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Attributable Factors to Learning Outcomes

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Abstract

Kenya education system has experienced many challenges which have compelled the Ministry of Education to formulate and implement policies to address these challenges. For instance, after new policies governing administration and marking of national examination was implemented, massive failures of candidates was reported.

The study uses final examination(KCSE score) to analyse how student attributes(age and gender), KCPE marks(entry behaviour), gender and category of school influences students ability to score C+ and above in KCSE. Also termly score of the students was followed to ascertain at what stage does these predictor variables affects learners most.

Data were from Limuru subcounty, Kiambu county, in Kenya. A sample data of 2015 cohorts were collected for the four years up to form four. Two sample t-test,logistic regression and multilevel linear model were used to examine data. Analysis of the data was done using SPSS, R and gretl softwares.

Some of the major findings were;first, factors affecting learning outcomes in Limuru subcounty were:KCPE marks(entry behavior), age and gender of the learners. Secondly, it is during the seventh term (term 1 form 3), tenth term and eleventh terms (corresponding to first and second terms in form four respectively) that performance of students declined most. Students are at the greatest risk to perform poorly during first term in form one and first term of form three. Lastly, form two and three averages have great relationship with the KCSE score of a learner.

Recommendation of this study include the following;since KCPE marks (entry behavior) was a major factor identified that determine the learning outcome, there is need to carry out similar study in primary level to address the challenge of poor academic achievement at an early stage. Also, learners performance should be followed closely monitored right from form one since they contribute to the final score of the learner in KCSE.

Declaration and Approval

I the undersigned declare that this dissertation is my original work and to the best of my knowledge, it has not been submitted in support of an award of a degree in any other university or institution of learning.

Signature

Date

JOHN MWANGI KAMAU

Reg No. I56/8158/2017

In my capacity as a supervisor of the candidate's dissertation, I certify that this dissertation has my approval for submission.

Signature

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Dedication

I dedicate this work to my beloved parents, Simon Kamau Mwaura and Mary Njoki Kamau and my siblings who prayed and supported me in many ways. Also I dedicate it to my workmates who advised me in various aspects of this project.

Acronyms and Abbreviations

KCPE-Kenya Certificate of Primary Education

KCSE-Kenya Certificate of Secondary Education

CEE-Common Entrance Examination

KAPE-Kenya African Preliminary Examination

SES-Social Economic Status

ICC-Intra-class Correlation Coefficient

MLM-Multilevel Linear Model

ANOVA-Analysis Of Variance

CAT-Continuous Assessment Tests

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John Mwangi Kamau

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1 Introduction

The aim of education have been always viewed more broadly that imparting of certain basic elements of knowledge and skills to youths. Indeed the fact that governments have become heavily involved in the financing and organization of education is an implicit recognition of the nature of education as public good, which contributes to individual well-being but also to the creation of national identity, to participation in democratic institutions and processes, and to national economic development. Although these are underlying objectives of education systems, the extent to which governments are successful in attaining them cannot always be assessed within the confines of education systems themselves.

Kenya has placed considerable importance in the role of education in promoting economic, political and social development since independence. Education provides the youth with opportunities to acquire knowledge and skills necessary to advance themselves and nation economically. Tinto (2005) points out that a nation that values and promotes the educational attainment of its citizens is a nation that is concerned with its ability to compete in the global economy. Secondary education plays a key role in providing the youths with opportunities to acquire human capital that will enable them to pursue higher education and to improve their skills leading to higher labour market productivity.

Development of education in Kenya has been marked by various challenges. These challenges include enrollment, access, retention, equity and relevance in education. The government of Kenya introduced free primary education after independence and this led to high demand of education. Student enrollment in primary and secondary schools increased from 900,000 and 30,000 in 1963 to 7.4 million and 926, 149 in 2004, respectively [Government of Kenya (2009)]. Even though access and enrollment has increased, high wastage and declining completion rates, low survival levels from primary to university and low female enrollment in science and technical courses has posed a challenge in the country (MoE, 2009). From the year 2003 to 2013, 200,000 young Kenyans have been pushed out of the education system and terminated their learning at primary school level.

In the last decade, the Kenya Government has embarked on expanding access to primary and secondary education through free primary and free day secondary education programs. According to UNESCO (2015), the number of children enrolled in both primary and secondary schools has increased significantly. This can be attributed to lowering of the cost education through government subsidies such as free primary education and free secondary education programs in 2003 and 2008 respectively (Gura, 2015). The Republic of

Kenya Constitution (2010) decries that basic education includes secondary education and is a fundamental human right of every Kenyan child. It is therefore critical to improve on access and quality of basic education in Kenya. More important of any education system is to measure the quality of graduates produced at the end of the system.

Education outcomes are measured through examinations which have been accepted as an important aspect of the educational system. Examinations have always been used as the main basis for judging a student's ability and also as means of selection for educational advancement and employment. However, a lot of students do not perform well in national examinations in many countries around the world, Kenya included. The poor performance has raised concern and efforts have been made to find out the reasons behind it. For poor performance of students in schools, many factors such as lack of facilities in school, lack of teachers, student indiscipline, unfavorable home environment, low intelligence, anxiety and students' need to achieve have been found as being some of the causes (Cantu, 1975; Maundu, 1980; and Ndirangu, 2007).

This study was carried out in Limuru sub-county of Kiambu county where statistics from the Limuru sub-county education office (2018) showed that; while some schools in this sub-county consistently performed well in KCSE examinations, others continued to perform poorly. What is not clear are the factors that have enabled a few schools to perform well while the majority keep performing poorly in KCSE.

The first data analyses were descriptive to ascertain the characteristics of the sample. Sample sizes of 2015 cohorts in Limuru subcounty, means, standard deviations and ranges were calculated. Differences between those who performed well and the school they studied from were examined as well as those differences among the covariates. Relationships and associations among demographic and achievement variables were reported.

The independent/predictor variables were selected in a more heuristic method from those available at the school. Several statistical models were used analysis of data. they include: two sample t-test, logistic regression model and multilevel model.

Multilevel growth model was conducted using longitudinal data on a cohort of 2015 students in form 1 in 2015 and followed for 4 years to 2018. The aim was to study academic progression of the students performance for the four years accounting for nesting of data within individual student.

After major reforms in the administration and marking of exams, which to large extend have eliminated leakage and earlier exposure to exams, there has been growing concern about the massive failure by students. In the 2017 exams, for instance, only 70,073 or 11.5 per cent of the 611,952 students, who sat the KCSE exams obtained at least C+, the minimum university entry grade. Worse still, 57.3 per cent of the students who registered

for the exams will not even qualify for diploma courses after 135,550 obtained grade D (plain), 179,381 scored D- (minus) while 35,586 were awarded grade E (total failure).

In 2018, the situation did not improve either, of the 651,540 candidates who sat for KCSE examination, only 90,377 scored C+ and above corresponding to 13.77% . Those who scored D- were 165,139 and E were 30840. This implies that 80.23% of the students will not secure direct entry to university.(source; KNEC report for 2017 and 2018)

A country that targets to become industrialized by 2030 need to take drastic measures to address this concern. A lot of research need to be undertaken to find out what is the major contributors to this outcome. This research endeavors to kick start the process of analyzing and suggesting remedial measures.

1.1 Statement of the Problem

The goal of any government in providing education to its citizens is that learners will go through all levels of education and come out of the system well refined to take up various activities that leads to economic development of the country. However, from the results of the national examinations, poor results observed limits many students from proceeding to tertiary level since hardly half of them obtain pre-requisite grade for their enrollment to tertiary level. In response to this problem, this study seeks to find out what major contributors to these massive failure are and how in future they can be mitigated.

1.2 Objectives of the Study

To investigate the relationship between the students attributes, category of school and their learning outcome in Limuru sub-county.

1.2.1 Specific objectives

- (i) To analyse difference in performance between categories of school and gender
- (ii) To establish the relationship between the student attributes(age and gender), prior achievement(KCPE marks), category of school and learning outcome.
- (iii) To establish whether school level scores impact on student level scores.

1.3 Research Questions

In order to undertake this study, the following questions were formulated:

- (i) Is there a difference performance between categories of school, gender.
- (ii) Does the student attributes, prior achievement and category of school influence the academic achievement of student?
- (iii) Do school level scores impact on student level scores?

1.4 Significance of the Study

The significance of this research finding will help government and ministry of education to device ways of improving the learning outcomes in the secondary level which of recent have been the main concern for all education stakeholders.

1.5 Limitations of the study

This study focused only on one Sub County and one more school in another sub county. Since in the country and county there are many schools and different area have unique challenges, this study many not be able to reflect what may be happening in different parts of the country.

There are several other limitations of this study which follow. First, due to different assessment schedules of the schools, some school usually have many exams during the term while other schools have less exams and CATs.

Secondly, the variables examined are those which were available for academic performance purposes. There are many other variables which were supposed to be included in the study, but due to limited resources, time and unavailability of these records they were excluded from the study. Moreover, since the study was mainly on past record, obtaining further information from the participant through interview could not be possible because it could have been toll order to locate them for the same.

Lastly, since data collection and data entry involve many people, human error is likely somewhere along the process. Therefore, unless one collects and enters all data personally, which would not automatically eliminate all errors, data quality may itself be a limitation.

1.6 Definition of Terms

- Learning Outcomes-What students will know and be able to do as a result of engaging in the learning process. Learning outcomes represent statements of achievement expressed from the learner's perspective. Learning outcome is gauged by student academic performance.

- Cohort-Cohort refers to students from the sample population who fit the study criteria. These are students who joined from one at the same time (beginning of the year 2015)
- Public school- A public school refers to an educational institution which is operated and controlled by state and local government (Johnson, Dupuis, Musial, Hall, & Gollnick, 1999).
- Time-dependent covariates - Time varying explanatory variables that may change in value over the course of observation.
- Multilevel linear modeling (MLM) is an ordinary least square (OLS) based analysis that takes the hierarchical structure of the data into account.
- Linearity: relationship between variables is straight line

2 Literature Review

A lot of research have been carried out to determine factors that influence learning outcomes. Of diverse factors used to determine academic achievement, the most relevant are: prior achievement (KCPE score), gender, rank of the school (national or not national), discipline record of the student, school attended (day or boarding), location of the school (urban or rural), social economic status of the parent and education level of the parent.

Educational research has shown prior achievement is the best predictor of future achievement (Goberna, Lopez & Pastor, 1987; House, Hurst & Keely, 1996; Mathiasen, 1984; Mekenzie & Schweitzer 2001; Wilson & Hardgrave, 1995; Zeezers, 2004). The origins of prior knowledge as a theoretical framework can be sourced in the work of Bloom in the 1970's (Bloom, 1976) who was interested in the extent that human characteristics such as intelligence and motivation could be influenced by experience (Bloom, 1964; Education-Encyclopedia, 2009). Glaser and De Corte in Dochy (Dochy, 1992; Dochy et al., 2002), observed that new learning is exceedingly difficult when prior informal as well as formal knowledge is not used as a springboard for future learning. They further noted that, in contrast to the traditional measures of aptitude, the assessment of prior knowledge and skill is not only a much more precise predictor of learning, but provides in addition a more useful basis for instruction and guidance. In addition they found out that even though students with inaccurate prior knowledge may be at a disadvantage, they still have the advantage over students with no prior knowledge as the latter group do not have relevant knowledge frameworks to validate and structure new information (Dochy et al., 1999). Students with prior knowledge were found to be more adept and discerning when note-taking in lectures (Etta-AkinAina, 1988). Thompson & Zamboanga (2004), demonstrated that prior knowledge was sole predictor of performance. Hailikari et al. (2008), asserted that prior knowledge predicted performance over all other variables (55%); academic self-beliefs had a strong influence on prior knowledge. Hailikari & LindblomYlanne (2007), through regression analysis, demonstrated that procedural and not declarative prior knowledge has influence on performance. Addison & Hutcheson (2001), found out that lack of prior knowledge made students ability to access new material difficult, inaccurate prior knowledge hindered learning process.

The study of the effect of gender on achievement has produced contradictory results. Some works suggest the existence of differential achievement due to differences in male's and female's learning styles (Lundeberg & Diemart, 1995; Martienez, 1997). In contrast, Clifton, Perry, Adams and Roberts(2004) found that grades were not associated with gender. Van den Berg and Hofman(2005) found that in the masters stage, females performed slightly

than male counterpart but in technical courses, male were performing better. Different countries have different level of access to education by a particular gender. Women in most cases are at a disadvantage position. Their education level is lower and experience less training opportunities. Muller (1990) noted that "More boys than girls particularly in poor economies of Africa, Kenya included, continue to go to school and work their way up the economic ladder". Families that are poor prefer to take boys than girls to school arguing that returns on boys is higher than in girls. That is, the boys once they are through with their studies, they fend for parents and their nuclear families but girls are married off to other families.

In analysis of effect of social economic status on schooling of children, Kombo(2005) established that families well off economically are able to educate their children early enabling them to complete schooling early than the rest and secure job opportunities earlier. These children have high completion rate compared to those from poor families whose drop out rates are high, since their parents are able to provide learning resources ranging from books to uniform and school fees. High drop out rate from families in low economic status is due to early marriages and looking for employment to cater for basic needs. Most of the experts argue that the low socioeconomic status has negative effect on the academic performance of students since their basic needs of students are not met affecting their concentration in schools. Adams (1996) and Sirin 2005 observed a positive relationship between social economic status (SES) of parents or guardians and their children performance in schools. According to them, children from low social economic status families have relatively low academic achievements and attainment. Also they argued that there is positive relationship between academic success of children and social economic status of parents. According to these authors, children from low socio-economic status families achieve dismally academically. Their schooling is characterized by high dropping rates than their counter-parts from well to do families.

Parents education level can motivate their children to learn. Parents who are educated are usually provides learning resources and right advice for their children academically. Parents achievements makes them role models to their children (Kombo, 2005). Literate parents are highly involved in academic activities of children both in school and at home. Bandura 1986,observed that children learn their behaviour partly by observing and by direct learning. Therefore educated parents are role model that their children can emulate to perform academically. A child from educated family aspire to be like parents which deter them from dropping out but work hard. Alok et al (2013), through a study found out that illiterate parents discourage their children from performing academically. They even refuse to provide to their children learning resources and paying their school fees. According to David (2007), provision of text books aids students from these illiterate families to study on their own since they lack of assistance from ignorant parents.

A lot of studies have been done to ascertain the effect of age on the academic achievement of learners. A study by Rumberger (1995), found that late entrance and repetition do not exert negative effects on academic performance. He found that older students performed better than those who go to school at an early age. The study also showed that those students who have an opportunity to repeat some grades perform better at secondary school level and that late entrance and repetition improved academic performance especially among older students. Piaget (1970), suggests that older children might enjoy an advantage over younger peers because they have a higher likelihood of progressing to a further stage of development. This viewpoint would assure that older children are more ready to take advantage of typical classroom instruction. Another study by Clark and Ramsay (1990), observed a negative relationship between age and academic attainment. Hedges (1978), found out that children who start schooling early achieve less than their counter-part who start later. He concluded that "earlier is not always better". Langer et al (1984), Trapp (1995) and Parks (1996) established a positive relationship between delayed schooling and improved academic attainment. Meta-analysis of comparison between of age and academic achievement done by La Paro and Pianta in 2000 established that older students performed better academically than younger students. Wood et al (1984) stated, "chronological age of children entering kindergarten within the range of 4 to 6 years, is unrelated to eventual success or failure". DeMeis and Stearns (1992) found no significant relationship between age of a learner and academic attainment. In another study in 1995, he studied oldest students delayed by parents to start school intentionally and failed to obtain difference between their performance and younger students. Effect of age on academic achievement have produced conflicting results. There is a general agreement that delaying or early entry to school of learners adds no value in academic achievement of learners and therefore they should start schooling at the right time.

In Kenya, secondary schools have been categorized into national, extra-county, county and district school. The rationale behind using these differentiating mechanisms is to homogenize the student population so that its educational needs can be met more effectively. But there is some concern that this stratification may work against the student achieving their academic potential. More so socio-economically disadvantaged students tend to join lower ranked schools due to lack of fees, since most national schools and extra-county schools charge high fees. The study of the effect of rank of school on academic achievement of learners is key. (Oakes, 2005)

Researchers, through various studies, agree on importance of discipline since for an organization to realize its goals, then players in the organization should observe high level of discipline which is a moral obligation (Ouma et al 2013). For schools, students who are discipline are the one who act and behave in conformity to rules and regulations set up by the institution (Ali et al 2014). Discipline should extend beyond observing rule and regulations but doing what is right at any given time (Gitome et al 2013). Conducive learning environment can only by students who are discipline (Masista, 2008). Njoroge and

Nyabuto(2014) observed in their study that discipline is paramount to realize academic achievement by individual or institution. Managing school can be easy if all students are well behaved and discipline enabling the institution realize its goal which is academic achievement(Nakodi 2010). Therefore if there is lack of discipline then the learners are indisciplined. Indiscipline manifest in various form like disobedience, destroying properties and other anti-social behaviours like stealing and rudeness.

Grades are universally recognized as indicators of academic achievement in educational systems (Goberna et al.,1987). Examination according to many may be viewed as a punitive way of measuring learning outcome but overtime it is a tool that by far can provide objective grading and selection of those to advance to the next level. History of examination in Kenya can be trace right from colonial era. Examinations were used by the colonial rule to deny Africans formal education. The examination known as the Common Entrance Examination (CEE) was administered at the end of the fourth year of primary school and the Kenya African Preliminary Examinations (KAPE), for those who wished to join secondary school. These examinations were very successful in eliminating and restricting Africa from attaining education. Very few, one or two students passed these examinations and qualified to proceed to the next level. Performance by African candidates in other examinations such as the secondary school examination was not better discouraging many from continuing withit (Mwiria,1991).The performance in KCSE examinations in the majority of the sub-counties in Kenya has not been very good safe for a few schools in the Nairobi area and a number of others in some urban centres. One of the aims of education is to help students acquire knowledge, skills and attitudes which will enable them to lead successful and productive lives. Examinations help assess to what extent these skills, knowledge and attitudes have been achieved.

When data are nested (e.g., students nested within schools) and the effect of predictor variables on a given outcome depend on that nesting, it is important that the nesting be factored in the model to avoid misrepresenting effects. Students nested within a school are more similar to each other than they are different and the observed effect of predictor variables may then depend, in part, upon their membership to a specific school. In nesting, residuals of students within the school are correlated – violating the independence of observations assumption of single-level regression (Raudenbush & Bryk, 2002). Roberts (2004) showed that, not accounting for nested structures may potentially have dramatic effects and can even reverse the fundamental findings of the study. If nesting of data structures is not accounted for, then aggregation bias, misestimated standard errors, and heterogeneity of regression will occur(Raudenbush & Bryk, 2002). Aggregation bias is when a variable have different meaning in its aggregated form than it does in its disaggregated form. Misestimated standard errors occur when we do not account for the dependence upon the higher-level units that is when the independence of observations assumption is violated. MLM corrects the estimation by including the higher-level units in the model so that observations within a unit are independent. Heterogeneity of regressions

occurs when the relation between a predictor variable and a specific outcome vary by some higher-level unit. Standard single-level regression would ignore this heterogeneity and assume the relation is constant across schools, while MLM can explicitly test and account for the heterogeneous relationships.

3 Research Methodology

3.1 Introduction

This study was based on analysis of secondary data that was available in schools. A longitudinal approach was employed for Multilevel growth model and a cross sectional approach for logistic regression model. A sample of secondary schools for 2015 cohorts were selected and their data analysed every term for growth model and KCSE results analysed in multilevel model and logistic analysis.

The goal of this investigation is to utilize t-test, logistic regression and Multilevel analysis as the method of inquiry to report the factors that affect academic achievement of learners.

3.2 Research Design

As stated in the introduction, the study relied on the analysis of secondary school data available from the sampled schools.

3.3 Target Population and Sampling

The population from which the sample was drawn was from selected secondary schools in Limuru Subcounty. The starting year was 2015 when the population was in form 1. Data were obtained for the subsequent years of study, 2016 through 2018 from these schools.

A letter requesting student data from the subcounty schools was sent from the subcounty educational office and taken to head of institutions. The subcounty approval was given under the following conditions: The data to be used were for the years 2015-2018, no additional data could be collected or used, confidentiality had to be assured for all participants. That is; all data had to be aggregated such that the school could not be identified as well as any other participants including parents, students and administration, Students data had to be destroyed when the project has been completed.

A total of 11 schools were sampled from the entire population of 24 secondary schools in the sub county. The total number of students in the collected sample was 518. Clustered random sampling was used to sample the schools ensuring complete representation in terms of gender and category of school. The data were coded by identification numbers only. These numbers were required to follow the data of a student for the four years. No names were used to ensure anonymity.

3.4 Data Collection Method

After identifying the schools whose data was to be used for the study, the researcher proceeded to collect data from the schools. Through the principals, the deans of studies who are the custodian of these records provided data for the requested years. Data were already in excel format which made it easy to compile them together therefore minimizing the error of entry of data. However, for the final results i.e. KCSE marks, the data was to be capture from the hard copy.

3.5 Data Analysis Method

Two sample t-test, logistic regression and multilevel methods were used to analyze data.

3.5.1 Two-Sample t-Test for Equal Means

The two-sample t-test is used to determine if two population means are equal. The two-sample t-test for unpaired data is defined as:

$$H_0 : \mu_1 = \mu_2 \text{ VS } H_1 : \mu_1 \neq \mu_2$$

For this study we have;

H_0 : KCSE mean score for male=KCSE mean score for Female

H_1 : KCSE mean score for male \neq KCSE mean score for Female

Also for the category of school,

H_0 : KCSE mean score for National schools=KCSE mean score for other category of schools

H_1 KCSE mean score for National schools \neq KCSE mean score for other category of schools

To test these hypothesis the test statistic is

$$\text{Test Statistic: } T = \frac{\bar{Y}_1 - \bar{Y}_2}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}}}$$

Where N_1 and N_2 are the sample sizes, \bar{Y}_1 and \bar{Y}_2 are the sample means, and S_1^2 and S_2^2 are the sample variances.

If equal variances are assumed, then the formula reduces to:

$$T = \frac{Y_1 - Y_2}{S_p \sqrt{\frac{1}{N_1} + \frac{1}{N_2}}}, \text{ where } S_p^2 = \frac{(N_1 - 1)S_1^2 + (N_2 - 1)S_2^2}{N_1 + N_2 - 2}$$

The level of significance chosen was $\alpha=0.05$. We reject the null hypothesis if

$$|T| > t_{(1-\frac{\alpha}{2}, \nu)}$$

Where $t_{(1-\frac{\alpha}{2}, \nu)}$ is the critical value of t distribution with ν degrees of freedom and

$$\nu = \frac{\left(\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}\right)^2}{\frac{\left(\frac{S_1^2}{N_1}\right)^2}{(N_1-1)} + \frac{\left(\frac{S_2^2}{N_2}\right)^2}{(N_2-1)}}$$

If equal variances is assumed, then $\nu = N_1 + N_2 - 2$

3.5.2 Logistic Regression Analysis.

Logistic regression analysis was applied to determine factors that influence the final grade a learner obtained. In logistic regression the dependent variable was dichotomous, obtaining C+ and above or not in KCSE.

To assist in sound interpretation, the assessment of the model will include an overall evaluation, tests of individual predictors, goodness of fit statistics and predicted probabilities of the model. A multiple regression model was adopted for this research. It is used to explore associations between one response variable (obtaining a C+ and above or not) and two or more predictor variables simultaneously. It combines a set of predictor variables to estimate the probability that a particular event will occur that is predict the probability of getting C+ and above or not. The response variable was binary categorical i.e. getting C+ and above or not and the predictor variables, some were categorical (gender and type of school) while others were continuous (age and KCPE marks)

Interpreting odd ratio.

The values of odd ratio range from zero to infinity. For the interpretation, we classify the possible values into three categories: (i) The values less than one (ii) The value of one (iii) Values greater than one. An odd ratio of one means that both groups had the same odds of the event of interest occurring. An odd ratio of less than one means that the event of interest is less likely to occur for the group in the numerator compared to the group in the denominator.

odds ratio < 1 implies odds of event for group A < odds of event for group B

Hence the event is less likely to occur for those in group A compared to those in group B. An odd ratio of greater than one means that the event of interest is more likely to occur for the group in the numerator compared to the group in the denominator.

Odds ratio > 1 implies odd of event for group A > odds of event for group B

Hence the event is more likely for those in group A compared to those in group B. This multiple logistic model is of the form

$$\ln\left(\frac{p}{1-p}\right) = \ln(\text{odd of an event}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$$

For this study we have;

$$\begin{aligned} \ln\left(\frac{p}{1-p}\right) &= \ln(\text{odd of getting C+ and above}) \\ &= \beta_0 + \beta_1 \text{Age} + \beta_2 \text{KCPE marks} \\ &\quad + \beta_3 \text{category of school} + \beta_4 \text{gender} \end{aligned} \tag{1}$$

p-is the probability of getting C+and above, 1-p-is the probability of getting less than C+. $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ are known as partial regression coefficients. They indicate the amount of change in the outcome variable for each unit change in one of predictor variable when all other predictors are held constant.

Since logistic regression model is a mathematical function, categorical predictor variables are assigned numerical values. These numerical values are called dummy variables. A dummy variable is a binary variable for which all cases falling into a specific category assume the value 1 and all cases not falling into that category assume the value of zero. The following dummy variables were created:

$$\begin{aligned} \text{gender} &\begin{cases} 0 & \text{for male} \\ 1 & \text{for female} \end{cases} \\ \text{type of school} &\begin{cases} 1 & \text{if national} \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

Measurement of response variable

Similar to categorical predictor variables, for mathematical manipulations, a dummy variable is created for the binary response variable. The category of event is assigned the value 1 and the other category serves as the reference level and is assigned the value 0. For this study if a student got C+ and above, the event is assigned 1 and C+ and below is assigned value 0.

Interpretation of logistic regression model output

Significance of model fit. Using the maximum likelihood ratio test statistic, the fitted model is statistically significant if the result of the test is significant. ($p\text{-Value} < \alpha$)

Interpretation of regression coefficients

If the partial regression coefficient is positive, its transformed log value will be greater than one, meaning the event of interest is more likely to occur. If partial regression coefficient is negative, its transformed log value will be less than one, meaning that the event of interest is less likely to occur. If partial regression coefficient is zero, it has a transformed log value of 1, meaning that this variable does not change the odds of the event one way or the other.

For a categorical predictor variable, one level of the variable is selected as reference and the other levels compared to it. For multiple logistic regression model, the odd ratio is an adjusted odd ratio since we adjust/control for other predictors when assessing the effect of one predictor on the response variable.

Significance of predictors.

There are two approaches to determining the significance of each predictor; Use the confidence interval obtained for odd ratio, Use Z-test statistics for the regression coefficient corresponding to the predictor being considered. Statistical significance implies statistical association between the response and the predictor while adjusting for all other predictors. When using confidence interval, a predictor is statistically significant if the value 1 is not included in the interval i.e. the lower confidence limit is greater than 1 or the upper

confidence limit is less than 1. Using Z-test for predictors the hypothesis is

$$H_0 : \beta = 0 \quad \text{vs} \quad H_1 : \beta \neq 0$$

The test statistics is $Z = \frac{\hat{\beta}}{se(\hat{\beta})}$ The said predictor is statistically significant if the p-value is less than the chosen level of significance.

Assessing for interaction in logistic regression.

An interaction occurs when a predictor variable has a different effect on response depending on the values of another predictor variable. Interaction term is the product of two or more predictor variable. An interaction term implies the effect of one predictor on the response depends on the value(or levels) of the other predictor. The interaction terms of two predictor variables are either a product of;(a)Two categorical variables (b)Two continuous variables (c) One categorical and one continuous variable.

In a logistic model $\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$, the variables X_1 and X_2 are called main effect variables and product term $X_1 X_2$ is called interaction effect variable. In the presence of interaction, we do not interpret the main effect, we interpret the interaction effect. For a model like the one above, $\exp(\beta_2 + \beta_3)$ is the effect of X_2 when $X_1 = 1$ and $\exp(\beta_1 + \beta_3)$ is the effect of X_1 when $X_2 = 1$.

Test of significance of interaction term.

To test for the significance of the interaction effect variables we carry out the test.

$$H_0 : \beta_3 = 0 \text{ vs } H_1 : \beta_3 \neq 0$$

If the test is significant then the interaction term is significant. When reporting results, we only interpret the interaction effect. We do not interpret the main effect since their effect are nested in the interaction effect. However, if this test is not significant, then we fit the model without it.

3.5.3 Multilevel Linear Model

Introduction

Multilevel linear modeling (MLM) is an ordinary least square (OLS)based analysis that takes the hierarchical structure of the data into account. Hierarchically structured data is

nested data where groups of units are clustered together in an organized fashion, such as students within schools. The nested structure of the data violates the independence assumption of OLS regression, because the clusters of observations are not independent of each other. MLM can also be called Hierarchical Linear modeling. Hierarchical linear modeling can be used for the purpose of prediction. It can also be used for the purpose of data reduction, and can be helpful for drawing out the causal inference.

The flexibility of MLM models have variety of applications for which it is used. There is substantial application of MLM models for the study of longitudinal data where observations are nested within individuals. Longitudinal MLM models, sometimes described as growth curve models, treat time in a flexible manner that allows the modeling of non-linear and discontinuous change across time and accommodates uneven spacing of time points and unequal numbers of observations across individuals.

In this study MLM is employed to study factors associated with performance of students in secondary level in KCSE. It provides a framework that incorporates variables on each level of the model. Student characteristics which includes age, gender and KCPE marks and school characteristics which was category of school, were modeled.

Assumptions:

Data does not need to meet the homogeneity-of-regression slopes requirement, data must be linear and normal, the assumption of homoscedasticity must be met and the assumption of independence is not required.

A two level multilevel linear model (MLM) was used in the study of cross-sectional data for the students who sat for KCSE in 2018 from the selected schools in Limuru sub-county. A two level model was used with students being in the first level and the school was in the second level. MLM was used to control for nesting and more accurately examine the effects of the predictors variables on the outcome.

Model Building.

Model building in MLM is usually systematic and theoretically based. We start with a null or empty model. Predictors are then added to the model in forward or backward elimination approach. Notation of null model can be displayed in two ways- by the level of analysis or in a single equation called "mixed model". Equations below shows basic two level MLM with no predictors variables displayed by level.

$$Y_{ij} = \beta_{0j} + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

Y_{ij} -represents the outcome Y for level one unit nested in level two unit

β_{0j} -is level one intercept

r_{ij} -is the unexplained variance or residual

γ_{00} -is the level two intercept

μ_{0j} -is the level 2 residual variance.

Level 2 random parameter μ_{0j} is what allows the model to vary by higher level unit. Equation 1 can also be displayed in mixed model form by substituting the level 2 equation into level 1 equation. We obtain;

$$Y_{ij} = \gamma_{00} + \mu_{0j} + r_{ij}$$

For this study the null mixed model for the performance of students in KCSE is given by

$$\text{KCSE score}_{ij} = \gamma_{00} + \mu_{0j} + r_{ij}$$

From the above equation, the KCSE score for student i nested in school j is equal to the average KCSE score of schools i.e. school level intercept γ_{00} , plus the random component related to the school the student attends i.e. the difference between the overall KCSE score average and KCSE average score for school j (μ_{0j}), plus a residual variance unique to the student and not captured by the model, r_{ij} . The random component μ_{0j} is what differentiate MLM from standard single level regression because it allows the intercepts of schools to vary, whereas in single level regression only one intercept would be calculated and assumed fixed or equal across schools. Decision to fit MLM or standard single-level regression model is based on intraclass correlation coefficient (ICC), defined as

$$\rho = \frac{\tau_{00}}{\sigma^2 + \tau_{00}}$$

Where;

ρ -the ICC

$\tau_{00} = \mu_{ij}$ -variance of level 2

$\sigma^2 = r_{ij}$ -variance at level 1

The ICC ranges from 0 to 1.0 and describes the proportion of the total variance that depends upon group membership. If there is a small amount of dependence on the higher-level groupings then the independence of observations assumption of single-level regression may not be violated, and thus may be an appropriate technique. However small ICCs may not warrant abandoning MLM given that additional dependence can arise after predictors have been entered into the model.

Entering predictor variables.

After need of MLM model is ascertained and warranted, predictor variables are then added to the model at level 1, level 2 or both. Predictor variables can be entered into an MLM analysis through a forward, backward elimination, or simultaneous “block-entry” approach. The choice of how to include predictors into the model often depends upon the a priori assumption about the relations between predictor variable (i.e., how they interact) and the overall purpose of the analysis.

Adding predictor variables to each level results in the following model.

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + \mu_{1j}$$

Where X_{ij} represent a predictor variable for individual i nested in j and W_j represents a predictor variable for level 2 unit j . Equation 4 can be displayed in its mixed form by substituting the terms from level 2 into level 1.

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}W_j + \gamma_{11}W_jX_{ij} + \mu_{0j} + \mu_{1j}X_{ij} + r_{ij}$$

For this study the variable included in the first level were: age of the student, gender of the school and KCPE marks of the student. As for the school level the predictor variables analyzed were; category of school and gender of the students in the school. This was done in progressive manner at each stage assessing the fit of the model.

Model Fit

The primary fit statistic used in MLM analyses is the *deviance* statistic. The deviance statistic is equal to $-2 \times$ the natural log of the likelihood ratio. We always begin model building with an unconditional, or null model so that we have a baseline from which to compare the deviance statistic to for subsequent nested models. Predictors are then entered at level 1, and the deviance for these conditional models are compared relative to the null model. Level 1 model is “settled” upon using deviance statistics, before proceeding to enter predictors at level 2, using the deviance from the final level 1 model for subsequent model fit comparisons.

Deviance represents “lack of fit”, with larger values indicating a poorer fitting model. The fit between two models can be statistically tested. Given that the difference between two deviance statistics follows a chi-square distribution, with the degrees of freedom equal to the difference in the number of parameters estimated in the two models. If the resulting value is significant, then the model with the lower deviance value fits the data significantly better.

Overall Model Fit

Once variables have been entered into the model, we can estimate a “pseudo R^2 ” statistic, which provides an indication of the amount of variance accounted for by comparing the variance component in an unconditional model to the same variance component in a conditional model.

Pseudo R^2 is calculated by applying the following formula:

$$PseudoR^2 = \frac{\sigma_{unconditional}^2 - \sigma_{conditional}^2}{\sigma_{unconditional}^2}$$

Applying Equation above provides an estimate of the proportional reduction in unexplained variance in the random parameter, accounted for by the predictor variables in the model. When exploring how predictor variables account for the variance in specific parameters, one would simply substitute the σ^2 terms for τ^2 's.

Growth Models

The concept of nesting that is students nested within schools, can be readily applied to the study of *change*. In education we are, of course, often interested in how students are changing. From a statistical perspective, the primary challenge to measuring growth is correlated residuals. That is, if students take a test at one point in time, the residual variance from those scores is likely to be correlated with the residual variance from scores taken at a later time, making it difficult, if not impossible, to parse out “growth” from idiosyncratic characteristics of the students. However, if we view the testing occasions as nested within the individual, then we can control for which student the testing occasions are nested within and we are better able to control for these dependencies within the data (i.e., the correlated residuals) by calculating a different slope for each individual, rather than a single average slope across students, which we can use to evaluate changes over time. Again, however, one must first have multiple data points over time for each individual involved in the study.

One of the primary advantages of modeling growth through MLM is that it is quite flexible and assumes little about the data structure. Students could be administered a set of repeated measures with equal or unequal intervals between administrations, have missing data points at any occasion (or multiple occasions), and have irregular measurement schedules for each student within the study.

Using growth model, this study uses two levels (*repeated measures* nested in *students*) and three levels (*repeated measures* nested in *students* nested in *schools*) to study how performance of an individual student changes right from the time he or she entered form one in 2015 to when they exit in form 4 in 2018. Therefore a longitudinal data for the students in the sample was used for the analysis in growth model.

Notation

Level one of a basic two-level model with a single predictor variable for growth model data is given by

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti}$$

The subscripts *ti* represent *time* nested within *individuals*. The level 1 model is often referred to as the “within-person”, “within-student”, or “within-subject” model. The first a_{ti} variables are coded to represent *time* between measurement occasions.

Level two of an MLM growth model is often referred to as the “between-person”, “between-student”, or “between-subject” model, where each coefficient from level 1 is defined by its own regression equation.

The level 2 model for growth model data with predictor variables and random effects is defined as;

$$\pi_{0i} = \beta_{00} + \beta_{01}X_i + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}X_i + r_{1i}$$

The specification of random effects as estimated or fixed is also important in growth models. Generally, researchers begin model building by specifying a “null growth” or “unconditional growth” model, with time entered as a predictor variable at level 1, and random effects estimated for both the intercept and the slope at level 2

Functional Form

One of the primary threats to the validity of growth model inferences is the functional form the data follow. That is, do students’ progress at a constant rate? Or, do the data follow some other pattern, such as beginning slowly then rapidly increasing? Including higher-order polynomial time variables can test the functional form of the data. In educational data, linear and decelerating quadratic functional forms are the most commonly encountered. In nearly all cases, higher order functional forms should be tested to avoid making inappropriate inferences about the data.

Testing functional form.

When testing for functional form, a “backwards elimination” approach is generally preferred. Backwards elimination includes the highest order polynomials of theoretical/empirical interest being entered into the model at the same time, with the highest order non-significant terms eliminated one by one, until a final functional form is settled upon. When testing for functional form, it is important to do so from *both* a theoretical and empirical basis. For example, in education we often observe a decelerating quadratic trend – the “learning curve”. We thus may theorize that a quadratic term may need to be included. However, prior to fitting the model, it is important to investigate the observed data for each student, or a representative sample of students if the data set is large. If, by visual inspection, the data for many students appear to follow a quadratic trend, then it would be important to include the term in the model. However, if the majority of students appear to simply follow a linear trend, then parsimony may rule and the analyst would be justified in running a basic linear model.

Three Level Models and Predictor Variables

Unconditional linear growth model for three level is defined by:

$$Y_{tij} = \pi_{0ij} + \pi_{1ij}X_{tij} + e_{tij}$$

$$\pi_{0ij} = \beta_{00j} + r_{0ij}$$

$$\pi_{1ij} = \beta_{10j} + r_{1ij}$$

$$\beta_{00j} = \gamma_{000} + \mu_{00j}$$

$$\beta_{10j} = \gamma_{100} + \mu_{10j}$$

This model is employed in this study to investigate the effect of school in the changes of the performance of students in the four year of study in the secondary level. As for this model simple one with less predictors at the three levels were used to minimize the confusion that arises in the interpretation of the model.

4 Analysis and Presentations

4.0.1 Introduction

The goal of this analysis is to determine what are the factors affecting the learning outcome using the KCSE results as the response variable. Since the study is dealing with nested data, then nesting is controlled in this analysis. A two level multilevel analysis is conducted using two level for the cross-sectional data and predictors inserted for the two level.

This chapter is divided into two main sections with subheadings. Section one contains descriptive statistics for the data for all statistical analysis. Section two reports the results of two test statistics, logistic regression and multilevel modelling analysis. Multilevel analysis is conducted for both cross sectional data and longitudinal data.

4.1 Descriptive Statistics of the sample

The data sample consisted of 518 students sampled from 11 schools using clustered sampling technique. In the sample there were 269 female students and 249 male students. The number of district schools sampled were three, county schools were three, extra-county were two and national schools were three. The number of students from district schools were 31, those from county school were 74, extra-county-74 and national 339. The table below summarizes the sample structure.

Table 1. frequencies and percentages of variable

Gender	Sample size	Category of schools			
		District	County	Extra-county	National
Male	249	15	44	31	161
Female	269	16	30	43	178
Total	518	31	74	74	339

4.1.1 Two sample t-test for equal means

Descriptive statistics

From the table, the mean KCSE score for the sample was 8.38 and upper quartile was 10.00. Number of male students in the sample were 248 and female were 231. As for the

Table 2. t-test descriptive statistics

KCSE score	gender	Category of school
Minimum=1.00	Male:248	National:335
1 st quartile:7.00	Female:231	Others:144
Median:9.00		
Mean:8.38		
3 rd quartile:10.00		
Maximum:12.00		

category of the school, 335 students came from national schools and 144 were from other category of schools.

Test for equality in variance: Using Levene test.

The null hypothesis is H_0 : population variances are equal. Conducting the test the following output was obtained.

```
leveneTest(KCSE score~ category of school)
Levene's Test for Homogeneity of Variance (center = median)
Df 1 F-value=6.7754 Pr(>F)=0.00953
```

```
leveneTest(KCSE score~ gender)
Levene's Test for Homogeneity of Variance (center = median)
Df 1 F-value=6.8677 Pr(>F)=0.009057
```

From the outputs, the null hypothesis for equality of population variances is rejected at 0.05 level of significance and we carry out t-test with non-equal variances.

T-test results.

t-test for equality of KCSE mean score for categories of schools

Comparing performance according to category of school, the following output was obtained from R software.

Welch Two Sample t-test

data: KCSE score by category of school

$t = 5.0148$, $df = 219.52$, $p\text{-value} = 1.094e-06$

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval: 0.6311293, 1.4483898

sample estimates:

mean in group NATIONAL= 8.692537 mean in group OTHERS=7.652778

Since p value is less than 0.05, we reject the null hypothesis that KCSE mean score for the two categories of school are equal.

t-test for equality of KCSE means score for gender

When t-test was conducted for gender the following output was obtained.

Welch Two Sample t-test

data: KCSE score by gender

$t = -1.869$, $df = 469.42$, $p\text{-value} = 0.06225$

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval: -0.67287902, 0.01686031

sample estimates:

mean in group F=8.221774 mean in group M=8.549784

The p-value was greater than 0.05 implying there is no statistical significant difference in the KCSE mean score of female students and male students.

4.1.2 Logistic Regression Analysis

The summary of variables used in the analysis is given in the table below. These are variables that the mean and quartiles are interpretable.

From the table the youngest student was 16 years old and the oldest was 20 years old, mean age was 18 years. As for the KCPE marks, the lowest marks was 103 and highest 435 and mean 357.

Table 3. summary of variables for logit

Age	KCPE_marks
Minimum :16.00	Minimum :103.0
1 st Quartile. : 17.00	1 st Quartile :355.0
Median:18.00	Median:378.0
Mean:17.89	Mean: 357.3
3 rd Quartile:18.00	3 rd Quartile:401.0
Maximum:20.00	Maximum:435.0

Having fitted the following model;

$$\ln\left(\frac{p}{1-p}\right) = \ln(\text{odd of getting C+and above}) = \beta_0 + \beta_1 \text{age} + \beta_2 \text{gender} + \beta_3 \text{category of school} + \beta_4 \text{KCPE marks} \tag{2}$$

p-is the probability of getting C+and above
 1-p-is the probability of getting less than C+

The following output was obtained from R software; The table below shows the intercept

Table 4. table of coefficients for logit

Coefficients:	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.4502	2.8968	0.846	0.3976
age	-0.4405	0.1677	-2.628	0.0086
gender:female	0.4861	0.2557	1.901	0.0573
category of school:National	-0.4607	0.3882	-1.187	0.2353
KCPE_marks	0.01983	0.0029	6.857	7.03e-16

and coefficients of the fitted model. Also displayed are the standard error, t-statistics and p-values for testing significance of each predictor.

Therefore the predicted logit of getting C+ and above = 2.4502 – 0.4405 * age + 0.4861 * gender – 0.4607 * category of school + 0.01983 * KCPEmarks . From the table below, the log of the odds of a student getting more than C+ in KCSE is negatively related to age, positively related to gender, negatively related to type of school and positively related to KCPE marks.

Overall Evaluation.

The results of the overall evaluation testing the global null hypothesis (all effects are null) indicates that the model is a better fit than the base-line (intercept-only) model. The test reports significance in the model being a better fit to the data than the null model. Looking specifically at the p-value, $p < .0002$. (p-value=0.0001238)

Tests of Individual Predictors.

Two of the four predictors variables were found to be statistically significant in the logistic regression model. Keying on odds ratios, the following output was obtained:

Table 5. table of odds ratio

(Intercept)	Age	gender:female	type_ of_ school:National	KCPE_ marks
11.5912917	0.6437079	1.6260102	0.6308164	1.0200238

KCPE marks is strongly related to the odds of getting C+ and above in the KCSE and from the odd ratio above, a student is 2% more likely to obtain C+ and above for unit increase in the KCPE marks. The age of a student was also found to be significant in relation to obtaining more than C+ in KCSE. The analysis indicates that the older a student is, the less the probability of the student getting C+ and above in KCSE, holding constant all other variables. To investigate the possibility of a “better model” being available, interaction variable was introduced to the model. The investigation incorporated interaction of the two statistically significant variables; age* KCPE marks. The results of the model with the additional interaction predictor in given in the table below;

Table 6. table of coefficients with interaction term

coefficients	Estimate	Std.Error	z value	Pr(> t
intercept	1.5433	11.3065	0.137	0.8914
age	-0.3884	0.6492	-0.598	0.5496
gender:female	0.4840	0.2569	1.884	0.0596
type of school:National	-0.4549	0.3943	-1.154	0.2486
KCPE marks	0.0227	0.0342	0.662	0.5077
Gender*KCPE marks	-0.0002	0.0019	-0.083	0.9339

All the predictors variables were no longer statistically significant in the model. The deviance residual did not even reduced in the model with interaction term. Therefore the previous fitted model is the best fit for the data.

4.2 Multilevel Linear Model

4.2.1 Cross Sectional Model

The study began with analysis of cross-sectional data in two ways - first with a single-level multiple regression analysis, then with a two-level MLM analysis. The analyses are conducted with the same dataset whose summary was given in descriptive statistics of the sample structure. The analyses are identical, with the exception of the MLM model accounting for the nesting of students within schools. The summary of the variables used in this analysis are summarized in the table below;

	age	KCPE marks	KCSE grade
Minimum	16.00	103.0	1.00
1 st quartile	17.00	355.0	7.00
Median	18.00	378.0	9.00
Mean	17.89	357.3	8.38
3 rd quartile	18.00	401.0	10.00
Maximum	20.00	435.0	12.00
NA	-	-	39

From the table, the youngest student was age 16 and the oldest was 20 years old. The second column summarises the KCPE score for the students with the least being 103 marks and the maximum being 435 marks. As for the last column it summarises the KCSE mean grade for the students in the sample with the highest being 12 and least 1. 39 students that were at the beginning of the study were not in the schools sample in their fourth year.

Also not included in the table are the sample size for various genders which was captured in previous table but what is important to report is the school gender from which the sample came from. 246 students came from the school whose gender was female, 224 students came from school whose school gender was male and 48 students came from schools which had mixed gender.

Model building

The study began by fitting a single level model with no predictor variables of the form;

$$\text{KCSE grade}_{ij} = \gamma_{00} + r_{ij}$$

And also a multilevel model with no predictors of the form;

$$\text{KCSE grade}_{ij} = \gamma_{00} + \mu_{0j} + r_{ij}$$

Meaning the student were nested in school. The reason for fitting these models is determine the need for nesting. The output from R software for the two models is as summarized in the table below;

Table 7. single level versus multilevel model

	intercept	Standard error	t-value	p-value
Single level model	8.380	008854	94.64	0
Multilevel model	7.179	0.6493	11.0553	0

From the table the intercept when nesting is not factored is 8.38 while nesting of data is factored it becomes 7.179. Also from the table and specifically from the p values, the two intercepts are statistically significant and represent the average score of a student in the KCSE.

Carrying out the ANOVA test of the model to ascertain the significance of nesting the following was the outcome from R software.

Table 8. single level versus multilevel ANOVA

Model	DF	AIC	BIC	Log likelihood test	Test	L.Ratio	p-value
1	2	1996.090	2004.43	-9960.05			
2	3	1881.057	1893.57	-937.53	1 VS 2	117.03	<0.0001

From the table, nesting is significant as depicted by p-value of less than 0.0001. Model 1 is the model with single level who's AIC and BIC values are given in the table above. Model 2 is the multilevel model which has be given in the second row with the AIC and BIC values. The comparison is made between model 1 and model 2 and found to be statistically different. Since model 2 has lower AIC and BIC value, it is a better fit for the values in the sample and therefore we carry out multilevel modelling. Calculating the ICC(intra class correlation coefficient) we obtain;

$$\rho = \frac{\tau_{00}}{\sigma^2 + \tau_{00}} = \frac{4.4606}{4.4606 + 2.6912} = 0.6237$$

This implies that 62.37% of variation in the student KCSE grade is accounted for by the school the learner belongs to. This furthermore explains the need for MLM as opposed to single level modelling.

Adding predictor variables to the model

Having ascertain that MLM is better model than single level model, the study included the predictor variables at the student level that explain the variation of the performance from one student to another. The important predictor variables identified were: age, gender and KCPE score of the student. Fitting them simultaneously to the model will of the form assuming the factors are fixed;

Hierarchical model

$$\text{KCSE grade}_{ij} = \beta_{0j} + \beta_{1j}\text{gender} + \beta_{2j}\text{KCPE marks} + \beta_{3j}\text{age} + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

Mixed effects model;

$$\text{KCSE grade}_{ij} = \gamma_{00} + \gamma_{10}\text{gender} + \gamma_{20}\text{KCPE marks} + \gamma_{30}\text{age} + \mu_{0j} + r_{ij}$$

The output from the R software for the model is summarized below;

Table 9. multilevel model with student level predictors

	value	Std.error	DF	t-value	p-value
Intercept	3.478	1.775	465	1.959	0.0507
KCPE marks	0.017	0.002	465	8.940	0.0000
Gender: Male	0.972	0.259	465	3.748	0.0002
Age	-0.099	0.094	465	-1.059	0.2903

The first table summarizes the coefficients for the predictor variables as well as the overall intercept. The standard error as well as the p-values to test for the significance of each

Table 10. standard deviation for intercept and residual

	intercept	residual
Standard deviation	0.7047	1.5886

predictor is reported. From the p-value KCPE marks and gender are statistically significant while age and intercept are not, if a significance level of 0.05 is selected. The second table is the standard deviation of the intercept and residuals. If the standard deviation is squared it gives variance which is a measure of variability of slopes in different school. Calculating ICC gives;

$$\rho = \frac{0.4966}{0.4966 + 2.524} = 0.1644$$

With the three student level fixed factors, 16.32% of the unexplained variation in student's KCSE grade is what can be accounted for by the school the student attended. The reduction is because most of the variations are now explained by the predictor variables in the model.

Conducting Anova for the null model and fitted model with predictor to determine which of the two model a better fit is, the following outcome was obtained from R software; From the table, the fitted model with predictor is a better fit since the p-value is less than

Table 11. Null versus fitted model ANOVA

model	DF	AIC	BIC	loglik	Test	L.ratio	p-value
1	2	1996	2004	-996			
2	3	1881	1893	-938	1 vs 2	117.0	<.0001
3	6	1835	1860	-911	2 vs 3	51.8	<.0001

0.05 and the AIC and BIC are less than for the previous model. A random slope model was not fitted because theoretically the effect of the predictors do not depend on the school the student attended but is the same across all the schools.

Next model with the level one factors and level two fixed factors was fitted. Two identified level two factors are; category of school and school gender. School gender is the gender of the students in that particular school. Any school is either consisting of female, male or mixed genders. For the categories of schools, it consisted of national, extra-county, county or district schools. The model fitted was of the form:

Hierarchical model

$$\text{KCSE grade}_{ij} = \beta_{0j} + \beta_{1j}\text{gender} + \beta_{2j}\text{KCPE marks} + \beta_{3j}\text{age} + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\text{school gender} + \gamma_{02}\text{category of school} + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

Mixed effects model

$$\text{KCSE grade}_{ij} = \gamma_{00} + \gamma_{01}\text{school gender} + \gamma_{02}\text{category of school} + \gamma_{10}\text{gender} + \gamma_{20}\text{KCPE marks} + \gamma_{30}\text{age} + \mu_{0j} + r_{ij} \tag{3}$$

The output of the model from R software is summarized in the table below; From the table

Table 12. model with school level factors

	value	Std.Error	DF	t-value	p-value
Intercept	7.7513	1.8490	463	4.1922	0.0000
KCPE marks	0.0125	0.0025	463	5.0667	0.0000
Gender:M	1.5812	0.5242	463	3.0161	0.0027
Age	-0.192	0.0942	463	-2.039	0.0420
Schgend:M	-1.400	0.5460	463	-2.564	0.0107
Schgend:Mixed	-0.7661	0.5743	463	-1.334	0.1829
Category of school:DISTRICT	-2.8447	0.6426	7	-4.427	0.0031
Category of school: EXTRA COUNTY	-0.2640	0.3365	7	-0.7846	0.4584
Category of school:NATIONAL	-0.5822	0.3467	7	-1.6790	0.1370

KCPE marks and male gender are positively related to KCSE grade, while the other factors are negatively related to KCSE grade. School level factor gender of school-mixed and categories of school extra county and national are not statistically significant predictor of KCSE grade a candidate had since their p-value is greater than 0.05.

A comparison was made between this model and model without school level predictors summarized with ANOVA table. The table below indicate that the model with school level factors is better fit than the one without. The AIC and BIC values have decreased slightly from the values of model without school level predictors. Also from the output, the ICC value have become very small implying that less of the variability in the performance of students can be explained by the school the student attended since most of the variability in performance is explained by predictor variables in the two levels.

Table 13. model comparison: model with school level factors

Model	DF	AIC	BIC	logLik	Test	L.Ratio	p-value
1	2	1996	2004	-996			
2	3	1881	1894	-938	1 vs 2	117.0	<.0001
3	6	1835	1860	-912	2 vs 3	51.8	<.0001
4	11	1811	1857	-894	3 vs 4	34.2	<.0001

The study also endeavored to find out whether the interaction between gender of the student and category of the school the student attended has any effect on the performance of the student. The following mixed factor model was also fitted to answer that question.

KCSE grade_{ij} =

$$\begin{aligned} & \gamma_{00} + \gamma_{01}\text{school gender} + \gamma_{02}\text{category of school} + \gamma_{10}\text{gender} \\ & + \gamma_{11}\text{gender} * \text{category of school} + \gamma_{20}\text{KCPE marks} + \gamma_{30}\text{age} + \mu_{0j} + r_{ij} \end{aligned} \quad (4)$$

The output from the R software is summarized as below;

Table 14. model with gender and category of school interaction

	Value	p-value
(Intercept)	7.669	0.0002
KCPE marks	0.013	0.0000
Gender:M	0.641	0.3931
Age	-0.223	0.0259
Schgend:M	0.367	0.6533
Schgend:Mixed	0.268	0.6914
Category of school: DISTRICT	-3.781	0.0042
Category of school:EXTRA COUNTY	0.144	0.7636
Category of school:NATIONAL	-0.082	0.8520
Gender(M):Category of school(DISTRICT)	2.085	0.0540
Gender(M):Category of school(EXTRA COUNTY)	-0.743	0.2220
Gender(M):Category of school(NATIONAL)	-0.969	0.1013

The ANOVA test is also summarized below

Table 15. ANOVA for interaction effects

model	DF	AIC	BIC	loglik	Test	L.ratio	p-value
4	11	1811	1857	-894	3 vs 4	34.2	<.0001
5	14	1807	1866	-889	4 vs 5	8.966	0.0297

From the tables above adding interaction between gender and category of school did not improve the model. Therefore the study relied on the outcome from previous model to make interpretation and conclusion.

4.2.2 Growth model.

Next in multilevel analysis was to fit growth model using longitudinal data from 2015 cohorts. The results of the students were followed for four years. Termly results were obtained for this analysis. Since the termly scores on an individual student are not independent, ordinary regression model could not have been used to study academic performance of student throughout the four years since assumption of independence of observations could have been violated.

Two level growth model

A two level growth model was fitted to evaluate the growth students made in their grade performance during the four years of study. There were 12 data points, three for each year- which were obtained termly from the performance of the students. To fit this model, time varying covariate was applied to indicate time at which students changed from one term to another.

The study began by fitting a simple linear model to the entirety of data depicted by model below;

$$Score_{ii} = \pi_{0i} + \pi_{1i}Term_{ii} + e_{ii}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

At the begging it was assumed that a linear slope reasonably modelled the observed data within each year. The variable 'Term' measures the time between testing occasions. The intercept represent students' score during the first testing occasion in form 1. Fitting the model in R software the following was the output;

The model displayed below suggested that students began, on average, scoring mean grade of 7 translating to C+ and progressed at a rate of -0.07 per term. The model also suggests that students differed slightly in their intercepts, with a standard deviation of 1.936, but not in their slopes.

Table 16. Growth model summary

	Value	Std.Error	DF	t-value	p-value
(Intercept)	7.274841	0.08907	5377	81.66	0
Term	-0.070859	0.00364	5377	-19.46	0

To study how students grades changed over the four year, a categorical term of term was included in model in place of continuous. The output from the model is as summarised below;

Table 17. Termly Growth model

	Value	Std.Error	DF	t-value	p-value
(Intercept)	7.515	0.0899	5367	83.69	0.0000
term 2	-0.072	0.0366	5367	-1.97	0.0486
term 3	-0.318	0.0369	5367	-8.62	0.0000
term 4	-0.553	0.0370	5367	-14.95	0.0000
term 5	-0.596	0.0371	5367	-16.04	0.0000
term 6	-0.687	0.0372	5367	-18.48	0.0000
term 7	-1.606	0.0373	5367	-43.09	0.0000
term 8	-1.326	0.0373	5367	-35.57	0.0000
term 9	-0.723	0.0374	5367	-19.31	0.0000
term 10	-1.819	0.0374	5367	-48.61	0.0000
term 11	-1.756	0.0374	5367	-46.93	0.0000
term 12	0.870	0.0374	5367	23.26	0.0000

Throughout the four years, the performance of the students decreased and only improved in the last term of form 4 KCSE. The most drop occurred during the seventh , tenth and eleventh term.

Student demographic variables were then added to the model as predictors of each level one parameter. Four demographic variables were included: (a) Gender, (b) sex, and (c) Age. All categorical variables were dummy-coded vectors, entered into the model uncentered. A backwards elimination procedure was followed, by which all predictors were added to the model simultaneously and evaluated together. The model was thus defined as:

$$Score_{ti} = \pi_{0i} + \pi_{1i}Term_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}Gender + \beta_{02}Age + \beta_{03}KCPEmarks + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}Gender + \beta_{12}Age + \beta_{13}KCPEmarks + r_{1i}$$

The output from the R software is summarized in the table below The addition of the

Table 18. Growth model with student level predictors

	Value	Std.Error	DF	t-value	p-value
Intercept	6.353	1.868	5377	3.399826	0.0007
Time	-0.071	0.004	5377	-19.595978	0.0000
Gender:M	0.237	0.165	514	1.441716	0.1500
Age	-0.131	0.105	514	-1.260063	0.2082
KCPE Marks	0.008	0.001	514	7.169299	0.0000

student covariates resulted in a significantly better fitting model as depicted by chi-square deviance test below.

Table 19. chi-square deviance test of predictors

model	DF	AIC	BIC	logLik	Test	L.Ratio	p-value
1	4	18192.53	18219.26	-9092.263			
2	7	18148.12	18194.89	-9067.058	1 vs 2	50.41026	<.0001

Two variables were significant predictors of students intercept, as displayed above with, on average males scoring 0.23 points higher than females. KCPE marks was the significant predictor of changes in the performance of students.

More complex model can be fitted comprising of random slopes and interaction of predictor variables and at each stage evaluating the fitness of the model vis a vis the previously fitted models.

5 Discussion, Interpretation and Conclusion

5.1 Two sample t-test

Testing for difference in the KCSE mean score for the categories of school, the t-test showed that category of school KCSE mean scores are statistically significant from each other. KCSE mean score for those in national school was higher than the KCSE mean score of the students in the other category of school.

Study also tested difference in KCSE mean score between female and male students using t-test. From the test, the mean score for male and female students were not significantly different. Therefore male and female students perform equally in the final examination according to this study.

5.2 Logistic regression analysis

5.2.1 Overall significance

The output of the fitted model was; predicted logit of getting C+ and above = $2.4502 - 0.4405\text{age} + 0.4861\text{gender} - 0.4607\text{category of school} + 0.01983\text{KCPE marks}$. Testing for overall significance of the model using likelihood ratio statistics, the fitted model was statistically significant with p-value of 0.0001238 which is less than α -value of 0.05 which was selected to test the hypothesis

H_0 : null model is better fit Vs H_1 : fitted model is better fit

Therefore the coefficient and odd ratio was interpreted after ascertaining that the model was a better fit.

5.2.2 Interpreting the individual predictors

Four predictors were used in the analysis. Two were found to be statistically significant. These were age of the student and KCPE marks $p - value < 0.05$. The other two, gender and type of school were not statistically significant.

5.2.3 Interpreting odd ratio

Age; a student is 35% less likely to obtain C+ and above in KCSE for every unit increase in age adjusting for gender, type of school and KCPE marks.

Gender; since female gender was reference with dummy variable of 0, a male student is 63% more likely to obtain C+ and above in KCSE compared to female student, keeping age, type of school and KCPE marks constant. This interpretation is not conclusive since this predictor was not statistically significant.

Category of school; the reference was other category of schools. Therefore a student in national school is 37% less likely to obtain C+ and above in KCSE adjusting for age, gender, type of school and KCPE marks. Similarly predictor of type of school was not statistically significant. KCPE marks; student is 2% more likely to get C+ and above for every unit increase in KCPE marks, holding other factors constant.

Even if the category of school and gender were not statistically significant, the study still retained the two factors as guided by previous study in the same topic as reviewed in the literature. KCPE marks was strongly related to probability of obtaining C+ and above in KCSE.

When the interaction term of the two significant factors was included in the model, the overall significance remained the same ($p - vale = 0.000124$). All the predictors including the interaction term were not statistically significant. Therefore the odd ratios were not interpreted.

5.3 Multilevel model

Multilevel model: cross-sectional data.

From initial analysis of data, there was need to ascertain whether multilevel modelling is warranted bearing in mind the nested structure of data used in this study. It was confirmed that there was need of MLM with 62.37% of variation in student KCSE grade was accounted for by the school the learner belonged to.

Predictor variables for both student level and school level were included in the model to improve its ability to explain the variation in response variable. The student level predictor variables included; age, gender and KCPE marks of the students. From the fitted model, the following was the outcome from R software;

$$\text{KCSE grade}_{ij} = 3.478 + 0.017\text{KCPE marks} + 0.972\text{gender} - 0.099\text{age}.$$

Therefore the mean KCSE grade for student i in school j is 3.48 controlling for other variables i.e. when student has scored zero marks in KCPE, being a female and having zero

age. The KCSE score increases by 0.017 for unit increase in KCPE marks and male students score 0.972 in KCSE more than their female counterparts. Of the three predictor variables included in the model, KCPE marks and gender of the student were significant predictors while age was not statistically significant at 0.05 level of significance. Estimate for random intercept (between schools) variance was 0.4966 while for within school (residual) variance was 2.5236. More unexplained variance was within than between schools. Calculating intraclass correlation coefficient (ICC) give 0.1644 implying after including the three student level fixed factors, only 16.32% of the unexplained variation in student's KCSE grade is was can be accounted by school the student attended. Overall fit of the model was compared to null model via chi-square deviance test, which indicated that model with predictor variables better fits the data.

Including two school level variables-school gender and category of school- the outcome was summarized using a table. From the table, KCPE marks was significant predictor of KCSE grade. For every unit increase in KCPE marks, there was an average increase of 0.0125 on KCSE grade score. Male students did significantly better than female students in KCSE. Male students on average scored 1.5812 higher than female students. Age of the student was also significant predictor of KCSE scores. For every unit increase in age the KCSE grade decreases by 0.192 controlling for other factors. For school gender, those students who studied in male gender schools scored 1.4 less than those in female gender schools. It was a significant predictor but those in mixed gender schools, school gender had no significant effect on the performance of students in KCSE grade.

For category of school, those who studied in district schools had significant effects on their performance. The KCSE grade was 2.8 less than those who studied in county schools. Model with school level predictors was statistically better model than the one with only student level predictors. A model incorporating interaction of gender of students and category of school was also fitted. From R software, the model did not seem to be a better fit since BIC (Bayesian Information Criterion) value was more than for previous model hence interpretation of model without interaction effects was adopted for this study.

Multilevel model: Growth Model

Growth model was fitted to sample of students' scores since the time they were in form 1 in 2015 to the scores in KCSE in 2018. Since scores from individual student in different terms are not independent, multilevel growth model was adopted for analysis of these longitudinal data. A two level growth model was fitted where the score of student i for term t was nested on an individual student.

The result of this model suggested that the students began on average with 7.27 mean grade translating to mean grade of C+ and progressed at a rate of -0.07 per term. The model also suggested that students differed slightly in their intercepts, with standard

deviation of 1.936. Student's demographic variables were then added to the model as predictors of each level. Considering the predictor variable gender, it was not statistically significant implying academic progression for both male and female students is the same. Only KCPE marks of the student was significant predictor of academic progression of students. Model with predictor variables was better fit when comparison is made between the two models via chi-square deviance test.

5.4 Findings

Using three statistical tools; two sample t-test, logistic regression and multilevel model, the factors affecting learning outcome of secondary school students were explored.

From two sample t-test, the KCSE mean score for those in national school was found to be higher than those for other category of schools. As for the gender, the study did not establish difference KCSE mean score for male and female students.

From logistic regression model, it was found out that KCPE marks (entry behavior) affect positively the performance of students in KCSE. Students who join secondary school with low marks are not able to perform better in high school. Emphasis should be in primary level if at all the performance in high school is to improve.

Age of the student was also found to affect the performance in KCSE. Older students performed relatively lower than younger students. Therefore delaying schooling for learners according to this study does not make them have advantage over others when it comes to academic achievement.

Since students are nested within schools, factors affecting achievement in KCSE can better be evaluated in context of nesting. Analyzing cross sectional data using multilevel model, age, KCPE marks and gender were found to be statistically significant predictors of KCSE scores. KCPE marks was positively related to KCSE score, male students performed better than their counterpart female students and older students performed slightly less than age appropriate students.

Academic progression of students was analysed using growth models in multilevel mixed models. A two level model was used with individual student scores nested within student. Learners started with score of C+ but their performance declined over time. Remarkable decline happened during seventh, tenth and eleventh terms corresponding to first term in form three, first and second term in form four respectively. More attention must be accorded during these periods.

5.5 Conclusion

The three methods used for this study have to some extent explored the four factors that affect learning outcomes in secondary level. KCPE marks was the main factor that affect performance in secondary schools. For improvement to be realized, more emphasis should be put in primary level of studies. Learners seems not to have strong education foundation in primary level. All stakeholders should address this challenge. Learners are only prepared to pass exams without in depth learning.

Learners should not be delayed in starting schooling or repeating classes since it has negative consequences to their performance. Also the performance of learners should be closely monitored during the four years of the study since the final performance is determined by prior performance in the course of their studies.

When investigating the relationship between yearly performance and KCSE score, it was noted that for improvement to be realized in KCSE, then more emphasis need to be put in form 2 and 3 performance. In form four, the average may not necessary translate to better score in KCSE. As opposed to the norm where the emphasis is placed in form four, for improvement to be realized in KCSE then learners should be closely monitored in form 2 and 3.

5.6 Future Research

Additional studies would be helpful to confirm some of the findings in the present investigation. The present study used a correlational approach and replicating this research may result in added evidence to these findings. Replication studies on other schools from different counties may be looked at and time frames may be lengthened or shortened depending on research queries of interest. A continuation of this study may be comprised of comparing local data to other locales in the country.

This study focused on one sub county schools academic achievement, future research could include factors such as social economic status of the parents, location of the school, ownership of the school-private or public, school facilities and disipline records of the students.

To further the study of the academic achievement, all factors mentioned may be investigated using more complex statistical analyses such as hierarchical linear modeling(HLM) and structural equation modeling (SEM). Also available are mixed methods approaches, a combination of qualitative and quantitative approaches, for a more robust description of the factors affecting learning outcomes of students.

Only a small number of variables were used in this multilevel that included age, KCPE marks, type of school and gender. Expanding on this research should include other empirically significant variables as well as interaction effects of various combinations. More complex models are required and a deeper investigation of all factors that play a part in students' academic lives should be investigated.

5.7 Recommendations

In this study, the variables of interest were those that a schools already had available. This limitation extends to an obvious recommendation to expand on the type of data collected by the schools for future use in research. Continuing this thought would be to expand on the length of time used in the longitudinal approach to the study. Results from the study showed that it may be much earlier than high school that the problems of at risk students may be beginning to develop.

Although the problems may start earlier, it manifests itself in secondary. It may very well be that 4 years' worth of data is not enough to pinpoint problematic periods in students' lives for a better understanding of the academic outcomes. Although there is much discussion on both sides of the issue for the instituting of national standards, it would at least give researchers the opportunity of looking at how the nation is doing educationally.

Involvement in their children's education by parents is a must for the academic success of students, especially those having difficulty due to the various factors that have not been explored in this research (Pong & Dong-Beom, 2000; Peterson, 1996). Educators also need to be aware that these students are experiencing a rough time in the process of getting an education. The concept of empathy, although easy to understand is much more difficult to implement in the everyday classroom. In this specific instance, we need drastic measures and reforms if there is to be success in the education of students.

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