi_0^*)^2$$

Where $\overline{w_{i.}} = \sum_{i'=1}^{I} w_{ii'}\pi_{.i'}$ And $\overline{w_{.i'}} = \sum_{i=1}^{I} w_{ii'}\pi_{i.}$

Cicchetti (1972) recommended another weights as

$w_{ii'} = 1 - \frac{|i-i'|}{(I-1)}$

Cicchetti used these weights to test for the significance of observer agreement through the Cicchetti test statistic Z_c

$Z_c = \frac{\pi_0^* - \pi_e^*}{\sqrt{\widehat{Var(\pi_0^*)}}}$

Where $\widehat{Var(\pi_0^*)} = \frac{1}{(n-1)}\left[\sum_{i=1}^{I}\sum_{i'=1}^{I} w_{ii'}^2 \pi_{ii'} - \pi_0^{*2}\right]$

Cohen (1968) has shown that under observed marginal symmetry, weighted kappa $\widehat{K_w}$ is precisely equal to the product-moment correlation by choosing the weights to be

$w_{ii'} = 1 - (i - i')^2$

Whenthe icategories are not only ordinal scale, but also assumed equal spaced along some underlying continuum. Discrete numerical integers such as 1, 2, ..., I can then be assigned to the respective classes (Barnhart and Williamson 2002).

Oden (1991) proposed a method to estimate a pooled kappa between two raters when both raters rate the same set of pairs of the body like eyes. His method assumes that the true left-eye and right-eye kappa values are equal and makes use of the correlated data to estimate confidence intervals for the common kappa.

The pooled kappa estimator is a weighted average of the kappa for the right and left eyes. We define letters Band D as follows

B= $\left(1 - \sum_{I=1}^{m}\sum_{I=1}^{m} w_{ij\rho_{i.}\rho_{.j}}\right)\widehat{K_{right}} + \left(1 - \sum_{I=1}^{m}\sum_{I=1}^{m} w_{ij\lambda_{i.}\lambda_{.j}}\right)\widehat{K_{left}}$

D= $\left(1 - \sum_{I=1}^{m}\sum_{I=1}^{m} w_{ij\rho_{i.}\rho_{.j}}\right) + \left(1 - \sum_{I=1}^{m}\sum_{I=1}^{m} w_{ij\lambda_{i.}\lambda_{.j}}\right)$

so that the pool kappa will be the ratio of the two letters,

$\widehat{K_{pooled}} = \frac{B}{D}$

where ρ_{ij}=proportion of patients whose right eye was rated iby rater 1 and j by rater 2, λ_{ij} =proportion of patients whose left eye was rated iby rater 1 and jby rater 2, w_{ij}=agreement weight that reflects the degree of agreement between raters 1 and 2 if they use rating iand jrespectively for the same eye, and

$\rho_{i.}, \rho_{.j}, \lambda_{i.}, \lambda_{.j}$

have their usual meanings. By applying the delta method, Oden obtained an approximate standard error of the pool kappa estimator.

Schouten (1993) also proposed another alternative method for paired data situation. He noted that the Cohen (1968); Fleiss et al. (1969) weighted kappa formula and its standard error can be used if the observed as well as the chance agreement is averaged over the two sets of eyes and then substituted into the formula for kappa. To this end, let each eye be diagnosed normal or abnormal, and let each patient be categorized into one of the following four categories by each rater:

Obs1/Obs2	**1 2 . . . I**	
1	$\pi_{11}\pi_{12} \ldots \pi_{1I}$	π_{1+}
2	$\pi_{21}\pi_{22} \ldots \pi_{2I}$	π_{2+}
.	. . .	.
.	. . .	.
.	. . .	.
I	$\pi_{I1}\pi_{I2} \ldots \pi_{II}$	π_{I+}
TOTAL	$\pi_{+1}\pi_{+2} \ldots \pi_{+I}$	1

classified into category iby observer 1 and into category *i*by observer 2.

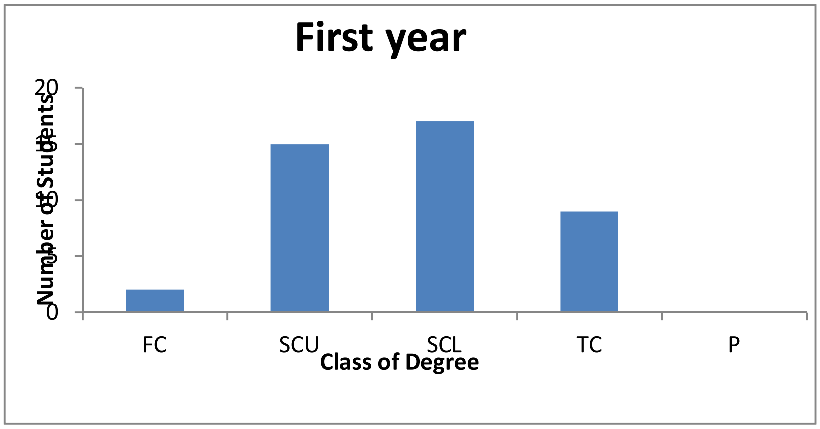
Data analysis

Here the data are analyzed using some descriptive statistical tools. Cohen's kappa Statistic is also used to measure the level of agreement between the first year and the final year result. Proportion of students that retained their first year academic class on completion of their studies in the University, proportion of students that improved their first year result on completion and Proportion of students that regressed were computed.

Faculty of science

Table 2: Distribution of Faculty of Science students using first year result against their final year result

		Final Year Result					
		1st Class	2^1	2^2	3rd	Pass	Total
First Year result	1st Class	1	1	0	0	0	2
	2^1	0	12	3	0	0	15
	2^2	0	3	14	0	0	17
	3rd	0	0	7	2	0	9
	Pass	0	0	0	0	0	0
	Total	1	16	24	2	0	43



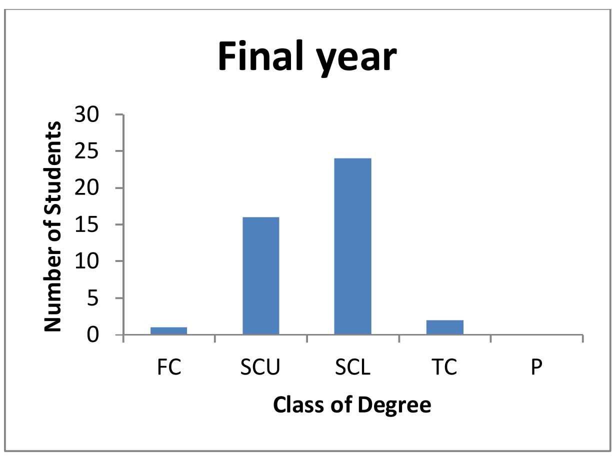


Figure 1&2: Bar-charts showing Faculty of Science Students class of Degree

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of Agreement	Kappa	.490	.106	4.771	.000
N of Valid Cases		43			

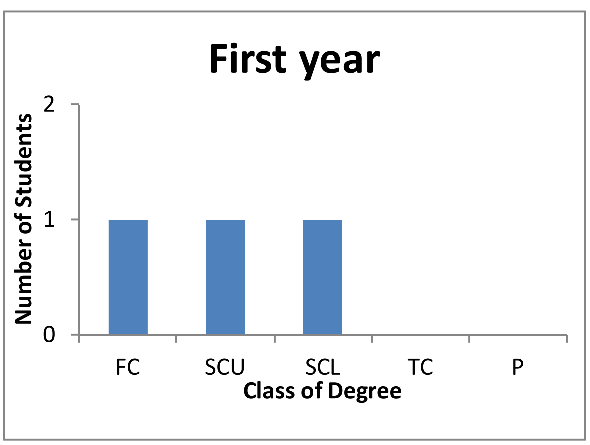
a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

B.Sc. Mathematics

Table 3: Distribution of B.sc Mathematics graduates using first year result against their final year result.

		Final Year Result					
		1st Class	2^1	2^2	3rd	Pass	Total
First Year result	1st Class	0	1	0	0	0	1
	2^1	0	1	0	0	0	1
	2^2	0	0	1	0	0	1
	3rd	0	0	0	0	0	0
	Pass	0	0	0	0	0	0
	Total	0	2	1	0	0	3



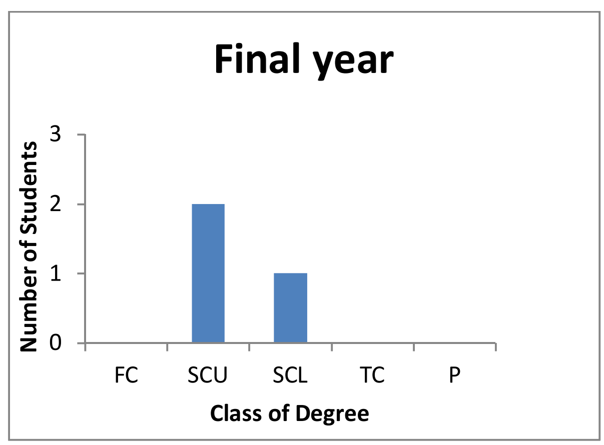
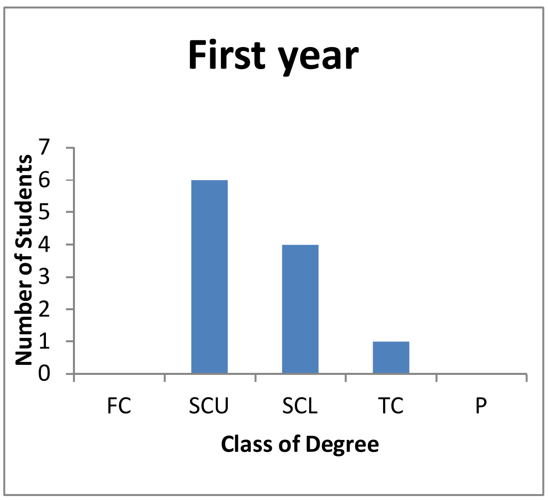


Figure 3 & 4: Bar-Charts showing B.Sc. Mathematics students class of Degree

B.Sc. Computer Science

Table 4: Distribution of B.Sc. Computer Science graduates using first year result against their final year result.

First Year result	Final Year Result						
		1st Class	2^1	2^2	3rd	Pass	Total
	1st Class	0	0	0	0	0	0
	2^1	0	4	2	0	0	6
	2^2	0	1	3	0	0	4
	3rd	0	0	1	0	0	1
	Pass	0	0	0	0	0	0
	Total	0	5	6	0	0	11



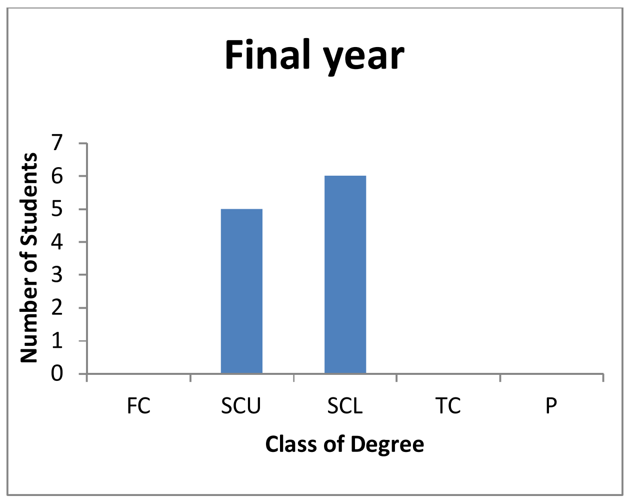


Figure 5&6: Bar-Charts showing B.Sc. Computer Science students class of Degree

B.Sc. Physics

Table 5: Distribution of B.sc Physics graduates using first year result against their final year result.

First Year result	Final Year Result						
		1st Class	2^1	2^2	3rd	Pass	Total
	1st Class	0	0	0	0	0	0
	2^1	0	1	0	0	0	1
	2^2	0	1	2	0	0	3
	3rd	0	0	0	1	0	1
	Pass	0	0	0	0	0	0
	Total	0	2	2	1	0	5

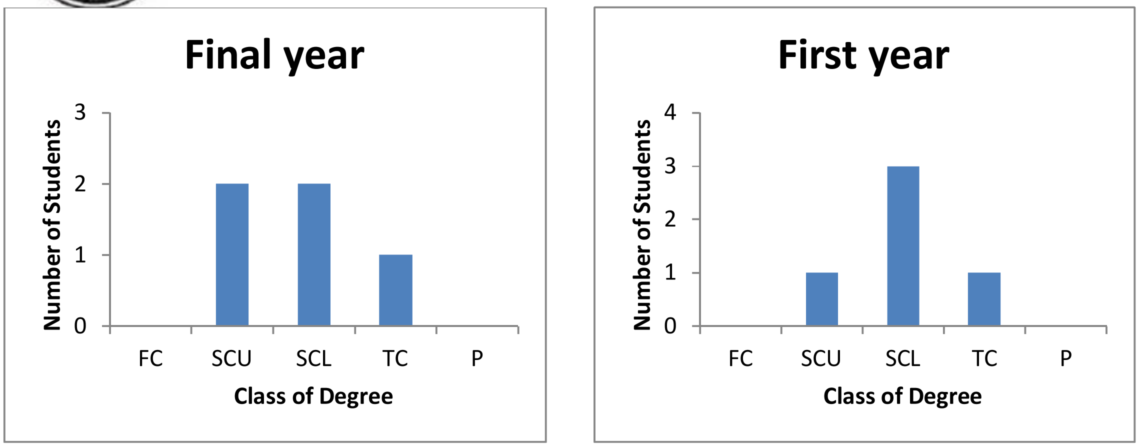


Figure 7&8: Bar-Charts showing B.Sc. Physics Students class of Degree

B.Sc. Chemistry

Table 6: Distribution of B.sc. Chemistry graduates using first year result against their final year result**.**

First Year result	Final Year Result						
		1st Class	2^1	2^2	3rd	Pass	Total
	1st Class	0	0	0	0	0	0
	2^1	0	3	1	0	0	4
	2^2	0	1	4	0	0	5
	3rd	0	0	2	1	0	3
	Pass	0	0	0	0	0	0
	Total	0	4	7	1	0	12

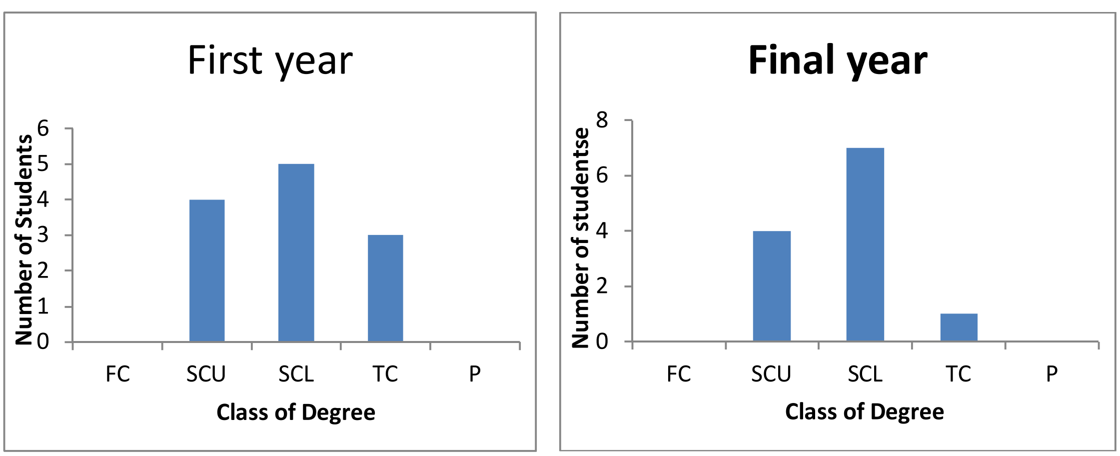
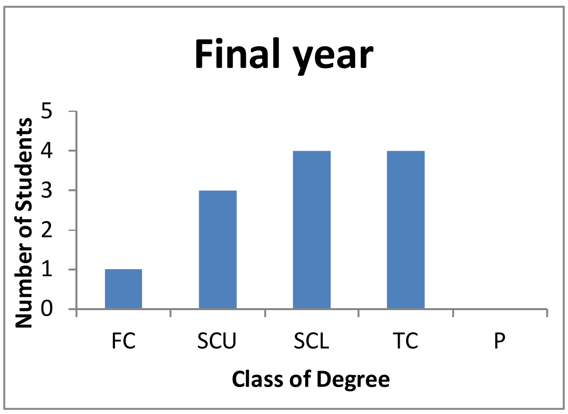


Figure 9&10: Bar-charts showing B.Sc. Chemistry students class of Degree

B.Sc. Biology

Table 7: Distribution of 12B.Sc. Biology graduates using first year result against their final year result.

First Year result	Final Year Result					
	1st Class	2^1	2^2	3rd	Pass	Total
1st Class	1	0	0	0	0	1
2^1	0	3	0	0	0	3
2^2	0	0	4	0	0	4
3rd	0	0	4	0	0	4
Pass	0	0	0	0	0	0
Total	1	3	8	0	0	12



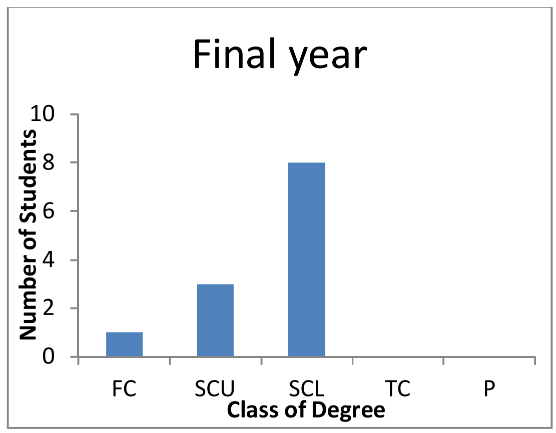


Figure 11&12: Bar-Charts showing B.Sc. Biology students' class of Degree

Discussion of results and conclusion

(i) The Cohen's Kappa procedure was used to investigate whether the first-year result can be used to predict the final year result of students of Federal University Kashere, using Faculty of Science students result.The proposed agreement index gave avalue of 0.49 which is considered to be a moderate agreement index.. This implies that the first year results of students of Federal University Kasherecan be used to predict their final year results fairlyaccurately. The same conclusion was made on some selected University of Ilorin Students by Adebayo and Jolayemi (1998, 1999) with moderate agreement index value 0.57.

From table 2, Sixty eightpercent (67.44% actually) of students of Faculty of science retained their first year academic classification on completion of their studies in the University, twenty three percent (23.26% actually) improved their first year result oncompletionwhile 9.30% regressed.

Coming down to Department level as contained in Table 3 to Table 6, the following conclusions are therefore made.

(ii) Sixty seven percent (66.7% actually) of Mathematics graduates retained their first year academic classificationon completion of their studies in the University, while 33.3% regressed.

(iii) Sixty four percent (63.64% actually) of Computer Science graduates maintained their first year academic classification on completion of their studies in the University, Eighteen percent (18.18% actually) improved their first year result oncompletion while Sixteen percent (18.18% actually) regressed.

(iv) Eighty percent (80%) of Physics graduates maintained their first year academic classification on completion of their studies in the University while twenty percent (20%) improved their first year result oncompletion.

(v) Sixty seven percent (66.7% actually) of Chemistry graduates retained their first year academic classification on completion of their studies in the University, twenty five percent (25%) improved their first year result oncompletion while eight percent (8.33% actually) regressed.

(vi) Sixty seven percent (66.7% actually) of Biology graduates retained their first year academic classification and thirty three percent (33.33% actually) improved their first year result oncompletion.

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