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Longitudinal studies of random effect model on academic performance of undergraduate students

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Abstract: This paper discussed the longitudinal studies of random effect model on academic performance of student using Federal University of Technology, Owerri Imo State Nigeria as a case study. Secondary data were adopted for the research work, and a SAS software package was used for the analysis. There appears to be some curvature in the average trend and individual profile plots, and hence a quadratic time effect was fitted to the data. From the individual profiles are the total observations collected for the analysis. From the profiles of the type of SSA, Entry Age, Entry Aggregate and Gender, it could be assumed that each profiles evolution follows a quadratic trend. Also, it could be concluded that most students who started with low GPA at semester one, improved in their performance to semester three and there was a downward trend before semester seven. Further, the mean profile for SSA was explored. From the chosen model among all models fitted to the data set, we conclude based on the results obtained that student's GPA depends on the SSA, Entry Age, Entry Aggregate and Gender). Student with high and medium admission aggregates scores high GPA and student with low admission aggregates scores low GPA at semester one, but on the average students with Low and Medium Entry Aggregate score higher GPA than students with High Entry Aggregate. The performance of GSS students is better as compare to that PSS at semester one and on the average. Meanwhile, in all the models it appeared, student GPA's increase from semester one to semester three and decreases after semester three. Generally students tend to perform better at the third semester. The analysis also revealed that the academic performance is dependent on the SSA, Entry Age, Entry Aggregate and Gender.

Keywords: Grade Point Average, Cumulative Grade Point Average, Random Effects, Random Intercept Model, Correlation Structure, Semesters, Mean Profile

1. Introduction

In the last few years, Universities in Nigeria have undergone considerable changes not only in terms of numerical expansion but also in the quality of academic work. It is evident that some rating agencies or organization ranks universities based on some other criteria as well as the quality of graduates they produced. This influenced the education policy makers of the academic Institutions including Federal University of Technology, Owerri (FUTO) to respond to developmental race of education.

To compete favorably in terms of high rate of global development, Nigeria must use education as a key of resurgence. At present, Nigeria needs both technological and educational advancement. The root of national wealth is based on excellent technological knowledge and education. There is a strong correlation between a country's development and the quality education provided within that country (Borahan and Ziarati, 2002).

Quality education can therefore be achieved by proper monitoring of what students are doing and what is affecting their progress in terms of performance. If there is no quality policy, it would be difficult for institutions to assess good performance at all levels. The public universities in Nigeria including Federal University of Technology, Owerri (FUTO) wants to produce good and quality technologist and high level standard students. In other to achieve this, frequent and proper measure of academic performance should be put in place; the relevant questions that must be answered are: What are some of the factors that will contribute to quality product? And how are we doing it? How would the university make sure that the planning and quality assurance department monitor and ensure quality production? These are some of the questions that come to mind when we talk about measurement of academic performance.

The basic purpose of any measurement system is to provide feedback relative to the goal that increases the chances of achieving these goals efficiently and effectively. Measurement gains true value when used as the basis for timely decisions. The purpose of measuring is not to know how we are performing but to enable us to perform better. The ultimate aim of implementing a performance measurement system is to improve the academic performance of institution(s). If the performance measurement is right, the corresponding data generated will direct where one is, how one is doing, and where one is going.

Admission into FUTO is based on results obtained in Senior Secondary School (SSS), JAMB, and PUTME. The main objective of admission system is to determine candidate who have the potential to excel in the field of interest in the university.

The quality of students admitted to the institution affects the prestige of the institution as well as development of the country, as this potential student's eventually become the key to development. Kenneth Mellamby (1956) observed that universities worldwide are not completely satisfied by the methods used for selecting undergraduates.

Institution care a lot about producing quality graduates, therefore the initial selection and admission of students from among all applicants is of utmost importance. The admission selection process should choose students who are likely to be successful and likely to provide the most glorious name to the institution. During this process, both objective and subjective criteria are used to determine eligibility and make selections. It is important that, when possible, criteria are genuine factors of the outcome of the institutions. One might assume that as long as there has been graduate level education, the institution offering it must have used a process to select students for their programs. An appropriate selection process provides benefit to the institution and student. Institutions want to prevent the admission of less-than-qualified individuals because that could diminish both the quality of education provided and academic reputation of the institution. Students prefer to attend the schools with the best reputation if possible, because in addition to receiving quality education, earning a degree from a highly respected graduate degree program can provide a competitive edge when seeking for employment. Performance measurements involve determining *what to measure, identifying data collection methods, and collecting the data*.

A Grade Point Average (GPA) as a measurement of academic performance would be used as a dependent variable in this paper. The GPA is basically a single score representing a student's performance in all the courses taken in a semester and is calculated to capture numerically a student's quality of academic performance. It is calculated by multiplying the marks obtained for each course by the credits of the particular course adding up the products and dividing by the total number of units of credit for the courses registered. An up to date assessment from the time the student entered the program of study is obtained by calculating Cumulative Grade Point Average (CGPA) which is ultimately used for the award of the degree. The (CGPA) therefore depends on the GPA.

In this paper, we will study how the identified factors can predict academic performance of students. In applied science many studies are often conducted using longitudinal data, the techniques devised for some of this data are SAS procedure which have been implemented in SAS version 9.1 for general linear models. This study would enable us to model the evolution of GPA over semesters, while adjusting for differences in some factors affecting some of the students.

According to Willett (1989) as cited by Doran (2005) a basic truism of learning implies that an individual student, not a student group, has increased in knowledge and skills during a specific period of time. As such, analytical methods concerned with student learning should reasonably reflect this basic principle and consider individual students as the unit of analysis with their growth trajectories employed as outcomes. Thus, when multiple waves of test-score-data are available, longitudinal analysis of student achievements are more likely to support inferences regarding school and teacher effects than cross-sectional methods of analysis.

Students are the main assets of universities. The students' performance (academic achievement) plays an important role in producing the best quality graduates who will become great leaders and manpower for the country, that is, who will thus be responsible for the country's economic and social development. The performance of students in universities should be a concern not only to the administrators and educators, but also to corporations in the labor market. Academic achievement is one of the main factors considered by the employer in recruiting workers especially the fresh graduates. Thus, students have to place the greatest effort in their study to obtain a good grade in order to fulfill the employer's demand. Students' academic achievement is measured by the Cumulative Grade Point Average (CGPA). CGPA shows the overall students' academic performance where it considers the average of all examinations' grade for all semesters during the tenure in a university. Many factors could act as barrier and catalyst to students achieving a high CGPA that reflects their overall academic performance

2. Review of Related Literatures

Longitudinal Studies are increasingly common in many scientific research areas. The longitudinal data are defined as the data resulting from the observations of subjects (human beings, animals, or laboratory samples, etc.) which are measured repeatedly over time.

According to Oladejo et al. (2004) a lot of researches have been done on students' Demographic features and their academic performance for example, for first year programming courses, Jarman et al. (2002) reported that there was a relationship between student learning style and academic performance, while Byrne and Lyons (2001) established that no such relationship exists. Also, Woodley and Parlett (1983) found that previous educational level, gender, age and occupation were associated with persistence and academic performance.

Similarly, it has been established that marital status, gender and financial stability contributed significantly to distance learners' academic performance. Conversely, Chacon-Duque (1985), Wang and Newlin (2002) found that educational level, age, gender, employment status and number of children in the family were not significant predictors of distance learners' academic performance. Based on the findings from above studies on the relationship between socio-demographic characteristics and academic performance, it appears the issue remains inconclusive.

Students are responsible for their own academic gain in college Davis & Murrell (1993). A student's activities can create environments conducive to or detrimental to learning. Previous studies, however, have reported mixed effects of the student's activities on his or her achievement or grades.

The research on Impact of Eyeglasses on the Academic Performance using random effect model by (Paul Glewwe, Albert Park and Meng Zhao, (2006)) shows the extent of which vision problems among students in developing countries and the impact of those problems on student academic performance. The school academic performance data included student's result of each semester's exams which is conducted regularly in each grade since the student enrolled was used for the research. First, to which extent can vision be correlated with other factors that determine academic performance like sex, ethnicity, birth date, and the occupation and education level of the head of the household (usually the father) in which the student lives? The test score data suggest that vision problems have little effect on students‟ academic performance.

The bias associated with viewing the descriptive relationship in estimation of the causal role that studying plays in the grade production process arises, in part, because students who spend more time in studying may be unable to perform very well. In mathematics not only is it not possible to know the size of the bias that is present if one views the correlations found directly, but it is also not possible to know the direction of the bias. In their paper they examine the effect of studying on college grade performance by using an Instrumental Variable (IV) approach that takes advantage of a real-world situation which they find closely resembles this ideal experiment, in this case the analysis was possible because they designed a sequence of surveys with the specific factors/goal. Finally, because they designed their own longitudinal survey with a well-defined issue in mind, they were able to directly examine the possible theoretical reasons that the instrumental variable might not be valid even in the presence of the random assignment the effect of studying on academic performance was statistically significant. From the practical standpoint, educational institutions need to find a "tool" that would allow them to measure whether they are meeting the needs of their customers. Customer feedback is an established concept of strategic planning. It is therefore critical that educational institutions monitor their performance on a regular basis. Marketing controls are necessary if the institution is to remain as an attractive proposition for potential students. (Lovelock, 1991)

Empirical research by (Ortinau et al, 1987) has found out that students‟ perceptions of importance with respect to specific course features influence their expectations of the course over time. The change justifies the use of performance analysis for the evaluation of the quality of educational services.

For (Ennew et al, 1993), the issue is to develop a better measurement for quality performance. He state that the qualitative nature of performance quality implies that cardinal scales of measurement are inappropriate, but the process of applying ordinal ranking (performance) to concepts is well established as a research methodology. (Ennew et al, 1993) state that a comparison of mean scores on the importance of performance attributes provides a straightforward measure of how well a performance meets its needs. (Cronbach's Anderson et al., 1994) studied the effect of some factors such as gender, student age, and students‟ high school scores in Mathematics, English and Economics, on the level of university attainment. According to their study, students who have better scores in high school also performed better in university. Another aspect discovered was that men had better grades than women and choose to drop from school less often.

(Timothy Rodgers 2005) in his paper titled Measuring value added in higher education came out that there was the natural tendency to what to keep measures simple, and this reflected in both tertiary and secondary education measures of the value added. However he said it has been shown that simplicity in this situation is at the expense of accuracy, from him the consequence of using simplistic measures of the "expected" school exam results is that the resulting measure of value added is not going to be very meaningful. The "exogenous" factors that influence school performance are involved and complex, and measuring their expected impact cannot be achieved by only examining the impact of previous academic achievement levels on performance but would be necessary to develop sophisticated modeling techniques if we are able to produce a credible measure of value added.

(Teck K et al 2009) in their paper that illustrates the analysis of longitudinal data using GEE (Generalize Estimation Equations) and showing how output from SAS macros can be streamlined and organized to aid interpretation of analysis. They said though using GEE through procedures such as SAS PROC GENMOD is becoming increasingly common place, as far as model evaluation is concerned, its widespread use is somehow limited by the lack of easily accessible measures to evaluate the model goodness-of-fit directly from the default SAS output. Their study gives an example of how this can be done by first building three goodness-of-fit indices, namely the marginal R2, QIC and QICU, in a SAS macro, using various working correlation matrices, for model comparison. Their work specifically illustrate with a longitudinal data set, how four models with different working correlation matrices specification with a binomial logit link function, were generated using the macro. The results shows that estimated coefficients for the four models were largely similar; in their view they Support (Zeger and Liang, 1986) point that misspecification of working correlation would still give consistency result. Their study also illustrates the procedure of data management and preliminary data analyses work needed before carrying out similar analyses using several simple SAS macros these include carrying out statistical procedures such as factor analysis for examining constructs reliability, calculating reliability index.

(Stewart S M et al, 2006) in their longitudinal data analyses on the relationship between stress related measures and academic performance during the first two years of medical school, medical students (n=121) were surveyed prior to beginning of classes and 8 months later variables predisposing to distress, stress response (depression and state anxiety), and stress management strategies were assessed. Pre-medical academic scores and grades at the end of five assessment periods over the course of the first 2 years of medical school were also obtained. The results shows that academic performance before and during medical school was negatively related to reported stress levels. On the bivariate correlations, there were numerous significant relationships between stress and academic performance.

(Micha Mandel and Rebecca A. Betensky, 2008) researching in Estimating time-to-event from longitudinal ordinal data using random-effects Markov models said Longitudinal ordinal data are common in many scientific studies, including those of multiple sclerosis (MS), and are frequently modeled using Markov dependency. They said several authors have proposed random-effects Markov models to account for heterogeneity in the population. In their paper, they went one step further and study prediction based on random-effects Markov models particular, they show how to calculate the probabilities of future events and confidence intervals for those probabilities, given observed data on the ordinal outcome and a set of covariates, and how to update them over time.

(Sano Paulo 2006) also research about growth status on academic achievement using multiple regression model analysis and univariate analysis of variance after assessing academic performance and measuring growth using standard procedure and height-for-age of 277 student selected randomly from his department. He came out that student whose growth move with their height and age perform better than those who do not grow well with their height and age (have retarded growth), which indicate that growth retardation have negative impact on academic performance.

According to Umar (2010) on his study on "The Effect of Social Factors on Students" Academic Performance in Nigerian Tertiary Institutions, concluded that academic performance is an excellent measure of the transfer of knowledge in modern society. He found out that students' cult is an academic impediment and perhaps an outright evil. Romantic relationships having the highest impact, and may be a psychological barrier to an effective learning process. Excessive sporting activities and involvement in clubs and organizations were found to be a threat, but an insignificant one. All of the research reviews support the hypothesis that student performance depends on different socio-economic, psychological, environmental factors. The findings of research studies focused that student performance is affected by different factors such as learning abilities because new paradigm about learning assumes that all students can and should learn at higher levels but it should not be considered as constraint because there are other factors like race, gender, sex that can affect student's performance(Hansen; 2000).

According to Goldstein (1979), as cited by Anderson et al (2006) longitudinal data are used in the research on growth, development, and change. Such data consist of measurements on the same subjects repeatedly over time. To describe the pattern of individual growth, make predictions, and gain more insight into the underlying causal relationships related to developmental pattern requires studying the structure of measurements taken on different occasions. The errors in longitudinal data often exhibit heteroscedasticity and dependence, which call for structured covariance models. Longitudinal data typically possess a hierarchical structure that the repeated measurements are nested within an individual. While the repeated measures are the first level, the individual is the second-level unit and groups of individuals are higher- level units Hox (2000). To take heterogeneity and dependence into account, one must include them as parts of the model Muthen & Satorra, (1989). Because the study was a longitudinal one a Linear Mixed-Effect Regression Model (MRM) is to be employed for the analysis. This is a statistical model that involves both fixed effect and random effects. They are the modified form of a linear regression model.

3. Materials and Methods

The researchers used a set of longitudinal data analysis that is, data analysis which involves a continuous observation of the variable, which is Grade Point average over Seven (7) semesters in our case. Because of the continuous nature of the data, Random Intercept model (RIM) is employed. The researcher used only the secondary type of data that is the Grade Point average for all the semesters from first semester to seventh semester of Statistics students from FUTO including their background information.

Table 1. *Sample of data used*

SERIAL NO.	CGPA	GENDER	SSA	ENTRY AGGREATE	AGE
1	48.00	1	1	2	2
2	48.00	1	2	2	1
3	62.00	1	2	3	1
4	47.00	1	2	2	1
5	50.00	1	1	2	1
6	39.00	1	2	3	2
7	36.00	1	2	2	1
8	51.00	1	2	1	2
9	47.00	1	1	3	2
1	48.00	1	2	2	1
11	45.00	2	2	3	2
12	54.00	2	2	2	2
13	60.00	2	1	3	1
14	44.00	2	1	2	1
15	47.00	2	1	2	1
16	47.00	2	1	1	1
17	62.00	2	2	2	1
18	47.00	2	2	3	1
19	62.00	2	1	2	2
20	60.00	2	2	2	2
21	55.00	2	1	3	2
22	54.00	2	1	3	1
23	54.00	2	1	2	1
24	61.00	2	2	2	2
25	65.00	2	1	2	1
26	47.00	2	2	2	1
27	40.00	2	1	2	2
28	48.00	2	1	3	2
29	42.00	2	1	2	1
30	39.00	2	1	2	2
31	55.00	2	2	2	1
32	42.00	2	2	2	2
33	61.00	2	1	2	1
34	27.00	2	1	2	2
35	46.00	2	2	2	1
36	51.00	2	2	3	1
37	40.00	2	2	2	1
38	55.00	2	1	2	1
39	71.00	2	1	2	1
40	51.00	2	2	1	1
41	49.00	2	2	2	1
42	51.00	2	2	3	1
43	43.00	2	2	3	2
44	66.00	2	1	2	2
45	55.00	2	2	2	1
46	58.00	2	1	2	2
47	42.00	2	2	2	2
48	81.00	2	1	2	2
49	45.00	2	2	3	2
50	63.00	2	1	2	1

The understanding of student performance is, at present, an issue of increasing concern among academics and policy makers. In this thesis, we try to address empirically this issue as regard students academic performance and factors that may affect their performance. This Longitudinal study was conducted by using a survey method (Simple Random sampling). Longitudinal data arise when repeated measurements are obtained for an individual (or unit of analysis) on one or more outcome variables at successive time points. Longitudinal data require the most elaborate modeling of the random variability.

The population was the population of the 2008-2013 Set Statistics Department, Federal University of Technology, Owerri. 50 students (40 males and 10 females) were selected randomly in proportion to the population of male and female students. The study was delimited to only demographic factors such as students' gender, entry age, entry aggregate, secondary school attended, parents' education and occupation. The quality of academic performance was measured by their achievement scores of their Grade Point Average (GPA) and their Cumulative Grade Point Average (GPA). Data regarding the variables such as parents' education, parents' occupation, students' gender, entry age, entry aggregate, secondary school attended were collected by using a Secondary data. Individual student's Cumulative Grade Point Average (CGPA) was used as the response (dependent) variable. The CGPA is calculated as the summation of all the products of marks obtained for each course by the credits of the particular course adding up the products and dividing by the total number of units of credit for the courses registered. Students' gender, entry age, entry aggregate, secondary school attended was treated as the independent variables. Table 1 shows sample of the data used and how it can be organized.

The coding system for the study is Male =2; Female = 1 and Government secondary School=1 and Private Secondary School=2. The Age above shows that 24 =2 and age below 24=1. Entry aggregate was divided into three classes with class size 30 each that is, 147- 189 (Low Aggregate) =1, 190- 207 (Medium Aggregate) =2 and 208-237 (High Aggregate) =3. Because the study is a longitudinal one a Linear Mixed-Effect Model (MRM) is seen as an appreciate tool for the analysis. This is a statistical model that involves both fixed effect and random effects. They are the modified form of a linear regression model.

3.1. Selecting a Correlation Structure for the Repeated Measurements

The random intercept model implies covariance structure which assumes constant variance $\sigma_v^2 + \sigma^2$ over time as well as equal positive correlation between any two measurements from the same student. This covariance structure is called compound symmetric while the common correlation is term as intra-class correlation. The intra-class correlation measures the degree of association of the longitudinal data within students

Fitting the Correct correlation structure to the data will ensure that model parameters and their standard errors are estimated correctly. A number of different covariance structures may be selected in PROC MIXED. The most common choices are:

- Exchangeable or compound symmetric - assumes that correlation between all pairs of repeated measurements are equal irrespective of the length of the time interval.
- Unstructured - with this structure, all correlations are assumed to be different.

Table 2. *Exchangeable or compound symmetry*

Compound symmetric	GPA1	GPA2	GPA	GPA	GPA	GPA	GPA
GPA	1	P	P	P	P	P	P
GPA		1	P	P	P	P	P
GPA			1	P	P	P	P
GPA				1	P	P	P
GPA					1	P	P
GPA						1	P
GPA							1

Table 3. *Unstructured data*

Exchangeable	GPA1	GPA2	GPA	GPA	GPA	GPA	GPA
GPA	1	p1	p2	p3	p4	p6	P7
GPA		1	P8	P9	p10	p11	p12
GPA			1	p13	p14	p15	p16
GPA				1	p17	p18	p19
GPA					1	p20	p21
GPA						1	p23
GPA							1

3.2. Random Intercept Model (RIM)

The simplest regression model for longitudinal data is one in which measurements are obtained for a single dependent variable at successive time points. Let Y_{ij} represent the measurement for the ith individual at the jth point in time.

$$Y_{ij} = \beta_0 + \beta_1 t_{ij} + \varepsilon_{ij} \qquad (1)$$

β_0 is the intercept, β_1 is the slope, that is the change in the outcome variable for every one-unit increase in time (Semester) and ε_{ij} is the error component. In this simple regression, the $\varepsilon_{ij's}$ are assumed to be correlated, and to follow a normal distribution [i.e., ε_{ij} ~ N (0, ε)]. β_0 represents the average value of the dependent variable when time = 0, and β_1 represents the average change in the dependent variable for each one-unit increase in time (Semester). There is a possibility that a student may start with low SWA and then increase over semesters as shown in figure 1 or no change in SWA over semesters as shown in figure b or start with high SWA and decrease over semester as in figure 3.

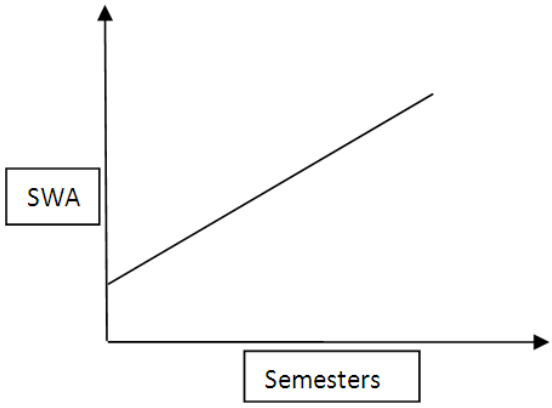

Fig.1: *Good performance of students*

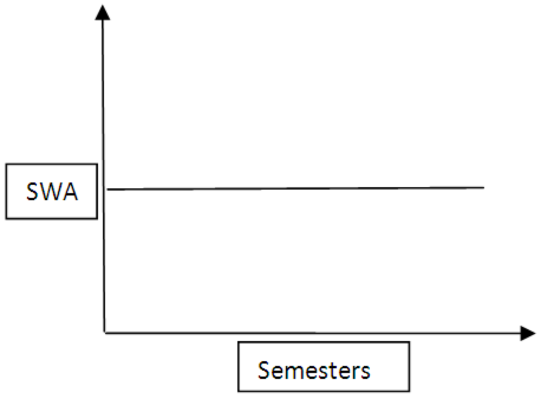

Fig.2: *Average performance of students*

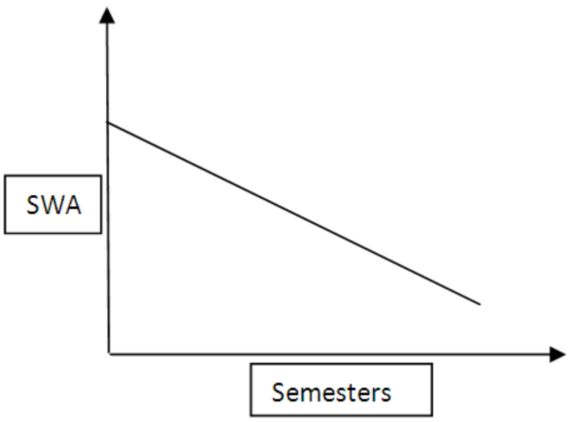

Fig.3: *Poor performance of students*

Figures 1, 2, and 3 are demonstrating the possible average change of SWA's over semesters. The implication was that on average student who performs well is depicted by figure 1. Figure 3 depicts that on the average such students is performing poorly.

The simple random effects model is the one which the intercept is allowed to vary across individuals (Students):

$$Y_{ij} = \beta_0 + \beta_1 t_{ij} + \upsilon_{0i} + \varepsilon_{ij} \qquad (2)$$

Where υ_{0i} represents the influence on individual I on his/her repeated observations. Note that if the individuals have no influence on their repeated outcome (SWA), then all the υ_{0i} will be equal to zero (υ_{0i}=0), but that may not be true, therefore υ_{0i} may have negative or positive impact on their SWA's therefore υ_{0i} may deviate from zero. For better reflection of this model on the characteristic individual, the model is partition into within-subjects and between-subjects.

Within- subjects

$$y_{ij} = b_{0i} + b_1 t_{ij} + \varepsilon_{ij} \tag{3}$$

Between- subjects

$$b_{0i} = \beta_0 + \upsilon_{0i} \tag{4}$$

$$b_{1i} = \beta_1 \tag{5}$$

Equation 4 indicates that the intercept for the ith individual is a function of a population intercept plus unique contribution for individual. We assume $\upsilon_{0i} \sim N(0, \sigma^2{}_{v0})$. This model also indicates that each individual's slop is equal to the population slope, β_1 , equation 5.

When both the slope and the intercept are allowed to vary across individual, the model is:

$$Y_i = \beta_0 + \beta_1 t_{ij} + \upsilon_{0i} + \upsilon_{1i} t_{ij} + \varepsilon_i \tag{6}$$

The within-subjects model is the same as

$$Y_i = b_{0i} + b_1 t_{ij} + \varepsilon_i \tag{7}$$

And between-subject model is:

$$b_{0i} = \beta_0 + \upsilon_{0i} \tag{8}$$

$$b_{1i} = \beta_1 + \upsilon_{1i} \tag{9}$$

The within-subject model indicates that the individual ith SWA at time j is influence by their initial level b_{0i} and the time trend or the slope b_{1i} . The between-subject indicate that the individual $i's$ initial level is determined by the population initial level β_0 plus the unique contribution of υ_{0i} . Thus each individual has their own distinct initial level. Intercept for the ith individual is a function of a population intercept plus unique contribution for that individual. As well, the slope for the ith individual is a function of the population slope plus some unique contribution for that subject. We assume

$$D = \begin{pmatrix} \sigma^2{}_{v0} & \sigma_{\upsilon 0}\sigma_{\upsilon 1} \\ & \sigma^2{}_{\upsilon 1} \end{pmatrix} \tag{10}$$

is the variance – covariance matrix of random effects. Correlation exists between the random slope and the random intercept, so that individuals who have higher values for the intercept (i.e. higher or lower values on the dependent variable at the baseline time point) will also have higher or lower values for the slope. The resulting linear model can now be written as:

$$Y_i = X_i \beta + Z_i b_i + \varepsilon_{1i} \tag{11}$$

$$b_i \sim N(0, D)$$

$$\varepsilon_{1i} \sim N(0, \sigma^2 I_{ni})$$

Assumptions:

$b_1 ... b_N, \varepsilon_1 ... \varepsilon_N, b's$ are independent

$\varepsilon_1 \sim N(0, \sigma^2 I_{ni})$ is the measurement error

The variance of the measurement is given below:

$$Vy_i = Z_i \textstyle\sum_{\upsilon} Z_i' + \sigma^2 I_{ni} \tag{12}$$

This model implies that conditional on the random effects, the errors are uncorrelated, as is displayed. This is seen in equation (12), since the error variance is multiplied by the identity matrix (i.e., all correlations of the error equal zero).

Table 4. *Sampled Data Computations*

S/N	GENDER	AGE	SSA	PUME + JAMB	ENTRY AGGREGATE	ENTRY_ AGGREGATE	GRADE POINT AVERAGE (GPA)(%)						
							1ST	2ND	3RD	4TH	5TH	6TH	7TH
1	1	2	1	387	194	2	39	42	46	47	48	49	67
2	1	1	2	380	190	1	45	45	48	47	49	50	52
3	1	1	2	425	213	1	52	57	64	62	66	67	69
4	1	1	2	389	195	1	48	49	50	49	46	47	42
5	1	1	1	362	181	1	47	45	48	47	53	54	56
6	1	2	2	430	215	2	41	39	38	38	40	39	37
7	1	1	2	387	194	1	44	44	38	34	32	31	32
8	1	2	2	351	176	2	47	46	52	53	50	53	53

S/N	GENDER	AGE	SSA	PUME + JAMB	ENTRY AGGREGATE	ENTRY_ AGGREGATE	GRADE POINT AVERAGE (GPA)(%)						
							1ST	2ND	3RD	4TH	5TH	6TH	7TH
9	1	2	1	419	210	2	45	52	52	46	45	43	41
10	1	1	2	389	195	1	35	48	50	47	50	52	53
11	2	2	2	473	237	2	45	43	46	43	43	47	48
12	2	2	2	379	190	2	47	54	57	55	57	52	54
13	2	1	1	433	217	1	45	55	60	63	63	65	67
14	2	1	1	375	188	1	43	48	48	46	43	40	41
15	2	1	1	390	195	1	44	48	49	49	47	45	45
16	2	1	1	293	147	1	42	39	47	46	49	53	56
17	2	1	2	408	204	1	45	57	63	68	69	68	68
18	2	1	2	457	229	1	59	51	50	49	44	39	39
19	2	2	1	379	190	2	56	55	65	65	65	64	61
20	2	2	2	393	197	2	64	64	60	61	58	56	56
21	2	2	1	415	208	2	67	61	58	51	52	50	48
22	2	1	1	421	211	1	55	55	54	52	52	54	54
23	2	1	1	391	196	1	56	58	56	53	52	51	49
24	2	2	2	371	186	2	46	56	62	64	67	68	68
25	2	1	1	382	191	1	56	65	66	64	67	70	68
26	2	1	2	391	196	1	37	46	49	49	47	51	53
27	2	2	1	376	188	2	53	45	38	41	38	33	30
28	2	2	1	420	210	2	56	50	50	48	45	45	43
29	2	1	1	382	191	1	27	45	47	43	43	45	44
30	2	2	1	374	187	2	36	48	43	39	37	34	36
31	2	1	2	363	182	1	43	52	59	59	57	57	56
32	2	2	2	366	183	2	38	42	43	45	43	41	40
33	2	1	1	380	190	1	64	69	61	62	59	55	54
34	2	2	1	398	199	2	32	28	24	23	26	27	27
35	2	1	2	396	198	1	46	44	46	46	46	47	47
36	2	1	2	465	233	1	48	59	57	52	49	44	45
37	2	1	2	401	201	1	42	38	41	41	39	38	41
38	2	1	1	387	194	1	61	59	58	57	53	49	49
39	2	1	1	380	190	1	57	68	71	71	75	77	77
40	2	1	2	342	171	1	53	55	55	51	48	48	46
41	2	1	2	402	201	1	55	52	52	53	45	43	43
42	2	2	2	416	208	1	55	51	51	51	50	50	47
43	2	2	2	424	212	2	30	32	45	47	50	48	49
44	2	2	1	392	196	2	74	70	69	65	63	61	60
45	2	1	2	389	195	1	69	60	57	55	51	48	47
46	2	2	1	363	182	2	64	63	59	54	55	54	54
47	2	2	2	389	195	2	42	49	43	42	42	39	38
48	2	2	1	362	181	2	78	77	81	82	83	83	81
49	2	2	2	430	215	2	52	48	48	45	44	41	39
50	2	1	1	392	196	1	62	64	65	64	64	62	61

4. Data Analysis and Results

4.1. Summary Statistics on the Data

This section deals with the analysis of the data. The students CGPA serve as the dependent variable while students' gender, entry age, entry aggregate, secondary school attended was treated as the independent variables. The ages of the students were considered and it was realized that the minimum age was 20years while the maximum age was 28years.

It was also seen that greater percentage of the students fell at age 24 and they represented 32 percent, the ages with the minimum representation were 19 and 20 and they had 2 percent each. I also took into account the sex distribution of the students. I observed that the sex status of 10 students were females which constituted 20 percent while males were 40, representing 80 percent. Also, the observed students who attended Government Secondary School were 24 representing 48 percent out of which 4 were female and 20 were males, while those who attended privately owned Secondary Schools were 26 out of which 6 were female and 20 were males, representing 52 percent.

Finally, the number of observed students who had an Entry Aggregate of 147 – 189 (Low Aggregate) represented 24 percent, 190-207 (Medium Aggregate) represented 50 percent, and student who had Entry Aggregate of 209-237 (High Aggregate) represented 26 percent on the randomly selected students.

4.2. Exploring the Data

One of the major components of a longitudinal data analysis is the exploratory analysis. For a good longitudinal data analysis it must begin by making displays that reveal the patterns important to the scientific question. In this portion of the work, various graphs would be used to explore the sample data. Graphs like the individual profile for the GPA Scores against the Semester was drawn to show the Students individual performance over the seven (7) semesters, the overall

Mean structure was also plotted to shown their general performance over the semester, how related the GPAs are between various semesters (correlation) and their variances were considered.

Knowledge of the individual profiles will inform us to identify general trends within subjects; it may also detect nonlinear change over time and also provides information about the variability at given times.

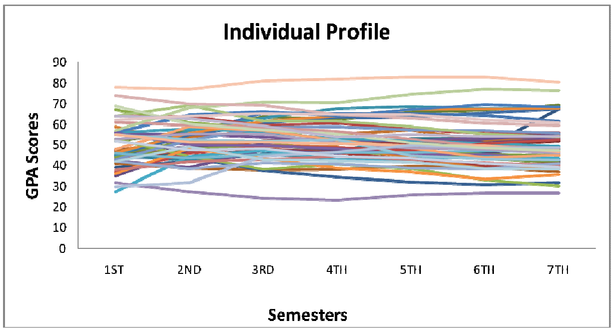

Figure 4. *The individual profiles of 50 students with respect to their GPA's (%) over seven semesters*

4.3. Individual Profiles

From the figure 4, we observed that some students start on different GPA scores at semester one. The students' GPA ranges between 27 percent and 74 percent. Also, we noticed that some students start with high GPA but the GPA decline in the second semester and rise again in the third semester, other students also begin on a certain GPA improve in the second semester but decline in the third semester and so on.

It is observed that most of the students start with a different GPA at semester one and that most students start with GPA above 40%. From figure 4, we can deduce that there exists some variability between and within GPA's for each student.

Table 5. *The Descriptive Statistics for the GPA scores*

	Mean	Std. Deviation	N
GPA1	49.7400	11.04501	50
GPA2	51.8000	9.84160	50
GPA3	52.7800	9.98425	50
GPA4	51.6800	10.34002	50
GPA5	51.1800	10.87909	50
GPA6	50.5400	11.48772	50
GPA7	50.6200	11.79050	50

The Figure above shows the mean profile of GPA scores of the fifty (50) randomly selected students. It is observed that the mean score of students increased from first semester to third semester (49.7400 - 52.7800 and later dropped to 50.6200 at the seventh semester.

Therefore there is an upward and downward trend in the mean performance of students over the semesters.

Table 6. *The Correlation Structure for the GPA scores*

	GPA 1	GPA 2	GPA 3	GPA 4	GPA 5	GPA 6	GPA 7
GPA1	1	.825	.690	.637	.544	.454	.358
GPA2		1	.905	.843	.775	.692	.603
GPA3			1	.972	.942	.894	.826
GPA4				1	.968	.923	.864
GPA5					1	.978	.932
GPA6						1	.965
GPA7							1

The correlation structure describes how GPAs correlate within semester. The correlation function depends on a pair of semester (time), does this pair of time simplify to the time lag. This is important since many exploratory and modeling tools are based on these assumptions. Since the structure varies with time, the variation may be captured by random effect model. A different way of displaying the correlation structure is using a scatter plot.

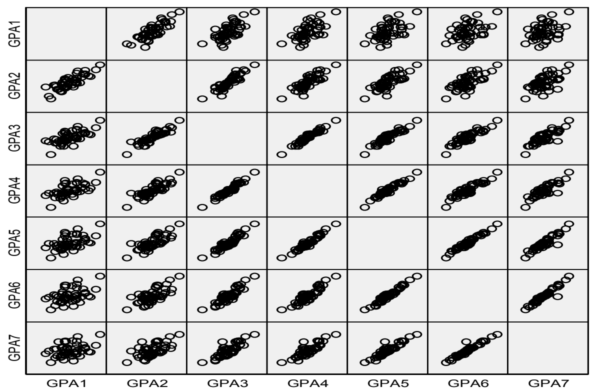

Figure 5. *The scatter plot of the correlation structure*

The figure 5 shows there is a high correlation between the pair-wise repeated GPA. This is due to the fact that the GPA�s were taken repeatedly for the same student over semesters. This can also been seen from the pair wise scatter-plots between two repeated GPA over semester. In figure it’s clearly seen that as the distance from the diagonal is increasing so also the degree of relationship is decreasing.

Table 7 shows the computed sample variance for each semester. We can observe that the variance decreases from semester one to semester three, increases from semester four to semester seven. This may indicate that the variation of the GPA�s are finite unstable and not homogeneous. However, the assumption of constancy of variance may not be too many because some of the variation may be accounted for by the individual effects.

Table 7. *The overall sample variance for each semester*

Semester	N	Variance
1	50	121.992
2	50	96.857
3	50	99.685
4	50	106.916
5	50	118.355
6	50	131.968
7	50	139.016
Valid N (listwise)	50	

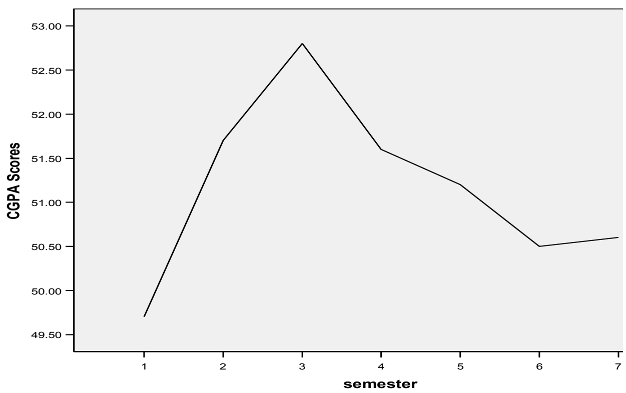

Figure 6. *Overall mean structure*

Figure 6 shows the overall mean of all the GPA at each semester. Here we observe that on the average all students GPA scores increases from semester one to semester three and then decreases moderately after semester four, semester five and semester six, there is a slight increase in the student GPA from semester six to semester seven.

Figure 7. *The Mean profile for female and male student.*

From figure 7 above shows the mean profile of GPA scores for both female and male students. From the figure, it is observed that male students have higher GPA scores than female students on the average. We can also observe that the mean GPA for male student was about 51% at semester one while that of female students was around 45%. The trend shows sharp increase after semester one to semester three, decreases moderately after semester four and slightly increases to semester seven. This observation is similar to the overall mean structure.

From figure 8 above shows the mean profile of GPA scores for both GSS and PSS students. From the figure, it is observed that GSS students have higher GPA scores than PSS students on the average. We can also observe that the mean GPA for GSS student was about 52.3% at semester one while that of PSS students was around 47%. The trend shows sharp increase after semester one to semester three, decreases moderately after semester three. This observation is similar to the overall mean structure.

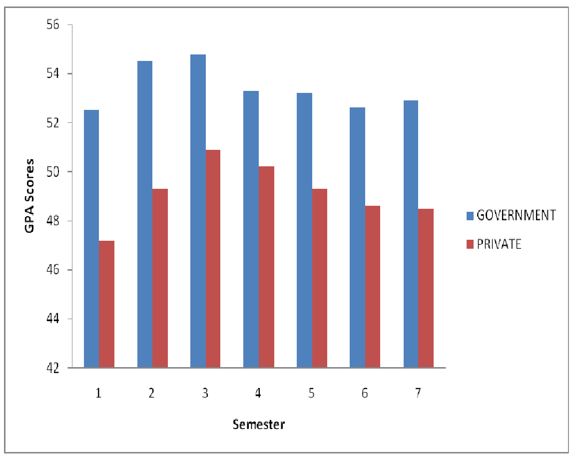

Figure 8. *The Mean profile for GSS and PSS student.*

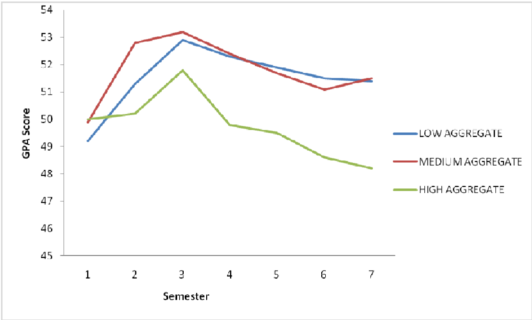

Figure 9. *The Mean profile for student with Low Entry Aggregate, Medium Entry Aggregate and High Entry Aggregate.*

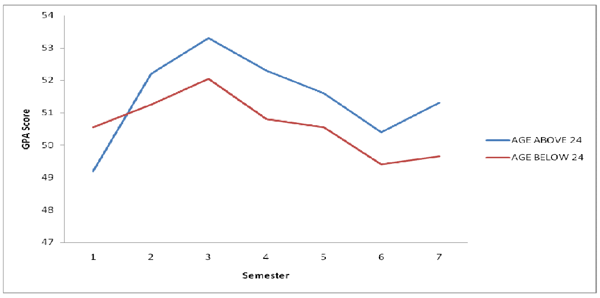

Figure 10. *The Mean profile for student with Age Below 24 and Age Above 24.*

Figure 9 shows the mean profile of GPA scores for both students with LEA, MEA and HEA. From the figure, it is observed that students with MEA have higher GPA scores than students with LEA and HEA on the average. We can also observe that the mean GPA for MEA student was about 53% on the average while that of students with LEA and HEA was around 52.5% and 51.5% respectively. The trend shows sharp increase after semester one to semester three, decreases moderately after semester three. This observation is similar to the overall mean structure.

Figure 10 shows the mean profile of GPA scores for both students at Age below 24 and Age above 24. From the figure, it is observed that students at Age Above24 have higher GPA scores than students at Age below 24 on the average. We can also observe that the mean GPA for student at Age Above24 was about 53.2% on the average while that of students at Age Below24 was around 51.9%. The trend shows sharp increase after semester one to semester three, decreases moderately after semester three. This observation is similar to the overall mean structure.

Table 8. *Comparison of achievement of students using Paired Sample t-test*

Response variable	Paired Differences							t	df
	gender	Mean	N	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			
						Lower	Upper		
GPA of students	female	47.61	10	6.9474216	2.196968	41.6301	51.5699	21.21105	9
	male	52.13	40	10.19097	1.611332	46.8658	53.3842	31.10800	39

*P<.05 level of significance, df=48

Table 9. *Comparison of achievement of students using Paired Sample t-test*

Response variable	Paired Differences							t-value	df
	SSA	Mean	N	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			
						Lower	Upper		
GPA of students	Government	53.39	24	11.69057	2.38633	47.4552	57.3282	21.9550	23
	Private	49.17	26	7.14193	1.40065	44.2807	50.0501	33.67400	25

*P<.05 level of significance, df=48

Table 10. *Comparison of achievement of students using Paired Sample t-test*

Response variable	Paired Differences							t-value	df
	Entry Aggregate	Mean	N	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			
						Lower	Upper		
GPA of students	Low_Aggregate	51.50	12	11.55469	3.33555	43.1585	57.8415	15.1400	11
	Medium_Aggregate	51.82	25	10.40900	2.08180	45.5194	54.1126	23.9290	24
	High_Aggregate	49.72	13	6.66656	1.84897	42.6868	50.744	25.26600	12

*P<.05 level of significance, df=48

Table 11. *Comparison of achievement of students using Paired Sample t-test*

Response variable	Paired Differences								
	Entry Age	Mean	N	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t-value	df
						Lower	Upper		
GPA of students	Age_Below24	51.58	30	8.21363	1.4996	47.5139	53.648	33.7300	29
	Age_Above24	50.61	20	11.85917	2.65179	43.0569	54.1574	18.33000	19

*P<.05 level of significance, df=48

As shown in Table 8, *t*-values (*t* =21.21105, 31.10800) indicate that there is a significant difference in the GPA of male and female students. The null hypothesis that there is no significant difference in the quality of academic performance of students in relation to their gender is therefore rejected. It is concluded that the academic performance is dependent on Gender and from the results obtained that male students perform better than the female (mean values of male students=50.16 and mean value of female students=46.60) in the GPA.

As shown in Table 9, *t*-values (*t* =21.9550, 33.67400) indicate that there is a significant difference in the GPA of students who attended GSS and PSS. The null hypothesis that there is no significant difference in the quality of academic performance of students in relation to the SSA is therefore rejected. It is concluded that the academic performance is dependent on the SSA and from the results obtained that male students perform better than the female (mean values of students who attended GSS=53.39 and mean value of students who attended PSS=49.17) in the GPA.

As shown in Table 10, *t*-values (*t* =15.1400, 23.9290, 25.2660) indicate that there is a significant difference in the GPA of students who had Low Aggregate, Medium Aggregate and High Aggregate. The null hypothesis that there is no significant difference in the quality of academic performance of students in relation to the Entry Aggregate is therefore rejected. It is concluded that the academic performance is dependent on the Entry Aggregate and from the results obtained students with Low Aggregate and Medium Aggregate perform better than students with High Aggregate (mean values of students with Low Aggregate, Medium Aggregate and High Aggregate=51.50, 51.82 and 49.72 respectively) in the GPA.

As shown in Table 11, *t*-values (*t* =33.73, 18.33) indicate that there is a significant difference in the GPA of students with Age below 24 and Age Above 24. The null hypothesis that there is no significant difference in the quality of academic performance of students in relation to the Entry Age is therefore rejected. It is concluded that the academic performance is dependent on the Entry Age and from the results obtained students with Age below 24 perform better than students with Age Above 24 (mean values of students with Age Below 24 and Age Above 24 =51.58 and 50.61 respectively) in the GPA.

5. Conclusion

Since there appears to be some curvature in the average trend and individual profile plots, a quadratic time effect was fitted to the data. From the individual profiles are the total observations collected for the analysis. From the profiles of the type of SSA, Entry Age, Entry Aggregate and Gender, it could be assumed that each profiles evolution follows a quadratic trend. In addition, there is some variability between and within students in each group. Also, it could be concluded that most students who started with low GPA at semester one, improved in their performance to semester three and there was a downward trend before semester seven.

Further, the mean profile for SSA was explored. We observe that the students from GSS on the average had high grade in GPA than those from PSS. We observe that SSA, Entry Age, Entry Aggregate and Gender were shown to have significant effect on the students‟ GPA scores. This result is the same for and for all the models considered.

From table 3 and figure 7, we observed that the correlation structure decreases slightly across the semesters generally. Furthermore all the correlation co-efficient were above 0.358 which is an indication of strong correlation between pairs of GPA's over semesters. The highest correlation coefficient occurs at semester five and semester six which is 0.978 and the lowest occurs at semester one and semester seven GPA6 with the value 0.358.

From the chosen model among all models, fitted to the data set, we conclude based on the results obtained that student's GPA depends on the SSA, Entry Age, Entry Aggregate and Gender). The older student's score higher GPA than the younger students on the average. Student with high and medium admission aggregates scores high GPA and student with low admission aggregates score low GPA at semester one, but on the average students with Low and Medium Entry Aggregate score higher GPA than students with High Entry Aggregate. The performance of GSS students is better as compare to that PSS at semester one and on the average. Meanwhile, in all the models it appeared, student GPA's increase from semester one to semester three and decreases after semester three. Generally students tend to perform better at the third semester.

The null hypothesis that there is no significant difference in the quality of academic performance of students in relation to the SSA, Entry Age, Entry Aggregate and Gender is therefore rejected, and it was concluded that the academic performance is dependent on the SSA, Entry Age, Entry Aggregate and Gender.

In conclusion of this research, we recommend that further research is needed to explore the problem on a large sample from more scattered geographical regions including other student factors, family factors, school factors, peer factors marital status, type of work, and family size, also a questionnaire can be designed to look at the attitude of students.

Appendix A.

Serial No.	GRADE POINT AVERAGE (GPA)							CGPA
	1ST	2ND	3RD	4TH	5TH	6TH	7TH	
1	1.95	2.1	2.28	2.33	2.39	2.43	3.36	2.41
2	2.25	2.23	2.4	2.35	2.45	2.49	2.6	2.40
3	2.6	2.85	3.18	3.12	3.29	3.33	3.46	3.12
4	2.4	2.44	2.49	2.43	2.31	2.33	2.09	2.36
5	2.35	2.23	2.38	2.36	2.66	2.68	2.78	2.49
6	2.05	1.95	1.9	1.91	1.99	1.97	1.85	1.95
7	2.2	2.18	1.88	1.72	1.61	1.55	1.6	1.82
8	2.35	2.31	2.62	2.64	2.52	2.66	2.63	2.53
9	2.25	2.62	2.6	2.31	2.27	2.17	2.06	2.33
1	1.75	2.38	2.52	2.36	2.5	2.59	2.64	2.39
11	2.25	2.13	2.28	2.14	2.17	2.34	2.39	2.24
12	2.35	2.69	2.86	2.76	2.86	2.62	2.72	2.69
13	2.25	2.74	3.02	3.15	3.15	3.27	3.36	2.99
14	2.15	2.38	2.41	2.31	2.14	1.98	2.05	2.20
15	2.2	2.41	2.47	2.43	2.34	2.26	2.24	2.34
16	2.1	1.95	2.37	2.29	2.46	2.64	2.78	2.37
17	2.25	2.85	3.15	3.38	3.43	3.39	3.42	3.12
18	2.95	2.54	2.49	2.47	2.19	1.93	1.96	2.36
19	2.8	2.74	3.27	3.26	3.25	3.2	3.07	3.08
20	3.2	3.18	2.98	3.03	2.88	2.79	2.81	2.98
21	3.35	3.03	2.9	2.57	2.62	2.48	2.42	2.77
22	2.75	2.77	2.7	2.62	2.6	2.69	2.68	2.69
23	2.8	2.9	2.82	2.64	2.61	2.53	2.47	2.68
24	2.3	2.79	3.08	3.2	3.36	3.38	3.39	3.07
25	2.8	3.23	3.31	3.2	3.36	3.48	3.41	3.26
26	1.85	2.31	2.47	2.44	2.37	2.53	2.63	2.37
27	2.65	2.23	1.9	2.03	1.92	1.66	1.51	1.99
28	2.8	2.51	2.49	2.41	2.27	2.27	2.13	2.41
29	1.37	2.23	2.37	2.14	2.15	2.23	2.18	2.10
30	1.8	2.41	2.17	1.94	1.85	1.68	1.79	1.95
31	2.15	2.62	2.93	2.95	2.87	2.86	2.8	2.74
32	1.9	2.1	2.15	2.23	2.15	2.07	2.01	2.09
33	3.2	3.46	3.07	3.08	2.95	2.77	2.7	3.03
34	1.6	1.38	1.22	1.17	1.29	1.34	1.34	1.33
35	2.3	2.18	2.28	2.32	2.32	2.37	2.36	2.30
36	2.4	2.95	2.85	2.61	2.43	2.19	2.25	2.53
37	2.1	1.92	2.07	2.03	1.93	1.92	2.05	2.00
38	3.05	2.97	2.92	2.83	2.64	2.47	2.43	2.76

Serial No.	GRADE POINT AVERAGE (GPA)							CGPA
	1ST	2ND	3RD	4TH	5TH	6TH	7TH	
39	2.85	3.41	3.54	3.53	3.73	3.86	3.83	3.54
40	2.65	2.77	2.77	2.55	2.42	2.4	2.3	2.55
41	2.75	2.62	2.59	2.63	2.24	2.16	2.13	2.45
42	2.75	2.56	2.57	2.53	2.49	2.48	2.33	2.53
43	1.5	1.59	2.23	2.33	2.49	2.42	2.45	2.14
44	3.7	3.49	3.47	3.23	3.15	3.03	2.98	3.29
45	3.45	3	2.86	2.77	2.55	2.42	2.36	2.77
46	3.2	3.13	2.97	2.7	2.76	2.72	2.71	2.88
47	2.1	2.46	2.15	2.12	2.08	1.93	1.91	2.11
48	3.9	3.85	4.05	4.1	4.15	4.15	4.03	4.03
49	2.6	2.38	2.41	2.23	2.18	2.06	1.96	2.26
50	3.1	3.18	3.25	3.22	3.22	3.1	3.03	3.16

Serial No.	GRADE POINT AVERAGE (GPA)(%)							CGPA (%)
	1ST	2ND	3RD	4TH	5TH	6TH	7TH	
1	39	42	46	47	48	49	67	48
2	45	45	48	47	49	50	52	48
3	52	57	64	62	66	67	69	62
4	48	49	50	49	46	47	42	47
5	47	45	48	47	53	54	56	50
6	41	39	38	38	40	39	37	39
7	44	44	38	34	32	31	32	36
8	47	46	52	53	50	53	53	51
9	45	52	52	46	45	43	41	47
1	35	48	50	47	50	52	53	48
11	45	43	46	43	43	47	48	45
12	47	54	57	55	57	52	54	54
13	45	55	60	63	63	65	67	60
14	43	48	48	46	43	40	41	44
15	44	48	49	49	47	45	45	47
16	42	39	47	46	49	53	56	47
17	45	57	63	68	69	68	68	62
18	59	51	50	49	44	39	39	47
19	56	55	65	65	65	64	61	62
20	64	64	60	61	58	56	56	60
21	67	61	58	51	52	50	48	55
22	55	55	54	52	52	54	54	54
23	56	58	56	53	52	51	49	54
24	46	56	62	64	67	68	68	61
25	56	65	66	64	67	70	68	65
26	37	46	49	49	47	51	53	47
27	53	45	38	41	38	33	30	40
28	56	50	50	48	45	45	43	48
29	27	45	47	43	43	45	44	42
30	36	48	43	39	37	34	36	39
31	43	52	59	59	57	57	56	55

Serial No.	GRADE POINT AVERAGE (GPA)(%)							CGPA (%)
	1ST	2ND	3RD	4TH	5TH	6TH	7TH	
32	38	42	43	45	43	41	40	42
33	64	69	61	62	59	55	54	61
34	32	28	24	23	26	27	27	27
35	46	44	46	46	46	47	47	46
36	48	59	57	52	49	44	45	51
37	42	38	41	41	39	38	41	40
38	61	59	58	57	53	49	49	55
39	57	68	71	71	75	77	77	71
40	53	55	55	51	48	48	46	51
41	55	52	52	53	45	43	43	49
42	55	51	51	51	50	50	47	51
43	30	32	45	47	50	48	49	43
44	74	70	69	65	63	61	60	66
45	69	60	57	55	51	48	47	55
46	64	63	59	54	55	54	54	58
47	42	49	43	42	42	39	38	42
48	78	77	81	82	83	83	81	81
49	52	48	48	45	44	41	39	45
50	62	64	65	64	64	62	61	63

Appendix B. *The mean of the various types of schools*

OBS	SEMESTER	MEAN OF GSS	MEAN OF PSS
1	1	52..5	47.2
2	2	54.5	49.3
3	3	54.8	50.9
4	4	53.3	50.2
5	5	53.2	49.3
6	6	52.6	48.6
7	7	52.9	48.5

Appendix C. *The mean of male and female students.*

OBS	SEMESTER	MEAN OF MALE	MEAN OF FEMALE
1	1	51	45
2	2	53	47
3	3	54	49
4	4	53	47
5	5	52	48
6	6	51	48
7	7	51	49

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