Longitudinal Analysis of Performance of Ugandan Rural Advanced-Level Students in Physics Practicals

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ABSTRACT
Hybrid e-learning was applied in two typical rural girls' advanced-level secondary schools (Ediofe and Muni) in the rural district of Arua. The intervention was meant to support the learning and teaching of Physics and Mathematics. Multistage sampling was done to identify 19 participants from both schools in advanced-level Physics Practicals. As the project progressed, the students sat four repeated external examinations in May, June, July and September 2007. Individual growth models were used to analyse the performance data. The intraclass correlation was found to be 32% which meant that 68% of the variability in scores is attributable to within-person factors. The hybrid e-learning was found to contribute 64% of a student's scores, making it a very viable proposition for disadvantaged rural schools. These results were discussed in light of the Ugandan national policies on science education.

Keywords: Advanced -Level Physics; Gender; Longitudinal Data; Multilevel Analysis; Rural Secondary Education;

1.0 INTRODUCTION

In Lating (2009) a hybrid e-learning intervention project was implemented in two girls' secondary schools in the rural District of Arua in Uganda. This is a type of training where the main content delivery platform are the interactive multimedia CD-ROMs that are developed based on the local curriculum. The participating schools were Muni and Ediofe. The project aimed at improving performance of female students in Physics and Mathematics at advanced level examinations. A total of nineteen Physics students in both schools were identified through multistage sampling: 12 from Ediofe and 7 from Muni. Individual performances of the participants in Physics Practicals (Physics Paper 3) were repeatedly measured in May, June, July and September 2007. The repeated measures performance data recorded were nested and multilevel analysis methods were used to analyse such data. The methodology was used for answering the following research questions:

What effects would introducing hybrid e-learning in rural advanced-level secondary schools have on the performance of the students in external examinations? How much of the variations in students performance scores can be attributed to the within-individual and between-individuals factors? What are the effects of school-level characteristics on the scores of students that are nested within such schools?

2.0 METHOD

2.1 Data

Table 2.1 shows the data which are the repeated measures scores in the external examinations which the students sat for. The data collected were standardized from the original raw data given in percentages. Note that a score of "1" is the best mark and "9" is the poorest mark in the standardized grading system. Intervals between measurement occasions were not equal making the data unbalanced. Furthermore, data from Muni were incomplete since there were missing marks.

Table 2.1: Performance scores in the examinations

Student ID	School	Initial Status, May 2007	June 2007	July 2007	September 2007
1	Ediofe	8	7	2	5
2	Ediofe	4	6	4	6
3	Ediofe	7	7	9	6
4	Ediofe	5	5	7	4
5	Ediofe	9	9	9	6
6	Ediofe	9	1	5	4
7	Ediofe	9	3	5	4
8	Ediofe	9	9	4	5
9	Ediofe	6	4	3	5
10	Ediofe	9	6	1	7
11	Ediofe	3	5	7	5
12	Ediofe	5	6	6	6
13	Muni	4	1	4	
14	Muni	6	9	7	
15	Muni	9	2		
16	Muni	3	3	3	
17	Muni	1	2		
18	Muni	9	4	6	
19	Muni		5	7	

2.2 Model Specification

2.2.1 Level-1 Model: Within Individual Model

Let Y_{ij} represent score for student *i* at measurement occasion *j*. There were 19 students in the study (*i= 1, 2, 3… 19*) and four measurement occasions (j = 1, 2, 3, 4.). The general form of the level-1 model can be expressed as:

$$SCORE(Y_{ij}) = \pi_{0i} + \pi_{1i} * DURATION_{ij} + \varepsilon_{ij} \qquad (1)$$

where $\varepsilon_{ij} \sim iid\ N(0, \sigma_e^2)$ - residual errors of student *i* during measurement occasion *j* and ε_{ij} is the proportion of student *i*'s outcome that is unexplained on measurement occasion *j*.

π_{0i} - the student *i*'s true initial score (at baseline when time *DURATION =1*) or intercept.

π_{1i} -the rate of change of the student *i*'s score per unit time. This is the slope which shows the rate of improvement in scores.

$DURATION_{ij}$ - level-1 predictor variable showing the duration of the hybrid e-learning intervention for student *i* on measurement occasion *j*.

2.2.2 Level-2 Models: Between Individuals Models

The Level-2 models specify parameters of the Level-1 model and they help to explain differences in scores between students depending on their schools where they were nested. The *SCHOOL* of student *i* is added as a level 2 predictor variable.

Predictors of baseline (initial status) performance can be modelled as:

$$\pi_{oi} = \gamma_{00} + \gamma_{01} * SCHOOL_i + \varsigma_{0i} \quad (2)$$

Similarly, predictors of initial rate of change in scores can also be modeled as:

$$\pi_{1i} = \gamma_{10} + \gamma_{11} * SCHOOL_i + \varsigma_{1i} \quad (3)$$

where γ_{00} and γ_{10} are the Level-2 intercepts and γ_{00} is the population average initial status (baseline) and γ_{10} is the rate of change in scores for each of the schools.

γ_{01} and γ_{11} are the effects of school characteristics on the initial status and rate of change in achievement scores respectively.

Residuals ς_{0i} and ς_{1i} are deviations of individual change trajectories around the population averages, where $\begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \sim iid\ N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right)$.

Variances in coefficients usually reflect important individual differences in either rate of change in scores or they may show sensitivity to contextual factors. Residuals reflect individual differences which can be input as predictors for other analyses.

2.2.3 The Composite Model

Substituting the Level-2 equations in the Level-1 model, the final combined model becomes

$$SCORE\ (Y_{ij}) = (\gamma_{00} + \gamma_{01} * SCHOOL_i + \zeta_{0i}) + (\gamma_{10} + \gamma_{11} * SCHOOL_i + \zeta_{1i}) * DURATION_{ij} + \varepsilon_{ij} \quad \ldots(4)$$

After re-arranging we finally get the combined model:

$$SCORE(Y_{ij}) = [\gamma_{00} + \gamma_{01} * SCHOOL_i + \gamma_{10} * DURATION_{ij} + \gamma_{11} * DURATION_{ij} * SCHOOL_i] + \\ + [\zeta_{0i} + \zeta_{1i} * DURATION_{ij} + \varepsilon_{ij}] \ldots\ldots(5)$$

Level-2 regression coefficients do not vary across level-2 units (therefore, they have no subscripts). They are referred to as *fixed effects*.

Similarly, level-1 regression coefficients can vary across level 2 units, these effects are called *random effects* (hence the terminology *random coefficients models*). The composite model has two parts:

(a) the fixed, deterministic or systematic portion;

$[\gamma_{00} + \gamma_{01} * SCHOOL_i + \gamma_{10} * DURATION_{ij} + \gamma_{11} * DURATION_{ij} * SCHOOL_i]$ (b) and the random error or stochastic part;

$[\zeta_{0i} + \zeta_{1i} * DURATION_{ij} + \varepsilon_{ij}]$.

3.0 RESULTS OF MODEL FITTING

To help understand the complex variabilities in the repeated measures data collected, three models were fitted: the unconditional means model (Model A) with no predictors at either level; the unconditional growth model (Model B) with DURATION of hybrid e-learning as the only predictor at level-1; and the composite model (Model C) with DURATION as level-1 predictor and SCHOOL as level-2 predictor. The results of fitting the three models are shown in tables 2. Ms Excel was used for most of the calculations.

3.1 The Unconditional Means Models -Model A

This is a model without any predictors. It is a null or empty model. The unconditional means model was used to determine the Intraclass correlation (ICC) using the equation

$$ICC = \rho = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_e^2} = \frac{Intercept\ Variance}{Intercept\ Variance + Residual\ Variance} \quad \text{........(6)}$$

$$= \frac{Between\ Variance}{Between\ Variance + Within\ Variance}$$

In this case, the overall ICC equalled $\frac{2.59}{2.59 + 5.45} = \frac{2.59}{8.04} = 0.3221$

ICC shows the proportion of variance that is between-persons. It also shows the average correlation among observations from the same person.

3.2 Unconditional Growth Models (with DURATION of Intervention as Predictor of Level-1 Models) –Model B

The unconditional growth models were used to obtain two psudo-R^2 statistics which showed the proportional reduction of the level-1 variance component when moving from the unconditional means model (Model A) to the unconditional growth model (model B). The statistic was a measure of the effect of the duration of the hybrid e-learning on the student's scores is given in equation (7).

$$\begin{aligned} R_s^2 &= \begin{pmatrix} Proportional\ reduction\ in \\ Level-1\ variance\ component \end{pmatrix} \\ &= \left(\frac{\sigma^2_{e,unconditional\ growth\ model} - \sigma^2_{e,unconditional\ means\ model}}{\sigma^2_{e,unconditional\ growth\ model}} \right) \quad \text{..........................(7)} \\ &= \left(\frac{5.45 - 1.971}{5.45} \right) \\ &= 0.638 \end{aligned}$$

3.3 The Composite Models with Level 2 Predictors, SCHOOL and Level-1 Predictor, DURATION, (Model C)

The composite model was used for studying the effects of the school characteristics on scores of students. For Ediofe, the initial status γ_{00} was 7.13 and slope γ_{10} of -0.551. For Muni, the initial status γ_{00} was 4.75 and a slope γ_{10} of 0.035. The difference in the initial status γ_{01} of the two schools was -2.37 while the difference in slopes γ_{11} was 0.586. Substituting the values of and in the level-1 equation

$$SCORE(Y_{ij}) = \pi_{0i} + \pi_{1i} DURATION_{ij}$$
$$SCORE(Y_{ij}) = 4.75 + 0.035 * DURATION_{ij}, \text{ for Muni} \qquad (8)$$
$$SCORE(Y_{ij}) = 7.13 - 0.551 * DURATION_{ij}, \text{ for Ediofe}$$

Performance trajectories of the two schools and the combined performance trajectory for both schools are depicted in the Fig. 3.1

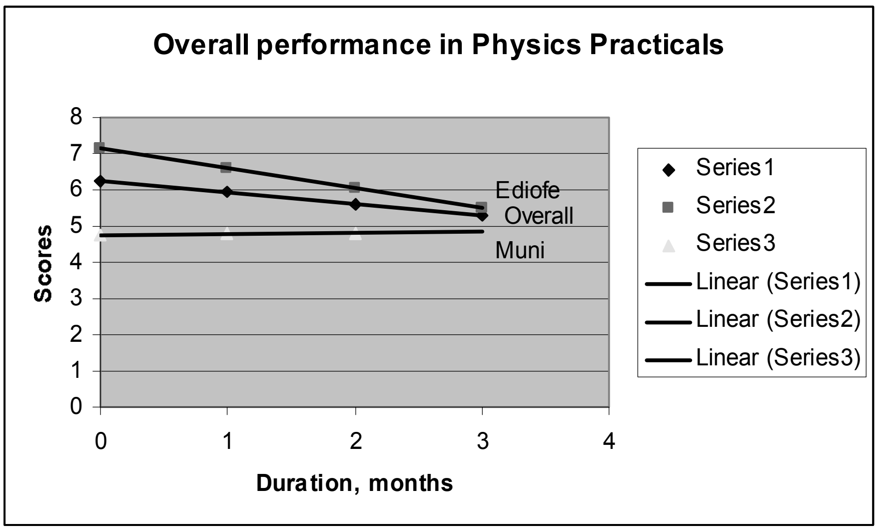

Figure 3.1: Trajectories of Performance in Physics Practical Examinations by Muni and Ediofe

4.0 DISCUSSION

In quantitative social science research, it is common to collect hierarchical, nested or clustered data. Furthermore, the data collected may not be balanced or complete due to missing measurements. Problems with ignoring hierarchical structure of data were well understood (Robinson, 1950;Burstein, 1976), but until recently, they were difficult to solve. Raudenbush first coined the term 'Hierarchical Linear Modelling'(HLM) to describe an efficient statistical procedure for the analysis of nested or clustered data. This methodology war first used in studying school effects by Raudenbush and Bryk (1986). In Statistics, HLM is also known as Multilevel Analysis. Snijders and Bosker (1999) describe multilevel analysis as 'a methodology for the analysis of data with complex patterns of variability with a focus on nested sources of variability'.

The simplest multilevel model is the longitudinal data. It is data that result from repeated measurements on the same subject or unit. Singer and Willett (2003) proposed the 'individual growth modelling' as a means of analysing change with increasing duration of an intervention. The procedure starts by fitting the fully unconditional means model (Model A), the conditional growth model (Model B) before fitting the fully conditional growth model (Model C). Method proposed by Bryk and Raudenbush (1987) is also suitable for modelling change.

In this study, ICC was estimated to be 0.3221. This means that 32.21% of the total variation in students' scores was attributable to differences between students. This finding serves to indicate that there was correlation among the repeated measures data which are also dependent. If the data were independent, ICC would be zero. Secondly, the finding also helped to confirm that the use of multilevel or hierarchical modelling approach was the most appropriate as compared to the traditional regression approaches. Mutlilevel models recognize the existence of nested or correlated data hierarchies by allowing for residual components at each level of the hierarchy. It is the unobserved variables which lead to correlation between outcomes of students from the same school. The low intraclass correlation (about 32%) indicates that there was more variability within students (68%) than between them. Therefore, it makes much more sense to focus the research intervention in rural schools on the students themselves. The student-level characteristics (like socio-economic status) are more severe and affect their outcomes. Effective intervention at the level of the student is more viable than support given at the school level.

The unconditional growth model (Model B) has the predictor variable at the level-1, *DURATION* of the intervention was added to the model. It was found that 63.8% of the within-person variation in scores was associated with linear time, *DURATION* of the intervention. This particular finding has a policy dimension. It is quite interesting that e-learning succeeds in a country that does not have a policy on e-learning in schools. Government should consider formulating e-learning policy for schools since it is beneficial. Uganda government has made science compulsory in all secondary schools in Uganda. Yet neither the government nor the schools have that money to invest in science infrastructure and personnel. In such situations, hybrid e-learning would be the right approach to take. Experiments could be simulated and students could do experiments virtually the way it was done in this project.

After fitting the fully conditional Model C, the estimated initial average performance of all the participants was 6.24 and the average for Muni was 4.74 while that of Ediofe was 7.13 giving an average difference in performance at the beginning of 2.39. Muni students performed well throughout even if they had problems of discipline with the school administration and their teachers were constantly being changed. Despite studying under complex situation in Muni, the students continuously performed better than Ediofe. Ediofe was a slow starter but did not manage to catch up with Muni. This is shown by the results of the analysis. The within person variability in Muni was only 1.078 as opposed to Ediofe's 2.336. It can be explained that Muni girls expected no support from their teachers and the school. They fully took advantage of the hybrid e-learning tools and applications. They formed themselves into effective study groups. The students of Ediofe were selfish and did not share ideas among themselves. They were not willing to do more since they were used to being spoon-fed by their teachers and the school leadership.

The findings of this study should be explained in terms of some policies of the Ugandan government. In situations where the government has made science education compulsory but has limited budget for building physical laboratories and providing enough qualified teachers, hybrid e-learning could be adopted to fill the gap. If female students are targeted, more will pass national examinations. This will enable them to join universities and other tertiary institutions. The end result will be that Uganda will achieve Millennium Development Goal No. 3: promote gender equality and empower women. This project has helped to rekindle hope and belief that rural female students can also pass external examinations.

5.0 CONCLUSIONS

After five months of using the hybrid e-learning tools, the female students were able to perform well at external examinations. For both schools average performance improved from 6.4 to 5.3 in four months.

Hybrid e-learning accounted for approximately 64% of the scores of a student. The implication is that the intervention alone is enough for a student to pass well enough at external examinations. Therefore, hybrid e-learning is quite suitable for financially constrained rural schools that lack functional science laboratories, libraries and qualified teachers.

After partitioning the sources of variability in scores, it was found that within-student factors were more prominent and account for 68% of the variabilities in scores. This means that for rural students, it is better to focus any interventions on the female student. There is need to address their socio-economic condition. Intervening at the school level will be counter productive.

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Geoid Determination In Uganda: Current Status

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ABSTRACT
Many professionals e.g. surveyors, engineers and GIS specialists are increasingly using Global Positioning System (GPS) or some other Global Navigation Satellite Systems (GNSS) for positioning and navigation. One of the greatest advantages of GPS is its ability to provide three-dimensional coordinates (latitude, longitude and height) anywhere in the world, any time irrespective of the weather. The GPS latitude and longitude can easily be transformed from the WGS84 reference system to a local reference (e.g. Arc 1960). However the GPS-determined heights, i.e. ellipsoidal heights, are geometrical heights which have no physical meaning and therefore cannot be used in surveying and engineering projects. Their conversion to more meaningful orthometric heights require knowledge of the geoidal undulations, which can be determined from high resolution geoid models. Its absence in Uganda means that the full potential of GPS cannot be fully realized. This paper gives an overview of the need for an accurate geoid model in Uganda, the current status of the geodetic network in Uganda and different methods of geoid determination. Pending further investigation, preliminary findings indicate that in Uganda, the EGM2008 is the best geoid modal for GPS/leveling projects.

Keywords: Geoid model; Global Positioning System; orthometric heights.

1.0 INTRODUCTION

The geoid is an equipotential surface, i.e. a level surface to which the direction of gravity is perpendicular. By definition, the geoid corresponds to the surface that approximates Mean Sea Level (MSL) globally (Veronneau *et al.*, 2006). However, MSL is not an equilibrium surface in the earth's gravity field due to ocean currents and other quasi-stationary effects. The Permanent Sea Surface Topography (SST) - the difference between the geoid and the actual MSL ranges globally from -1.8 m to +1.2 m (Veronneau *et al.*, 2006). Consequently, at the 'cm' accuracy level, a regional geoid model is defined as the level surface which optimally fits MSL at a selected set of tide gauges used for defining the vertical datum of a national or continental height system (Torge, 2001).

The geoid is the reference surface for orthometric heights. Orthometric heights are traditionally determined using spirit leveling techniques. This is a very expensive and tedious venture especially when one considers that for a country like Uganda the reference tide gauge is located 1,800km away at Mombasa port in Kenya. This makes height determination using GPS a very attractive alternative. However, the GPS derived heights are ellipsoidal heights whose reference surface is the WGS84 ellipsoid and not the geoid. The ellipsoidal heights can nonetheless be transformed into orthometric heights using the simple geometrical relationship:

$$h = H + N \qquad (1)$$