

Original Research Article

An Extended Six-parameter Generalised Linear Mixed Effects Model for Achievement Gaps among Public and Private Basic Schools of Ghana.

Abstract

The mixed generalized linear model extension has distinct advantages over generalised linear models, hierarchical linear and hierarchical linear models by reducing estimation and precision errors, and increasing power. This paper was aimed at building a six parameter Generalised Mixed linear Model with five structural parameters that explains students, teachers, and administrative-logistic characteristics and interaction effects as well as random effect parameter. Our model, which has Bernoulli response and Logit link function outperformed existing models and was robust across varied sample sizes on the basis of AIC and BIC. Parameters of the model were estimated by Maximum Likelihood Estimation Method. The nonparametric contour-3D stratification was used to compare performance of public and private school pupils directly with respect to their BECE performance under each element of a given factor at a time. Our advanced model simultaneously takes into account the variance as a result of the relatively small samples taken from each category of private school as well as any bias that may have been introduced by the different participation rates between the private and public-school categories. It is recommended for the inferences made in this paper to be used by stake-holders of the basic schools to help optimise teaching and learning processes which will in the long run enhance performance of the pupils in the BECE examination.

Keywords. Private School, Public-school, Performance gaps, Generalised Mixed Effects, BECE, Basic Education

1. Introduction

Recent discussions have brought attention to the importance of school sector (whether private or public) and its impact on students' academic success. According to conventional opinion and prior studies, private schools perform better academically [1-4]. Disparities in academic achievements among basic school learners learning under same environmental and learning conditions have been studied and found to differ. Teaching Methods and teachers' effectiveness in using content knowledge, professional values and skills have also been found to control basic school learners' attitude and believes about the subjects they learn at school [1-4].

Many recent works have reported the long-standing issue of private schools outperforming public-schools in the Basic Education Certificate Examination (BECE) [5-11], in addition to the abundance of research works to understand the causes of learners' performance [12-21].

In order to close the achievement gap between public elementary school students and those in private schools, there is a difficulty with maximizing the learning outcomes of these students. The causes of the differences have been well investigated in the scholarly literature, but the mechanics and dynamics of these influences on BECE performance are still unknown or cannot be quantified appropriately. Stakeholders can better influence particular variables to improve learning outcomes when these dynamics have been well investigated and understood.

By a wide margin, hierarchical linear and **hierarchical generalised linear** models have been the main tools used to examine national student performance disparities. Organizations that conduct research on student performance, including well-known authorities like the National Assessment of Educational Progress (NAEP), which is well-known in the USA, and the International Finance Corporation (IFCo), a subsidiary of the World Bank that is also well-known for its educational reports in many countries, have used hierarchical linear and **hierarchical generalised linear** models to produce their findings. These studies as well as others [22-27] have reported that the widely used hierarchical linear and **hierarchical generalised linear** models do not have the ability to handle heterogeneous and unequal variance situations, unequal sample size, strong correlation situations, unequal numbers of repeats, or the ability to capture random factors. The mixed generalized linear model extension has distinct advantages over these models and is able to address these issues while maintaining the benefits of the hierarchical linear and **hierarchical generalised linear** models. It can reduce estimation errors, increase power and precision, and decrease precision errors [28-38].

Since each group has a unique role in shaping how children are educated, [39]'s research identified parents, students, and supervisors (heads, proprietors) as major stakeholders that should be the primary sources of information to optimize their contributions. As a result, the current study seeks to build a six parameter Generalised Linear Mixed Model with five structural parameters that explains students, teachers, and administrative-logistic characteristics and two interaction effects as well as random effect parameter.

2. Method

The probit GLMM and the Clog-log models will be compared to our developed model since they all have binary response distribution. Our developed model has Logistic Link specified as follows:

$$\text{Logistic (logit) link: } \log\left(\frac{\pi_i}{1-\pi_i}\right) = x_i^t \beta \quad (1)$$

symmetric, linear between 0.2 and 0.8, underlying tolerance dbn is logistic dbn, commonly used in medical field; fitted values are the logarithm of the “odds”

The probit GLMM and the Clog-log have the following link functions.

$$\text{Probit link: } \pi_i = \Phi\left(\frac{t_i - \mu}{\sigma}\right) \Rightarrow \Phi^{-1}(\pi_i) = x_i^t \beta^* \quad (2)$$

symmetric, similar to logit, tolerance *dbn* is Normal (μ, σ^2); Complementary log-log link:

$$\log(-\log(1 - \pi_i)) = x_i^t \beta \quad (3)$$

asymmetric, tolerance *dbn* is Gumbel (extreme value) *dbn*.

To compute the required sample size with confidence interval 95% ($Z = 1.960$), proportion of 50% (for unknown population) and 6.965% margin of error, the required sample of size n , was calculated using Cochran's sample size estimator as;

$$n = \frac{z^2 \times \hat{p}(1 - \hat{p})}{\varepsilon^2} = \frac{1.96 \times \frac{50}{100} \times \left(1 - \frac{50}{100}\right)}{0.06965^2} \approx 198. \quad (4)$$

Two alternative criteria are instrumental in comparing survival models both in discrete and criterion (AIC) and the Bayesian Information Criterion (BIC). They are designed to handle complex models such as nonlinear models, in spite of the possibility of over fitting. In such cases, there is an alternative to conduct split-analysis by estimating the model with 75% of the data, holding back 25% to check the validity of the model; continuous data even in the event of misspecification. These include the Akaike's information

The Akaike information criterion (AIC) is given by:

$$AIC = -2 \log L + 2K \quad (5)$$

and the Bayesian information criteria (BIC) by:

$$BIC = -2 \log L + K \log(N) \quad (6)$$

Where p is the number of model parameters; L is the maximum likelihood.

The Maximum Likelihood Estimation will be the basis for parameter estimation. The Akaike Information Criterion (AIC) was used to compare models for the Bayesian Information Criterion (BIC) study [40].

The Generalised Linear model as show in (a) would be modified to Generalised Linear Mixed Effect Model

$$E(Y|\beta) = g^{-1}(\beta X) \quad (7)$$

The exponential family form as explicated in Equation (b) will be used to extract the canonical parameters of the Bernoulli response distribution [41-45].

$$f(y, \theta, \varphi) = \exp \left[\frac{y\theta - b(\theta)}{a(\varphi)} + c(y, \varphi) \right] \quad (8)$$

The canonical parameter is θ , the dispersion parameter is φ ; $b(\theta)$ is the cumulant function

For Bernoulli response, Equation (8) equivalence of the exponential family yields Equation (9) as follows;

$$\left\{ \begin{array}{l} a(\varphi) = 1 \\ c(y, \varphi) = 0 \\ b(\theta) = \log(1 + \exp\{\theta\}) \\ \theta = \log\left(\frac{\pi}{1 - \pi}\right) \end{array} \right. \quad (9)$$

3. Generalised Linear Mixed Effect Model Formulation

Consider the response Y_{ij} with $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, m_i$ which are based on the assumption of conditionally independent given the random effects under the random Z_1, Z_2, \dots, Z_n .

Generalized linear models incorporate other types of distributions from the exponential family, and include a link function $g(\cdot)$ relating the mean μ , or stated differently, the estimated fitted values $E(y)$, to the linear predictor $X\beta$, often denoted η . The general form is thus

$$\left\{ \begin{array}{l} g(\mu) = \beta X \\ g(\mu) = \eta \end{array} \right. \quad (10)$$

$$E(y) = \mu = g^{-1}(\eta) \quad (11)$$

Consider the Generalised Linear Mixed Model (GLMM) that contains a linear mixed model inside the inverse link function. This model component is referred to as the linear predictor,

$$E(Y|\rho, \varpi) = g^{-1}(\rho X_0 + \varpi Z) \quad (12)$$

Where Y represents the $(n \times 1)$ vector of observed data and Z is a $(r \times 1)$ vector of random effects. X_0 represents observed structural component.

Equation (13) represents the structural component broken into three components that measure teacher factors, Pupils factors and Administrative-Logistic factors

$$E(Y|\varpi) = g^{-1}(\rho(X_{0T} + X_{0P} + X_{0A}) + \varpi Z) \quad (13)$$

Equation (14) introduces interaction component due to a possible interaction between Pupil and Teacher factors.

$$E(Y|\varpi) = g^{-1}(\rho_{0T} X_{0T} + \rho_{0P} X_{0P} + \rho_{0A} X_{0A} + \rho_{PT} X_{0T} \cdot X_{0P} + \varpi Z) \quad (14)$$

Equation (15) is a further extended form of Equation (14) with added interaction between Teacher and Administrative-Logistic factors.

$$E(Y|\varpi) = g^{-1}(\rho_{0T} X_{0T} + \rho_{0P} X_{0P} + \rho_{0A} X_{0A} + \rho_{PT} X_{0T} \cdot X_{0P} + \rho_{AT} X_{0T} \cdot X_{0A} + \varpi Z) \quad (15)$$

where $g(\cdot)$ is a differentiable monotonic link function and $g^{-1}(\cdot)$ is its inverse.

The matrix X is a $(n \times p)$ matrix of rank k , and Z is a $(n \times r)$ design matrix for the random

Due to the underlying stakeholder relationship that tends to complement the overall purpose of education, the two interaction terms were included.

Our response variable, Y , is assumed to follow the Bernoulli distribution for the purposes of this study, and hence the probability mass function (PMF) has the following form:

$$f(y, \theta, \varphi) = \exp\left[\frac{y\theta - b(\theta)}{a(\varphi)} + c(y, \varphi)\right] \quad (16)$$

Let Equation (16) be a PMF on $(0, \infty)$ of a positive random variable ξ , which characterizes a two-parameter exponential family of distributions for positive random variables. The Bernoulli response variable has the form as explicated in Equation (17),

$$f(y) = P(Y = y) = \mu^y (1 - \mu)^{1-y} = \begin{cases} \mu & \text{if } y = 1 \\ 1 - \mu & \text{if } y = 0 \end{cases} \quad (17)$$

The range of y is $\{0, 1\}$.

$$f(y|\mu) = \exp(y \log \mu + (1 - y) \log(1 - \mu)) \quad (18)$$

The logarithm of the probability mass function is

$$\log(p(y|\mu)) = \log(1 - \mu) + y \log\left(\frac{\mu}{1 - \mu}\right), 0 < \mu < 1, y = 0, 1. \quad (19)$$

Thus, the canonical link function (also known as the natural parameter) is the logit link

$$\theta = \eta = g(\mu) = \log\left(\frac{\mu}{1 - \mu}\right) \quad (20)$$

When $\mu = P[y = 1]$, thus the students belong to a private school, the quantity $\frac{\mu}{1 - \mu}$ is the odds ratio (in the range $(0, \infty)$) and g is the logarithm of the odds ratio, sometimes called “log odds”. The inverse link is

$$\mu(\eta) = g^{-1}(\eta) = \frac{e^\eta}{1 + e^\eta} = \frac{1}{1 + e^{-\eta}} \quad (21)$$

For the canonical link function, the derivative of its inverse is the variance of the response.

To that end,

$$\frac{d\mu}{d\eta} = \frac{e^\eta}{(1+e^\eta)^2} = \frac{1}{1+e^{-\eta}} \cdot \frac{e^{-\eta}}{1+e^{-\eta}} = \mu(1-\mu) = \text{Var}(y) \quad (22)$$

The log-linear and logistic link functions are used to connect μ_i and p_i to covariates for the purposes of interpretation. The logit of 'success' is also known as the log-odds.

The binary response model for the clustered and longitudinal data is given in Equation (23).

$$\ln(\mu_i) = \rho_{0T} X_{0T} + \rho_{0P} X_{0P} + \rho_{0A} X_{0A} + \rho_{PT} X_{0T} \cdot X_{0P} + \rho_{AT} X_{0T} \cdot X_{0A} + \omega Z \quad (23)$$

Therefore, following from Equation (7), our five-parameter modified Generalised mixed effect model assumed to follow Bernoulli Exponential Family with four structural component parameters and one random effect parameter assumed to be conditionally independent is given by Equation (24).

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) = \rho_{0T} X_{0T} + \rho_{0P} X_{0P} + \rho_{0A} X_{0A} + \rho_{PT} X_{0T} \cdot X_{0P} + \rho_{AT} X_{0T} \cdot X_{0A} + \omega Z \quad (24)$$

4. Analysis and Discussion

4.1. Checking for Model Assumptions

According to Figure 1, since the Filliben Correlation coefficient of 0.9468 at 5% significance level is less than 0.9927, we reject the null hypothesis that the dataset came from a population with a normal distribution. Hence, we apply the Generalised Linear Mixed Model for non-normal outcome of this nature. This will transform the nonlinear component with a link function. Alternatively, the percentiles in the sample and the theoretical percentiles do not relate in a linear way. The requirement that the error terms be regularly distributed is not satisfied which a required condition for Generalised linear modelling. The quantile residual plot against the index reveals no significant problems with outliers. There are no solitary residuals that seem to have departed from the typical random distribution of residuals, thus there is no outlier issue.

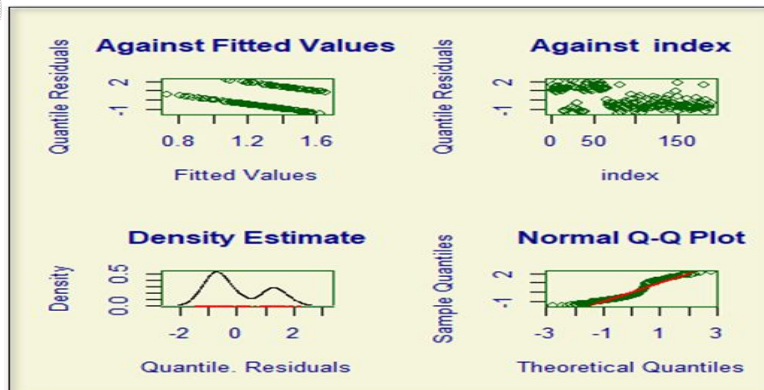


Figure 1. Graphical test for nonlinearity, outliers and homoscedasticity

4.2 Assessing Strength of Correlation

We convert the factor level type to numeric in order to produce a heat map with the Spearman method-calculated coefficient of correlation as shown in Figure 2. It is obvious that there is a serious issue with collinearity in our dataset because the entire heat map appears dark. This is a sign that MIXED models will handle the correlated data and unequal variances better than GLM; the stronger the correlation between any two being compared, the larger the number and darker the hue. In cases when survey respondents or test subjects are repeatedly measured, strongly correlated data such as those in our scenario are frequently observed. GLM's repeated measurements models are extended by MIXED to support an uneven number of repetitions. Additionally, when experimental units are nested in a hierarchy, it can handle more complicated circumstances.

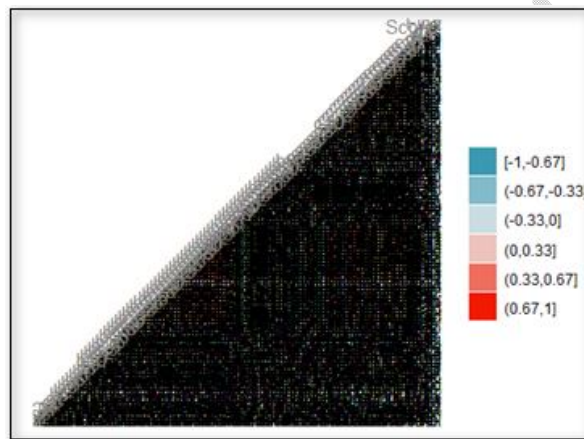


Figure 2. Graph of Heat map Correlation Check

4.3 Two-Way ANOVA Test

A significant P-value ($p < 0.05$) for Factor1 will mean the Gender of pupils significantly affect performance at private and public-school. A significant P-value ($p < 0.05$) for Factor2 will mean the Religion of pupils significantly affect performance at private and public-school.

Table 1. Two-Way ANOVA Test: Dependent Variable: Type of School

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	11.448 ^a	28	0.409	2.245	0.001
Intercept	14.663	1	14.663	80.526	0
PupilGd*TeacherGd	0.931	1	0.931	5.115	0.025

TeacherGd* Subjtot	2.022	2	1.011	5.551	0.005
TeacherGd*Rel.Deno	3.005	3	1.002	5.5	0.001

The normality assumptions of residuals homogeneity of variance (Levene's test) were satisfied for two-way ANOVA

The results of the two-way ANOVA demonstrate that a number of variables, including interaction between student-gender and instructor-gender, have a significant impact ($p < 0.05$) on BECE performance levels in both public and private schools. This indicates that some students think they will perform better if they take certain subject classes from teachers of a particular gender. This is supported by another finding that suggest that there is a significant interaction effect between the teacher's gender and the subject(s) he/she teaches on the BECE performance of students from both private and public-school s ($p < 0.05$). Due to the strong connection between teacher gender and school characteristics (such as the sort of religious group that works with government), this have been found to significantly affect BECE performance.

4.4 Model Selection Criteria

Table 2 shows the model selection criteria and determination of robustness. The output shows that our modified GLMM was robust across sample sizes where it remained the best model with the lowest values of AIC and BIC. The selected model is significantly robust since the AIC difference between the selected model and each of the other two candidate models is generally more than 2 units irrespective of sample size variation.

Table 2. Model Selection Criteria by AIC, BIC

Sample Variation	Model	BIC	AIC	Delta (AIC)
100%	Modified GMM	323.7	213.6	0
	Probit GMM	339.4	219.6	6
	Clog-log GMM	344.8	221.8	8.2
70%	Modified GMM	258.32	248.61	0
	Probit GMM	263.46	250.51	1.9
	Clog-log GMM	260.51	250.8	2.19

50%	Modified GMM	267.43	248.02	0
	Probit GMM	268.69	252.5	4.48
	Clog-log GMM	271.04	251.63	3.61
30%	Modified GMM	269.71	250.3	0
	Probit GMM	270.95	254.76	4.46
	Clog-log GMM	274.94	252.29	1.99

The essence of the Delta (AIC) is to compare the difference of tentative models to the Modified model. Automatically, the Modified model's comparison to itself will be zero. But the main interest is the Delta (AIC) for tentative models. A Delta (AIC) of at least 2 signifies statistical significance.

Table 3. Reduced Model Estimations

Factors	Parameter Estimates (E)	P-value	Standard Error	Exp(E)
Teacher Factors				
Identifies and remediates learners' difficulties or misconceptions	0.87447	0.00902	0.1989	2.4
meaningfully communicates progress clearly to parents and learners	0.9036	0.00221	0.33489	2.5

Enhanced parent-teacher relationship	0.6094	0.01442	0.2491	1.8
Highly supervised to achieve set targets	0.63720	0.042448	0.31403	1.9
Reflects to modify outputs	0.8141	0.00571	0.2946	2.3
Pupil Factors				
Influence of Private Home Tutor	1.09589	0.01798	0.46317	3
Engages in Holiday Classes	0.4303	0.0305	0.1989	1.5
Class competition	1.06365	0.048147	0.53827	2.9
Well organised, disciplined with time management due to school culture that translates into academic life	0.70675	0.044826	0.35227	2
Prep Time Culture	0.6593187	0.03842	0.3184649	1.9
Pupil well managed and supervised at home by parents to focus on academics as a continuity from school	0.6775728	0.04168	0.3326766	2
Adm. Log. Factors				
Daily Quality Supervision of Head teacher and Teacher by superiors	1.42558	0.000875	0.42836	4.2
Timely Provision of Books and learning materials by Parents/Stakeholders for Pupils	1.4006656	0.00136	0.4374075	4.0

Conducive Teaching /Learning environment	1.2121599	0.03617	0.5785873	3.4
Interaction Factors				
Concern and parents' support parents towards their Pupils' Academic Output (PTA)	1.1848393	0.04422	0.5888820	3.3

Random Effects: Variance = 0.933

Table 3 shows the parameter estimates of the reduced model which captures fifteen (15) significant factors (out of 70 factors examined) that explains the disparities in BECE performance among private and public basic school student. The random Effect Variance was 9.017. Table 3's findings indicate that private school teachers are twice as likely to detect and correct their students' misconceptions or learning difficulties (B21 factor), which results in better BECE performance than their public-school counterparts ($B = 0.87447$, $p < 0.05$, $se = 0.1989$). As a result, private school students are twice as likely to receive positive feedback regarding their misconceptions or learning difficulties.

4.4.1 Factor B21: Identifies and remediates learners' difficulties or misconceptions

Figure 3 displays a contour graph of the area projected to be affected by this factor in terms of BECE performance, with the red area representing performance in public-school s and the yellow region representing performance in private schools. The 3D figure provides a sharper picture, showing that private candidates perform 34% better than public candidates in the BECE with regard to the “**Identifies and remediates learners' difficulties or misconceptions**” factor.

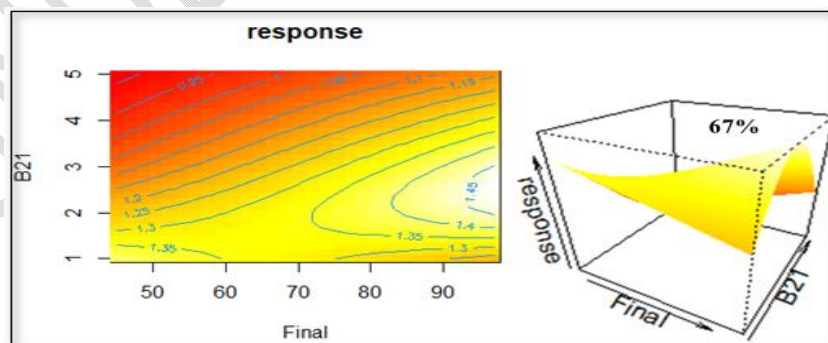


Figure 3. Graph Predicting Performance with respect to Factor “Identifies and remediates learners' difficulties or misconceptions”

4.4.2 Meaningfully communicates progress clearly to parents and learners

Teachers in private schools tend to be three times more effective than those in public-schools at significantly and plainly communicating progress to students and parents according to Table 3 ($B = 0.9036$, $p < 0.05$, $se = 0.33489$). Figure 4 shows a contour graph of the area expected to be impacted by this factor in terms of BECE performance. A clearer picture is given by the 3D figure, which demonstrates that private candidates outperform public candidates in the BECE with regard to the B24 factor by 8%.

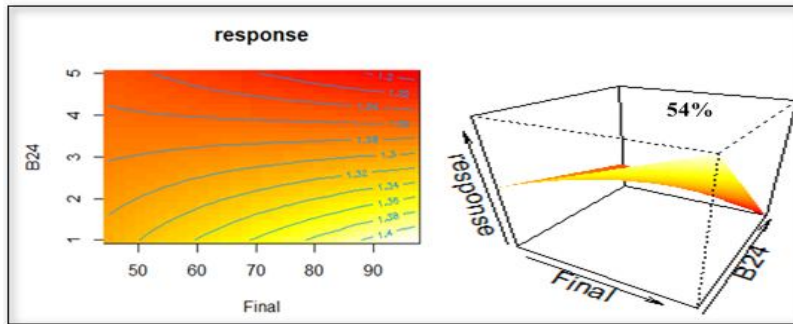


Figure 4. Graph Predicting Performance with respect to Factor “Meanfully communicates progress clearly to parents and learners”

4.4.3 Enhanced parent-teacher relationship

The positive effects of enhanced teacher-parent relationship (B18) on performance in BECE examination is 2-fold greater in private school than in the public-school ($B = 0.6094$, $p < 0.05$, $se = 0.2491$). According to the contour graph in Figure 5, private school students perform 56% better on the BECE as a result of improved parent-teacher ties, which enable parents to give their children timely interventions.

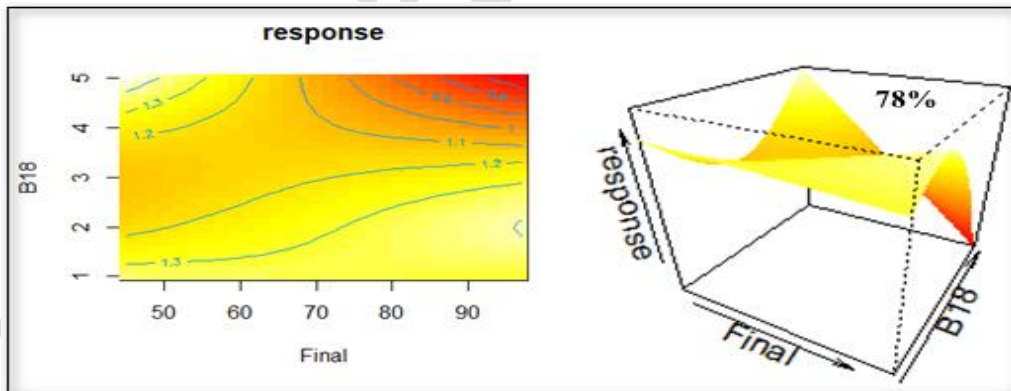


Figure 5. Graph Predicting Performance with respect to Factor “Enhanced parent-teacher relationship”

4.4.4 Highly supervised to achieve set targets

Due to the frequent monitoring, they receive from their superiors and the eventual instillation of the culture of alertness and vigilance to improve students' output, private teachers are twice as likely to exhibit numerous high-quality composure and constant alertness to achieve short-to long-term academic goals ($B = 0.63720$, $p < 0.05$, $se = 0.31403$). Figure 6 demonstrates how

the BECE scores of private school students were 18% higher than those of public-school students as a result of private instructors' improved ability to respond to Factor “**Highly supervised to achieve set targets**”.

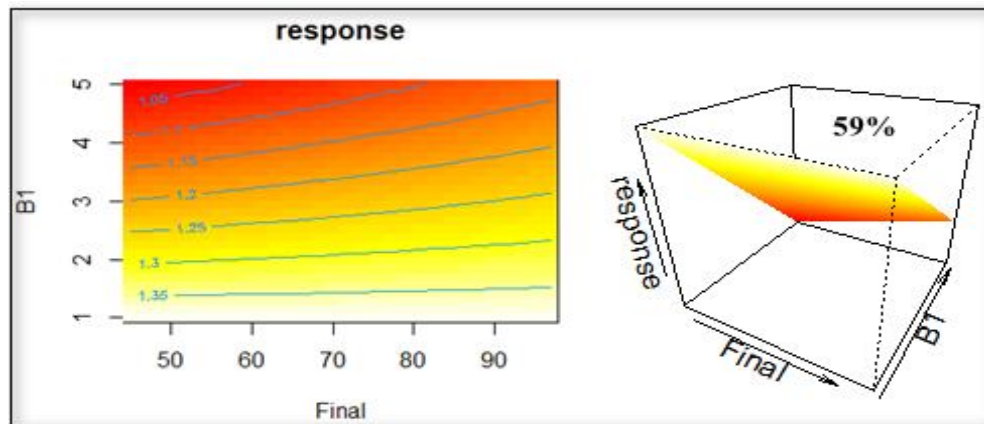


Figure 6. Graph Predicting Performance with respect to Factor “Highly supervised to achieve set targets”.

4.4.5 Reflects to modify outputs

Private school teachers are two-fold better able to evaluate their work and see the need to change it to produce effective results ($B = 0.63720$, $p < 0.05$, $se = 0.31403$). According to Figure 7's result, Factor B3's influence is responsible for private school pupils performing 10% better on the BECE than their public-school counterparts.

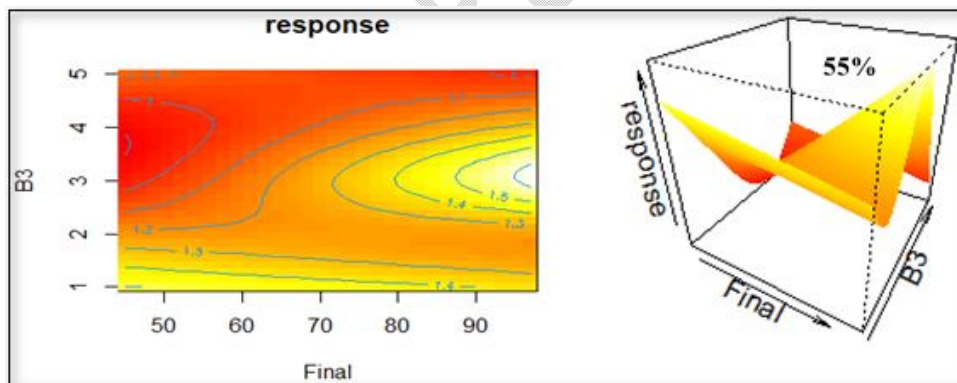


Figure 7. Graph Predicting Performance with respect to Factor “Reflects to modify outputs”

4.4.6 Influence of Private Home Tutor

Private school pupils are three times as good in academics due to the Influence of Private Home Tutor compared to the performance of public-school students who has no influence of a home teacher ($B = 1.09589$, $p < 0.05$, $se = 0.46317$). Figure 8 suggests that Factor

“**Influence of Private Home Tutor**” accounts for a 28% improvement in BECE performance for students in private schools compared to those in public-school s.

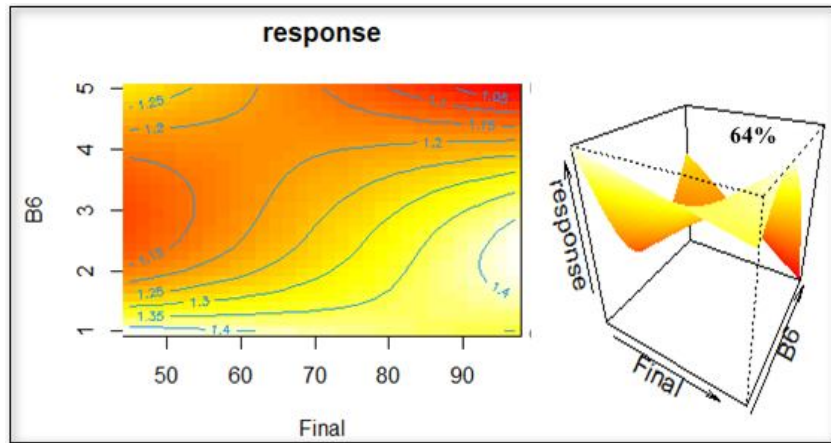


Figure 8. Graph Predicting Performance with respect to Factor “Influence of Private Home Tutor “

4.4.7 Engages in Holiday Classes

Private students tend to attend Extra or Holiday classes who makes them outperform students in public-school s in terms of academic achievement by a factor of two ($B = 0.4303$, $p < 0.05$, $se = 0.1989$). From Figure 9, it can be concluded that Factor “**Engages in Holiday Classes**” is responsible for the 12% improvement in BECE scores for students in private schools as compared to those in public-school s.

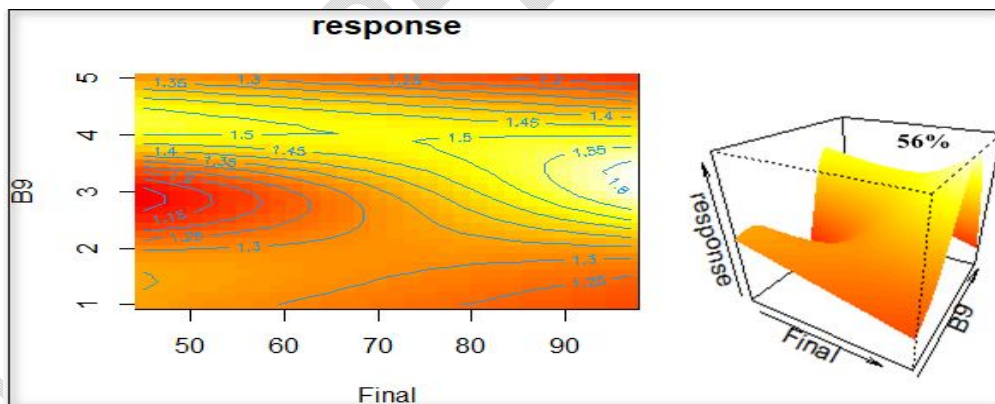


Figure 9. Graph Predicting Performance with respect to Factor “Engages in Holiday Classes”

4.4.8 Class competition

There is a three-fold higher tendency for students in private schools to outperform those in public-school s in BECE, which can be attributed to the highly competitive atmosphere among students, where they strive for academic brilliance to increase their class performance rank ($B = 1.06365$, $p < 0.05$, $se = 0.53827$). Figure 10 suggests that Factor” **Class competition**” is responsible for the 60% improvement in BECE scores between pupils in private schools and those in public-school s.

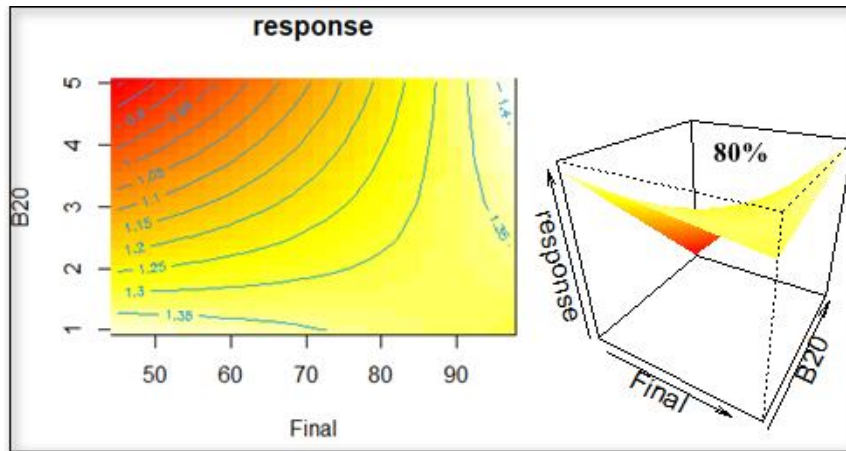


Figure 10. Graph Predicting Performance with respect to Factor “Class competition”

4.4.9 Well organised, disciplined with time management due to school culture that translates into academic life

Private school students typically exhibit greater levels of organization, discipline, and time management, which are traits and qualities developed from proper school culture and translate into their academic life, giving them a two-fold advantage over their public-school counterparts in BECE success ($B = 0.70675$, $p < 0.05$, $se = 0.35227$). Figure 11 suggests that Factor “**Well organised, disciplined with time management due to school culture that translates into academic life**” is responsible for the 50% improvement in BECE performance in private school students as compared to public-school students.

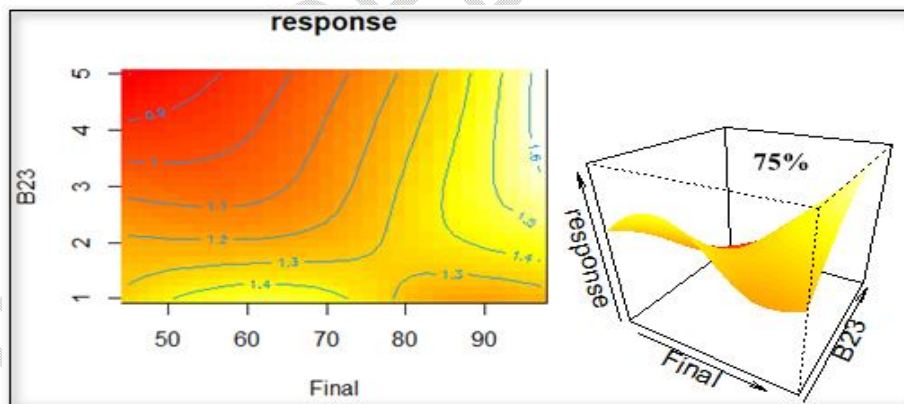


Figure 11. Graph Predicting Performance with respect to Factor “Well organised, disciplined with time management due to school culture that translates into academic life”

4.4.10 Prep Time Culture

Students in private schools have a stronger propensity to adhere to the Prep Time Culture, which translates into a 2-fold greater propensity to pass the BECE than candidates from public-school s ($B = 0.6593187$, $p < 0.05$, $se = 0.3184649$). Figure 12 suggests that Factor “**Prep Time Culture**” is responsible for the 32% improvement in BECE performance among students in private schools compared to those in public-school s.

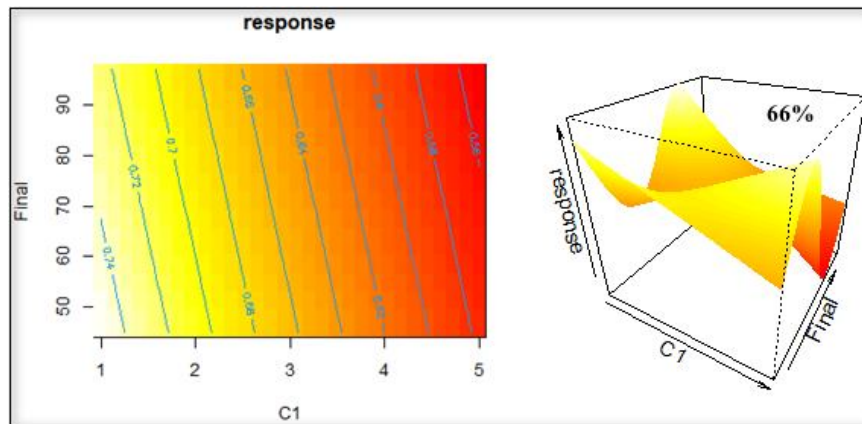


Figure 12. Graph Predicting Performance with respect to Factor “Prep Time Culture”

4.4.11 Pupil well managed and supervised at home by parents to focus on academics as a continuity from school

Since private school students are typically well-managed and closely watched at home by their parents, they are more likely than pupils from public-schools to succeed in the BECE exam by a factor of two ($B = 0.6775728$, $p < 0.05$, $se = 0.3326766$). Figure 13 suggests that Factor “**Pupil well managed and supervised at home by parents to focus on academics as a continuity from school**” is responsible for the 50% improvement in BECE scores between pupils in private schools and those in public-schools.

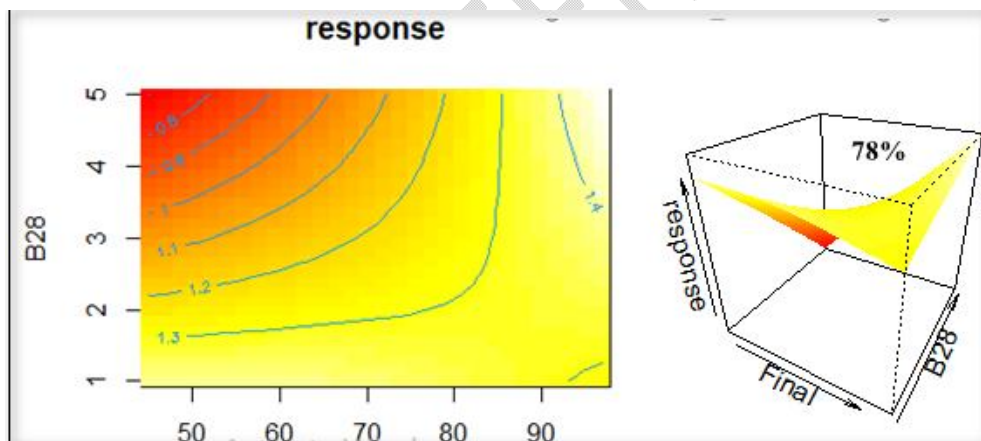


Figure 13. Graph Predicting Performance with respect to Factor “Pupil well managed and supervised at home by parents to focus on academics as a continuity from school”

4.4.12 Daily Quality Supervision of Head teacher and Teacher by superiors

Daily high-quality teacher monitoring by school owners and teacher supervision by school heads results in excellent teaching and learning, which contributes for a 4-times greater likelihood for private school students to succeed in BECE than for students in public-schools ($B = 1.42558$, $p < 0.05$, $se = 0.42836$). Figure 14 suggests that Factor “**Daily Quality Supervision of Head teacher and Teacher by superiors**” is responsible for the 74% improvement in BECE performance among students in private schools compared to those in public-schools.

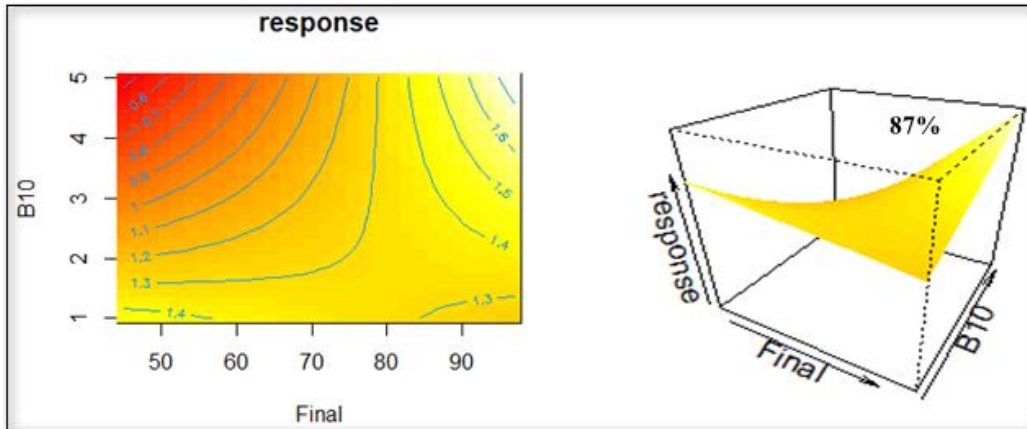


Figure 14. Graph Predicting Performance with respect to Factor “Daily Quality Supervision of Head teacher and Teacher by superiors”

4.4.13 Timely Provision of Books and learning materials by Parents/Stakeholders for Pupils

Private school students are four times more likely than public-school students to succeed in the BECE as their parents tend to provide the required books and materials on time as instructed by the school ($B = 1.4006656$, $p < 0.05$, $se = 0.4374075$). Figure 15 suggests that Factor “Timely Provision of Books and learning materials by Parents/Stakeholders for Pupils” is responsible for the 58% increase in BECE performance among students in private schools as compared to those in public-school s.

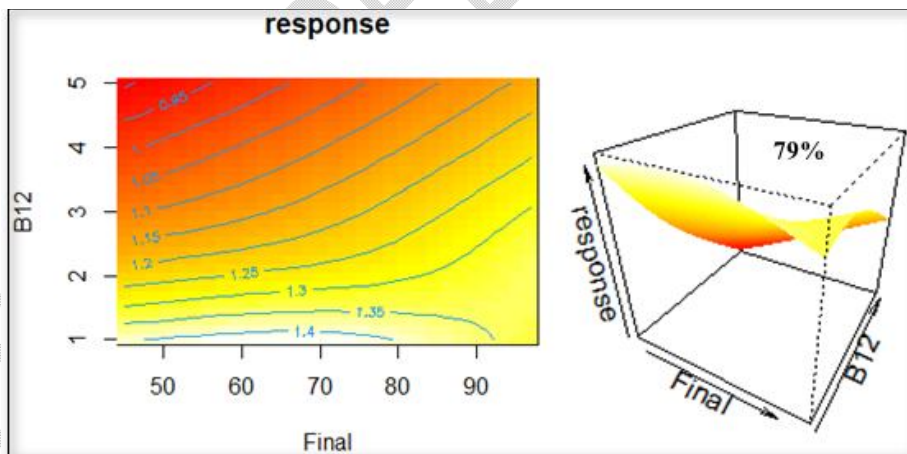


Figure 15. Graph Predicting Performance with respect to Factor “Timely Provision of Books and learning materials by Parents/Stakeholders for Pupils”

4.4.14 Conducive Teaching /Learning environment

Due to the teaching and learning environment, BECE results are typically better for students from private schools. In the BECE, pupils from private schools have a three times greater tendency to score better than those from public-school s as a result of this factor ($B = 1.2121599$, $p < 0.05$, $se = 1.2121599$). Figure 16 suggests that Factor “Conducive Teaching

/Learning environment “is responsible for the 64% improvement in BECE performance among students in private schools compared to those in public-school s.

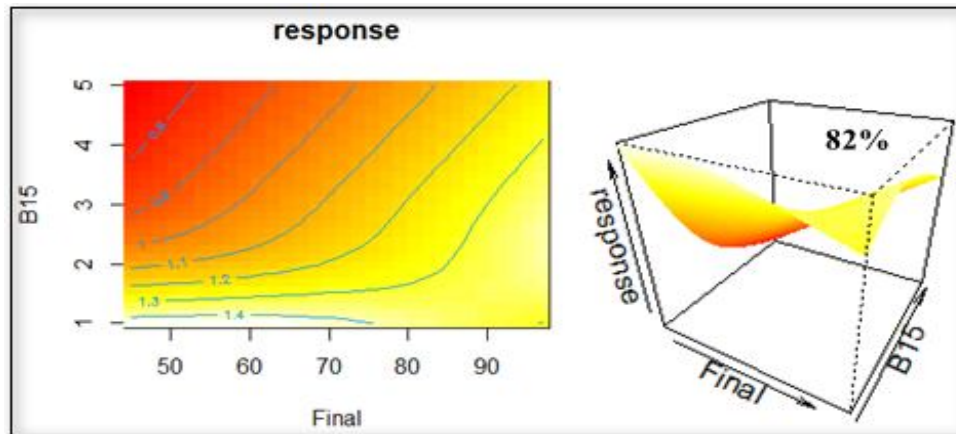


Figure 16. Graph Predicting Performance with respect to Factor “Conductive Teaching / Learning environment “

4.4.15 Concern and parents’ support parents towards their Pupils’ Academic Output (PTA)

The performance of students attending private schools tends to be three times better than that of students attending public-school s in the BECE due to the high level of parental participation and desire to support the aims of the private schools attended by their wards ($B = 1.1848393$, $p < 0.05$, $se = 0.5888820$). Figure 17 indicates that Factor “**Concern and parents’ support parents towards their Pupils’ Academic Output (PTA)**” is responsible for the 50% improvement in BECE performance among students in private schools as compared to those in public-school s.

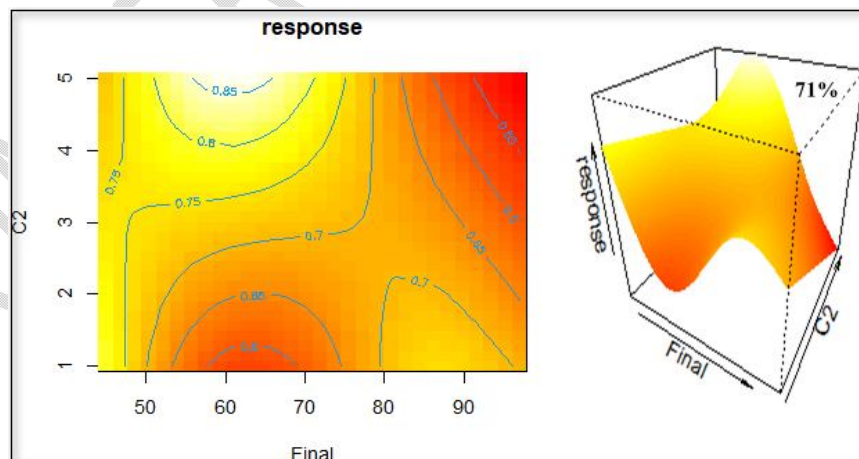


Figure 17. Graph Predicting Performance with respect to Factor “Concern and parents’ support parents towards their Pupils’ Academic Output (PTA)”

5. Conclusion

The study sought to build a six-parameter Generalised Mixed linear Model with five structural parameters that explains students, teachers, and administrative-logistic characteristics and two interaction effects as well as random effect parameter. The study identified fifteen (15) significant factors out of 70 factors examined to be responsible for disparities in BECE performance among private and public basic school student. The probabilities associated with the dynamics of each of the significant factors have been estimated by the parameters of the model. Our model has been found to be efficient across varied sample sizes as opposed to existing models. The two-way ANOVA was used to assess Mean difference of significant factors including interaction effects. The top five drivers of the performance gaps included respectively included Daily Quality Supervision of Head teacher and Teacher by superiors, Timely Provision of Books and learning materials by Parents/Stakeholders for Pupils, Conducive Teaching /Learning environment, Concern and parents' support parents towards their Pupils' Academic Output and Class competition.

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