Factors contributing to fourth graders' mathematics achievement: a multilevel study

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ABSTRACT

This study aims to determine the factors that influence the mathematics achievement of grade 4 students in Indonesia at the student and school level using Trends in International Mathematics and Science Study (TIMSS) 2015 data. Sample in this study were all grade 4 students in Indonesia who participated in TIMSS 2015. There are 4,025 students from 230 schools. The TIMSS 2015 data used in this study was analyzed using a multilevel model (MLM) using the R package 'lme4' software. The results of this study indicate that i) the school visited by each student accounts for the majority of the variance in the mathematics achievement of Indonesian grade 4 students (51%); ii) factors related to students' self-construction of mathematics such as attitude-toward mathematics (ATM) and self-concept and factors related to schools such as socioeconomic status (SES) school, self-concept school, school readiness, general school resources, and teacher education level was found to influence students' mathematics achievement positively and significantly, where self-concept school was the strongest predictor compared to other predictors; and iii) variables at the student and school level explain 35% of the total variance in Indonesian grade 4 students' mathematics achievement.

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1. INTRODUCTION

In recent years, researchers and policy makers around the world have made use of Trends in International Mathematics and Science Study (TIMSS) data for good reason. As we know, TIMSS is an international study conducted every four years by the International Association for the Evaluation of Educational Achievement (IEA) and Boston College with the aim of mapping the level of achievement in mathematics and science among grade 4 and grade 8 students in all participating education systems [1]. TIMSS is part of the international large-scale assessments (ILAs), where results are often presented in descriptive statistics (e.g., mean, standard deviation (SD), and position of schools from high to low ratings). However, referring to several previous studies, TIMSS data is actually associated with many factors that can affect student achievement, including student background, student attitudes towards subjects, student self-concept, class characteristics, and school resources [2]–[6]. Thus, the TIMSS data offers various principles of benefit which are very helpful to the government in determining education policies that are oriented towards improving the quality of education.

The TIMSS 2015 results show that the average math score of Indonesian grade 4 students is still far below the TIMSS average [7]. More specifically, the 2015 TIMSS results show that Indonesian students are still difficulties in solving math problems. This shows that there are still problems that must be overcome in the mathematics education system in Indonesia. Some of the results of previous studies stated that the achievement of students' mathematics scores is closely related to non-cognitive factors such as attitude-toward mathematics (ATM) and mathematics self-concept (MSC) [8]–[11]. This shows that student internal factors such as ATM and MSC greatly influence student achievement in mathematics. In addition, school factors also give an important role in explaining the variance of students' mathematics achievement scores, such as school readiness (SR), general school resources (GSR), and teacher education level (TEL) [2], [3], [5], [12], [13]. This shows that external student factors such as the school environment and the quality of educators greatly influence student achievement in mathematics. Therefore, in an effort to improve students' mathematics achievement, it is necessary to make improvements in students' internal and external (school) factors.

The role of socioeconomic status (SES) has been studied within the framework of the education system in various countries in the context of educational equity [3], [7], [8], [14]. The results showed that there was a significant positive relationship between SES and mathematics achievement, both at the student and school levels [3], [8]. The strong relationship between SES and academic achievement at the individual and school level is a serious threat to equality of education and learning opportunities [15]. It is not from the burden of payment when registering for a new school, but personal (family) expenses for children's education which are very different when viewed from the educational background of the parents [3]. In a society like Indonesia, disparities in personal spending on education based on parents' educational background can increase the gap in academic achievement and learning opportunities [7], [16]. However, the representation of SES is still being debated in educational research, and it is generally the theoretical approach that is applied when conceptualizing SES. Usually, SES is only associated with economic factors, but several previous studies have shown that SES measures have a multidimensional structure [17]. In TIMSS, the scale of home resources for learning is used to represent student SES and the average school-level SES of students describes school-level SES [18].

Another non-cognitive factor that plays an important role in explaining students' mathematics achievement is ATM. In mathematics, ATM is defined as a student's behavior to accept or reject mathematics. Several previous studies stated that there was a statistically significant positive relationship between ATM and students' mathematics achievement [4], [19]. In other literature, ATM also contributes to explaining the variance score of elementary school students' mathematics achievement [20], [21]. Students with a low (negative) ATM index tend to be caused by their bad scores or math failure [4]. The students tend to avoid tasks that involve mathematics and even expect undesirable results [22]. That is, high mathematics achievement increases positive attitudes towards mathematics [9]. In other words, there is a reciprocal relationship between ATM and students' mathematics achievement. Therefore, it is important to develop students' ATM through literacy and numeracy activities from an early age at home or preschool [23]. It because not only contributes positively to student mathematics achievement it also contributes to the school level [24].

Not only ATM, MSC is also always associated with student achievement in mathematics. In fact, in recent years increased attention to MSC has been demonstrated worldwide among policy makers, educators and scholars [25]. MSC refers to students' perceptions of their ability and competence in understanding mathematical knowledge [26], [27]. Research results related to MSC, and students' mathematical achievement show varying results. Several previous studies have shown that there is a relationship between MSC and students' mathematics achievement [8], [10], [28], [29]. Other findings showed that MSC has a statistically significant negative effect on mathematics achievement, both at the student and school level [24]. In addition, MSC is also the strongest predictor in predicting student mathematics achievement [24], while in other findings SES is the strongest predictor beating other predictors including MSC [3], [8], [30]. The strategy that can be used to develop students' MSC is through literacy and numeracy activities that are carried out early on at home or preschool [23].

School readiness is an illustration of the students can perform literacy and numeracy tasks during elementary school. Students may have acquired literacy and numeracy skills through preschool or home family education, or even both [3]. Previous research stated that SR through preschool education plays an important role in increasing academic achievement in the future [31]. This is reinforced by several research results at the elementary school level which show that students who attend preschool education with good SR tend to have high mathematical achievements [32]–[34]. However, preschool education will make the learning achievement gap wider because not all students can enjoy preschool education, especially students with low SES family backgrounds [13]. Family education that is carried out from an early age at home through various literacy and numeracy activities can be a solution to narrow the gap in student academic achievement, ATM, and MSC. Therefore, there is no reason not to pay attention to student SR, because it is also related to student achievement in mathematics and can be done through preschool activities or family education at home or even both.

Other school factor than SR that also play an important role in playing the high and low scenario of students' mathematics achievement scores are GSR and TEL. Several previous studies have shown varying findings related to GSR and students' mathematics achievement. Some studies state that GSR has a significant positive impact on students' mathematics achievement [35], some of them say that it is not significant [5]. Several previous studies have linked GSR with the use of technology in classroom learning which will greatly assist teachers in presenting learning concepts that are more efficient and easily understood by students [12], [36]. The use of technology in classroom learning requires a lot of teacher experience and a high level of education. Previous research stated that the average teacher with the highest level of master's education tends to utilize technology in classroom learning, so that students' desire to learn and understand mathematics increases, and in the end, it will have a positive impact on students' mathematics achievement [2].

Previous research related to the factors that affect students' mathematics achievement has been carried out a lot and tends to highlight two things. First, previous research has paid a lot of attention to SES factors at the student and school level as the strongest predictor in explaining the variance of scores from student mathematics achievement [3], [7], [8], [14]. Second, previous research has paid a lot of attention to ATM and MSC factors at the student level which are associated with student mathematics achievement [4], [8], [10], [19], [28], [29]. Based on these two research tendencies, previous research related to student mathematics achievement that focused on paying attention to school factors such as school-level MSC, GSR, SR, and TEL has not been done much [2], [5]. In addition, previous research using multilevel analysis modeling paid less attention to missing data.

Therefore, research related to mathematics achievement by including SES control variables at the student and school level, ATM and MSC predictor variables at the student level, predictor variables MSC-school, SR, GSR, and TEL while paying attention to handling missing data is urgent to be done. This study specifically aims to determine the factors that influence the mathematics achievement of grade 4 students in Indonesia based on TIMSS 2015 data. To be able to answer these specific objectives, several research questions were prepared which will be elaborated on in the discussion section of this article, namely: i) "what percentage of the variance in Indonesian grade 4 students' mathematics achievement is distributed within and between schools?"; ii) "what factors in the final multilevel model (MLM) are statistically significant predictors of Indonesian grade 4 students' mathematics achievement?"; and iii) "what percentage of variance in Indonesian grade 4 students' math achievement is explained by the variables at the student and school level?".

2. RESEARCH METHOD

2.1. Type of research

This is descriptive exploratory research with a quantitative approach. By using several dependent variables, this study analyzed the factors that influence the mathematics achievement of grade 4 students in Indonesia. This study used documentation data from TIMSS 2015 international results, by utilizing the results of mathematics tests and questionnaires. TIMSS is a program by the IEA since 1995. This program aims to understand the impact of different educational policies and practices around the world. In this program, students in grades 4 and 8 are selected to be measured in math and science every four years. TIMSS also provides useful data for countries to evaluate achievement standards and goals and to monitor progress in student achievement in an international context.

2.2. Samples

The study focuses on TIMSS 2015 class 4 data collected in Indonesia because early mathematics learning and achievement are important in learning and prevent decisions to drop out of school later [37]. In this study, we do not use TIMSS 2019 data because Indonesia did not participate in that international assessment in 2019. There were 4,025 students from 230 participating schools. In addition to achievement tests that measure students' mathematical ability, the TIMSS questionnaire also includes questions about MSC, ATM, SES, SR, GSR, and mathematics learning achievement which are useful for answering the desired research questions.

2.3. Variables

2.3.1. Dependent variable

The dependent variable used in this study is the average of five sets of plausible value (PV) of students' mathematics achievement obtained by calibrating the responses of the test takers' answers to the math items in TIMSS 2015 using the item response theory (IRT) approach [38]. The score in the TIMSS 2015 uses an average of 500 with a SD of 100. In the TIMSS 2015 mathematics framework, the assessment covers three cognitive domains (knowing, applying, and reasoning) and several content domains (for fourth graders, for example regarding numbers, geometric shapes and measures, and data display).

2.3.2. Independent variables

Independent variables were divided into two levels: student level and school level. For student level predictor variables, student SES is measured by two components, namely the number of books at home and the highest level of education of either parent. ATM is related to students' confidence in mathematics (for example, "I like to solve mathematics problems"), the perceived usefulness of mathematics (for example, "I learn many interesting things in mathematics"), and enjoyment of mathematics (for example, "I enjoy learning mathematics"). MSC measures students' perceptions of current ability to learn mathematics (e.g., "I am good at working out difficult mathematics problems"). The selection of items for each predictor variable was adjusted to those used in previous studies [6], [14], [24]. The items from the ATM and MSC variables were initially ranked on a four-category Likert scale, namely 1 (strongly agree), 2 (agree), 3 (disagree), and 4 (strongly disagree) in the student mathematics questionnaire.

There are seven items from the variable ATM and the four MSC variables must be reversed so that a higher rating represents greater agreement (positive). Table 1 provides information that the Cronbach's alpha coefficient of the ATM and MSC variables has the same magnitude, namely 0.8. In addition, the results of the factor analysis show that the factor of each item of the ATM and MSC variables is greater than or equal to 0.4, which represents a strong correlation between each item in the predictor variable [30], [39]. To obtain a composite score or index of ATM and MSC predictor variables use the IRT approach. All student-level variables except ATM were then aggregated to the school level to represent predictors at the school level. This method is an approach commonly used in several previous multilevel studies and at the same time provides empirical evidence for predictive validity between predictors and student achievement [8], [24].

Table 1. Descriptive statistics and factor loadings of items for the two student-level predictors

Variable	α	Factor loadings	Items
Attitude toward mathematics (ATM)	0.8	0.7	I enjoy learning mathematics
		0.7	I wish I did not have to study mathematics
		0.8	Mathematics is boring
		0.6	I learn many interesting things in mathematics
		0.8	I like mathematics
		0.6	I like any schoolwork that involves numbers
		0.4	I like to solve mathematics problems
		0.6	I look forward to mathematics lessons
		0.7	Mathematics is one of my favorite subjects
Mathematics self-concept (MSC)	0.8	0.6	I usually do well in mathematics
		0.6	Mathematics is harder for me than for many of my classmates
		0.6	I am just not good at mathematics
		0.6	I learn things quickly in mathematics
		0.7	Mathematics makes me nervous
		0.5	I am good at working out difficult mathematics problems
		0.6	My teacher tells me I am good at mathematics
		0.7	Mathematics is harder for me than any other subject
		0.8	Mathematics makes me confused

In addition, there are two predictor variables that are also included at the school level, namely SR and GSR. SR measures children's literacy and numeracy skills acquired in preschool or kindergarten (for example, "Recognize most of the letters of the alphabet"). GSR is defined as facilities and services to achieve a fun and effective learning experience (for example, "Computer technology for teaching and learning"). The selection of items on the SR and GSR predictor variables was adjusted to those used in previous studies [2], [3], [5]. The SR predictor variable is rated on a scale of four categories, namely 1 (less than 25%), 2 (25–50%), 3 (51–75%), and 4 (more than 75%). GSR predictor variables are also ranked on a scale of four categories, namely 1 (not at all), 2 (a little), 3 (some), and 4 (a lot).

Table 2 provides information that the Cronbach's alpha coefficient of the SR and GSR variables is 0.9 and 0.8, respectively. In addition, the results of the factor analysis showed that the factor of each item of the SR and GSR variables was greater or equal to 0.4, which represented a strong correlation between each item in the predictor variable [30], [39]. To obtain the composite score or index of the SR and GSR predictor variables, an IRT approach was used. In addition to the predictor variables, at this school level a control variable is also included in the form of teacher education level, which is ranked in four categories, namely 1 (did not complete bachelor's or equivalent), 2 (bachelor's or equivalent), 3 (master's or equivalent), and 4 (doctor or equivalent).

Table 2. Descriptive statistics and factor loadings of items for the two school-level predictors

Variable	α	Factor loadings	Items
School readiness (SR)	0.9	0.8	Recognize most of the letters of the alphabet
		0.9	Read some words
		0.9	Read sentences
		0.8	Write letters of the alphabet
		0.9	Write some words
		0.7	Count to 100 or higher
		0.7	Recognize written numbers A from 1-10
		0.8	Recognize written numbers higher than 10
		0.8	Write numbers from 1-10
		0.9	Do simple addition
		0.9	Do simple subtraction
General school resources (GSR)	0.8	0.5	Instructional materials
		0.5	Supplies
		0.7	School buildings and grounds
		0.7	Heating/cooling and lighting systems
		0.7	Instructional space
		0.7	Technologically competent staff
		0.5	Audio-visual resources for delivery of instruction
		0.7	Computer technology for teaching and learning

2.4. Data analysis

In this study, the MLM was carried out using the R package 'lme4' software [40]. The MLM construction process starts with a null model. The null model contains only the dependent variable, namely mathematical achievement, and no other dependent variables except the intercept. The null model is statistically the same as the one-way random effects analysis of variance [41]. The null model serves two purposes. First is to estimate the average magnitude of mathematics achievement with adjustments for student clustering in schools and different sample sizes in schools [24]. Second is to estimate the available component of the variance by decomposing the total variance in mathematics achievement into the variance assigned to students (variance within schools) and the variance assigned to schools (variance between schools) [42]. In practical terms, the null model serves as the baseline model against which the results of the final model are compared. The final model was developed by adding student level variables into the null model (model 1) and school into model 1 (model 2). The final model includes student-and school-level variables that show a statistically significant relationship with math achievement.

Multilevel model assumptions including missing data, multivariate collinearity, normality, and outliers were tested [6]. Missing data in MLM can cause parameter estimation results to be invalid [43]–[46], so the use of multiple imputation in several previous MLM studies was considered as a valid approach to address missing data [10], [47]. In this study, multiple imputation was applied to ATM (2.0-4.0% missing data), self-concept mathematics (2.0-4.0% missing data), SR (1.0-1.3% missing data), and GSR (0.4-2.2% missing data), according to the suggestion from Immekus *et al.* [48] that the percentage of missing data for multiple imputation should be less than 10%. The multiple imputation process is carried out with the help of the R package 'mice' using a machine learning method, namely random forest (RF) [48].

Multivariate collinearity resulting from strong correlations between predictor variables can also lead to difficult parameter estimation and limitations in the relationship between predictor and dependent variables [49]. Following the guideline that the variance inflation factor (VIF) value of the predictor variable is greater than 10 indicate the presence of multivariate collinearity [50], [51]. The estimation results for variables at the student level show VIF values ranging from 1.00 to 1.17 (M=1.11), and for school-level variables ranging from 1.06 to 1.70 (M=1.36). In addition, there is no correlation coefficient above .90 in the studies (Table 3), additional evidence to suggest there is no multivariate collinearity problem [52]. It used residuals vs. fitted plots and density plots to confirm that the normality assumptions and no outliers are fulfilled [53].

3. RESULTS AND DISCUSSION
3.1. Descriptive statistics

The results of the descriptive statistical analysis are presented in Table 3. It contains information regarding the average score (M) and SD, as well as the correlation matrix between variables. Apart from the math-score variable, the two independent variables at the student level, SES-student and attitude-toward, have the strongest and weakest correlations with the math-score variable, respectively. Meanwhile, at the school level, the independent variables with the strongest and least correlations to the math-score variable are SES-school and teacher education level, respectively. These findings show that the SES variable has the strongest correlation with the math score variable at both the student and school levels.

Table 3. Descriptive statistics and correlation matrix for all variables in the study

Level	M (SD)	Correlation 1	2	3	4	5	6
Student							
1. SES-student	5.80 (2.710)	-	-0.02	0.13	0.38		
2. Attitude-toward*	–0.11 (0.79)	-0.02	-	0.37	0.06		
3. Self-concept*	–0.03 (0.85)	0.13	0.37	-	0.34		
4. Math-Score	399.47 (84.34)	0.38	0.06	0.34	-		
School							
1. SES-school	5.80 (2.710)	-	0.33	0.46	0.62	0.26	0.49
2. Self-concept school*	–0.03 (0.85)	0.33	-	0.12	0.28	0.15	0.37
3. SR*	0.07 (0.89)	0.46	0.12	-	0.43	0.21	0.30
4. GSR*	0.20 (0.93)	0.62	0.28	0.43	-	0.15	0.40
5. TEL	2.02 (0.61)	0.26	0.15	0.21	0.15	-	0.23
6. Math-Score	399.47 (84.34)	0.49	0.37	0.30	0.40	0.23	-

*Variables measured on a logit scale (M=0, SD=1)

3.2. Multilevel model analysis
3.2.1. Step 1: models without explanatory variables (null models)

The results of the MLM analysis are presented in Table 4. The null model is a random effects model that allows the effect of school on students' mathematics learning achievement. In equation (1), this model shows that looking at the school effect, the average student achievement in all schools is 390.30. More specifically, the average student achievement in each school is estimated as 390.30+u_{0j}, where u_{0j} is the school residual. A u_{0j} value that is greater than zero indicates that the school has a higher average achievement than the average across schools, while a value less than zero indicates that the school has an average achievement below all of school average.

Table 4. Results from the two-level MLM predicting US grade 4 students' mathematics achievement

Parameter	Model 0 (null)	Model 1	Model 2
Fixed effect			
Intercept	390.30 (4.13)	371.53 (4.33)	305.53 (15.26)
Student-level			
SES-student		3.73* (0.43)	3.11* (0.43)
Attitude-toward		3.81* (1.33)	3.67* (1.33)
Self-concept		21.87* (1.21)	21.28* (1.22)
School-level			
SES-school			8.18* (2.29)
Self-concept school			37.00* (8.26)
SR			10.69* (3.59)
GSR			11.54* (4.03)
TEL			13.68* (5.08)
Random effect			
Within-school variance (σ^2)	3542.64	3151.35	3151.81
Between-school variance (τ)	3633.39	2849.33	1643.13
Variance within school (%)		5%	5%
Variance between school (%)		11%	28%

Model 0 (null) provides information that the variance within schools (σ^2) is 3542.64 and the variance between schools (τ) is 3633.39. Thus, based on these two variance values, the intra-class correlation (ICC) value, which represents the proportion of variance in students' mathematics attainment within and between schools, can be estimated as 0.51 ($\tau/\tau + \sigma^2$). This could imply that 51% of the total variance in mathematics achievement was due to differences between schools, while the remaining 49% of the total variance in mathematics achievement was attributed to differences in student levels within the same school. Parameter estimation shows that the value of the dependent variable increases with a one-point increase in the independent variable. The values in parentheses represent the standard errors of the parameter estimates.

3.2.2. Step 2: adding student-level explanatory variables to the random intercepts model

Model 1 provides information that by adding three predictor variables related to students themselves, both the unexplained variance at the student and school levels was reduced by 3151.35 and 2849.39 points, respectively. This reduction indicates that the large variance in mathematics learning achievement at the student and school level is due to the student's background and variables related to student self-construction (ATM and MSC) included in this model 1. Specifically, about 16% (5% within-school and 11% between-school) of the total variance (49% within-school and 51% between-school) variance that could not be explained in student mathematics achievement was explained by student level variables in model 1. However, there are still many variances that cannot be statistically explained both at the student level and the school level in this model 1.

If viewed from the magnitude of the coefficients produced in model 1 as shown in (1), all explanatory variables in the model are statistically significant predictors in predicting student learning achievement, because the estimated coefficient is more than twice the SE [54], [55]. More specifically, with other predictor variables held constant, students' mathematics learning achievement will increase by 3.73 points for each additional SES at the student level. Furthermore, students' mathematics learning achievement will increase by 3.81 and 21.87 points for each additional attitude-toward and self-concept unit for each student, with other predictor variables remaining constant. Overall, the strongest predictor in model 1 is the MSC variable, then ATM, and finally SES-student.

$$Math\ Score_{ij} = \beta_{0j} + 3.73(0.43)SES_{student} + 3.81(1.33)ATM + 21.87(1.21)MSC + e_{ij} \quad (1)$$

Where $\beta_{0j} = 371.53(4.33) + u_{ij}$.

3.2.3. Step 3: adding school-level explanatory variables to the model

After analyzing student-level variables and finding that there are still unexplained variances, the next step is trying to find out whether SES_school, MSC, SR, GSR, and TEL can explain the differences that still exist. The equation (2) shows that the MSC school variable is one of the most powerful predictors in influencing the model, because it has the largest and most significant estimated coefficient. This means that student who study in schools with higher levels of self-concept, will tend to get better results on math tests. In addition, other variables at the school level that are statistically significant as predictors influencing the model are SES_school, SR, GSR, and TEL. Overall, the school-level variables added to this model have a positive contribution in influencing students' mathematics achievement because they reduce unexplained variance by 17%.

$$\begin{aligned} Math\ Score_{ij} = \beta_{0j} &+ 3.11(0.43)SES_{student} + 3.67(1.33)ATM + 21.28(1.22)MSC + \\ &8.18(2.29)SES_{school} + 37.00(8.26)MSC_{school} + 10.69(3.59)SR + \\ &11.54(4.03)GSR + 13.68(5.08)TEL + e_{ij} \end{aligned} \quad (2)$$

Where $\beta_{0j} = 305.53(15.26) + u_{ij}$.

3.3. Interpretation of the final model

Model 2 provides information that by considering all backgrounds, both those related to the students themselves and variables related to the school, almost half (35%) of the total unexplained variance in students' mathematics achievement was successfully explained, because the total variance decreased from 7176.03 to 4671.86. Specifically, model 2 succeeded in explaining 30% of the 51% total variance that could not be explained at the school level after adding six predictor variables, namely SES_school, MSC_school, SR, GSR, and TEL, with an increase of 19% from model 1. Overall, model 2 has a good fit, because all predictor variables are statistically significant and are able to explain most of the unexplained variance.

If viewed from the magnitude of the coefficients produced in model 2, with other predictor variables held constant, students' mathematics achievement will increase by 3.11 and 8.18 points for each additional SES unit at the student and school level. Furthermore, students' mathematics learning achievement will increase by 21.28 and 37.00 points for each additional MSC unit at the student and school level, while for each additional ATM unit students are only able to increase 3.67 points, with other predictor variables remaining constant. In addition, students' mathematics learning achievement will increase by 10.69 and 11.54

points for each additional unit of SR and GSR, with other predictor variables remaining constant. Finally, students' mathematics learning achievement will increase by 13.68 points if most of the teachers in the school have at least a bachelor's or master's degree or higher, with other predictor variables remaining constant.

3.4. Goodness-of-fit measures and effect sizes

Table 5 describes the fit size (GoF) and effect sizes of each model. Model 2 has the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC) values, which indicate that the model is better than model 1. In particular, the minimum difference between models can be said to be different or to experience a significant model improvement. of 3.8 points or equivalent to a critical value of 95% for the Chi square distribution with one degree of freedom. In the comparison of the models in Table 5, a significant improvement occurred from model 1 to model 2 with quite a large difference in values, namely in the range of 60 to 130 points.

According to the suggestion from Levine *et al.* [53], in addition to AIC and BIC information, it is also important to display information related to the effect of each model. Model 2 shows a good multilevel R2 value of 35% with a reduction in the proportion of within-group (WG-PRV) variance of 11% (5% of 49% total variance) and between groups (BG-PRV) of 55% (28% of 51% of the total variance). This means that model 2 can reduce the variance within schools by 11% and the variance between schools by 55%. From these results it can be seen in Table 5 that model 2 has a contribution in reducing the variance between schools which is quite large compared to model 1, so that it can accommodate the contextual impact on students' mathematics learning. WG-PRV is within-group proportion reduction in variance, while BG-PRV is between-group proportion reduction in variance.

Table 5. GoF measures and effect sizes for each model

Goodness-of-fit	Model 1	Model 2
AIC	44469	44361
BIC	44507	44431
Effect sizes		
Multilevel R^2 value	0.08	0.35
WG-PRV	11%	11%
BG-PRV	22%	55%

3.5. Discussion

This research shows that the variance in students' math achievement can be explained by differences at both student and school levels. The results of the multilevel analysis highlight that factors such as student and school characteristics can make a significant contribution in explaining differences in student mathematics achievement. More specifically, 51% of the total variance can be explained by differences between schools, and the remaining 49% can be explained by differences within one school itself. This finding is generally in line with previous studies showing that a sizeable proportion of the variance in student mathematics achievement can be explained at the student and school level [8], [10], [24]. This suggests that school factors should not be neglected in explaining differences in student mathematics achievement, because significant differences can occur in student performance between schools.

Student SES and school average SES are positive predictors of student mathematics achievement. The results of this study support the results of previous studies which state that student SES and the school's average SES are significant positive predictors of student mathematics achievement [3], [8]. In addition, school SES predictors have a much stronger effect than student SES, which is also supported by the results of previous studies [8], [30]. These findings show that the education system in Indonesia is still marked by social injustice, where students with different backgrounds do not have the same probability of succeeding in school. More specifically, Indonesian schools appear to be reinforcing social inequalities, not overcoming them, because students attending schools with low SES averages are outperformed in mathematics by their classmates' attending schools with more affluent SES. This is coupled with an inflexible school admissions system, further strengthening social injustice, because students in Indonesia are placed in schools using a zoning system (based on the area where students live). Such an approach only results in different influences from the socio-economic composition of schools [56].

Students' ATM on mathematics is another predictor that also contributes to explaining the variance in students' mathematics achievement. This predictor has a significant positive effect and is stronger than the predictor of student SES. The results of this study are in line with the results of previous research which stated that student math achievement is closely related to student ATM [4], [19], in fact the two have a significant reciprocal relationship, where ATM on math achievement is not greater when Mathematics achievement affects students' ATM, especially in the middle of the semester towards the end of the semester

[9]. In addition, previous research also emphasized the importance of developing students' ATM through early literacy and numeracy activities at home or preschool [23], because in addition to contributing positively to student mathematics achievement it also contributes to the school level [24].

Another non-cognitive factor that is no less important in predicting students' mathematics achievement is MSC. The results of this study indicate that students' MSC is related to mathematics and the average MSC at the school level is proven to be a positive and significant predictor of students' mathematics achievement. This finding contradicts the results of previous research which stated that MSC has a negative effect on mathematics achievement at the student and school level in Indonesia [24]. This study provides additional insight into the mixed results regarding whether MSC predicts mathematics achievement only at the student and/or class/school level, since several previous studies have only shown it at the student level [8], [10], [28], [29]. This research provides empirical evidence that MSC predicts mathematics achievement at the student and school level, meaning self-concept not only for students but also in terms of building a classroom or school culture that collectively builds students' self-concept in science. In addition, student MSC and average MSC at school level were the strongest predictors compared to other predictors (including school SES) in predicting student mathematics achievement, in line with research by Thien *et al.* [24], but contradicts several previous studies which made school SES the strongest predictor in predicting student mathematics achievement [3], [8], [30].

The school readiness factor for schools is a predictor that contributes to explaining the variance of students' mathematics achievement. The results of this study support the results of previous studies which state that students with a low level of readiness for school tend to have low mathematics achievement [3]. In addition, previous research also stated that pre-school education plays an important role in future academic achievement by increasing school readiness [31], including mathematics achievement [34]. Students with low SR levels tend to choose to attend schools with minimal achievement and come from poor families and have low levels of education [13]. On the other hand, students whose parents have high SES levels tend to attend schools with high achievement, even their parents are very active in helping their children to complete homework, social and cultural development, and preparation for future education [3]. This suggests that school selection based on SES level will widen the gap in mathematics achievement among students. According to Meinck *et al.* [13], greater attention should be paid to early literacy and numeracy activities at home as a form of SR to reduce achievement differences based on SES.

School-related factors such as GSR and TEL were found to be significant positive predictors of influencing students' mathematics achievement. The results of this study are in line with the results of previous studies which state that GSR has a positive impact on students' learning and academic performance in mathematics [35]. However, the results of this study contradict the results of a study by Wardat *et al.* [5] which states that GSR has a negative and insignificant impact on students' mathematics achievement. On the other hand, some previous research results state that schools equipped with the use of technology in classroom learning will greatly assist teachers in presenting learning concepts that are more efficient and easily understood by students [12], [36]. Coupled with the average TEL at the master's level, of course it will greatly support the use of technology in classroom learning, so that students' desire to learn and understand mathematics increases and will ultimately have a positive impact on student mathematics learning achievement [2]. To be able to do that, the role of the school principal is needed as the main actor in developing teacher competence, providing instructional supervision and leadership in order to improve student mathematics achievement [5].

Overall, the predictors added to the final MLM explained 35% of the total unexplained variance in math achievement. More specifically, 11% and 55% of the within-school and between-school differences, respectively, were explained by the variables described in the multilevel analysis. However, there is still a statistically significant unexplained variance (65%). This suggests that future research should also consider including more variables that can explain the remaining variance.

4. CONCLUSION

This research contributes to the development of current research that focuses on addressing the gap in students' mathematics achievement among developing countries. In terms of methodology, this study contributes additional insights into handling missing data in secondary data such as Program for International Student Assessment (PISA), TIMSS, and others by utilizing machine learning methods such as RF to use multilevel analysis with more accurate results. In terms of results, this study contributes to complementing previous literature that does not highlight the self-concept factor at the school level in explaining the gap in students' mathematics achievement in developing countries, such as Indonesia. This research has generated a unique view of student mathematics achievement by identifying factors that can statistically predict the mathematics achievement of 15-year-old students in Indonesia. The results of this study indicate that the school visited by each student accounts for a large part of the variance in students' mathematics achievement. In addition, the final MLM demonstrated the predictive power of student background characteristics, i.e., student SES which was found to influence student achievement positively and significantly in mathematics. In addition, the results of the analysis also show the importance of students' self-constructions about mathematics, such as ATM and self-concept, because they are found to be statistically significant in influencing mathematics achievement. Finally, factors related to schools such as SES-school, self-concept school, SR, GSR, and TEL, were also found to influence students' mathematics achievement positively and significantly, where self-concept school is strongest predictor compared to other predictors. Overall, these findings suggest that policy makers, educators, and parents should consider factors such as SES, ATM, MSC, SR, school resources, and TEL in designing policies and curricula of education. The results of this study provide additional information about the factors that influence the mathematics achievement of 15-year-old students in Indonesia and make a significant contribution to knowledge formation and fill gaps in the existing research literature.

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