



Factors Influencing Indonesian Students' Performance on PISA 2018

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Abstract. Education plays a pivotal role in national development, and assessing its quality is crucial. One widely recognized international assessment is the OECD's PISA, which evaluates mathematics, science, and reading abilities among 15-year-old students globally. In 2018, Indonesian students scored below the OECD average, highlighting deficiencies in the education system. This study investigates the determinants influencing Indonesian students' PISA scores using 2018 data. Multiple linear regression is employed to analyze three models: mathematics, science, and reading scores as dependent variables. Independent variables include age, gender, study time in mathematics, science, and reading, economic, social, and cultural status, family wealth, home ICT ownership, teacher feedback, and school discrimination perception. The findings reveal varying influences on PISA scores across domains: age does not affect mathematics scores, gender does not affect science scores, and all variables significantly impact reading ability scores at the 5% confidence level.

Keywords. Indonesia, Linear Regression, Mathematics, Reading, Science, PISA 2028.

1. INTRODUCTION

Education is one of the crucial factors in the development of a nation. One way to measure the quality of education is through assessments. The emergence of various international educational assessments over the past two decades has consistently provided researchers, especially in the field of education, with a database containing various types of variables (such as student achievement and background, school practices, etc.) that can be further investigated. The most well-known international assessment is the Program for International Student Assessment (PISA), conducted by the OECD to measure the mathematics, science, and reading abilities of 15-year-old students worldwide.

PISA is believed to have had a significant impact on the development of educational research in recent years (Gamazo et al., 2016). It has been observed that educational policies in several advanced countries are often influenced by reports and analyses conducted by the OECD through PISA. This is because PISA is the first international assessment presented to the public for free (Wiseman, 2013). The OECD reports and analyses may be somewhat limited due to the multitude of variables in PISA, making it the responsibility of educational researchers to further study this database, identify relationships among the variables, and draw conclusions that may enrich educational research beyond what the OECD reports offer.

Secondary analysis using PISA databases has been conducted using various methods. One of the most common approaches is multilevel regression analysis, which allows researchers to account for variability at both the student and school levels simultaneously, as demonstrated by Willms (2010). Other researchers employ different

methodologies such as structural equation modeling, as seen in Acosta & Hsu (2014) and Barnard-Brak (2018), or covariance analysis, as explored by Smith et al. (2018) and Zhu & Kaiser (2020). Data mining techniques have also emerged in recent years as a method to analyze PISA databases, exemplified by Gamazo & Martínez-Abad (2020), Martínez-Abad (2019), and She et al. (2019).

The low PISA scores of Indonesian students in 2018, below the OECD average, indicate that there are numerous factors needing improvement within Indonesia's education system. This background motivates the current research. Using the PISA database, this study aims to examine the factors influencing PISA scores among Indonesian students. Prior research in Indonesia has typically examined factors affecting PISA scores within specific domains, such as mathematics (Ulkhq, 2022a, 2023a), science (Ulkhq, 2023b), and reading/language (Ulkhq, 2022b). Therefore, this study seeks to comprehensively investigate the factors influencing PISA scores across mathematics, science, and reading abilities in Indonesia. Three multivariate linear regression models will be presented, with dependent variables being PISA scores in mathematics, science, and reading. Ten independent variables will be examined for their impact on these dependent variables: student age and gender; study time in mathematics, science, and reading; economic, social, and cultural status indices; family wealth index; home ownership of information and communication technology (ICT); teacher feedback index in class; and perceived school discrimination index by students.

2. MATERIALS AND METHODS

PISA, which stands for Programme for International Student Assessment, is an international assessment organized by the Organisation for Economic Co-operation and Development (OECD) to evaluate the education systems worldwide by measuring the academic performance of 15-year-old students in mathematics, science, and reading abilities (OECD, 2023). Its goal is to provide comparable data so that countries can improve education policies and enhance the quality of education. PISA also includes measures of cross-curricular competencies, such as collaborative problem-solving (Berger, 2014). The first PISA was conducted in 2000 and has been held every three years since then. The primary focus alternates between reading, mathematics, and science in each cycle. In the 2018 edition, PISA primarily assessed reading proficiency, with science and mathematics as secondary areas. Approximately 600,000 students from 79 countries and economies participated in PISA 2018 (OECD, 2019).

This research aiming to investigate the factors influencing Indonesian students' PISA 2018 scores is a quantitative study. Quantitative research involves collecting and analyzing numerical data using statistical methods to understand patterns, relationships, or differences within the data (Cresswell & Cresswell, 2018). Furthermore, this study adopts a correlational research design, where statistical correlations are used to describe and measure the degree or association between two or more variables (Creswell, 2012).

Data used in this study were obtained from the PISA 2018 database, which includes information on student, school, and parental status. There are three reported scores: mathematics, science, and reading proficiency. These PISA scores will serve as the dependent variables. Dependent variables are those that depend on independent variables, which are the outcomes or consequences of the influence of independent variables (Cresswell & Cresswell, 2018). The independent variables in this study consist of ten data points. The first is the age of the student at the time of the PISA assessment (AGE). The second is gender (GENDER). Next are the student's study times for mathematics (MMINS), science (SMINS), and reading (RMINS). Following these are the student's economic, social, and cultural status index (ESCS); then the family wealth index (WEALTH), home ICT ownership index (ICT), feedback index from teachers in class (PERFEED), and school discrimination index (DISCRIM). Table 1 displays these ten independent variables along with their explanations and indicators.

Table 1. Independent variable

Variable name	Description and indicators:
AGE	Student's age
GENDER	Student's gender
MMINS	Time for learning in mathematics
LMINS	Time for learning in reading
SMINS	Time for learning in science
ESCS	Index of economic, social, and cultural. Indicators: <ul style="list-style-type: none"> • Parental occupation • Parental education • Household possessions
WEALTH	Family wealth index Indicators: Do you have this item at home? <ul style="list-style-type: none"> • Own room

Variable name	Description and indicators:
	<ul style="list-style-type: none"> • Internet • Washing machine • Refrigerator • Car • Television • Bathroom with shower or bathtub • Smartphone with internet access • Computer (desktop computer, portable laptop, or notebook) • Tablet computer (e.g., iPad, BlackBerry, PlayBook) • E-book reader (e.g., Kindle, Kobo, Bookeen)
ICT	<p>Home ICT ownership index</p> <p>Indicators: Do you have this item at home?</p> <ul style="list-style-type: none"> • Educational software • Internet • Smartphone with internet access • Computer (desktop computer, portable laptop, or notebook) • Tablet computer (e.g., iPad, BlackBerry, PlayBook) • E-book reader (e.g., Kindle, Kobo, Bookeen)
PERFEED	<p>Perceived classroom feedback index from teachers</p> <p>Indicators: How often does this happen in class?</p> <ul style="list-style-type: none"> • Teachers tell me how well I am doing in a subject. • Teachers give me feedback on my strengths in that subject. • Teachers tell me which parts I can still improve. • Teachers tell me how I can improve my performance. • Teachers advise me on how

Variable name	Description and indicators:
	to achieve my learning goals.
DISCRIM	School discrimination index Indicators: Do teachers at your school: <ul style="list-style-type: none"> • Have misunderstandings about the history of some cultural groups • Say negative things about people from certain cultural groups • Blame people from certain cultural groups for issues faced by Indonesia • Have lower academic expectations for students from certain cultural groups

To analyze how these factors (independent variables) influence student performance measured in PISA scores in mathematics, science, and reading, the following multivariate regression equations are used:

Model 1 (mathematics):

$$PV_MATH_i = \alpha_1 + \beta_{11}AGE_i + \beta_{12}GENDER_i + \beta_{13}SMINS_i + \beta_{14}MMINS_i + \beta_{15}RMINS_i + \beta_{16}ESCS_i + \beta_{17}WEALTH_i + \beta_{18}ICT_i + \beta_{19}PERFEED_i + \beta_{110}DISCRIM_i + \varepsilon_{1i}, \dots$$

(1)

Model 2 (Science):

$$PV_SCIE_i = \alpha_2 + \beta_{21}AGE_i + \beta_{22}GENDER_i + \beta_{23}SMINS_i + \beta_{24}MMINS_i + \beta_{25}RMINS_i + \beta_{26}ESCS_i + \beta_{27}WEALTH_i + \beta_{28}ICT_i + \beta_{29}PERFEED_i + \beta_{210}DISCRIM_i + \varepsilon_{2i}, \dots$$

(2)

Model 3 (Reading):

$$PV_READ_i = \alpha_3 + \beta_{31}AGE_i + \beta_{32}GENDER_i + \beta_{33}SMINS_i + \beta_{34}MMINS_i + \beta_{35}RMINS_i + \beta_{36}ESCS_i + \beta_{37}WEALTH_i + \beta_{38}ICT_i + \beta_{39}PERFEED_i + \beta_{310}DISCRIM_i + \varepsilon_{3i}, \dots$$

(3)

where PV_MATH_i , PV_SCIE_i , dan PV_READ_i are PISA scores of mathematics, science,

and reading of i th student, respectively; α_1 , α_2 , and α_3 are intercepts or constants for each respective model; β_{jk} are regression coefficients for model j ($j = 1, 2, 3$) and independent variable k ($k = 1, 2, \dots, 10$); and ε_{ji} represents the error term (statistical noise) for student i in model j .

3. RESULTS AND DISCUSSION

Regression parameters were estimated using the ordinary least squares (OLS) method. The estimation results of the regression parameters are shown in Table 2. For each model:

- Model 1 (Mathematics): All independent variables have coefficients that are statistically significant except for the student's age (AGE). This indicates that all analyzed independent variables, except age, have a statistically significant influence at the 5% significance level on Indonesian students' mathematical abilities measured by the 2018 PISA mathematics scores.
- Model 2 (Science): All independent variables have coefficients that are statistically significant except for the student's gender (GENDER). This indicates that all analyzed independent variables, except gender, have a statistically significant influence at the 5% significance level on Indonesian students' science abilities measured by the 2018 PISA science scores.
- Model 3 (Reading): All independent variables have coefficients that are statistically significant. This indicates that all analyzed independent variables have a statistically significant influence at the 5% significance level on Indonesian students' reading abilities measured by the 2018 PISA reading scores.

Thus, the analysis results indicate that the factors considered in this study significantly influence the performance of Indonesian students in PISA for all three domains: mathematics, science, and reading.

Table 2. Estimation of regression parameters

Parameters	Estimation	Std. Error	p -value	VIF
Model 1				
Intercept (α_1)	438.796	39.69477	0.000*	-
AGE	1.448	2.505	0.563	1.00
GENDER: Male	-5.331	1.418	0.000*	1.03

MMINS	0.033	0.007	0.000*	3.79
SMINS	0.062	0.005	0.000*	2.31
RMINS	-0.808	0.006	0.000*	2.88
ESCS	9.801	1.052	0.000*	2.84
WEALTH	-4.322	1.362	0.002*	4.94
ICT	26.323	1.325	0.000*	4.09
PERFEED	-9.544	0.756	0.000*	1.01
DISCRIM	-14.629	0.685	0.000*	1.04
Model 2				
Intercept (α_2)	314.551	34.227	0.000*	-
AGE	9.570	2.160	0.000*	1.00
GENDER: Male	-0.215	1.223	0.860	1.03
MMINS	0.027	0.006	0.000*	3.79
SMINS	0.051	0.004	0.000*	2.31
RMINS	-0.069	0.005	0.000*	2.88
ESCS	9.950	0.907	0.000*	2.84
WEALTH	-6.607	1.174	0.000*	4.94
ICT	24.863	1.143	0.000*	4.09
PERFEED	-6.425	0.652	0.000*	1.01
DISCRIM	-17.051	0.590	0.000*	1.04
Model 3				
Intercept (α_3)	363.150	36.327	0.000*	-
AGE	-17.907	2.292	0.011*	1.00
GENDER: Male	5.817	1.298	0.000*	1.03
MMINS	0.0385	0.007	0.000*	3.79
SMINS	0.054	0.005	0.000*	2.31
RMINS	-0.083	0.006	0.000*	2.88
ESCS	11.959	0.963	0.000*	2.84
WEALTH	-4.324	1.247	0.001*	4.94
ICT	22.715	1.213	0.000*	4.09
PERFEED	-6.831	0.692	0.000*	1.01
DISCRIM	-20.546	0.627	0.000*	1.04

*statistically significant at the level of 5%

Not only the significance, but also the signs and values of the regression coefficients need to be considered. The sign of a regression coefficient can be interpreted as follows: A positive coefficient indicates that as the value of the independent variable increases, the expected value of the dependent variable tends to increase as well, and vice versa. The coefficient value indicates how much the expected value of the dependent

variable changes when the independent variable shifts by one unit, while keeping other independent variables constant. This property is crucial as it allows us to assess the influence of each variable separately from others.

In Model 1, the variable GENDER (Male) has a negative sign, indicating that female students tend to have better mathematical abilities compared to male students. However, this trend does not hold in Model 3, where the same variable has a positive sign, suggesting that male students perform better in reading ability than female students. This variable was not analyzed in Model 2 because it was not statistically significant at the 5% level.

Next, let's analyze the variables MMINS (Study time for Mathematics), SMINS (Study time for Science), and RMINS (Study time for Reading). The MMINS variable shows a positive sign with a moderate coefficient across all models. This indicates that as students spend more time studying mathematics, their PISA scores not only in mathematics but also in science and reading tend to increase. Similarly, the SMINS variable also shows a positive sign in all models, indicating that more study time in science is associated with higher PISA scores.

In contrast, the RMINS variable has a negative sign across all models. This finding suggests that spending less time on improving reading skills is associated with higher PISA scores. An initial observation here is that this variable refers to the time spent improving reading skills, rather than simply time spent reading materials or course content.

The positive value of ESCS indicates that higher socioeconomic, cultural, and educational status of students correlates with higher PISA scores. Since direct income measures from students' parents are not available in the PISA database, indicators such as household possessions, parents' occupations, and their highest level of education are used to approximate students' socioeconomic, cultural, and educational status. This finding confirms results from other studies, such as those by Perelman & Santín (2011) and Salas-Velasco (2020).

A positive sign is also found for ICT (across all models), indicating that as more students have access to ICT-related devices (e.g., desktop computers, tablets, smartphones), their PISA scores tend to be higher. The coefficient value for ICT is notably larger compared to other independent variables, suggesting that ICT contributes relatively more significantly to PISA scores compared to other variables. This finding also supports other research indicating that ICT influences student performance (Ulkhay, 2022c, 2022d,

2023c).

Next, both PERFEED and DISCRIM variables have negative coefficients across all models. For PERFEED, the results are somewhat unexpected because more frequent teacher feedback (e.g., informing students of their performance, giving advice on improvement) correlates with lower PISA scores for Indonesian students. Conversely, the negative coefficient for DISCRIM is logical because less perceived discrimination among students leads to higher PISA scores. The DISCRIM coefficient is also notably high (second highest after ICT), indicating a substantial contribution of this variable to Indonesian students' PISA scores. The implication is that schools should strive to create a non-discriminatory environment for students to enhance their academic performance.

Then, we will demonstrate that the model we constructed passes the classical assumption tests by performing several tests. The tests include normality test for residuals, multicollinearity test, and heteroskedasticity test. Firstly, the normality test for residuals is conducted to assess whether the residuals (errors) are normally distributed. This test is performed using a kernel density plot. The plot is shown in Figure 1. As seen in Figure 1, the residual plot resembles a normal distribution (bell-shaped), indicating that the model passes the normality test for residuals. Normality of residuals can affect the accuracy and confidence of hypothesis testing and confidence intervals for regression coefficients, as both rely on the standard error of estimation, which is dependent on the normality of residuals.

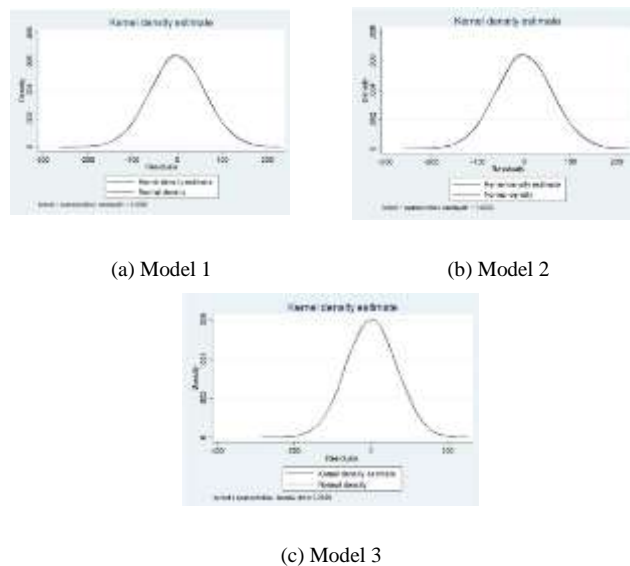


Figure 1. Normality residuals test

The next test is the heteroskedasticity test, which checks whether the variance of

residuals is homogenous (constant) rather than heterogenous. This is done by plotting residuals against fitted values. In a well-fitted model, there should be no discernible pattern when residuals are plotted against fitted values. If the variance of residuals is not constant, it is considered "heteroskedastic". A common graphical method to plot residuals against fitted values is shown in Figure 2. The figure demonstrates no heteroskedasticity because there is no pattern observed between residuals and fitted values.

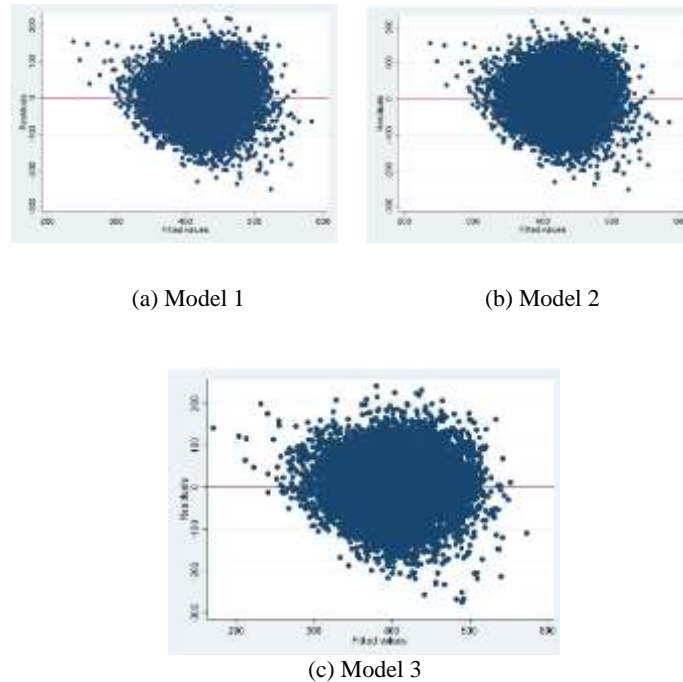


Figure 2. Heteroscedasticity test

The last test is for multicollinearity, which states that two or more independent variables are highly linearly related. When more than two variables are involved, it is termed multicollinearity. The primary concern is that as multicollinearity increases, the regression model's estimates of coefficients become unstable and the standard errors of coefficients may increase unpredictably. To check for this issue, we use the variance inflation factor (VIF). As a rule of thumb, independent variables with VIF values greater than 10 may warrant further investigation for multicollinearity. The results are shown in Table 2 (under the column "VIF"). Note that the VIF values for all independent variables are less than 10, indicating no multicollinearity issues.

4. CONCLUSION

This study investigates the factors influencing the performance of Indonesian students as measured by the 2018 PISA scores in mathematics, science, and reading. Multivariate linear regression was employed to address these research questions. The findings indicate that Indonesian students' PISA scores are influenced by several independent variables. For mathematics, out of the ten independent variables examined, only student age did not show a significant impact. For science, gender of the student did not show a significant influence. However, for reading proficiency, all examined independent variables had a significant impact at a 5% confidence level. Classical assumption tests (normality of residuals, heteroskedasticity, and multicollinearity) were also conducted to validate the estimations.

The results of this study can serve as a guide for policymaking, particularly in education. For instance, recognizing that ICT has a positive impact on raising a student's PISA score (Ulkhay, 2022c, 2023c), it becomes crucial in today's digital age to equip students with digital devices. This approach has been implemented in Catalonia, Spain, where the government provided one laptop per child (Program Escuela2.0: One laptop per child) (Feliciano et al., 2021; Mora et al., 2018). Additionally, ESCS also significantly influences Indonesian students' PISA scores positively. ESCS indicators such as parents' occupation, income, and household possessions indicate that attention should not only be focused on students but also on the welfare and education of their parents.

The primary limitation of this study lies in the selection of independent variables. There may be other factors influencing a student's PISA score that were not included in this research. Furthermore, this study is constrained by its use of the OECD's PISA database, limiting the analysis to the data available within that database. For future research, panel data regression could be employed to further investigate whether the factors examined in this study also influence Indonesian students' PISA scores in subsequent editions or even previous editions. Moreover, comparisons with other countries are needed to determine whether the factors influencing PISA scores in Indonesia are similar to those affecting students in other countries (Ulkhay, 2021, 2023d).

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