



## **GROWTH MINDSET, SCHOOL CONTEXT, AND MATHEMATICS ACHIEVEMENT IN INDONESIA: A MULTILEVEL MODEL**

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### **Abstract**

Shifting students to a growth mindset can increase their achievements. Nevertheless, only a few studies have been conducted on this topic in developing countries. This study aims to examine the relationship between growth mindset, school context, and mathematics achievement in Indonesia. Using a multilevel model on the PISA 2018 data, this study explored the variables that contributed to mathematics achievement. The multilevel analysis showed that students' gender, growth mindset, index of economic social, and cultural status were statistically significant predictors of students' mathematics achievement. Girls have been reported to have a higher mathematics achievement than boys in Indonesia. As the students' growth mindset increases, so do their mathematics achievement.

**Keywords:** PISA 2018, Mathematics, Multilevel, Growth Mindset

### **Abstrak**

Keyakinan siswa terhadap *growth mindset* atau pemikiran yang berkembang dapat meningkatkan prestasi belajar mereka. Namun hanya beberapa penelitian yang telah dilakukan pada topik ini di negara berkembang. Penelitian ini bertujuan menyelidiki hubungan antara *growth mindset*, konteks sekolah, dan prestasi belajar matematika siswa di Indonesia. Menggunakan model multilevel pada data PISA 2018, penelitian ini mengeksplorasi variabel-variabel yang berkontribusi pada prestasi belajar matematika. Analisis multilevel menunjukkan bahwa jenis kelamin siswa, *growth mindset*, indeks sosial ekonomi dan status budaya merupakan prediktor yang signifikan secara statistik terhadap prestasi belajar matematika siswa. Pelajar perempuan dilaporkan memiliki prestasi matematika yang lebih tinggi dibandingkan pelajar laki-laki di Indonesia. Seiring meningkatnya *growth mindset*, prestasi matematika siswa juga mengalami peningkatan.

**Kata kunci:** PISA 2018, Matematika, Multilevel, Pemikiran Berkembang

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In December 2019, the Organization of Economic Cooperation and Development (OECD) published the result of the Programme for International Student Assessment (PISA) 2018, which placed Indonesia in the quadrant of low performance and high equity (Avvisati et al., 2019). The average mathematical score of Indonesian students were 379, far below the average mathematical score of all PISA participants which equaled to 489. In the first participation in the year 2000, Indonesian students had obtained an average of 367 for mathematics score. From 2003 to 2015, the average mathematics score fluctuated between 360 and 386 (Nugrahanto & Zuchdi, 2019). As a consequence, large efforts should be done to improve students' mathematical ability.

The PISA is a routine evaluation or assessment held by the Organization of Economic Cooperation and Development (OECD) to measure the literacy of students around the world (Stacey, 2011). Besides the scores obtained from standardized tests, some additional data are collected from

students, parents, and teachers using questionnaires. Consequently, the result of the PISA test can be compared at various levels and further analyzed to find a way for improving the educational quality.

For a long time, some Indonesian as well as foreign researchers were trying to explain the PISA results using their datasets. Thien et al. (2015) used multilevel analysis on PISA datasets to compare the mathematics performances of students from Indonesia, Malaysia, and Thailand. This study found that attitude towards learning outcomes and mathematics self-efficacy were the main factors affecting student level performance in Indonesia. Pakpahan (2016) used correlation analysis on the PISA 2012 data and found that students' discipline, socioeconomic and cultural conditions, computer ownership, and textbooks were the main factors influencing the achievement of Indonesian students' mathematical literacy. Kartianom and Ndayizeye (2017) used the multilevel model to analyze the PISA 2015 data and found that the socio-economic status of the family, the socio-economic average of the school, and students' sense of belonging to mathematics affect the Indonesian students' mathematics achievement. In Serbia, a multi-level analysis revealed that students' achievement in mathematics is affected by gender, non-cognitive characteristics, habits of study, student-perceived teaching quality, and several school-level factor (Lazarević & Orlić, 2018). Using a binary multilevel model to analyze the PISA 2012 data, Karakolidis et al. (2016) found that students' gender, immigration status, self-constructs in mathematics, and the mean socio-economic status (SES) in school significantly affect the students' mathematical achievement in Greece. Using the hierarchical linear model, Anderson et al. (2009) analyzed the students' mathematical literacy based on the PISA 2006 data.

In PISA 2018 test, a new important variable has been added into the student questionnaire, namely growth mindset. A growth mindset is the belief that someone's ability and intelligence can develop over time (Caniëls et al., 2018). Blackwell et al. (2007) as well as Dweck (2007) show that students with a growth mindset are more likely to believe that learning and understanding require efforts. When faced with challenges, they may be more willing to make more effort and take more risk. A growth mindset is also related to poverty, where more students from a lower-income family exhibit a fixed mindset (Claro et al., 2016). Change in students' mindsets can be affected by academic experiences, peers, and formal learning (Limeri et al., 2020).

Related to the mathematics ability, students in all levels may explore mathematics if they know that mathematics can be learned (Alpar & Van Hoesve, 2019). However, the belief that ability is a fixed trait (instead a growth trait) is particularly common and may be a key reason for students' underperformance and disinterest in mathematics (Sun, 2018). In United States, it has been proven that a short intervention in growth mindset can improve grades among lower-achieving students and increased overall enrolment to advanced mathematics courses in secondary education (Good et al., 2012; Yeager et al., 2019). Similarly, a fixed mindset may contribute to poor student performance, inequitable participation, and disinterest in mathematics (Horn, 2007; Boaler et al., 2018). However, a large meta-analysis by Sisk et al. (2018) shows that the overall effect of growth mindset on academic achievement

was weak. Despite these differences, the growth mindset still becomes a popular research topic around the world (Sun, 2019).

The PISA 2018 result shows that the majority of students across OECD countries has a growth mindset, as evident by their responses (“disagree” or “strongly disagree”) with the statement “Your intelligence is something about you that you can’t change very much”. In contrast, at least 60% of students in Indonesia believe that their intelligence is something that they cannot change by themselves, which represents the fixed mindset (Avvisati et al., 2019). Similar results have been observed in students from Dominican Republic, Kosovo, Panama and the Philippines, which are countries with low achievement in the PISA 2018 test.

The dominance of fixed mindsets in Indonesian students leads us to explore the PISA 2018 data and examine whether a growth mindset contributes significantly to their mathematics achievement. To ensure the effects, we examine several variables that significantly affect students’ mathematics achievement. Following some earlier studies using PISA datasets (e.g. Kartianom & Ndayizeye, 2017), this study uses the multi-level model framework to see the effects on both the student and school levels.

## **METHOD**

### ***Data Collection***

The data set used in this study are the PISA 2018 data. The PISA is a triennial survey of 15-year-old students assessing to what extent they have acquired the key knowledge and skills that are essential for full participation in society. The assessment focuses on proficiency in reading, mathematics, science and an innovative domain, and as well as on students’ well-being (OECD, 2019). The Indonesian PISA 2018 data set includes all observations from 12,098 students and 397 schools. The response variable is students’ mathematics achievement which is calculated by averaging ten plausible values of the mathematics scores. The structured data were found in PISA 2018 in Indonesia, where the level-1 of hierarchy is the students and the level-2 is the school. The level-1 predictors in this study are students’ gender, students’ growth mindset, and students’ socio-economic status which is estimated by the PISA index of economic, social, and cultural status (ESCS). The level-2 predictor is student-to-teacher-ratio (STR). As missing values were found in the growth mindset, ESCS, and STR variables, the comprised samples became 9,196 students and 308 schools.

*Socio-demographic variables* were gender (female or male) and ESCS. The students’ ESCS is derived from several variables relating to home and background information of students and ranged from -8.17 to 4.21 (OECD, 2016).

*Growth mindset* was assessed by responses toward the following statement: “Your intelligence is something about you that you can’t change very much.” Responses were coded as 1: Strongly disagree, 2: Disagree, 3: Agree, 4: Strongly agree. As the growth mindset represents belief that an individual can improve his/her abilities over time, then the coded responses must be reversed from 1: Strongly agree up to 4: Strongly disagree. As a result, 1 indicates the lowest growth mindset score, while 4 indicates

the highest growth mindset score for each individual. In this study, the growth mindset is treated as a continuous predictor in order to have insightful interpretation.

### **Data Analysis**

A total of 9,196 students and 308 schools with all variables of interests were used to investigate the effects of gender, growth mindset, students' ESCS, and STR on mathematics achievement by fitting two-level multilevel models. Descriptive statistics were calculated to provide information about the sample characteristics. The parameters of the multilevel model were estimated using the restricted maximum likelihood (REML) method through the use of `lme()` function in R statistical software version 3.6.0 from `nlme` package (Pinheiro et al., 2021). Three random intercept models and one random slope model were fitted to the data. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to select the best model, where lower value indicated a more parsimonious model. Since the PISA 2018 data consists of school-level data and students-level data, in this study, we used the multilevel analysis as follows.

### **Random Intercept Model**

A random-intercept model is a simple multilevel model with only one random level-1 coefficient (Finch et al., 2019). The level-1 of the random intercept model is given as,

$$y_{ij} = \beta_{0j} + \varepsilon_{ij} \quad (1)$$

The level-2 of the random intercept model is expressed as

$$\beta_{0j} = \gamma_{00} + U_{0j} \quad (2)$$

where the  $ij$  subscript refers to the  $i$ th student in the  $j$ th school,  $y_{ij}$  represents the mathematics achievement score for the  $i$ th student in the  $j$ th school,  $\varepsilon_{ij}$  is assumed to follow a normal distribution with a mean of zero and a constant variance of  $\sigma^2$ ,  $\varepsilon_{ij} \sim N(0, \sigma^2)$ . Model (1) predicts the mathematics achievement from just an intercept which allows to vary randomly within school. The  $\gamma_{00}$  represents an average or general intercept value that holds across schools,  $U_{0j}$  is a school-specific effect on the intercept assuming a normal distribution with a mean of zero and a constant variance value denoted as  $\tau_{00}$ ,  $U_{0j} \sim N(0, \tau_{00})$ . The  $\gamma_{00}$  is a fixed effect because it remains constant across all schools, and  $U_{0j}$  is a random effect because it varies between schools. It is assumed that both variances  $\tau_{00}$  and  $\sigma^2$  are uncorrelated. Model (2) allows the intercept differs across schools which leads to the random intercept. Model (1) and (2) can be combined as

$$y_{ij} = \gamma_{00} + U_{0j} + \varepsilon_{ij} \quad (3)$$

Model (3) is also known as an unconditional mean or null or empty model in the multilevel modelling context.

In Equation (1), the mathematics achievement score of students  $i$  in school  $j$  ( $y_{ij}$ ) is modelled as a function of the mean score in mathematics achievement for school  $j$  ( $\beta_{0j}$ ) plus a residual term that

reflects individual student differences around the mean of school  $j$  ( $\varepsilon_{ij}$ ). In Equation (1), the mathematics achievement mean score for school  $j$  ( $\beta_{0j}$ ) is modelled as a function of a grand-mean score in mathematics achievement ( $\gamma_{00}$ ) plus a school-specific deviation from the grand mean ( $U_{0j}$ ). Equation (3) is important for researchers since it facilitates the writing of the syntax commands on statistical software packages.

As the students are clustered within a school unit, the correlation among students' scores within school structure can be derived using the intraclass correlation (ICC) which is expressed as,

$$ICC = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \quad (4)$$

The ICC is a measure of proportion of variation in the outcome variable that occurs between groups versus the total variation present. ICC values between 0.05 and 0.20 are common in multilevel modelling in social research studies (Peugh, 2010). The need for a multilevel analysis is not only based on a non-zero ICC but also the design effect. The design effect is used to justify for accounting the multilevel structure in the analysis (Maas & Hox, 2005). The design effect is determined by

$$Design\ effect = 1 + \frac{(n_c - 1)}{ICC} \quad (5)$$

where  $n_c$  is the number of students per school. The value of design effect estimates greater than 2.0 indicate a need for multilevel modelling (Muthén, 1991; 1994; Muthén & Satorra, 1995).

Adding three predictors of level-1 in the random intercept model is extending the empty model into four equations in the level-2. The scales of two continuous variables are centered around the grand mean. Thus, the grand mean centering variables with zero values represent the overall mathematics achievement mean score across all schools. The level-1 of the random intercept model with three predictors of level-1 is expressed as,

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{1ij} + \beta_{2j}(x_{2ij} - \bar{x}_{2..}) + \beta_{3j}(x_{3ij} - \bar{x}_{3..}) + \varepsilon_{ij} \quad (6)$$

The level-2 of the random intercept model with three predictors of level-1 is formulated as,

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + U_{0j} \\ \beta_{1j} &= \gamma_{10} \\ \beta_{2j} &= \gamma_{20} \\ \beta_{3j} &= \gamma_{30} \end{aligned} \quad (7)$$

Combining Eq. (6) and (7) yield,

$$y_{ij} = \gamma_{00} + \gamma_{10}x_{1ij} + \gamma_{20}(x_{2ij} - \bar{x}_{2..}) + \gamma_{30}(x_{3ij} - \bar{x}_{3..}) + U_{0j} + \varepsilon_{ij} \quad (8)$$

The first term in Equation (8) is identical to Equation (2) where  $\gamma_{00}$  is the grand mean and  $U_{0j}$  is a residual that allows the mathematics achievement mean scores to vary across schools. Equation (6) illustrates the definition of a fixed effect model in level-1: the impact of gender ( $x_{1ij}$ , 1 for male and 0 for female), growth mindset ( $(x_{2ij} - \bar{x}_{2..})$ , the growth mindset of student  $i$  at the school  $j$  is centered around the grand mean), and students' ESCS ( $(x_{3ij} - \bar{x}_{3..})$ , the ESCS of student  $i$  at the school  $j$  is centered around the grand mean) on mathematics achievement across each school ( $\beta_{1j}$ ,  $\beta_{2j}$  and  $\beta_{3j}$

respectively) are captured by single estimates that express the average effect of gender, growth mindset, and students' ESCS on mathematics achievement across all schools ( $\gamma_{10}$ ,  $\gamma_{20}$  and  $\gamma_{30}$  respectively).

The addition of three predictors of level-1 and one predictor of level-2 in the random intercept model is expressed as,

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{1ij} + \beta_{2j}(x_{2ij} - \bar{x}_{2..}) + \beta_{3j}(x_{3ij} - \bar{x}_{3..}) + \beta_{4j}(w_j - \bar{w}) + \varepsilon_{ij} \quad (9)$$

where  $w_j$  is the predictor at level-2 which represents the STR at school  $j$ . The predictor  $w_j$  is also centered around its grand mean.

The level-2 of the random intercept model with three predictors of level-1 and one of predictor level-2 is formulated as,

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + U_{0j} \\ \beta_{1j} &= \gamma_{10} \\ \beta_{2j} &= \gamma_{20} \\ \beta_{3j} &= \gamma_{30} \\ \beta_{4j} &= \gamma_{40} \end{aligned} \quad (10)$$

Combining Equations (9) and (10) yield,

$$y_{ij} = \gamma_{00} + \gamma_{10}x_{1ij} + \gamma_{20}(x_{2ij} - \bar{x}_{2..}) + \gamma_{30}(x_{3ij} - \bar{x}_{3..}) + \gamma_{40}(w_j - \bar{w}) + U_{0j} + \varepsilon_{ij} \quad (11)$$

where the addition of  $\beta_{4j}$  represents the impact of STR on mathematics achievement across each school that is captured by a single estimate of  $\gamma_{40}$ .

### Random Slope Model

A random slope model involves the mean scores from each of many schools as an outcome to be predicted by group characteristics (Raudenbush & Bryck, 2002). The random slope model in this study uses Equation (9) as the level-1 model, whereas the level-2 model is given as follows,

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + U_{0j} \\ \beta_{1j} &= \gamma_{10} \\ \beta_{2j} &= \gamma_{20} \\ \beta_{3j} &= \gamma_{30} \\ \beta_{4j} &= \gamma_{40} + U_{1j} \end{aligned} \quad (12)$$

where there is one level-2 predictor  $w_j$  (STR). Substituting Equation (12) into Equation (9) yield the combined model as follows,

$$\begin{aligned} y_{ij} &= \gamma_{00} + \gamma_{10}x_{1ij} + \gamma_{20}(x_{2ij} - \bar{x}_{2..}) + \gamma_{30}(x_{3ij} - \bar{x}_{3..}) + \gamma_{40}(w_j - \bar{w}) + \\ &U_{0j} + U_{1j}(w_j - \bar{w}) + \varepsilon_{ij} \end{aligned} \quad (13)$$

where  $\begin{bmatrix} U_{0j} \\ U_{1j} \end{bmatrix} \sim N(\mathbf{0}, \boldsymbol{\tau})$ ,  $\boldsymbol{\tau} = \begin{bmatrix} \tau_{00} & \tau_{10} \\ \tau_{01} & \tau_{11} \end{bmatrix}$ , and  $\varepsilon_{ij} \sim N(0, \sigma^2)$ . The  $\tau_{00}$  is the variance in intercepts between schools (and the level 2 variance at STR equals to 0),  $\tau_{11}$  is the variance in slopes (STR) between

schools, and  $\tau_{01}$  or  $\tau_{10}$  is the covariance between intercepts and slopes. Finally, four combined models for multilevel analysis are developed in this study, namely the models in Equation (3), (8), (11), and (13).

## RESULTS AND DISCUSSION

### *Descriptive Statistics*

Students' mean score in mathematics was 399.98 with a standard deviation of 79.91, while approximately 53 percent of students' mathematics scores were below the mean. Given that PISA standardized the mathematics score with an average of 487 (SD=89) across the OECD countries, Indonesian students appeared to perform worse than the OECD average. Table 1 shows that more boys than girls in Indonesia had mathematics scores below the mean. The students with higher belief that growth mindset can improve their abilities over time had much larger mathematics mean scores than those with less belief.

The range of students ESCS variable was between -5.78 and 2.97 where its mean score was -1.40 and standard deviation was 1.11, while the student-to-teacher ratio variable ranged from 1.54 to 100 where its mean score was 18.19 and standard deviation was 7.46. Although the Pearson's correlation between the students' ESCS and the mathematics score was low, it showed that the two variables had a significant relationship. Also, there was a significant relationship between the student-to-teacher ratio and the mathematics score.

**Table 1.** Gender, Growth Mindset, Student-to-Teacher Ratio, and Mathematics Achievement

Variable	N (%)	Mean mathematics score (SD)	Percentage of students with maths below the means
<b>Gender</b>			
Boys	4,495 (48.88%)	394.85 (80.65)	53.26%
Girls	4,701 (51.12%)	404.87 (78.90)	52.80%
<b>Growth Mindset</b>			
1	1,991 (21.65%)	380.68 (69.06)	52.59%
2	4,077 (44.33%)	382.38 (71.76)	53.50%
3	2,199 (23.91%)	436.30 (81.38)	50.52%
4	929 (10.10%)	432.53 (91.64)	48.65%
Student ESCS	-	0.39 (<0.0001)*	-
Student-to-Teacher Ratio	-	0.05 (<0.0001)*	-

*Note:* \*Pearson's correlation coefficient (p-value), N(%) represents the total of students in each category of the variable, SD represents the standard deviation.

### **Two-Level Multilevel Models**

In this study, the multilevel analysis was developed in a few steps, starting with the most straightforward model and gradually moving to a more complex model. The scales variables were centered on the grand mean for the purposes of this analysis.

#### **Step 1: Model without Fixed Predictors (MWFP)**

Equation (3) represents the simplest model that considers school effects on the mathematics achievement. The multilevel model shown in Equation (3) was estimated and results are shown in the first column of Table 2. A significant non-zero grand-mean score in mathematics achievement was observed,  $\hat{\gamma}_{00} = 390.63, p < 0.001$ . The level-1 variance component estimate shows the magnitude of mathematics achievement score variation across students within a school,  $\hat{\sigma}^2 = 2,641.25$ . The variance component in the mathematics achievement mean scores across schools was  $\hat{\tau}_{00} = 3,717.04$ . The estimated ICC can be obtained by substituting these two-variance component estimates in the following equation:

$$\widehat{ICC} = \hat{\tau}_{00}/(\hat{\tau}_{00} + \hat{\sigma}^2) = 3,717.04/(3,717.04 + 2,641.25) = 0.58.$$

The ICC estimate showed that 58% of the mathematics achievement variance occurred across schools. The average number of students per school in the PISA 2018 Indonesian dataset was  $n_c = 9,196/308 = 29.86$ . The design effect estimate is computed by:

$$Design\widehat{Effect} = 1 + (n_c - 1)\widehat{ICC} = 1 + (29.86 - 1)(0.58) = 17.74.$$

The ICC estimate of 58% (>0%) and the design effect estimate of 17.74 (>2) indicate the clear need for multilevel modelling of mathematics achievement data.

#### **Step 2: Adding Student-Level Predictor to Model (Level 1: Fixed)**

The multilevel model shown in Equation (8) was estimated and results are shown in the second column of Table 2. Results again showed a significantly non-zero mean score in mathematics achievement ( $\hat{\gamma}_{00} = 392.23, p < 0.001$ ). All of the level-1 predictors included in the model were found to be statistically significant predictors of students' achievement in mathematics where it was moderately significant for the gender effect ( $\hat{\gamma}_{10} = -1.89, p < 0.10$ ). More specifically, boys had underperformed in mathematics compared with girls. The first regression slope indicates that mathematics achievement increases in growth mindset associated with approximately an eight-point increase in achievement, on average ( $\hat{\gamma}_{20} = 8.43, p < 0.001$ ). Meanwhile, the second regression slope shows that about a three-point increase in mathematics achievement on average was associated with an increase in students' ESCS ( $\hat{\gamma}_{30} = 3.07, p < 0.001$ ). By including all these level-1 predictors in the multilevel model, the between-school variance component ( $\tau_{00}$ ) considerably decreased from 3,717.04 to 3,308.57. This suggests that much of the variance between schools was attributable to the students' background and growth mindset. The variance within schools also declined from 2,641.25 to 2,589.72.



As the level-two variance component was about 11% explained by the student-level variables in this model, it was also important to find the predictor at the school level.

**Table 2.** Model Summaries of Several Multilevel Models. MWFP denotes the model without fixed predictors (Equation 3); level-1: fixed denotes the random intercept model with the fixed level-1 predictors (Equation 8), level-1 & 2: fixed denotes the random intercept model with fixed level-1 and 2 predictors (Equation 11), and level-2 denotes the random slope model with fixed level-1 and 2 predictors and random level-2 predictor (Equation 13)

Parameters	MWFP	Level-1: fixed	Level-1 & 2: fixed	Level-2: random
<i>Regression coefficients (fixed effects)</i>				
Intercept ( $\gamma_{00}$ )	390.63 (3.54)***	392.23 (3.39)***	393.42 (3.38)***	393.77 (3.42)***
Gender (male)	-	-1.89 (1.12)*	-1.85 (1.12)*	-1.85 (1.12)*
Growth Mindset	-	8.43 (0.62)***	8.43 (0.62)***	8.43 (0.62)***
Student ESCS	-	3.07 (0.63)***	3.07 (0.63)***	3.07 (0.63)***
Student-to-Teacher Ratio	-	-	1.08 (0.38)**	1.29 (0.42)**
<i>Variance components (random effects)</i>				
Residual ( $\sigma^2$ )	2,641.25 (39.62)	2,589.72 (38.85)	2,589.57 (38.85)	2,589.62 (38.85)
Intercept ( $\tau_{00}$ )	3,717.04 (310.70)	3,308.57 (277.48)	3,236.68 (272.10)	3,257.23 (302.21)
Slope ( $\tau_{11}$ )	-	-	-	0.21
Correlation ( $\tau_{01}$ )	-	-	-	0.56
<i>Information criteria</i>				
AIC	99,669.55	99,458.94	99,453.04	99,456.36
BIC	99,690.93	99,501.69	99,502.92	99,520.49

Parameter estimate and standard errors listed in parentheses.

\*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , •  $p < 0.10$

**Step 3: Adding School-Level Predictor to Model (Level 1 and 2: Fixed)**

Having analyzed the variables at the student level and finding that there was still a lot of unexplained variation at the school level, the next step was to determine whether the student-to-teacher ratio could explain the remaining variation between schools. The results of implementing the multilevel analysis given in Equation (11) shows that the student-to-teacher ratio was found to be a statistically significant predictor of the mathematics achievement with the estimated coefficient ( $\hat{\gamma}_{40} = 1.08, p < 0.01$ ) which is about three times its standard error (SE=0.38). Results again showed a significantly non-zero mean score in mathematics achievement ( $\hat{\gamma}_{00} = 393.42, p < 0.001$ ) whereas all of the level-1

predictors were found to be statistically significant predictors of students' mathematics achievement except for gender. The positive value of the coefficient suggests that there was a large score in mathematics achievement among the students who study at schools with high numbers of STR. The inclusion of the STR variable in the model resulted in a slight reduction in the between-school variance from 3,308.57 to 3,236.68, indicating that about 2 percent of the between-school difference in mathematics achievement was explained by the school's mean STR attended by students, whereas a small decrease 2,589.72 to 2,589.57 was seen in the variation within schools.

In Equation (11), the level-2 predictor was assumed as a fixed effect. Moreover, Equation (13) allows the impact of STR on mathematics achievement to vary from one school to another. The multilevel model shown in Equation (13) was estimated and results are shown in the fourth column of [Table 2](#). The STR is statistically significant related to the mathematics achievement ( $\hat{\gamma}_{40} = 1.29, p < 0.01$ ). The variation across schools is due to the impact of STR on the mathematics achievement ( $\hat{\tau}_{11}$ ) is 0.21, suggesting that the coefficient does not differ too much between schools. The unexplained variation at level 2 increased slightly from 3,236.68 to 3,257.23, as well as the unexplained variation at level 1 from 2,589.57 to 2,589.62. The interaction between gender and growth mindset was tested but not shown in the method section and found to have no significant effect on mathematics achievement ( $p = 0.13$ ). This means that the growth mindset is the same for both boys and girls.

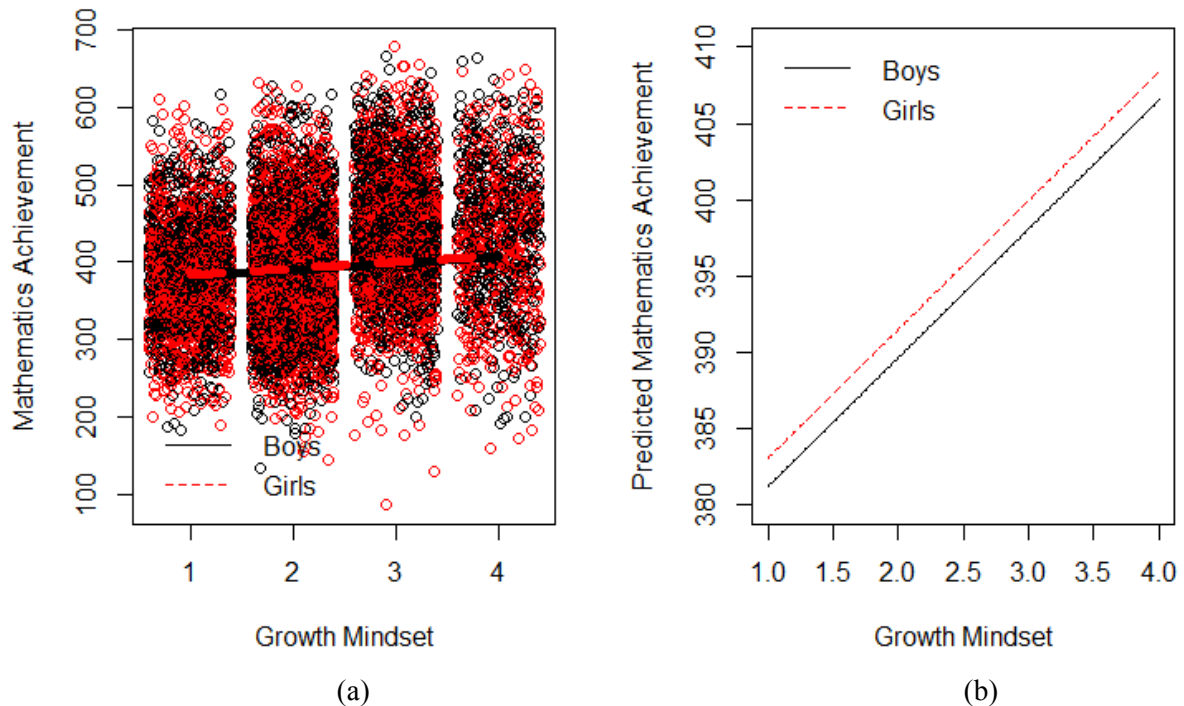
Comparing across models, the multilevel model in Equation (11) is selected as the best model as it has the lowest AIC (AIC = 99,453.04) in comparison with the other three models. Although, the BIC of the multilevel model in Equation (11) is similar to model in Equation (8), the significant coefficient of STR suggests that this variable should be included in the model. The final estimated model is given as follows,

$$\widehat{Math}_{ij} = 393.42 - 1.85Male_{ij} + 8.43Growth_{ij} + 3.07ESCS_{ij} + 1.08STR_j + \hat{U}_{0j}$$

with the two variance components of  $\hat{\tau}_{00} = 3,236.68, \hat{\sigma}^2 = 2,589.57$ . It is important to remember that the last three independent variables are mean centered.

[Figure 1\(a\)](#) shows a significant increase in mathematics achievement as students' growth mindset increased. Fitting two levels multilevel model in Equation (11) without grand mean centering yields [Figure 1\(b\)](#). [Figure 1\(b\)](#) suggests that the mathematics achievement scores increase as the students' growth mindset increases, where girls perform better than boys.

The MWFP (Equation 3) suggested that about 58% of the variance was attributed to differences between school and 42% to differences within school. The final multilevel (Equation 11) model reveals that girls in Indonesia outperformed boys in mathematics achievement. This finding is supported by previous research which found that girls had scored 10 points higher than boys in mathematics achievement based on the 2015 Trends in International Mathematics and Science Study (TIMSS) (Luschei, 2017). The significance of gender to the students' mathematics achievement was also revealed in previous PISA 2012 result (Pakpahan, 2016).



**Figure 1.** (a) The observed student growth mindset versus mathematics achievement at the averages of students' ESCS and STR for each gender along with the two regression lines, (b) The student growth mindset versus predicted mathematics achievement at the averages of students' ESCS and STR for each gender

The findings of this study suggested that growth mindset, students' ESCS and STR are important factors to predict the mathematics achievement. This is in line with what Dweck and Yeager (2019) proposed, namely that believing in our effort is a positive thing that can help us grow instead of a negative thing that leads to deficient ability. More specifically, the finding of positive relationship between the growth mindset and mathematics achievement is in line with the result from Boaler et al. (2018). They found that students with higher growth mindset showed that their mathematical perceptions improved as the subject became more interesting and seen a creative subject.

The finding on how the increased students' ESCS yields higher mathematics achievement is in accordance with the previous studies from Incikabi et al. (2012), Thien and Ong (2015) as well as Cheng and Hsu (2016). This result suggests that when discussing about mathematics achievement, social economic status should be addressed. This situation can lead to the inequality in mathematics achievement between the students' higher and lower socioeconomic status.

The finding on how the increased STR yields higher mathematics achievement is contrary to the finding of Koc and Celik (2015) which pointed out that cities in Turkey with greater number of students per teacher tend to have a lower achievement. This result can be explained by the fact that highly successful schools in Indonesia tend to have higher student-to-teacher ratio as they have more students with relatively similar numbers of teachers compared to other schools. For example, a highly successful

school can have 1,560 students with 58 teachers, compared to a non-highly successful school with 400 students and 30 teachers.

The predictors of student-level and school-level in the final model contributed to a decrease in the unexplained variation between schools. More specifically, the final equation model explained the 13% of the unexplained variance at the school-level. The student-level variables especially student growth mindset, made a great contribution to the decrease of the level-two unexplained variance components besides the school-level variable of STR.

In contrast with the PISA 2015 which focused on mathematics ability, the main focus of PISA 2018 was reading ability. As a consequence, the recent PISA test does not accommodate many specific variables related to mathematics. To obtain more information, we could sum up the results of two consecutive PISA tests as follows. In the student level, factors that contribute to their achievement in mathematics are growth mindset, gender, students' social-economic status, mathematics self-efficacy, attitudes toward learning outcomes, anxiety, mathematics self-concept, mathematics behavior (Thien et al., 2015), and students' sense of belonging toward mathematics (Kartianom & Ndayizeye, 2017). In the school level, the student-to-teacher ratio, average of socio-economic status (Kartianom & Ndayizeye, 2017), average students' sense-of-belonging, average openness to problem-solving, and average mathematics efficacy (Thien et al., 2015) affects the student performance in mathematics. To confirm the significance of these factors to student performance, an assessment at the national level should be conducted. Otherwise, we may wait until the next PISA is held with a focus on mathematical ability.

It is also important to note that the PISA test in Indonesia was done on various school levels. A large sample has been taken from two provinces, namely DKI Jakarta and DI Yogyakarta so that the result from these areas can be compared to the result from other areas in Indonesia as well as other countries (Avvisati et al., 2019). For future research, more variables can be analyzed, with special attention to the differences between Indonesian provinces.

This study implies that growth mindset can be considered as important part of policy making especially in Indonesia. As Indonesian students achieve lower in Mathematics than other students in other countries, growth mindset can be used for increasing the score, as well as to be more competitive students. Two policies can be considered for government and universities, such as providing a large-scale intervention for increasing and maintaining growth mindset among students, and providing a curriculum design which includes growth mindset as a part of teaching mathematics. The former can be done by recommending these results to the government institution called the Center for the Development and Empowerment of Educators and Education Personnel for Mathematics to include this insight for teaching mathematics through their regular training program for mathematics teachers. The program can be quite short, done online and scalable as conducted by Yeager et al. (2019) in the United States. The latter can be recommended on the online sharing platform managed by government to share how important growth mindset in predicting mathematics achievement, especially among Indonesian students. By sharing this insight, teachers can understand the role of growth mindset in teaching

mathematics and apply that into the classroom settings. These two recommendations can at least give a shine on how to increase mathematics achievement. Besides those, government should consider how important socio-economic status and school condition for predicting students' mathematics achievement. However, other factors that affect the low performance in mathematics should be addressed at the national level in order to increase the mathematics ability of the students. Even though the results of our study are not conclusive, some of the factors that influence the low performance on mathematics in the PISA 2018 test can be considered for the policy makers in education of the country to start fixing this complex problem, if we want to produce literate people that can help in fully participating in the society.

## CONCLUSIONS

Programme for International Students Assessment (PISA) is a large-scale assessment in mathematics, science, and reading ability for students in various countries. The PISA 2018 showed that Indonesian students exhibited low performance in mathematics. A multilevel analysis shows that several student-level factors contributed significantly to this result, namely gender, growth mindset, as well as students' economic and socio-cultural status (ESCS). Girls outperform boys in mathematics achievement. As the student growth mindset increases, so does the students' mathematics achievement, as well as the students' ESCS. At the school level, we found that a higher student-to-teacher ratio is related to higher students' mathematical performance. In sum, students' mathematics achievement should be seen within the context of psychological, social and school factors, instead of merely about teaching mathematics. Further research is needed to grasp the effect of other variables, as well as comparing the results between schools in different provinces in Indonesia. Even then, these results can help policy makers in education of Indonesia to address this problem for the present and future development of the society.

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