Bayesian Regression Modelling With Interaction Effects of Mathematical Literacy Using the Results of the Programme for International Student Assessment 2018

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Abstract: Mathematical Literacy is the capacity of students to analyze and solve mathematical problems that can be applied in a practical situation. Based on the Program for International Student Assessment in 2018, the Philippines scored lower in Mathematical Literacy than other participating countries. This study aims to determine the relationship between students' mathematical literacy and student-level and school-level variables during the PISA 2018. The student-level variables are students' gender, socioeconomic status, and parental support while the school-level variables are teachers' hindering, students' hindering, parental support, and socioeconomic status. The missing data were addressed by Multiple Imputations using Additive Regression, Bootstrapping, and Predictive Mean Matching. The Cronbach Alpha was first used to assess the reliability and consistency of the questionnaire used in the assessment, followed by constructing a Multilevel model and a Bayesian Regression model with interaction effects to compare the relationship between mathematical performance and its predictors. At the student level, the results showed that higher indices of socioeconomic status are associated with higher performance in mathematics; female students tend to outperform males in mathematics; parental support is a positively influential factor for mathematics performance. At the school level, both models showed that high indices of student hindrance are associated with lower mathematics achievement; higher indices of teacher hindrance factors are associated with higher scores in mathematics. A cross-level interaction between parental support and student hindrance was also discovered.

Key Words: Mathematical Literacy, Student-level, School-level, Multilevel Model, Bayesian Regression Model

1. INTRODUCTION

Students' capacity to analyze, justify and express ideas effectively, as well as comprehend mathematical problems is the emphasis of Mathematical Literacy (Lailiyah, 2017). Mathematical Literacy is important to students as this allows them to apply concepts learned in Mathematics in their daily lives (Rizki & Priatna, 2019). However, the results of the Programme for International Student Assessment (PISA) conducted in 2018 showed that students from the Philippines had lower scores in Mathematical Literacy compared to other participating countries (OECD, 2019). As such, the primary purpose of this study is to predict Mathematical Literacy among high school students in the Philippines by applying the concepts of Bayesian Multilevel modeling.

Given the state of Mathematical literacy here in the Philippines, the result of this study hopes to establish the relationship between mathematical literacy and students' gender, socioeconomic status, parental support, teachers' hindering behaviors, and students' hindering behaviorThis will be useful to the Department of Education in the Philippines, school institutions, faculties in their future reforms to efficiently improve student's mathematical performance. The result of this study will also enable students and parents to act accordingly on how to improve mathematical performance. For the future researchers, the results will serve as a reference data in conducting new research related to this study.

Ömür (2020) conducted a correlational study to investigate the relationship between students' literacy scores and student-level and school-level variables in Turkey using PISA 2018 results. Multilevel structural modeling (MSEM) was applied to analyze the data which includes students' gender, socioeconomic status, and parental support for student-level variables (Ömür, 2020). On the other hand, teachers' hindering, students' hindering, parental support, and socioeconomic status were used under school-level variables (Ömür, 2020). The samples were 6,800 students from different regions in Turkey and it showed that both student-level and school-level variables showed significant relationships towards students' literacy scores (Ömür, 2020). The findings would contribute to the improvement of the quality of education in Turkey. With that, the researchers want to conduct a Bayesian multilevel modeling approach to Mathematics Literacy scores based on students' gender, socioeconomic status, parental support, teachers' hindering behaviors, and students' hindering behavior using the results of PISA 2018.

To further investigate the relationship between mathematical literacy and students' gender, socioeconomic status, parental support, teachers' hindering behaviors, students' hindering behavior, the researchers individually reviewed related literature of the aforementioned variables and its relationship with mathematical literacy.

Gender. Human gender differences have been studied in a variety of disciplines. In terms of mathematical performance, there are several perspectives and conclusions on gender and academic achievement in mathematics. In the study of Anjum (2015), Females outperform males in mathematics achievement. This finding is supported and is consistent with the findings of NCERT (2014), Linnakyla et al. (2004), Ogle et al. (2003), Spearrit (1977), NAEP (1973), Brown (1991), and Breakley et al. (1988) (As cited in Anjum, 2015). Meanwhile, in the study of Contini et al., (2016), Males outperform females in mathematics achievement, which is supported and is consistent with the study of Fennema, (2000), Muthukrishna, (2010) (As cited in Ajai et al., 2015), Felson & Trudeau, (1991), and Rodriguez et al. (2015). Another perspective is that there are no significant gender differences in math skills (Hyde et al., 2008; Ajai et al., 2015; Scheiber et al., 2015).

Socioeconomic status. A study conducted by Kalaycıoğlu (2015) looked into the relationship between socioeconomic status, math self-efficacy, anxiety, and mathematical achievement in England, Greece, Hong Kong, Netherlands, Turkey, and the USA using structural equation modeling. The researchers used the results from PISA 2012 with 8,806 students as samples from the aforementioned countries. It was found out that socioeconomic status has a significant effect on mathematics achievement. Further, The relationship between socioeconomic status and mathematics achievement is highest in the Netherlands and lowest in Hong Kong (Kalaycıoğlu, 2015). Another study conducted by Alordiah et al. (2015), investigated the influence of gender, school location, and socio-economic status on students' mathematical achievement in Nigeria. Using two instruments namely: mathematics objective test (MOT) and socio-economic status questionnaire (SESQ), the results showed that students with high socioeconomic status performed better than students with low socioeconomic status. In addition, urban students performed better than rural students (Alordiah et al., 2015).

Parental Support. In an exploratory study conducted by Cai et al. (1999), they investigated the relationship between parental support and the achievement in Mathematics of students, where the guardians of the students were given a Parental Involvement Questionnaire (PIQ) that will assess what type of parental support they are giving to their child. The results showed that parental involvement is a significant predictor of the achievement in Mathematics of students (Cai et al.,1999). Also, it showed that students who have the most supportive parents have better mathematical achievement compared to those students who have the least supportive parents (Cai et al., 1999). Moreover, Huang et al. (2021) studied the relationship between the three types of parental involvement and the achievement in Mathematics of students among 2866 early adolescents and their parents in China. The three types of parental involvement are cognitive involvement, behavioral involvement, and personal involvement (Huang et al. 2021). Based on the results, only the cognitive and behavioral involvements have a significant relationship with the Mathematics achievement of students which means that those parents who are more concerned with the academic performance of their children may result in a better performance of their children in mathematics (Huang et al. 2021).

Teachers' Hindering Behaviors. Teachers play a vital role in a student's education. Teacher's behavior may hinder students' learning. PISA 2018 interviewed school principals about some of the teacher behaviours that can create an unpleasant school climate and hinder student learning, such as teachers not meeting individual students' needs; teacher absenteeism; school staff resisting change; teachers being too strict with students; and teachers not being well-prepared for classes. Based on the results of PISA 2018, On average across OECD countries, it is reported that teacher behavior does not or just slightly affect students' learning (OECD, 2019). However, the disadvantaged schools were more likely to indicate that teacher behaviors hinder learning (OECD, 2019). Ideally, teachers' hindering behaviors such as not meeting individual students' needs, absenteeism, school staff resisting change, being too strict with students and unpreparedness are more likely to negatively affect student's mathematical performance. However, there are several contrasting conclusions on the effects of the mentioned behaviours on student's mathematical performance. In particular, in the study of Atetwe (2012), results found a positive relationship between teacher absenteeism and student's mathematical achievement, which were consistent with the findings of Ballou, 2000, Paul &Faustin, 2005, Mukyanuzi,2003. Meanwhile, Rogers et. al (2004), Bayard, (2003), Antrell, (2003) had a contrasting conclusion (As cited in Atetwe, 2012). Another conclusion by Brouillette (2012) found no statistically significant relationship between teacher absenteeism and student's mathematical performance.

Students' hindering behaviors. One of the factors that affect students' academic performance is students' attitude and behavior towards their education. The study of Mazana et al. (2019) have investigated students' attitude towards learning mathematics in Tanzania. It was found out that there is a significant positive weak correlation between students' attitude and performance. Specifically, hindering behaviors are students' behaviors that negatively affect their academic performance and well-being (Török et al., 2018). Based on PISA 2018, examples of student hindering behaviors are "truancy, bullying other students, usage of illegal drugs and alcohol, lack of respect for teachers, skipping classes and not being attentive" (Ömür, 2020). The study of Hendy et al. (2014) concludes that poor math behaviors among college students would lead to high math anxiety, and low math confidence, which affect students' mathematical achievement.

This study is to focus on determining the relationship between students' mathematical literacy and with the following variables: students' gender, socioeconomic status, parental support, teachers' hindering behaviors, students' hindering behavior. Results from PISA 2018 will serve as the data for analysis and will only focus on data pertaining to 15-year-old students from the Philippines. The design of this study will be a quantitative study design using Bayesian Multilevel Modelling as the statistical model.

This study is limited to students' mathematical literacy and will not look into the relationships between the aforementioned variables and with other academic subjects. Furthermore, the data to be used is outdated since only the results from PISA 2018 are available to the researchers.

2. METHODOLOGY

2.1 Data

The data used in the study comes from the results of PISA 2018. The PISA data was then filtered to get the data on the students from the Philippines. The researchers subsetted the data using SAS 9.4 to focus on variables and covariates of interest. The data of the study consists of two levels: the student level (level 1) and the school level (level 2). The dataset for the student level contains n = 7233 observations for the test scores and the indicators of interest. The data in the student level is from the student questionnaire administered to the selected students in the Philippines. There are 187 observations for student and teacher hindrance at level 2, the school level. The data for the school level are produced by the school questionnaire, which is answered by the principals or heads of the selected schools in the Philippines. Table 1 provides the variables and the description of each variable.

Table 1. Description of the variables

Variable	Description
ESCS	Index of Economic, Social, and Cultural Status, level 1 variable
PERFMATH	Performance in the PISA Mathematics Test, level 1 variable
GENDER	Student's Gender (1 - Female, 2 - Male), level 1 variable
PARENT SUPPORT	Index of Parental Support, level 1 variable
CNTSCHID	School Identifier, level 1 and 2 variable

STUDENT HINDRANCE	Student hindrance index in schools, level 2 variable
TEACHER HINDRANCE	Teacher hindrance in schools, level 2 variable

The data is then subjected to data imputation to address the missing data. Multiple Imputation using Additive Regression, Bootstrapping, and Predictive Mean Matching were used in order to impute the missing data. The HMisc package in R was used to aid in the imputation of the missing observations. The data was also checked for any outliers or extreme observations.

2.2 Descriptive Statistics and Reliability Checking

After addressing the missing data in the data, the data is explored through descriptive statistics and plots. The means and standard deviations of the variables of interest will be computed, and histograms will also be used to check the distribution of the variables of interest. Then, the reliability of the questionnaire is checked. The Cronbach Alpha will be used to assess the reliability and consistency of the questionnaire. A Cronbach Alpha of 0.70 is the minimum for the questionnaire to be considered reliable. Questions that make the reliability of the questionnaire lower will be removed from the analysis.

2.3 Multilevel Model

After assessing the reliability of the questionnaire, the researchers first fitted a Multilevel Model using the level 1 and level 2 predictors of the study. First, an intercept only model was fitted in order to measure how much variability is present in the data set, and if there is a significant amount of variance in the two levels. From this, an estimate for the Intraclass Correlation Coefficient (ICC) was calculated. The model for the intercepts only model is:

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

where

γ_{00} = the common intercept

u_{0j} = error term for between schools

r_{ij} = error term for within schools

The next step to building the multilevel model is to add the level 1 and level 2 effects of the study. Level 1 effects are the gender, parental support, and index of economic and social status of each student. Level 2 effects on the other hand are the index of student and teacher hindrance in each school. The initial model is denoted by:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(Gender_{ij}) + \beta_{2j}(ESCS_{ij}) + \beta_{3j}(P.Support_{ij})$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(S.Hindrance_j) + \gamma_{02}(T.Hindrance_j) + u_{0j}$$
$$\beta_1 j = \gamma_{20}$$
$$\beta_2 j = \gamma_{20} + \gamma_{21}(S.Hindrance_j) + \gamma_{22}(T.Hindrance_j) + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(S.Hindrance_j) + \gamma_{32}(T.Hindrance_j) + u_{3j}$$

In this model, the effect of gender will not vary across schools. However, the effects of Parental Support and ESCS will be allowed to vary across schools, accounting that different types of schools have different general socio-economic statuses as mentioned in the related literature. After forming the initial model, stepwise selection of the random effects will first be done to ensure that only significant random effects are left in the model. After removing non-significant interaction effects, the non-significant fixed effects will be removed, provided that these fixed effects are not involved in any of the significant mixed effects. Certain assumptions were also checked. These assumptions include linearity, normality of residuals in level 1 and level 2, and homoscedasticity (Ushakova & Watterson, 2019).

2.4 Bayesian Regression Model with Interaction Effects

After selecting the best multilevel model from the previous step, the researchers will then fit a Bayesian Regression Model with Interaction Effects using the level 1 and 2 predictors of the study that are significant from the first multilevel model. This was done to compare the models made by the HLM procedure and its corresponding Bayesian regression modelling procedure. The Bayesian Model is given by:

$$PERFMATH_{ij} \sim N(\beta^T X,\ \sigma^2 I)$$

where

$\beta^T = [\beta_0\ \beta_1\ \beta_2 \ldots\ \beta_{10}]$, the parameters of the predictors

X = Matrix that includes the predictors, fixed effects, and interactioneffects of the model.

In the model, there are a total of 10 parameters to be estimated: The intercept, the main effects of gender, parental support, ESCS, student hindrance, and teacher hindrance, and the two way interactions of parental support and ESCS with student and teacher hindrance. Due to the scarcity of available research on the possible distribution of the coefficients of the predictors, non-informative priors will be used as the prior distribution for the coefficients of the model. The sampling will be done through the Monte Carlo Markov Chains (MCMC) method, with 4 chains and 10000 iterations using the rstanarm, rstan, and brms packages of R. The estimates and a 95% High Density Interval / Credible Intervals will also be computed. Similar to Hierarchical Linear Modelling, non-significant effects will be eliminated to find the final and most parsimonious model.

3. RESULTS AND DISCUSSION

3.1 Reliability Analysis

The researchers analyzed the data by first looking at the reliability of the questionnaire used in the assessment. Table 1 shows the Cronbach Alpha of each question in the student questionnaire for parental support, and Table 2 shows the Cronbach Alpha of each question in the school questionnaire. Both questionnaires are found to be reliable, as the overall Cronbach alpha measures for the student and teachers questionnaires were 0.9085 and 0.9215 respectively. Since none of the Cronbach alpha statistics increased after deletion of any of the questions, none of the questions were removed from the analysis.

Table 1. Cronbach Alpha for Parental Support Questionnaire

Deleted Question	Cronbach Alpha
ST123Q02NA: My parents support my educational efforts and achievements.	0.870450
ST123Q03NA: My parents support me when I am facing difficulties at school.	0.866616
ST123Q03NA: My parents encourage me to be confident.	0.869437

Table 2. Cronbach Alpha for Student and Teacher Hindrance Questionnaire

Deleted Question	Cronbach Alpha
SC061Q01TA: Extent to which student learning is hindered by: Student truancy	0.918037
SC061Q02TA: Extent to which student learning is hindered by: Students skipping classes	0.915195
SC061Q03TA: Extent to which student learning is hindered by: Students lacking respect for teachers	0.914486
SC061Q04TA: Extent to which student learning is hindered by: Student use of alcohol or illegal drugs	0.914895
SC061Q05TA: Extent to which student learning is hindered by: Students intimidating or bullying other students	0.916446
SC061Q11TA: Extent to which student learning is hindered by: Students not being attentive	0.914914
SC061Q06TA: Extent to which student learning is hindered by: Teachers not meeting individual students' needs	0.908116
SC061Q07TA: Extent to which student learning is hindered by: Teacher absenteeism	0.911117
SC061Q08TA: Extent to which student learning is hindered by: Staff resisting change	0.912844
SC061Q09TA: Extent to which student learning is hindered by: Teachers being too strict with students	0.919573
SC061Q10TA: Extent to which student learning is hindered by: Teachers not being well prepared for classes	0.910757

3.2 Descriptive Statistics

After assessing the reliability of the questionnaires for parental support and hindrances on student learning, the descriptive statistics were then computed for the variables of interest. Table 3 summarizes the descriptive statistics of the quantitative variables.

Table 3. Descriptive statistics of the quantitative variables

Variable	Mean	Std Dev
ESCS	-1.4404175	1.1101742
PERFMATH	351.8614420	71.799770
parent_support	3.2413828	5
teacher_hindrance	1.8989631	0.7438493
student_hindrance	2.1889258	0.6568397
		0.5901121

In terms of parent support, the overall consensus found that there is a somewhat strong extent of parental support of education of the students. There is also some extent of student learning hindrance due to the students and the teachers. The index of ESCS was also found to be low, which likely states that most of the students who took the PISA are not from financially-well families and households.

Aside from checking the descriptive statistics of the variables, the distributions were also checked through the use of histograms. This was done in order to ensure correct priors are used in later analyses. Figures 1 through 5 show the histograms of ESCS, PERFMATH, parent support, teacher hindrance, and student hindrance respectively.

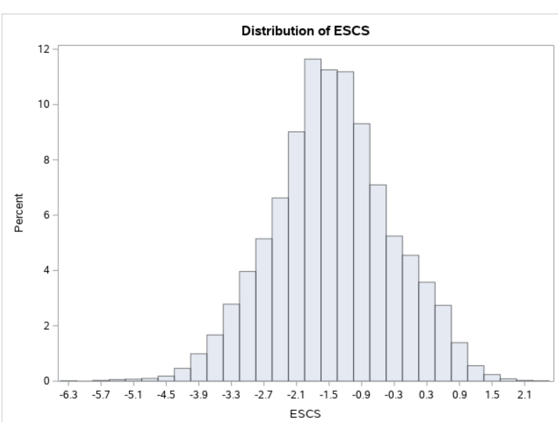


Figure 1: Histogram of ESCS

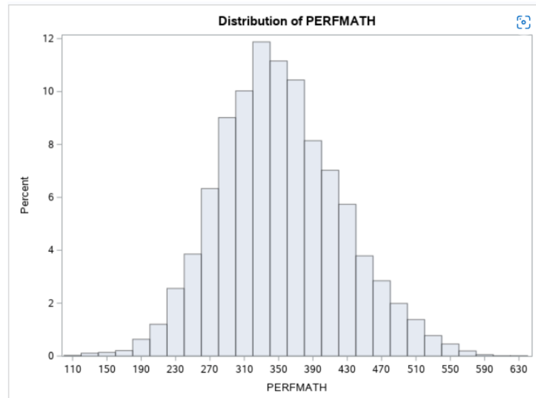


Figure 2: Histogram of PERFMATH

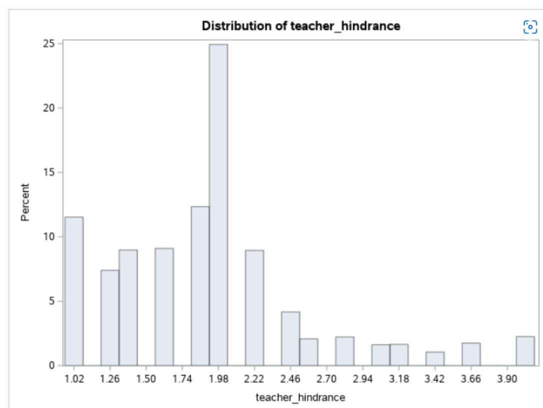


Figure 3: Histogram of teacher hindrance

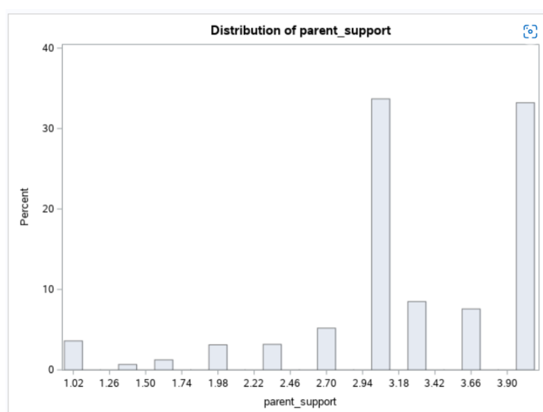


Figure 4: Histogram of Parent Support

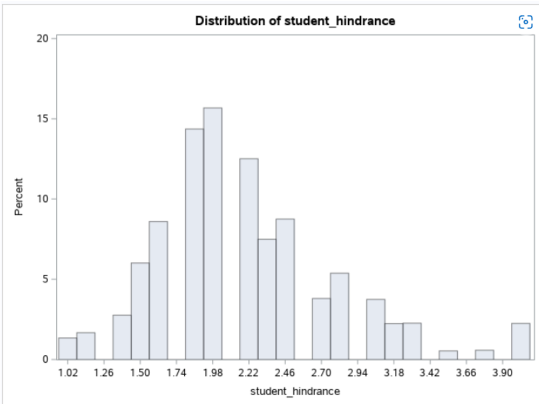


Figure 5: Histogram of student hindrance

From the histograms, only the variables ESCS and PERFMATH seem to follow a normal distribution. Thus the priors for these two variables may have a normal distribution. A flat prior distribution was used for the other three variables due to the shape of the distributions not following from a common family, and the lack of information about the probable distribution and parameters of these variables.

The researchers also investigated the distribution of the sex and schools of the students who took the exam. The frequency table of the sex of the students is shown on table 4. The distribution of the schools however will not be shown through a table due to the large number of schools that participated in the PISA 2018. Thus, a frequency plot will be shown. This is presented on figure 6. It was found that 53.48% of the participants are females, while the rest are males. The distribution of the schools also seems to be uniform except for around 16 out of 187 schools that have significantly lower numbers of students that took the exam.

Table 4. Frequency Distribution of the Sexes of the Participants

Gender	Frequency	Percent
Male	3365	46.52
Female	3868	53.48

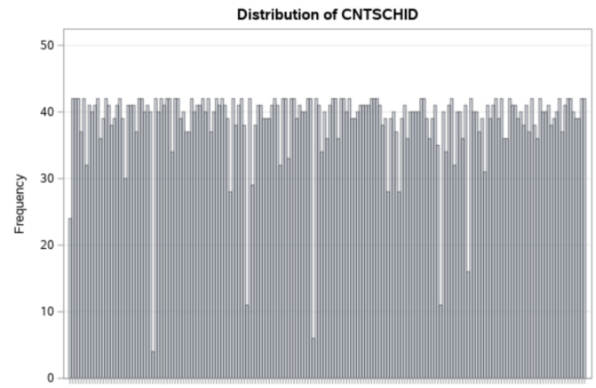


Figure 6. Frequency plot of the distribution of schools.

3.3 Multilevel Model

After investigating the properties of the data set, the researchers attempted to fit a multilevel model to model PERFMATH. As a first step, two intercepts-only models were fitted: the first only has a fixed intercept, while the second has an additional random intercept. This was done to estimate the intracluster correlation coefficient (ICC) and test if the variance of the intercept at level 2 significantly different from 0. The ICC estimate was computed to be 0.3485, meaning that 34.85% of the variance in the performance in the math test is a function of the school where they belong. Further, the variance of the level two intercept was found to be significantly different from 0 ($p < 0.0001$). Thus, a model that allows random variation for PERFMATH among schools is a better fit than a model that does not allow such variation.

After testing if a multilevel model is appropriate, the researchers then fitted a multilevel model with all the predictors and interaction terms. The full model was found to be significantly different from the model with only the intercepts ($p < 0.0001$). This implies that the full model has a good fit for PERFMATH. Table 5 summarizes the coefficients for the full model.

Table 5. Parameter Estimates for the Full Model.

Parameter	Estimate	t-value	p > |t|
Intercept	322.0756	14.2049	0.0000
ESCS	6.2072	1.8113	0.0701
Parent Support	14.6205	3.1572	0.0016
Gender	8.7297	6.3625	0.0000

Student Hindrance	-39.6933	-2.8137	0.0054
Teacher Hindrance	30.2849	2.3704	0.0188
ESCS*StudentHindrance	0.3378	0.1587	0.8739
ESCS*TeacherHindrance	1.6630	0.8748	0.3817
ParentSupport*StudentHindrance	5.4480	1.8793	0.0602
ParentSuport*TeacherHindrance	-2.3990	-0.9108	0.3624

As shown in the table, there are parameters that are not significant in the model. Since a simpler model is preferred, backward selection was implemented to remove terms that are not significant in explaining the variance. In order to achieve a hierarchical model, the interaction terms were first removed from the model. Table 6 shows the parameter estimates for the model selected by backward selection.

Table 6. Parameter Estimates of the Reduced Model

Parameter	Estimate	t-value	p > |t|
Intercept	322.0756	14.2049	0.0000
ESCS	6.2072	1.8113	0.0000
Parent Support	14.6205	3.1572	0.0033
Gender	8.7297	6.3625	0.0000
Student Hindrance	-39.6933	-2.8137	0.0005
Teacher Hindrance	30.2849	2.3704	0.0003
ParentSupport*StudentHindrance	5.4480	1.8793	0.0464

Before the model found with coefficients in table 6 can be used, certain assumptions are checked. These assumptions include linearity, normality of residuals in level 1 and level 2, and homoscedasticity (Ushakova & Watterson, 2019). Figures 7, 8, 9 show the results of the model diagnostics for linearity, residual normality at level 1, residual normality at level 2 respectively, while table 7 and figure 10 shows the Levene's test for homoscedasticity across clusters.

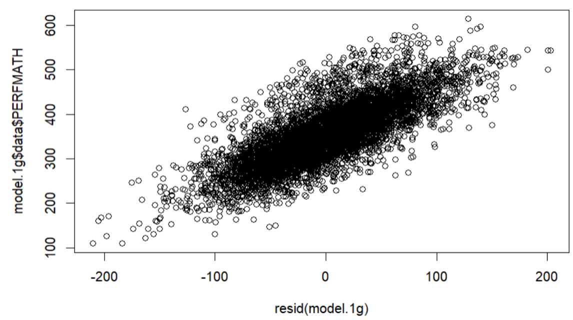


Figure 7: Residuals vs Observed Values

Figure 7 shows the plot of the residuals and observed values. Non-normality is evident if the plot follows some kind of non-linear relationship. Since the plot clearly shows a linear relationship, it is safe to assume that linearity in the model is satisfied.

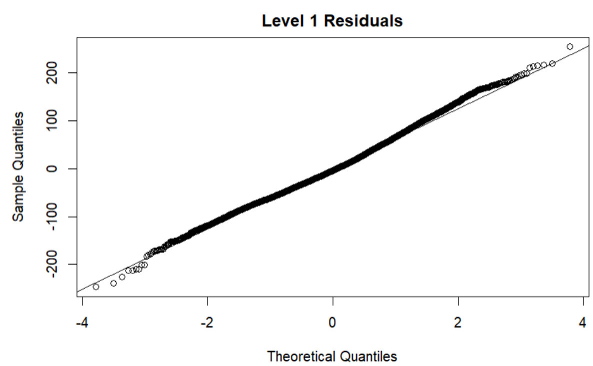


Figure 8, Q-Q plot of the level 1 residuals

Figure 8 shows the quantile-quantile plot of the residuals at level 1 – the student level. Ushakova & Watterson (2019) recommended the use of Q-Q plots to assess the normality at the two levels, and explained that the plots should closely follow the diagonal line to safely assume normality. Since the plots follow the y = x line closely, it is safe to assume that level 1 residual normality is satisfied.

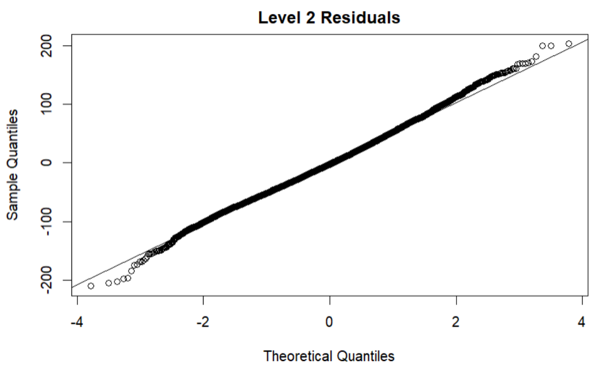


Figure 9: Q-Q plot of the level 2 residuals

Figure 9 shows the quantile-quantile plot of the residuals at level 2 – the school level. Similar to Figure 8, the plots seem to follow the y = x diagonal line with only a slight departure at the tails. Thus, it is safe to assume that residual normality at level 2 is satisfied.

Table 7. Levene's Test for Homoscedasticity

Effect	Sum of Sq	df	Mean Square	F	p
CNTSCHID	60445	186	324.97	0.112	1
Residuals	18365640	6353	2890.86		

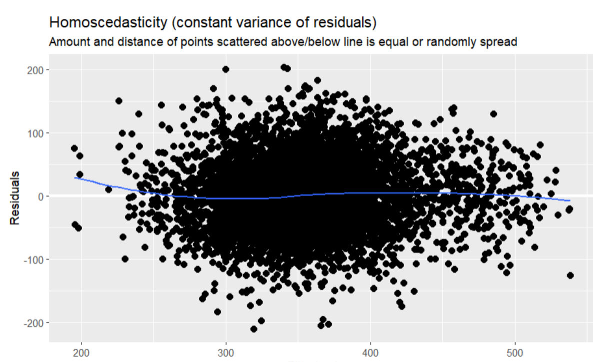


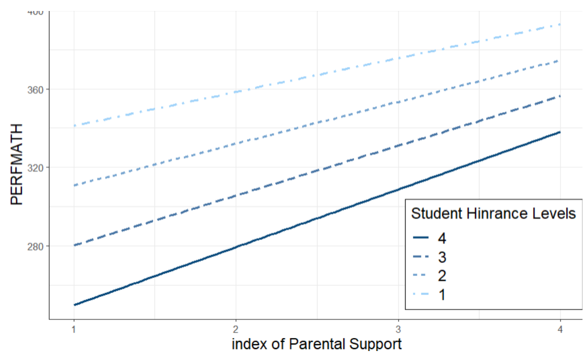
Figure 10: Fitted values vs residuals plot

Table 7 and Figure 10 shows the results for the diagnostics tests for homoscedasticity in the model. It was found that there is no significant difference for the variances in level 2 across the different groups (F = 0.112, p = 1). Figure 10 also confirms this as there is an equal spread, and an absence of a cone-shaped pattern of the plots. Thus, the assumption of homoscedasticity is satisfied.

Since the reduced model has satisfied all the assumptions of multi-level modelling, the model selected from backward selection is the model used as the final model by the researchers. In this model, the level 2 variables Student Hindrance (t = -2.8137, p=0.0054) and Teacher Hindrance (t=2.3704, p =0.0018) are significant. Acting as fixed effects, this indicates that when holding other variables constant, the index of performance in math decreases by 39.6933 per one unit increase in the index of student hindrance, and an increase of 30.2859 in the index of performance in math per unit increase in the index of teacher hindrance. Further, this also indicates that there is significant slope variation for ESCS and Parental Support between schools. Without accounting for interaction effects, these results may imply that higher student hindrance levels in schools nullifies the positive influence of parental support and economic status. For instance, an increase of 1 unit in ESCS, student hindrance, and parental support while holding other factors constant decreases the index of performance in math by 18.8656 points (-39.6933+14.05+6.2072). On the other hand, high levels of teacher hindrance levels tend to amplify the positive influence of ESCS and parental support. From the results, an increase of one unit in the indices of ESCS, Parental Support, Teacher Hindrance increases the index of mathematics achievement by 51.1126 (30.2849+14.05+6.2072).

Another important result from the model is that the cross-level interaction between Parental Support and Student Hindrance is significant. This indicates that the degree of parental support varies as a function of the student hindrance levels in schools. Figure 7 shows the interaction plot of Student Hindrance Levels and Parental Support. The slightly varying slopes confirm that there is an interaction between parental support and student hindrance levels. At higher student hindrance levels, the graph seems to be steeper indicating that higher student hindrance levels may have a positive effect on the slope of the parental index, Further, it is important to note that lower levels of student hindrance and higher levels of parental support have higher trajectories for performance in mathematics.

Figure 7. Interaction plot for Parental Support and Student Hindrance Levels



3.4 Bayesian Model

After fitting a multilevel model, the researchers then fitted a Bayesian regression model with interaction terms to compare the relationships made by the two models. It is important to note that flat non-informative priors were used in the final model. Furthermore, from the descriptive statistics and histogram of PERFMATH as shown in table 3 and figure 2, the likelihood function used in the study assumes that PERFMATH follows a normal distribution with mean 351.861 and standard deviation of 71.8. Table 7 summarizes the estimates of the coefficients of the final Bayesian Regression model after removing non significant effects. Figures 8 and 9 show the posterior distribution and the convergence of the estimated coefficients of the model. Lastly, Figure 10 shows the posterior predictive check of the model plotting the posterior predictive distribution against the actual distribution of the data.

Table 8. Parameter Estimates for the Bayesian Regression Model

Effect	Estimate	Lower Limit 95% CI	Upper Limit 95% CI
Intercept	334.77	294.90	374.82
ESCS	10.09	8.38	11.79
Gender	8.83	6.11	11.53
Parent Support	13.43	4.47	22.32
Student Hindrance	-34.24	-53.01	-15.52
Teacher Hindrance	17.07	7.77	26.43
Parent Support*StudentHindrance	3.96	0.07	7.90

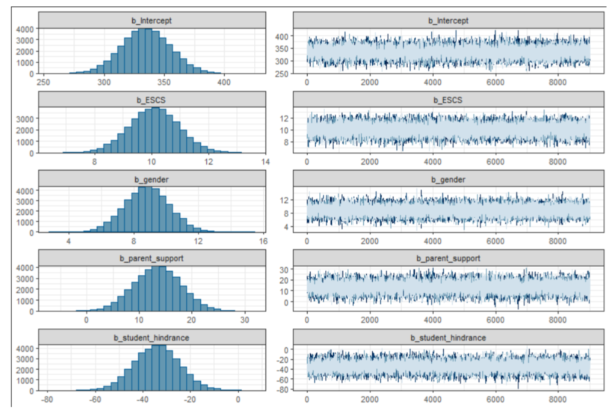


Figure 8. Posterior Distribution and Chain Convergence Plot of the Intercept, ESCS, Gender, Parent Support, and Student Hindrance.

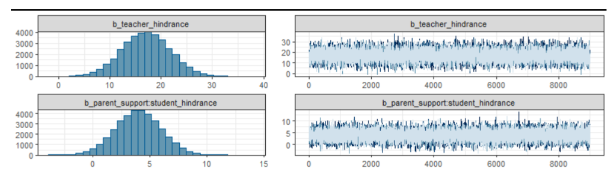


Figure 9. Posterior Distribution and Chain Convergence Plots of the Teacher Hindrance and interaction effect between Parental Support and Student Hindrance.

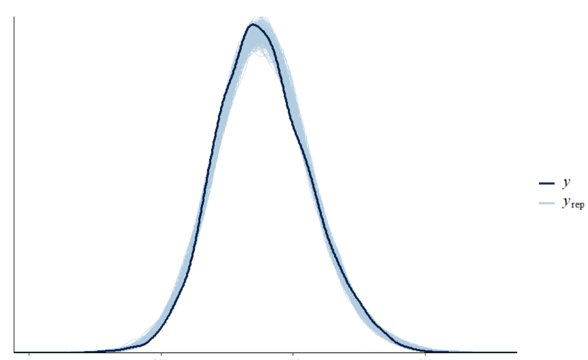


Figure 10: Posterior Predictive Distribution (y rep) compared to the original distribution of the data (y)

Similar to the multilevel model, the Bayesian model's significant effects are the ESCS, Gender, Parent Support, Student Hindrance, Teacher Hindrance, and the Interaction effect between parental support and student hindrance. From figures 8 and 9, the posterior distributions of the coefficients follow a normal distribution with means corresponding to their parameter estimates. The R-hat estimates for all of the coefficients of the model are 1.00, indicating that all the coefficients' parameter estimates have converged successfully. This convergence is also shown by the chain convergence plots in figures 8 and 9. The model's predictions also closely mimics the distribution of the dataset as modeled in figure 10. This indicates that the formed Bayesian model has a good fit for the data, and can be used for interpretation.

3.5 Discussion

The constructed Multilevel Model and Bayesian Regression model, albeit having slightly different parameter estimates, show similar relationships between the predictors and PERFMATH. First, both models show that higher indices of Socio Economic Status is associated with higher performance in mathematics. This supports the study of Kalaycıoğlu (2015) where it was established that socioeconomic status has a significant effect on mathematics achievement among students based on the results of PISA 2012. Similarly, the results are aligned with the study of Alordiah et al. (2015) in Nigeria where students that have high socioeconomic status have better mathematical performance as compared to students that have low socioeconomic status. Then, both models also show that female students tend to perform better than males in mathematics. This is supported by the case study of Anjum (2015) which showed that female students at upper primary school had better performance in Mathematics compared to male students. These findings can also be explained by the study of Ajai and Imoko (2015) where they found that female students performed better in mathematics than male students. These findings are congruent with the studies of NCERT (2014), Linnakyla et al. (2004), Ogle et al. (2003), Spearrit (1977), NAEP (1973), Brown (1991), and Breakley et al. (1988) (As cited in Anjum, 2015). However, other studies have opposing results where male students performed better in mathematics than their female counterparts (Fennema, 2000, as cited in Ajai et al., 2015; Muthukrishna, 2010, as cited in Ajai et al., 2015; Felson & Trudeau, 1991; Rodriguez et al., 2015). Parental support has also shown to be a positively influential factor for mathematics performance. This result can be supported by the work of Cai et al. (1999) where it showed that parental support is a significant predictor of students' performance in mathematics. The results also suggest that students with more supportive parents tend to have a better mathematics performance compared with least supportive parents Cai et al. (1999). Moreover, the study of Huang et al. (2021) corroborates the results of this study as the results showed that students who have hands-on parents greatly contributed with their performance in mathematics. At the school level, both models show that high indices of student hindrance are associated with lower mathematics achievement. The findings are related with the study of Mazana et al. (2019) that there is a significant positive weak correlation between students' attitude and performance on mathematics. Attitude will always go hand in hand with behavior. Thus, students that have a negative attitude are most likely to participate in hindering behaviors. Therefore, the results of the model are aligned with the results of the study of Hendy et al. (2014) where it was found out that poor math behaviors lead to high math anxiety, and low math confidence which affect students' mathematical performance.

Interestingly, higher indices of teacher hindrance factors are associated with higher scores in mathematics. This is in accordance with the study of Atetwe (2012), results found a positive relationship between teacher absenteeism and student's mathematical achievement, which were consistent with the findings of (Ballou, 2000; Paul &Faustin, 2005; Mukyanuzi, 2003). It also follows that when a teacher is always absent, the teacher also does not meet the individual students' needs. Furthermore, in the study of Jiang (2021), the findings indicate that teacher strictness was positively related to that of East Asian students which is in accordance also with the findings of this study. One can infer that self-studying may be beneficial for students to improve their performance in mathematics.

Lastly, both models found that the interaction between Parental Support and Student Hindrance is significant. This indicates that there is a cross-level interaction between parental support and student hindrance, implying that the influence of parental support to achievement in mathematics is affected by the levels of student hindrance in school. The finding is in line with the study of Stormshak (2000), where the result shows that low levels of warm involvement were especially common among parents of children who displayed high levels of oppositional behavior. Consequently, those with low levels of parental support, tend to have low performance in mathematics (Cai et al., 1999).

4. CONCLUSIONS

For the multilevel model, the final model was the model selected from backward selection. In this model, the student level (level 1) variables gender, parental support, index of economic and social status of each student, and the school level (level 2) student hindrance and teacher hindrance were found to be significant. Furthermore, only the interaction between Parent Support and Student Hindrance was found to be significant. Then the Bayesian regression model with interaction effects was constructed using the level 1 and 2 predictors of the study that are significant from the first multilevel model.

After the comparison between the constructed Multilevel Model and Bayesian Regression model, results show similar relationships between the predictors and PERFMATH. At the student level, both models show that higher indices of Socio Economic Status is associated with higher performance in mathematics; female students tend to outperform males in mathematics; parental support is a positively influential factor for mathematics performance. At the school level, both models show that high indices of student hindrance are associated with lower mathematics achievement; high indices of student hindrance were associated with lower mathematics achievement; higher indices of teacher hindrance factors are associated with higher scores in mathematics. Lastly, both models show that there is a cross-level interaction between parental support and student hindrance.

The researchers recommend that future researchers can look into the relationships between the aforementioned variables and with other academic subjects. The researchers also recommend using an updated data set which is the PISA 2021 whenever it will be available. For the current government administration, it is recommended to focus on interventions that will aid students' socio-economic needs. Other than providing free tuition, the government should also consider the daily allowances that the student needs to continue in studying. For academic institutions, the researchers recommend creating more school activities or events involving the parents of the students. In this way, parents are committed and involved in their children's education plans and can collaborate with teachers to meet student's needs.

5. ACKNOWLEDGMENTS

The researchers would like to thank Dr. Shirlee R. Ocampo from the Mathematics and Statistics Department for gently guiding us through this study

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APPENDIX A: R Codes Data Preparation

```
library(haven)
library(dplyr)
library(writexl)
setwd("C:/Users/albert go/Desktop/Schoolworks/BAYESTA/Project FIles")
schqq <- read_sas("sch_quest.sas7bdat")
stuqq <- read_sas("stu_quest.sas7bdat")

schqq_phl <- schqq %>% filter(CNT=="PHL")
stuqq_phl <- stuqq %>% filter(CNT=="PHL")

schqq_phl_var <- schqq_phl[,c("CNTSCHID","STRATUM","SC061Q01TA","SC061Q02TA","SC061Q03TA"
                ,"SC061Q04TA", "SC061Q05TA", "SC061Q11HA","SC061Q06TA"
                ,"SC061Q07TA","SC061Q08TA","SC061Q09TA","SC061Q10TA")]

stuqq_phl_var                                                                    <-
stuqq_phl[,c("CNTSCHID","ST004D01T","ST123Q02NA","ST123Q03NA","ST123Q04NA","ESCS","PV1MATH",
                "PV2MATH","PV3MATH","PV4MATH","PV5MATH","PV6MATH","PV7MATH","PV8MATH"
                ,"PV9MATH","PV10MATH")]
#Note: ST004D01T - Gender with 1 - Female 2 - Male
#
View(stuqq_phl_var)

library(DataExplorer)
get_all_vars(stuqq_phl_var)
create_report(schqq_phl_var)
create_report(stuqq_phl_var)

#Merge Data Sets
qq_phl_merged <- merge(schqq_phl_var, stuqq_phl_var, by=c("CNTSCHID"))
qq_phl_merged          <-          qq_phl_merged          %>%          mutate(student_hindrance
=(SC061Q01TA+SC061Q02TA+SC061Q03TA+SC061Q04TA+SC061Q05TA+SC061Q11HA)/6
                                                              ,   teacher_hindrance   =
(SC061Q06TA+SC061Q07TA+SC061Q08TA+SC061Q09TA+SC061Q10TA)/5
                                                                   ,   PERFMATH   =
(PV1MATH+PV2MATH+PV3MATH+PV4MATH+PV5MATH+PV6MATH+PV7MATH+
                              PV8MATH+PV9MATH+PV10MATH)/10
                  , parent_support = (ST123Q02NA+ST123Q03NA+ST123Q04NA)/3
                  , gender = recode(ST004D01T, '1'=1,'2'=0))
View(qq_phl_merged)
write_xlsx(qq_phl_merged, "Bayestat Data.xlsx")
```

APPENDIX B: R Codes Analysis

```
---
title: "BAYESTA Multilevel Modelling"
output: html_notebook
---

```{r}
library(haven)
library(dplyr)
library(writexl)
library(readxl)
library(nlme)
library(rstanarm)
library(rstan)
library(brms)
library(lme4)
library(effects)
library(sjPlot)
library(mitml)
setwd("C:/Users/albert go/Desktop/Schoolworks/BAYESTA/Project FIles")

```

```{r}
qq_phl_merged <- read_excel("Bayestat Data.xlsx")
qq_phl_merged_complete$CNTSCHID <- as.factor(qq_phl_merged_complete$CNTSCHID)
```

```{r}
#Traditional Multilevel Model
#Step 1 - Examine the Intraclass Correlation Coefficient in mixed-effect models (ICC(1)) of the outcome

#ICC(1)
Null.Model <- lme(PERFMATH ~ 1, random = ~1|CNTSCHID, data = qq_phl_merged_complete,
        control=list(opt="optim"))

VarCorr(Null.Model)
1806.535/(1806.535+3377.601)

Null.gls <- gls(PERFMATH ~1, data = qq_phl_merged_complete)
anova(Null.gls,Null.Model)

#There is significant intercept variation. 34.85% of the variation in PV1MATH scores is a function of the school
#where they belong. Thus, a model that allows for random variation in PV1MATH among schools is a better fit than a
        model that does not allow random variation
```
```{r}
#Step 2 - Explain Level 1 and Level 2 Intercept Variance
#Level 1 - ESCS, parent_support, gender
#Level 2 - student_hindrance, teacher_hindrance
```
```

~~~~
Model.1a<-lme(PERFMATH~ESCS+parent_support+gender,
    random=~student_hindrance+teacher_hindrance|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

Model.1b<-lme(PERFMATH~ESCS+parent_support+gender+student_hindrance*ESCS+teacher_hindrance*ESCS
    ,random=~student_hindrance+teacher_hindrance|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

Model.1c<-lme(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance,random=~student
    _hindrance+teacher_hindrance|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

summary(Model.1a)
coef(Model.1a)

summary(Model.1b)
summary(Model.1c)
Model.1c
```

```{r}
anova.lme(Null.gls,model.1d)

model.1d <-
    lme(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance+ESCS:student_hind
    rance+ESCS:teacher_hindrance+parent_support:student_hindrance+parent_support:teacher_hindrance,
    random=~parent_support+ESCS|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

summary(model.1d)

model.1e <-
    lme(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance+ESCS:teacher_hind
    rance+parent_support:student_hindrance+parent_support:teacher_hindrance,
    random=~parent_support+ESCS|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

summary(model.1e)

model.1f <-
    lme(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance+ESCS:teacher_hind
    rance+parent_support:student_hindrance, random=~parent_support+ESCS|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

summary(model.1f)

model.1g <-
    lme(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance+parent_support:stu
    dent_hindrance, random=~parent_support+ESCS|CNTSCHID,
   data=qq_phl_merged_complete,control=list(opt="optim"))

summary(model.1g)
~~~~

~~~~
VarCorr(Null.Model)
VarCorr(model.1g)
```
```{r}
plot.model.1g.linearity <- plot(resid(model.1g), model.1g$data$PERFMATH)

plot.model.1g.linearity2 <- plot(model.1g$fitted[,2],resid(model.1g) )
plot.model.1g.linearity2 <- plot(model.1g$fitted[,1],resid(model.1g) )


qqnorm(model.1g$resid[,1], main="Level 1 Residuals")
qqline(model.1g$resid[,1])
qqnorm(model.1g$resid[,2], main="Level 2 Residuals")
qqline(model.1g$resid[,2])




plot_model(model.1g, type="diag")

resids_lvl1_sq <- (model.1g$resid[,1])^2
levene.level1resid <- lm(model.1g$resid[,2]~CNTSCHID, data = qq_phl_merged_complete)
anova(levene.level1resid)
```


```{r}
model.1d <- lme(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance+ESCS:student_hindrance+ESCS:teacher_hindrance+ESCS:student_hindrance:teacher_hindrance,
    random=~parent_support+ESCS|CNTSCHID,
    data=qq_phl_merged_complete,control=list(opt="optim"))

summary(model.1d)
```

lmer
```{r}
library(lme4)
library(lmerTest)
library(ggplot2)
library(interactions)
finalmodel.lmer <- lmer(PERFMATH~ESCS+parent_support+gender+student_hindrance+teacher_hindrance+student_hindrance*parent_support + (parent_support+ESCS|CNTSCHID),data=qq_phl_merged_complete)
summary(finalmodel.lmer)

interact_plot(finalmodel.lmer, pred = parent_support, modx = student_hindrance,  modx.values=c(1,2,3,4), y.label = "PERFMATH", x.label = "index of Parental Support", legend.main="Student Hindrance Levels") +
theme_bw()+
theme(legend.background=element_rect(fill="white",
~~~~

```
size=0.5, linetype="solid",color ="black"),
legend.position = c(0.83, 0.21),
axis.title.x = element_text(color="black", size=14),
axis.title.y = element_text(color="black", size=14),
legend.title = element_text(color="black", size=14),
legend.text = element_text(color="black", size=14)
)

```

```{r}
#Bayesian Multilevel Model
options(contrasts = c("contr.sum","contr.poly"))

#Step 1 - Intercept only Model
brms_interceptonly <- brm(PERFMATH ~ 1 + (1|CNTSCHID),
                        data = qq_phl_merged_complete,
                        warmup = 100,
                        iter = 200,
                        chains = 2,
                        cores = 2)
```

```{r}
get_prior(PERFMATH~ESCS+gender+parent_support+student_hindrance+teacher_hindrance+(student_hindrance+te
                acher_hindrance|CNTSCHID),
          data=qq_phl_merged_complete)

mod1<-brm(PERFMATH~ESCS+gender+parent_support+student_hindrance+teacher_hindrance
                +parent_support:student_hindrance +(ESCS + parent_support|CNTSCHID),
          data=qq_phl_merged_complete,
          family = gaussian(),
          warmup=1000,
          iter = 10000,
          chains=4,
          cores = 4)

posterior_summary(mod1, pars = c("^b_", "^sd_", "sigma"), probs = c(0.025, 0.975) )

```

```{r}
library(ggplot2)
mod1
mod1 %>% plot(combo = c("hist","trace"), widths = c(1,1.5), theme = theme_bw(base_size=8))
```

```{r}
hyp1 <- hypothesis(mod1, "ESCS = 0")
hyp1
plot(hyp1, theme = theme_bw(base_size = 20))
```

```
hyp2 <- hypothesis(mod1, "gender = 0")
hyp2
plot(hyp2, theme = theme_bw(base_size=20))

hyp3 <- hypothesis(mod1, "parent_support = 0")
hyp3
plot(hyp3, theme = theme_bw(base_size=20))

hyp4 <- hypothesis(mod1, "parent_support = 0")
pp_check(mod1,ndraws=200)
```

APPENDIX C: SAS Codes

```
 proc datasets;
        contents data=BAYESTA.PHLDATA order=collate;
quit;

ods noproctitle;

/*** Analyze categorical variatbles ***/
title "Frequencies for Categorical Variables";

proc freq data=BAYESTA.PHLDATA;
        tables STRATUM / plots=(freqplot);
run;

/*** Analyze numeric variables ***/
title "Descriptive Statistics for Numeric Variables";

proc means data=BAYESTA.PHLDATA n nmiss min mean median max std;
        var CNTSCHID ESCS student_hindrance teacher_hindrance PERFMATH
                parent_support gender;
run;

title;

proc univariate data=BAYESTA.PHLDATA noprint;
        histogram CNTSCHID ESCS student_hindrance teacher_hindrance
                PERFMATH parent_support gender;
run;
```

APPENDIX D: Contribution of Members

ANGELES, Carlo Angelo M. - Filled in the introduction and related literature, contributed to the discussion of the results. Contributed to the ppt presentation. Presented the introduction, descriptive statistics, conclusions and recommendations.

BOCATO, Lyka Janine A. - Conducted descriptive analyses and Bayesian modelling, contributed to the introduction (related literature) and discussions. Presented the reliability analysis and discussion

GO, Albert Thimothy M. - Enumerated the Methodology, Contributed in the Review of Related Literature, Conducted Data Preparation, Cleaning, Hierarchical Linear Modelling and Bayesian Modelling. Organized the presentation and discussion of the results. Explained the results in the presentation.

MEDALLO, Kiah Khyle S. - Conducted Hierarchical Linear Modelling, contributed to the related literature and discussion. Discussed the entire methodology in the presentation and contributed to the lay out of the ppt presentation, and final edit for the video presentation.