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Multilevel Model Analysis to Investigate Predictor Variables in Mathematics Achievement PISA Data

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Abstract

This study aims to examine the relationship between predictor variables at the student and school levels and the interaction between variables in predicting mathematics achievement in Indonesia. Stratified analysis was implemented in Indonesia's Programme for International Student Assessment (PISA) 2018 data. The variables of student level encompassed gender, economic, social, and cultural status (ESCS), metacognition, and learning time. This study revealed that the variables of ESCS, metacognition and learning time possessed a significant positive effect on mathematics achievement. The variables of school level are class size, school type, school size, and student-teacher ratio. This study demonstrated that only the data of class size produced a significant effect on mathematics achievement. Furthermore, the interaction between the learning time and class size also significantly affected learning achievement in mathematics. Therefore, variables increasing students' mathematics achievement are ESCS, metacognition, learning time, class size, and interaction of learning time and class size.

Keywords: Multilevel modelling, mathematics achievement, PISA data, Student level, and school level

Introduction

Indonesia has been accepted as a part of international assessments since PISA 2001 (Stacey, 2011). This program is a collaboration of the Organization for Economic Cooperation and Development (OECD) countries which determines students aged 15 years old on literacy in reading, mathematics, and science (OECD, 2017b). Mathematical measurement in PISA examines individual abilities through defining, utilizing, and understanding mathematics in various situations (OECD, 2019a). Indonesia's 2018 PISA data is at a low level, below the average of 28% compared to 76% (Avvisati et al., 2018). The total sample size is a combination of students from several different classes (Peugh, 2010). Individual students in a sample are considered a hierarchy of nested groups in educational institutions (Hox et al., 2018). To ascertain the reason for the low ability of students, levels from the student to the school are explored. Gender is a predictive variable in various research that is still debatable at the student level (Karakolidis et al., 2016a). While some studies (Karakolidis et al., 2016; Ketonen & Hotulainen, 2019) indicate that gender impacts mathematics achievement, others demonstrate that this impact is negligible (Chen, 2016). Economic, social, and cultural status (ESCS), a composite variable at the student level (Milford et al., 2010), is expected to have an impact on math performance (Karakolidis et al., 2016; Sakellariou, 2017; Areepattamannil, 2014).

Metacognition is another aspect at the student level evaluated in PISA, which this aspect is divided into three, UNDREM (understanding and remembering), METASUM (summarizing), and METASPAM (assessing credibility) (Areepattamannil, 2014). Learning time is the primary element of learning achievement, where effective learning time does not depend on the length of time (Eriksson et al., 2019). In addition to the predictor variables at the student level, it also embodied predictor variables at the school level in the form of school type, school size, class size, and student-teacher ratio (stratio). The variance between public and private schools (school type) is evaluated by the economic status of school students (ESCS) (Sakellariou, 2017). Another possible student variable is school size (Giambona & Porcu, 2018). School size is the number of students aged 15 studying in the school (Karakolidis et al., 2016a). Class size must be reduced in order for teachers to pay closer attention to each student and their learning style (O'Grady et al., 2012). As a proxy for class size, the student-teacher ratio variable (stratio) is the number of students attending school divided by the teacher ratio (Giambona & Porcu, 2018). As a result, variables that affect mathematical achievement will be investigated in this study, as will the effects on mathematics achievement. The study perceived the characteristics that were considered to be relevant at the student level, such as gender, ESCS, metacognition, and learning time, as well as various aspects at the school level, such as school type, school size, class size, and student-teacher ratio (stratio).

Methods

To analyze the mathematical abilities of Indonesian students in PISA 2018 by employing Multilevel Modeling (MLM). MLM is administered to analyse explanatory variables at the student level (level 1) and school level (level 2). The explanatory variables to be examined at the student level (level 1) were gender, ESCS, metacognition, and learning time, while at the school level (level 2), the type of school, school size, class size, and student-teacher ratio. Student and school variables were determined based on the Indonesia student data assessment results. Sampling in the 2018 PISA data was administered in two steps. The first step was selecting a sample percentage with an average of 150 schools, perceiving supporting factors such as geographic location (state or province, and urban or rural location) (OECD, 2019b). The second step is to identify the sample of students with the condition that the participants are 15 years old; hence, between 4000 and 8000 students are obtained according to a country's population (OECD, 2017c). In Indonesia, 12,098 students were involved in PISA 2018 from 397 schools. After analyzing the data, a sample of 9,991 students was attained by observing the missing data in the explanatory variable to be scrutinized.

In the PISA data, each data from various countries has been divided into two level variables, the student level (level 1) and the school level (level 2) (OECD, 2017a). The sample design employed in school observations (clusters) is similar to other observational studies (OECD, 2017b). Multilevel analysis was used in detecting nested data within schools and students nested within it (Tarling, 2009). Multilevel modeling is a broad word for analyzing the relationship between measurable variables at multiple levels (Hox et al., 2018). Furthermore, it enables the investigator to explore the nature of group variability as well as the group-level characteristics of each person (Gromping, 2015). The Nlme package from the R program was utilized in this study (Pinheiro et al., 2012). The collected sample data were entered into

Microsoft Excel. Following that, it was analyzed using R. The R data analyzer seeks the standard error value for each parameter. Table 1 displays these values. Each result will be compared to the parenthesized parameter estimate standard error.

Results and Discussion

Multilevel study yields stratified data linkages between factors defining nested people at the group level (Hox et al., 2018). The Multilevel Modeling (MLM) stratified model was utilized to analyze the 2018 PISA data in this study. Theoretically, there are no maximum or minimum PISA scores. The scores are scaled to reflect the normal distribution, with an average score of ± 500 points and a standard deviation of ± 100 points following an impact size (Cohen's d) of 0.01 and a 10-point difference with an effect size of 0.10 (OECD, 2019a). Meanwhile, the MLwiN program design centers on the mean of the conventional PISA explanatory scale for OECD nations with a mean of 0 and a standard deviation of 1 (Rabash et al., 2015).

Step 1: Model without explanatory variables (null model)

Simple linear model with fixed effects school represented in equation (1), the average student is expected on the math test 397.65. The random model null model of equation (2) allows the effect of school, which is evaluated on mathematics achievement information between the variance in the number of schools. $MathAch_{ij}$ reveals the mathematics achievement of student i at school j, β_0 displays the average intercept and e_{ij} presents the residual level of students.

$$MathAch_{ij} = \beta_{0j} + e_{ij} = \beta_0 + u_{oj} + e_{ij} \tag{1}$$

u_{0j} denotes the variance in school j around the intercept. The prediction equation (1) is presented in the following equation:

$$\widehat{MathAch}_{ij} = \hat{\beta}_0 = 397.65 \tag{2}$$

where $\hat{\sigma}_{u0}^2 = 3{,}467$ represents the level-2 variance estimate and $\hat{\sigma}_e^2 = 2{,}555$ represents the level-1 variance estimate.

Step 2: adding student-level explanatory variables into the random intercept model

The explanatory variables for the student level in equation (3) with the data demonstrated in Table 1 encompass the gender, ESCS, Metacognition, and learning time. Equation 3 is obtained in accordance with equation 1. The number obtained in equation 3 derives from the standard error (SE) value in Table 1. Then, this explanatory variable is administered to analyze students' mathematics achievement.

$$\widehat{MathAch}_{ij} = 412.01(3.41) + 0.08(1.07)Gender_{ij} + 4.65(0.60)ESCS_{ij} + 21.76(0.77)Metacognition_{ij} + 0.01(0.00)LearningTime_{ij} \tag{3}$$

in which $\hat{\sigma}_{u0}^2 = 2{,}662$ represents the level-2 variance estimate and $\hat{\sigma}_e^2 = 2{,}350$ represents the level-1 variance estimate.

Step 3: adding school-level explanatory variables into the random intercept model

After examining student-level variables and determining that numerous explanatory variables can be investigated further, the next stage will be identifying explanatory variables at the school level. These variables incorporate school type, school size, class size, and student-teacher ratio.

Based on the results of Sakellariou (2017), it is discovered that in most developed countries in Latin America, private schools are superior to public schools, while in developing countries, public schools are more stable in learning performance (Sakellariou, 2017). This finding is in accordance with the condition in Indonesia as a developing country that based on the data from the Central Bureau of Statistics (BPS), state schools dominate more than private ones. Following Bank's (2012) research, students from large schools, in terms of population, obtain better results than schools with small populations. Johnson and Christensen (2014) examined that small populations tend to escalate achievement compared to larger populations (Johnson & Christensen, 2014). The research unveiled that the teacher-student ratio (station) positively affects mathematics learning achievement (Giambona & Porcu, 2018).

The explanatory variables for the school level in equation (4) with the data in Table 1 encompass the gender, ESCS, Metacognition, learning time, school type, school size, class size, and student-teacher ratio. Equation 4 is attained in accordance with equation 1. The number obtained in equation 4 derives from the standard error (SE) value in Table 1. Then, this explanatory variable is employed to analyse and identify explanatory variables at the school level.

$$\widehat{MathAch}_{ij} = 405.53(7.36) + 0.10(1.07)Gender_{ij} + 4.60(0.60)ESCS_{ij} + 21.75(0.77)Metacognition_{ij} + 0.01(0.00)LearningTime_{ij} - 1.79(1.62)SchoolType_{ij} + 0.00(0.00)SchoolSize_{ij} + 0.34(0.16)ClassSize_{ij} - 0.03(0.04)Stratio_{ij} \quad (4)$$

where $\hat{\sigma}_{u0}^2 = 2{,}635$ represents the level−2 variance estimate and $\hat{\sigma}_e^2 = 2{,}350$ represents the level-1 variance estimate.

Step 4: adding interactions between explanatory variables to the model

Incorporating explanatory variables in the model allows for variable interactions. According to the multilevel organization theory (MOT), the interaction process may occur at both the lower (student level) and higher levels (Thien et al., 2015). From sixteen interactions possible from the combination of the explanatory variables of student level and school level, it has attained one significant interaction between learning time and class size. Equation 5 is acquired based on equation 1. The number obtained in equation 5 derives from the standard error (SE) value in Table 1.

$$\widehat{MathAch}_{ij} = 408.42(7.45) + 0.15(1.07)Gender_{ij} + 4.60(0.60)ESCS_{ij} + 21.76(0.77)Metacognition_{ij} + 0.00(0.01)LearningTime_{ij} - 1.78(1.62)SchoolType_{ij} + 0.00(0.00)SchoolSize_{ij} + 0.26(0.16)ClassSize_{ij} - 0.03(0.04)Stratio_{ij} - 0.00(0.00)LearningTime_{ij} \times ClassSize_{ij} \quad (5)$$

where $\hat{\sigma}_{u0}^2 = 2{,}635$ represents the level-2 variance estimate and $\hat{\sigma}_e^2 = 2{,}348$ represents the level-1 variance estimate.

Table 1

Summary of Multilevel Models for Indonesia in PISA 2018

Parameters	Unconditional	Level-1	Level-2	Interaction
	b (SE)	b (SE)	b (SE)	b (SE)
Fixed				
Intercept	397.65 (3.13)***	412.01 (3.41)***	405.53 (7.36)***	408.42 (7.45)***
Level-1 Student				
Gender	-	0.08 (1.07)	0.10 (1.07)	0.15 (1.07)
ESCS	-	4.65 (0.60)***	4.60 (0.60)***	4.60 (0.60)***
Metacognition	-	21.76 (0.77)***	21.75 (0.77)***	21.76 (0.77)***
Learning Time	-	0.01 (0.00)***	0.01 (0.00)***	0.00 (0.01)***
Level-2 School				
School Type	-	-	-1.79 (1.62)	-1.78 (1.62)
School Size	-	-	0.00 (0.00)	0.00 (0.00)
Class Size			0.34 (0.16)*	0.26 (0.16)*
Stratio	-	-	-0.03 (0.04)	-0.03 (0.04)
Learning Time-Class Size	-	-	-	-0.00 (0.00)*
Random				
Variance in achievement between schools	3,467	2,662	2,635	2,635
Variance in achievement within schools	2,555	2,350	2,350	2,348

Parameter estimate standard error specified in parentheses

***p < 0.001, **p < 0.01, *p < 0.05

The best model based on the AIC and BIC

To determine the best compatibility model, four distinct models were developed. The Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) for each multilevel model are shown in Table 2.

Table 2

Model Comparison

Random Intercept	AIC	BIC
Model without explanatory variable	101,924.8	101,946.3
Adding student-level explanatory variables	101,088.0	101,152.3
Adding school-level explanatory variables	101,122.5	101,215.4
Adding interactions between explanatory variables	101,131.0	101,216.8

Table 2 displays that the addition of student-level explanatory variables (model 2) possesses the lowest AIC and BIC scores. The second model incorporates the variables gender, ESCS, metacognition, and learning time.

Discussion

The null model without explanatory variables in equation (2) is administered to detect significant differences between schools. The likelihood ratio (LRT) test was conducted to compare the random zero effect to the implemented fixed effects model. LRT statistics are elaborated as $\chi^2 = [-2\log L_{ReduceModel}] - [-2\log L_{FullModel}]$ (Peugh, 2010). Based on equation (2), it is revealed that $\chi^2 = [(-2)(-54{,}490.01)] - [(-2)(-50{,}961.47)] = 7{,}058.02$ refers to the LRT statistic, which corresponds to the chi-squared distribution and three degrees of freedom $\chi^2(3) = 7{,}058.02 > 16.27$. The variance of mathematics learning achievement between schools is $\hat{\sigma}^2_{u0} = 3{,}467$ with a standard deviation of 58.88, and within schools $\hat{\sigma}^2_e = 2{,}555$ with a standard deviation of 50.54. The values attained from the variance estimation level-1 and level-2 are imported into the formula $ICC = \hat{\sigma}^2_{u0}/(\hat{\sigma}^2_{u0} + \hat{\sigma}^2_e)$ (Gromping, 2015), then the value of $ICC = 0.58$. Therefore, 58% was incorporated with inter-school achievement and 42% at school. The ICC value is substituted into $Design\ Effect = 1 + (n_c - 1)ICC$ (Peugh, 2010).Thus, the estimate of 14.98 uncovers that multilevel modelling is suitable for implementation.

The results in equation (3) display that gender does not possess a significant relationship with mathematics achievement ($b = 0.08, SE = 1.07, p > 0.05$). The insignificant results are similar to Chen's (2016) research when the student gender does not significantly affect mathematics achievement (Chen, 2016). The ESCS explanatory variable displays that the data owns a significant effect on mathematics achievement ($b = 4.65, SE = 0.60, p < 0.001$). The positive coefficient estimate indicates that the higher the ESCS, the higher the mathematics achievement (Karakolidis et al., 2016b). Student metacognition possesses a significant relationship with mathematics learning achievement ($b = 21.76, SE = 0.77, p < 0.001$). The positive coefficient on student metacognition is similar to Muszynski's (2015) research when higher metacognition ability resulted in higher mathematical achievement. Learning time produces a significant relationship with mathematics achievement with the coefficient of estimation ($b = 0.01, SE = 0.00, p < 0.001$). Learning time positively affects student achievement, which is the same as Erikson & Ryve's (2010) research when achievement is affected by how much effective time is implemented by teachers in the learning process (Milford et al., 2010). It is indicated that effective mathematics learning is not time-consuming but can employ time effectively.

Then of the four variables added to equation (4), merely the class size explanatory variables presented significant results on mathematics achievement ($b = 0.34, SE = 0.16, p < 0.05$). The positive coefficient on class size corroborates the research of Johnson and Christensen (2014), that the higher the class size, the more influential it is on mathematics achievement (Johnson & Christensen, 2014). The school type has no effect on mathematics learning achievement with an estimated coefficient ($b = -1.79, SE = 1.62, p > 0.05$), contrary to research by Ozdemir (2016), which displays that school type is statistically significant (Özdemir, 2016). School size is not significant in mathematics learning achievement ($b = 0.00, SE = 0.00, p > 0.05$), but this result contrasts with the research of Giabona and Porcu (2018), which identifies that students' mathematics learning achievement is affected by the school size (Giambona & Porcu, 2018). Furthermore, stratio presents insignificant data on mathematics learning achievement ($b = -0.03, SE = 0.04, p > 0.05$). This finding is contrary to the results of the analysis by Milford, Ross and Anderson (2010), which unveiled that it significantly affects mathematics achievement in the United States and Mexico (Milford et al., 2010). Several analyses revealed that data is not significant for mathematics learning achievement, following the research of Chen (2016) and Teodorović (2012), which demonstrates that student mathematics achievement is more due to student factors than school factors.

Based on equation (5), the interaction between learning time and class size is significantly related to mathematics achievement $(b = -0.00, SE = 0.00, p < 0.05)$. The negative coefficient implies that the interaction between ESCS and the student-teacher ratio (stratio) affects a decrease in mathematical performance. This result is contrary to Peugh's research that the interaction between learning time and class size affects an increase in mathematical performance (Blatchford et al., 2011).

According to the PISA 2018 Indonesia data, the impacts of explanatory variables on mathematics performance are more influential at the student than at the school level. This finding is consistent with Chen and Teodorovic's study, which revealed that student factors influence students' mathematics performance more than school factors (Chen, 2016; Teodorović, 2012).

Conclusion

This study investigates the elements that influence students' mathematics achievement in Indonesia. According to the findings of the multilevel analysis, there are significant predictor variables at the student-to-school levels, while others are not.

At the student level, the predictor variables of ESCS, metacognition, and learning time significantly affected mathematics achievement. At the same time, gender revealed that the data had no significant effect on mathematics achievement. Gender data analysis is not significant following Chen's research that gender cannot be employed as a basis for determining students' mathematics achievement levels (Chen, 2016). The class size predictor variable at the school level was significant for mathematics achievement. The school type, school size, and student-teacher ratio display that the data do not significantly influence mathematics learning achievement. The interaction between learning time and class size significantly affects mathematics learning achievement. Further analysis of the predictor variables affecting mathematics learning achievement is required to be conducted to complement the limitations of this research.

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References

Areepattamannil, S. (2014). International Note: What factors are associated with reading, mathematics, and science literacy of Indian adolescents? A multilevel examination. *Journal of Adolescence*, *37*(4), 367–372. https://doi.org/10.1016/j.adolescence.2014.02.007

Avvisati, F., Echazarra, A., Givord, P., & Schwabe, M. (2018). What 15-year-old students in Indonesia know and can do. *Programme for International Student Assessment (PISA) Result from PISA 2018*, 1–10.

Bank, T. W. (2012). Learning outcomes in Thailand: what can we learn from international assessments? *Report No 64801-TH*. http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2012/01/25/000386194_20120125004047/Rendered/PDF/648010ESW0whit0nal0Report0Formatted.pdf

Blatchford, P., Bassett, P., & Brown, P. (2011). Examining the effect of class size on classroom engagement and teacher-pupil interaction: Differences in relation to pupil prior attainment and primary vs. secondary schools. *Learning and Instruction*, *21*(6), 715–730. https://doi.org/10.1016/j.learninstruc.2011.04.001

Chen, Q. (2016). *A Multilevel Analysis of Singaporean Students' Mathematics performance in PISA 2012* (pp. 17–33).

Eriksson, K., Helenius, O., & Ryve, A. (2019). Using TIMSS items to evaluate the effectiveness of different instructional practices. *Instructional Science*, *47*(1), 1–18. https://doi.org/10.1007/s11251-018-9473-1

Giambona, F., & Porcu, M. (2018). School size and students' achievement. Empirical evidences from PISA survey data. *Socio-Economic Planning Sciences*, *64*(March 2017), 66–77. https://doi.org/10.1016/j.seps.2017.12.007

Gromping, U. (2015). Multilevel modeling using R. *Journal of Statistical Software*, *62* (Book Review 1). https://doi.org/10.18637/jss.v062.b01

Hox, J. J., Moerbeek, M., & Schoot, R. Van De. (2018). Multilevel Analysis Techniques and Applications. In *Library of Congress Cataloging-in-Publication Data*. Library of Congress Cataloging-in-Publication Data.

Johnson, R. B., & Christensen, L. (2014). *Educational research quantitative, qualitative, and mixed approaches*. Library of Congress Cataloging-in-Publication Data.

Karakolidis, A., Pitsia, V., & Emvalotis, A. (2016). Examining students' achievement in mathematics: A multilevel analysis of the Programme for International Student Assessment (PISA) 2012 data for Greece. *International Journal of Educational Research*, *79*, 106–115. https://doi.org/10.1016/j.ijer.2016.05.013

Ketonen, E. E., & Hotulainen, R. (2019). Development of low-stakes mathematics and literacy test scores during lower secondary school – A multilevel pattern-centered analysis of student and classroom differences. *Contemporary Educational Psychology*, *59*(July), 101793. https://doi.org/10.1016/j.cedpsych.2019.101793

Milford, T., Ross, S. P., & Anderson, J. O. (2010). An opportunity to better understand schooling: The growing presence of PISA in the AMERICAS*. *International Journal of Science and Mathematics Education*, *8*(3), 453–473. https://doi.org/10.1007/s10763-010-9201-z

Muszyński, M. (2015). *Learning strategies and reading*. *February 2016*.

O'Grady, G., Yew, E. H. J., Goh, K. P. L., & Schmidt, H. G. (2012). *One-Day, One-Problem*. Springer Singapore Heidelberg.

OECD. (2017a). Main Survey School Sampling Preparation Manual Overview. *Pisa 2018, February*. https://www.oecd.org/pisa/pisaproducts/MAIN-SURVEY-SCHOOL-SAMPLING-PREPARATION-MANUAL.pdf

OECD. (2017b). PISA 2015 Technical Report. *OECD Publishing*, 1–468. https://doi.org/10.1021/op8002129

OECD. (2017c). PISA for Development Assessment and Analytical Framework. *OECD Publishing*. https://doi.org/10.1787/9789264305274-en

OECD. (2019a). How PISA results are reported: What is a PISA score? *Programme for International Student Assessment (PISA) Result from PISA 2018, I* (Volume I), 41–47. https://doi.org/10.1787/35665b60-en

OECD. (2019b). PISA 2018 insights and interpretations. *OECD Publishing*, 64. https://www.oecd.org/pisa/PISA 2018 Insights and Interpretations FINAL PDF.pdf

Özdemir, C. (2016). Equity in the Turkish education system: A multilevel analysis of social background influences on the mathematics performance of 15-year-old students. *European Educational Research Journal*, *15*(2), 193–217. https://doi.org/10.1177/1474904115627159

Peugh, J. L. (2010). A practical guide to multilevel modeling. *Journal of School Psychology*, *48*(1), 85–112. https://doi.org/10.1016/j.jsp.2009.09.002

Pinheiro, J., Bates, D., DebRoy, S., & Sarkar, D. (2012). *nlme: Fit and Compare Gaussian Linear and Nonlinear Mixed-Effects Models.* R. Package Version 3.1-104.

Rabash, J., Steele, F., Browne, W. J., & Goldstein, H. (2015). A user's guide to MLwiN. In *England: Centered for Multilevel Modelling*. England: Centered for Multilevel Modelling.

Sakellariou, C. (2017). *Private or public-school advantage? Evidence from 40 countries using PISA 2012-Mathematics*. *1*, 582. https://doi.org/10.12681/elrie.820

Stacey, K. (2011). The PISA view of mathematical literacy in Indonesia. *Journal on Mathematics Education*, *2*(2), 95–126. https://doi.org/10.22342/jme.2.2.746.95-126

Tarling, R. (2009). Statistical Modelling for Social Researchers. In *Statistical Modelling for Social Researchers*. Statistical Modelling for Social Researchers. https://doi.org/10.4324/9780203929483

Teodorović, J. (2012). Student background factors influencing student achievement in Serbia. *Educational Studies, 38*(1), 89–110. https://doi.org/10.1080/03055698.2011.567027

Thien, L. M., Darmawan, I. G. N., & Ong, M. Y. (2015). Affective characteristics and mathematics performance in Indonesia, Malaysia, and Thailand: what can PISA 2012 data tell us? *Large-Scale Assessments in Education*, *3*(1). https://doi.org/10.1186/s40536-015-0013-z

Van de Walle, J. A., Karp, K. S., Bay-Williams, J. M., Wray, J., & Brown, E. T. (2019). Elementary and Middle School Mathematics: Teaching Developmentally (10^{th} Ed.). NY, NY: Pearson.