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Determinants of students' academic achievements in Ethiopia by multilevel analysis approach: The case of Wolaita Sodo University

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Abstract
Education is a very important human activity, through which every organizational, national and international development goals could be attained. This study is identify the determinants of academic achievement of second year regular students by multilevel approach with specific objectives to assesses students' academic achievement variations across departments; to investigate how covariates measured at the two levels affect the academic achievement of students and to compare multilevel linear regression model with single level linear regression model. Data were obtained from primary and secondary sources. A cross-sectional survey was conducted on a total of 260 students assigned in 18 departments from five colleges, using multistage stratified sampling technique. A designed questionnaire was used to obtain primary data. Factor analysis, multiple linear regression and multilevel linear regression were used to analyze the data. From the study, it was found out that multilevel modeling is better than the classical linear regression model in fitting the data and in explaining the variations of the academic achievement at different levels. The results revealed that there is high variation of academic achievement between students than between departments. The results also showed that the academic achievement of students was affected by factors: satisfaction in medium of instruction, instructor interest to teach, standard of lecturing and presenting, study hour and entrance results. Emotional in test, future goal related to education, perception to most subjects, sex, high school type, satisfaction in department administration, and absence of quizzes, tests and assignments were also found significant factors. Emotionality in test, high school type, and absence of quizzes, tests and assignments are negatively related with the achievement of students. Finally, we recommended, the university should set goals for giving training to strength student's motivation, self-concept, and language proficiency. Also, the facilities related to academics and non-academic factors should be accessed and improved may help to derive quality education.

Keywords: multilevel analysis, academic achievement, wolaita sodo University

1. Introduction

Education is a very important human activity. It is a key through which every organizational, national and international development goals could be attained. Academic achievement is an important factor in national education because it can be seen as an indicator of whether the education in a country is successful or not. [5] States that over the past couple of decades society has placed infinitely more emphasis on the academic achievement of its citizens. The academic achievement (CGPA) of students is an important indicator of academic success at university level. Students with higher levels of achievement at University are more likely to obtain good employment and salaries. University is an institution that is expected to produce high quality graduates that will become the workforce of the country in distant future. Higher education system now and then still in need of thorough research activities through academic performance in making sure the institutions can produce the best human capital [9]. Large numbers of students start university every year with different marks obtained at Grade 12, from different socio-economic and various school backgrounds. The management of the University transforms them through the process of teaching and learning and the students output is seen through their academic achievement [17]. Schools, Colleges and Universities have no worth without students. Students are most essential assets for any educational institute. 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 leaders and manpower for a country thus responsible for the country's economic and social development [1]. We measure the student academic performance through several ways like CGPA, GPA and test result. Most of researchers around the world used the GPA to measure the student performance [8, 2, 20]. They used GPA to measure student performance in a particular semester. Other researchers measure student performance through the result of particular subject or the previous year result [13, 21]. Academic performance can be influenced by many factors that occur inside and outside school. These factors may be termed as student factors, family factors, school factors and peer factors [4]. So, identifying and assessing key factors affecting achievement of students at student level and department level would be important to know the variation sources. Since different stake holders of the university are responsible to influence and solve the problems associated with them.

2. Methodology

2.1. Factor analDysis (FA)

In this study, factor analysis is used to identify the underlying factors or constructs or latent variables that may influence academic achievement of student from psychological factors. Factor analysis simultaneously examines multiple variables to determine if they reflect larger underlying dimensions. It is a method of quantitative multivariate analysis with the goal of representing the interrelationships among a set of continuously measured variables (usually represented by their inter correlations) by a number of underlying, linearly independent reference variables called factors. The essential purpose of factor analysis is to describe, if possible, the covariance relationships among many variables in terms of a few underlying, but unobservable, random quantities (factors).

2.1.1. The Orthogonal Factor Model

The factor model postulates that Z is linearly dependent upon a few unobservable random variables $F_1, F_2, \ldots, F_N$ called common factors, and p additional sources of variation $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_N$, called errors or specific factors. The factor model is given by

$$\mathbf{Z}_{px1} = \boldsymbol{\mu}_{p\times 1} + \mathbf{L}_{p\times m}\mathbf{F}_{m\times p} + \boldsymbol{\varepsilon}_{p\times 1} \cdots\cdots\cdots \quad (1)$$

Where L= (l_{ij}) is matrix of loadings of ith variable on jth factor for i=1….p and j=1….m. The orthogonal factor model (1) should satisfy the following conditions. $\boldsymbol{F}$ and $\boldsymbol{\varepsilon}$ are independent; E($\boldsymbol{F}$)= $\mathbf{0}$, $Cov(\boldsymbol{F})= \boldsymbol{I}$; E($\boldsymbol{\varepsilon}$)= $\mathbf{0}$, $Cov(\boldsymbol{\varepsilon})= \boldsymbol{\Psi}$, where $\boldsymbol{\Psi}$ is a diagonal matrix and $Cov(\boldsymbol{\varepsilon}, \boldsymbol{F}) = \mathbf{0}$

2.1.2. Estimation of Loadings

Given observations $x_1, x_2, \ldots, x_n$ on p generally correlated variables, factor analysis seeks to answer the question, does the factor model with the small number of factors, adequately represent the data? If the off diagonal elements of sample covariance S are small or those of the sample correlation matrix, R essentially zero, the variables are not related. This implies that a factor analysis will not prove useful and in these circumstances, the specific factor plays a dominant role. If covariance matrix appears to deviate significantly from a diagonal matrix, then a factor model can be entertained and the initial problem is one of estimating the factor loading L_{ij} and specific variance Ψ_i. There are two most popular methods of parameter estimation, the principal component method and the maximum likelihood method. The solution from either method can be rotated in order to simplify interpretation of factors. However, for this study, we considered the principal component method.

2.1.3. The Principal Component Method

The spectral decomposition of covariance Σ having eigenvalue-eigenvector pairs (λ_i, e_i) with $\lambda_1 > \ldots > \lambda_p > 0$ is given as follows:

$$\Sigma = \lambda_1 e_1 e_1{}' + \lambda_2 e_2 e_2{}' + \cdots + \lambda_p e_p e_p{}' \quad (2)$$

From above equation, we can obtain the loadings,

$$L = (\lambda_1 e_1, \lambda_2 e_2, \ldots, \lambda_p e_p) \quad (3)$$

2.1.4. The Contribution to the Total Sample Variances

In applying the principal component to perform factor analysis, we can use the sample covariance matrix (S) or the sample correlation matrix (ρ).

Observe that $S_{11} + S_{22} + \cdots + Spp$ = tr(S) trace of sample covariance matrix and $\lambda_1 + \lambda_2 \cdots + \lambda_p = p$ trace of sample correlation matrix (ρ), where, λ_i's, $i = 1, \ldots, p$, are the estimated Eigenvalues of S. The proportion of total sample variance due to the jth factor is given by, λ_j/ tr(S).

2.1.5. Factor Rotation Method

Factor rotation is an orthogonal transformation of the factor loadings, as well as the implied orthogonal transformation of the factors. If L is the p × m matrix of estimated factor loadings obtained by any method, then L*=LT, where,$TT' = T'T = I$, and I is the identity matrix which is a p×m matrix of "rotated" loadings. This shows that the estimated covariance (correlations) matrix remains unchanged.

2.2. Multiple Linear Regression Model

Regression analysis is a statistical technique for investigating and modeling the relationship between a continuous dependent variable and explanatory variable(s). The multiple linear regression model relating the response variable Y_i to several predictors has the form:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots\ldots + \beta_k X_{ki} + \varepsilon_i \quad i = 1, 2, \ldots, n. \quad (4)$$

In matrix notation, the above equation can be rewritten

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta}$$

$$\mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ . \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & . & . & x_{1k} \\ 1 & x_{21} & . & . & . \\ . & . & . & . & . \\ 1 & x_{n1} & . & . & x_{nk} \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ . \\ \beta_k \end{bmatrix}, \text{ and } \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ \varepsilon_n \end{bmatrix}$$

The parameters $\beta_0, \beta_1, \ldots \beta_k$, are called regression coefficients, ε_i is the residual term which provides for random variation in Y_i not explained by the x variables. This random variation may be due partly to other variables that affect Y_i but are not known or not observed.

2.2.1. Assumptions

- There exists a linear relationship between the dependent and the independent variables.
- Error terms are assumed to be distributed normally with mean zero and constant variance σ^2, i.e. $\varepsilon_i \sim N(0, \sigma^2)$

2.2.2 Parameter Estimation

The ordinary least square (OLS) estimator of the parametervector is given by:

$$\hat{\beta} = (X'X)^{-1} X'Y$$

2.3. Multilevel Linear Regression Model

The multilevel modeling was used to identify factors affecting achievements and to distinguish the variance in achievement uniquely at student and department levels. Multilevel linear regression model is applied in educatio nal research since many problems in education have multilevel characteristics i.e. students are nested within departments. Thus, it is used as a standard approach to handle such nested structure of educational data [11].

2.3.1 Model Specification

A multilevel linear regression model is a statistical expression enabling the study of simultaneous effects from students' level-one, and departments' level-two factors on academic achievement of students.

2.3.2. The Null Model

$$Y_{ij} = \beta_0 + U_{oj} + \varepsilon_{oij} \quad (5)$$

the index i indicating student, j indicating department, U_{oj} is level two error, ε_{oij} is level one error, β_0 is **i**nterpreted as the overall average of academic achievement and Y_{ij} is academic achievement of ith student in the jth department.

The null model is used for different purpose such as to decompose the total variance, to estimate the intra-class correlation (ICC) and to measure how much of the variation is explained by the model with no predictors included. The total variance is decomposed as the sum of the department-level and student-level variances:

$$Var(Y_{ij}) = Var(U_{oj}) + Var(\varepsilon_{oij}) = \sigma_u^2 + \sigma_\varepsilon^2 \quad (6)$$

The variances σ_u^2 and σ_ε^2 estimate the variation among schools and students, respectively. It is, therefore, possible to decompose the variance at two levels to assess how much of the variation is due to students themselves and how much is due to departments.

The interclass correlation (ICC) is given as follows:

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\varepsilon^2} = \frac{\sigma_u^2}{\sigma_Y^2} \quad (7)$$

2.3.3. The Random Intercept Model

$$Y_{ij} = \underbrace{\beta_o}_{\text{overallmean}} + \underbrace{\beta_1 X_{1ij} + \ldots + \beta_m X_{mij} + \varepsilon_{ij}}_{\text{studentlevel}} + \underbrace{\beta_{m+1} X_{m+1j} + \ldots + \beta_n X_{nj} + U_j}_{\text{departmentlevel}} \quad (8)$$

Where: Y_{ij} = is achievement of students,

ε_{ij} = is level one variance component,

U_j = is level two variance component,

m= number of student-level explanatory variables,

n-m= number of department-level explanatory variables

The proportions of variance explained by the final model at student level and department level, respectively, are:

$$R_1^2 = \frac{\sigma^2_{\varepsilon(null)} - \sigma^2_{\varepsilon(final)}}{\sigma^2_{\varepsilon(null)}}$$

$$R_2^2 = \frac{\sigma^2_{u(null)} - \sigma^2_{u(final)}}{\sigma^2_{u(null)}}$$

Where $\sigma^2_{(null)}$ and $\sigma^2_{(final)}$ are variances of null and final models, respectively.

The final model (the random coefficient model) is used to assess whether the slope of any of the explanatory variables has a significant variance component between the groups.

2.3.4. The Random Intercept and Slope Model

This model is obtained by extending the random intercept model. The effect of level 1 predictor may be different in different departments. In this case we add random slopes. We assume the clusters have varying intercepts and also slopes. For instance, with one level, one predictor X_{1ij}, the model looks like the following:

$$Y_{ij} = \underbrace{\beta_o}_{\text{overallmean}} + \underbrace{\beta_1 X_{1ij} + \ldots + \beta_m X_{mij} + \varepsilon_{ij}}_{\text{studentlevel}} + \underbrace{\beta_{m+1} X_{m+1j} + \ldots + \beta_n X_{nj} + U_j}_{\text{departmentlevel}} + \underbrace{U_{1j}}_{slope} X_{1ij}$$

Assumptions for the multilevel model are: There exists a linear relationship between the dependent and explanatory variables at each level; the random errors in different levels ε_{ij} and U_j are independent. i.e. $\mathrm{Cov}\ (\varepsilon_{ij}, U_j) = 0$; The random errors ε_{ij} 's are i.i.d. normally distributed with mean 0 and constant variance, σ_ε^2. i.e, $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$ and the random errors U_j 's are i.i.d. normally distributed with mean 0 and constant variance, σ_u^2. i.e. $U_j \sim N(0, \sigma_u^2)$

2.3.5 Methods of Parameter Estimation

The data consist of observations y_{ij} where j indicates the level-2 unit and i the level-1 observation within that unit. Typically, the level-2 units are a random sample but not the level-1 units (this means that to estimate the second level, we start by giving initial values for first level and then use it to estimate level 2 and iterate until convergence is obtained and finally, we may get final estimates for both levels]. Furthermore, if we model the structure using a mixed model then, y_{ij} are not the only random quantities to consider. The random effects $\mathbf{u}_j$ also have a distribution. Thus, the natural starting place in constructing the likelihood is with the joint density function $f(y, \mathbf{u}_j)$. From elementary probability theory we can write:

$$f(y_{ij}, \mathbf{u}_j) = g(y_{ij} \mid \mathbf{u}_j) h(\mathbf{u}_j) \quad (3.10)$$

Here, $g(y_{ij} | \mathbf{u}_j)$ is the distribution of the observed data assuming the values of the random effects are known. This will be the probability model we assume for our data at level 1. $h(\mathbf{u}_j)$, is the distribution of the random effects. Thus, the joint likelihood of our data and the random effects is given by the following:

$$L(\boldsymbol{\beta}, \boldsymbol{\sigma}^2, \boldsymbol{\tau} | y_{ij}, \mathbf{u}_j) = \prod_{j=1}^{m} f(y_{ij}, \mathbf{u}_j) = \prod_{j=1}^{m} g(y_{ij} | \mathbf{u}_j)\, h(\mathbf{u}_j)$$

The random effects are generally treated as nuisance parameters and by integrating those out we can obtain the marginal likelihood of our data.

$$\begin{aligned} L(\boldsymbol{\beta}, \boldsymbol{\sigma}^2, \boldsymbol{\tau} | y_{ij}) &= \int L(\boldsymbol{\beta}, \boldsymbol{\sigma}^2, \boldsymbol{\tau} | y_{ij}, \mathbf{u})\, d\mathbf{u} \\ &= \int \prod_{j=1}^{m} f(y_{ij}, \mathbf{u}_j)\, d\mathbf{u}_j \\ &= \prod_{j=1}^{m} \int f(y_{ij}, \mathbf{u}_j)\, d\mathbf{u}_j \\ &= \prod_{j=1}^{m} \int g(y_{ij} | \mathbf{u}_j)\, h(\mathbf{u}_j)\, d\mathbf{u}_j \end{aligned}$$

Given the vector of outcome variable, Y, matrix of explanatory variables at either levels X and the diagonal matrix $\mathrm{V} = \mathrm{E}[(\mathrm{Y} - \mathrm{X}\beta)(\mathrm{Y} - \mathrm{X}\beta)']$, the maximum likelihood based (Iterative generalized least square (IGLS)) method of estimation was used to estimate the parameters (Goldstein, 2003). We get,

$$\hat{\beta} = \left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Y$$

2.3.6 Model Diagnostics and Checking Assumptions Residual Plots

Multilevel linear regression analysis assumes normality and linearity, and inspection of the residuals can be used to examine the assumptions. Many different residual plots can be used [12]. The residual vector is given by:

$$\hat{p} = \left(I - X(X^{t} V^{-1} X)^{-1} X^{t}\right) Y = (I - H) Y, \qquad (3.11)$$

Where, H is the hat matrix, $\hat{p}$ is the residual**.**

2.3.7 Goodness of Fit of the Model

The likelihood ratio test statistic which is chi-squared based statistic is computed as *-2 log* L_1*-(-2 log* L_2*)* under the null hypothesis H_0 follows a chi-squared distribution on q degrees of freedom, where q is the difference in the number of parameters between the two nested models. Suppose $Model_1 = L_1$ is null model and $Model_2 = L_2$ is the final model. Then**,** $2 * \log(L_2/L_1) = 2 * (\log L_2 - \log L_1) \sim \chi^2_q$**,** Where, q = number of additional perimeters in $Model_2$, *- 2 log L* is the deviance and the higher the deviances value the poor the model fit.

3. Results and Discussion

3.1 Discussion of Results

This study was designed to identify some factors affecting the academic achievement of students in Wolaita Sodo University. The study used both primary and secondary data. Factor analysis, multiple linear regression and multilevel linear regression models were used to analyze the collected data. The results obtained are discussed below.

Most of the respondents are on the average age category of 20-22 years and 70% of them are males. The age category of the students is uniform. This indicates that there could be little variation regarding academic achievement of students. The demographic characteristic of the students are much identical in terms of age, region, and religion. This similarity may help to reduce the challenges of diversity in class for an instructor and may simplify the social life of the students. The academic background of the students indicated that 52% of the students had been joined the university with sore 350 and below but they have better knowledge in scholastic aptitude. The majority of the students were come from illiterate and high school level educated family with income source farming activities. But the descriptive statistics confirmed that these students perform higher mean academic achievement than others. In addition to this students perform better if they had been interested in their field of study, did not absent from class, not satisfied with medium of instruction, contact advisors sometimes, and not influenced by peer attitude towards education. Satisfaction to medium of instruction alone may not be able to achieve better academic achievement of students. Most students were satisfied the assessments or grading system of the current curriculum. The multiple linear regression analysis indicated that sex, high school type, study hour after class, entrance result, test anxiety (emotional), future goal related to education and self-concept (Positive perception to most academic subjects), instructors interest towards the course they had been teaching, student satisfaction by department administration, and absence of quizzes, tests and assignments were statistically significant determinant factors for students' academic achievement. The entrance result of students also found to be statistically significant effect on academic achievement of students. The result showed that students whose entrance score was high better perform than others. This result is consistent to a study conducted [10]. Students who come from rural and urban areas did not differ in terms of their academic achievement. Similar discussions were made by [22]. But students who attended high school education at private school did not score better academic achievements than government schools. This may be due to students lack some facilities provided to them at private schools. The result is consistent to a study on secondary school level (Grade 10) [7]. Different discussions were made by [18] with a study done on grade 8 students' academic achievements. He pointed out that private students achieve better than government students. Class size is not statistically significant with academic achievement of students. This may be due to the fact that all students learn in a large class size i.e. on average 57 students per class. This result is not consistent with a study conducted on student population growth in the colleges of sciences of higher learning institutes in Ethiopia: its effect on quality education [19]. A study on department administration refers to managing resources by attending teachers, supervising students on time and answer questions raised from students, checking implementation of their plan and strategies to achieve quality of education and it was found to be statistically significant with negative coefficient. Meaning that the higher student satisfaction on department administration the less the CGPA. This may be due to the effect of satisfaction on department administration may be dependent on other factors. Absence of quizzes, tests and assignments had statistically significant effect on academic achievements of second year students. Meaning the more the students take quizzes, tests and assignments the more they achieve. Test anxiety is negatively related with CGPA, which is consistent to a study [12, 3]. In this study, the multilevel linear regression model was better than multiple linear regression models. The analysis based on multilevel linear regression provided estimates for variances of the random effects and interclass correlations. The estimates for each level were different, suggesting that the variance composition of academic achievement was different at student and department levels. The estimate of the interclass correlation was small (merely less than 0.5) implying variation between department was smaller than variation within a department. This may be due to all the departments was taken from the same university and managed and coordinated by the university they were in. This result is inconsistent with previous study that variation of CGPA of commerce second year students was higher among departments [6] The multilevel linear regression model result also showed that the predictors: sex, high school type, study hour after class, student satisfaction on medium of instruction, entrance result, test anxiety, academic motivation and self-concept from student level, and instructors interest towards the course they have been teaching, student satisfaction by department administration and absence of quizzes, tests and assignments enable as to explain the variation of academic achievement of students among the department. A study conducted by [16] on TVET students is not consistent to this study that states English language proficiency is a significant factor affecting student performance. Different discussions were made by another study conducted by [14]. They 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.

Estimates for random intercept model adding fixed effect
1: random intercept model with level-1(student) predictor

Table 1

Fixed effects				
	Value	**Std. Error**	**t-value**	**p-value**
(Intercept)	1.5760	0.3182	4.9535	0.0000
Sex(male)	0.1535	0.0547	2.8084	0.0054
HST(private)	-0.1604	0.0817	-1.9623	0.0509
StHr	0.0613	0.0134	4.5783	0.0000
MedInst(medium)	-0.2541	0.1124	-2.2617	0.0246
MedInst(high)	-0.2013	0.1127	-1.7852	0.0755
Entrance	0.0037	0.0009	4.2802	0.0000
Perception(subject)	0.1020	0.0253	4.0298	0.0001
Anxiety(Emotiona)	-0.0740	0.0260	-2.8473	0.0048
Future goalnrelated	-0.0636	0.0259	-2.4548	0.0148

Approximate 95% confidence intervals

Random Effects 2

Table 2

Level: Department			
	lower	**est.**	**upper**
sd((Intercept for dept)	0.0510	0.1050	0.2160
Within-group standard error:	0.3369	0.3689	0.4039

X2=as.numeric (2*(logLik (mod2)-logLik (mod0)))

Estimates for random intercept model adding fixed effect at both levels
3: Final random intercept model

Table 3

Fixed effects				
	Value	**Std.Error**	**t-value**	**p-value**
(Intercept)	1.4255	0.3278	4.35065	0.0000
Sex (male)	0.1265	0.0533	2.373161	0.0185
HST (private)	-0.1925	0.0790	-2.437306	0.0156
StHr	0.0701	0.0129	5.446956	0.0000
MedInst (medium)	-0.2836	0.1107	-2.562722	0.0110
(high)	-0.2226	0.1102	-2.019125	0.0447

Entrance	0.0037	0.0008	4.567161	0.0000
Perception(subject)	0.0853	0.0251	3.400560	0.0008
Anxiety(emotional)	-0.0814	0.0251	-3.242323	0.0014
Future goal unrelated	-0.0538	0.0258	-2.088622	0.0379
DeptAdmin (medium)	-0.1323	0.0859	-1.540098	0.1249
(high)	-0.2019	0.0810	-2.490681	0.0135
LecPresents (medium)	0.1981	0.0850	2.329912	0.0207
(high)	0.2598	0.0894	2.905544	0.0040
TeachInterest (undecid)	0.2029	0.0795	2.550438	0.0114
(agree)	0.1557	0.0688	2.264713	0.0245
AbsenceQTA (undecid)	-0.1367	0.0654	-2.089189	0.0378
(agree)	-0.1667	0.0523	-3.184949	0.0017

Random Effects 4

Table 4

Level: Department			
	lower	**est.**	**upper**
sd((Intercept for dept))	0.0073	0.05075	0.3534
Within-group standard error:	0.3158	0.3458	0.3788

3.2. Conclusions and recommendations

Based on the results and discussions of study, we conclude as shown below.

- Since students' academic achievement or performance can be influenced by many factors related with student itself, family, institution and peer factors, there is no a single factor that affect students' academic achievement.
- The result revealed that variables like sex, high school type, study hour after class, entrance result, emotional in exam, future goal unrelated to education and positive perception to most academic subjects, instructors interest towards the course they have been teaching, student satisfaction by department administration, and absence of giving quizzes, tests and assignments were statistically significant factors that affect students' academic achievement.
- Test anxiety (emotionality), enjoy in learning new ideas, attending high school education at private school, satisfaction on department administration had negative effect on academic achievement of students.
- Satisfaction on medium of instruction, instructor's interest to teach, standard of lecturing and presenting, study hour and entrance result were found to be the most determinant factors of academic achievement of students.
- The result also revealed that the variation of academic achievement of second year students was similar among departments while there was heterogeneous among students.
- Even though facilities related to health, cafeteria, laboratory, electricity, library were not statistically significant with academic achievement of students, most students agree that they were not satisfied with this services.
- Finally, the multilevel linear regression model is better than the classical liner regression model to fit the data and explain the variations of the students' academic achievement with levels.

3.3 Recommendations

- The government and the concerned bodies like students, teachers, management of the university and policy makers need to work together to design and implement the policies in order to improve the academic achievement of students.
- The university should give training to strength self-concept, motivation, and study habit of the students.
- Instructors should assess their students by giving more assignments and tests by taking feedbacks and follow up their progress.
- Accessibility of leaning facilities to the students like ICT, computer lab, course materials and so on should be provided in order to run practical sessions effectively.
- The department should assign instructors to teach courses towards their interest.
- Further study should be done by considering different batches and universities to make comparison of the statistical models.
- Some issues listed in the literature review can be considered and the results could be improved.

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