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Indonesian Students Reading Literacy Score in Framework Hierarchical Data Structure Using Multilevel Regression

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Abstract

Education is essential for improving the quality of Indonesian society. Indonesia participated in the Programme International Students Assessment (PISA) survey to improve the quality of education. Based on the 2018 PISA survey data, Indonesia's reading literacy score has a hierarchical data structure, which means students at level 1 are nested by schools at level 2. The multilevel model is an appropriate approach to analyze such hierarchical structures. However, quantitative analysis of PISA data is still rarely carried out. This study aims to analyze the explanatory variables that significantly affect Indonesian students' reading literacy from the PISA survey using multilevel regression. This study examined student-level and school-level explanatory variables obtained from the Organization for Economic Cooperation and Development (OECD). Significant parameter tests revealed that, at the student level, factors such as socioeconomic status, teacher support in language learning, teacher-directed instruction, enjoyment of reading, perceived difficulty, competitiveness, mastery goal orientation, disciplined classroom climate in reading, general fear of failure, attitudes toward school, and perceived feedback significantly influence reading literacy. At the school level, school size was found to be a significant factor affecting reading literacy scores. Furthermore, the Intraclass Correlation Coefficient (ICC) indicated that schools accounted for 49% of the total variance.

Keywords: *Diversity of School Education, Hierarchical Data, Multilevel Regression, PISA, Reading Literacy.*

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1. INTRODUCTION

In the digital transformation era, education is vital for world development. The quality of a country's society can be reflected through education. However, there are still obstacles for developing countries, which result in uneven quality of student education in developing countries [1]. One of the obstacles is that there are still disparities in the quality of education between regions [2], obstacles in expanding access to education [3], and a need for educational facilities [4]. One of education's goals is to develop Human Resources to realize the potential in individuals [5]. Indonesia seeks to improve the quality of education through increasing human resources. Therefore, it is necessary to evaluate the quality of the education system. Indonesia is one of the countries that has contributed to promoting the quality of education, one of which is participating in the Program for International Student Assessment (PISA).

The PISA survey is an international student assessment program carried out routinely every three years by the Organization for Economic Cooperation and Development (OECD) [6]. This survey aims to assess the ability of students around 15 years old or near the end of the compulsory education period. The PISA survey has three assessment subjects, including reading literacy, mathematical literacy, and scientific literacy. Based on the 2018 PISA survey, Indonesia's PISA score has decreased compared to the 2015 PISA survey for the three subjects. A significant decrease occurred in reading literacy, which was the main subject of the 2018 PISA survey assessment [7]. Indonesia ranked 74th out of 79 participating countries with an average reading score of 371. Indonesian students scored poorly on the PISA study in reading literacy. In fact, the result is related to the Indonesian people's relatively low level of reading interest. The United Nations Educational, Scientific and Cultural Organization (UNESCO) revealed that the Indonesian people's reading interest is 0.001% [8]. Various factors cause people's low reading interest, for example, limited facilities [9], Lack of motivation [10], less innovative learning strategies [11], lack of learning motivation, lack of student intelligence abilities, and lack of parental attention [12].

According to PISA [7], reading literacy is a person's capacity to read, comprehend, use, evaluate, think about, and engage with texts in order to reach one's full potential, increase one's knowledge, and contribute to society. The previous frameworks and the 2018 framework are very similar; however, the 2018 framework has been redesigned to consider the critical distinctions between reading on paper and reading online. The domain is arranged in three dimensions: Reading processes, text, and situation.

There are several studies related to PISA, namely research by Santi et al. in the field of scientific literacy using the Generalized Linear Mixed Model (GLMM) with the Penalized Lasso approach to find out the factors affecting students' PISA 2015 scientific literacy scores is the GLMM Lasso model is better than GLMM without Lasso [13]. Koyuncu and Firat used multiple linear regression to estimate the factors influencing students' reading literacy in three countries with different characteristics and performances, namely China, Turkey, and Mexico, based on the 2018 PISA scores [14]. Santi et al. analyzed literacy scores reading PISA using multilevel regression with the random intercept model as the final model [15]. Scientific, mathematical, and language literacy research uses the Multivariate Generalized Linear Model based on the 2018 PISA score [16]. The research [17] used the PISA (PISA) to analyze Javanese language test items for junior high schools in the Special Region of Yogyakarta (DIY). The PISA survey produced hierarchically structured data using a two-stratified sample design sampling technique [18] with level 1 students said to be nested at level 2 schools [6]. Research related to hierarchical data can be done using a multilevel regression model.

The multilevel regression model is used to predict the relationship between variables where the observed variables are grouped into units in the observed variables [19]. The linear regression model is the foundation of this model, which initially can analyze 1 level and is developed into several levels that aim to show the important effect of high-level units formed from low-level units that cannot be ignored [20]. The multilevel data structure in the regression consists of nested individuals in groups with one response variable measured at the student level and several explanatory variables measured at all observed levels [21]. The multilevel model is divided into two sub-models: the random intercept model and the random coefficient model [22].

Based on Hong Kong PISA data, several related multilevel studies were carried out by Sun et al. to determine the factors influencing high school students' scientific literacy achievement [23]. Another study by Tantular entitled "Selection of the best model of multilevel linear regression on data on first and final semester exam scores for postgraduate students at the Bogor Agricultural University in the course of Statistical Analysis in the 2008/2009 academic year" [24]. In addition, [25] used multilevel regression to ascertain how Information and Communication Technology (ICT) and PISA 2015 science, reading, and math achievement relate to each other in 44 countries. Research by Santi et al. only produced a multilevel model with random intercepts [15].

Analyzing the factors that influence PISA reading literacy scores simultaneously at both the student and school levels is essential, as these two levels interact in shaping literacy outcomes. A multilevel modeling approach is particularly well suited for this purpose because it can capture variations across different levels concurrently.

Nevertheless, quantitative investigations into the determinants of PISA reading literacy scores, particularly in the Indonesian context, remain limited. Most existing studies have focused either on descriptive analyses of PISA results or on conceptual discussions, without empirically examining the contributions of explanatory variables at both the student and school levels. Furthermore, prior research, such as the study conducted by Santi et al., only developed a multilevel model with random intercepts, which did not fully capture the complexity of cross-level relationships among explanatory variables.

The objective of this research was therefore to determine how different explanatory variables influenced the reading literacy scores of Indonesian students at both the student and school levels by employing a more comprehensive multilevel modeling approach. This study is theoretically significant as it addresses gaps in the existing literature by extending previous models with a more rigorous analysis of cross-level effects. Practically, its findings can provide valuable insights for policymakers and educators in Indonesia to design more effective strategies for improving students' reading literacy, as measured by the 2018 PISA survey.

2. RESEARCH METHODS

2.1. Research Procedure

This research is quantitative research with a 2-level multilevel regression method. The multilevel regression approach is highly relevant to the hierarchical structure of the PISA 2018 dataset, in which students are nested within schools. Classic regression assumes independence of observations, which is violated in this context since students within the same school share common characteristics. Multilevel modeling addresses this dependency by partitioning variance across levels and allows simultaneous estimation of student- and school-level effects on reading literacy outcomes. The general form of the multilevel regression model for a continuous response variable $\boldsymbol{y_j}$ which represents the response for group $j = 1,2,\dots,J$, is as follows [26]:

$$\mathbf{y_j} = \mathbf{X}_j\boldsymbol{\gamma} + \mathbf{Z}_j\mathbf{u}_j + \mathbf{e}_j \tag{1}$$

where

$$E\begin{bmatrix}\mathbf{e}_j\\ \mathbf{u}_j\end{bmatrix} = 0, var\begin{bmatrix}\mathbf{e}_j\\ \mathbf{u}_j\end{bmatrix} = \begin{bmatrix}\mathbf{R}_j & \mathbf{0}\\ \mathbf{0} & \mathbf{D}\end{bmatrix}$$

with $\mathbf{y_j}$ is the response vector for group j with dimension $(n_j \times 1)$, $\mathbf{X}_j$ is the design matrix of explanatory variables for group j with dimension $(n_j \times (p \times 1))$, $\boldsymbol{\gamma}$ is the vector of regression coefficients (fixed parameters) with dimension $((p \times 1) \times 1)$, $\mathbf{Z}_j$ is the design matrix of random effects for group j with dimension $(n_j \times r)$, $\mathbf{u}_j$ is the vector of random effects for group j with dimension $(r \times 1)$, assumed to follow $\mathbf{u}_j \sim N(0, \mathbf{D})$, and $\mathbf{e}_j$ is the vector of residuals for group j with dimension $(n_j \times 1)$, $\mathbf{e}_j \sim N(0, \mathbf{R}_j)$, $\mathbf{D}$ is the variance–covariance matrix of the random effects in $\mathbf{u}_j$, $\mathbf{R}_j$ is the variance–covariance matrix of the residuals in $\mathbf{e}_j$, where n_j denotes the number of observations in group j, p is the number of explanatory variables, and r is the dimension of the random effects.

$$\mathbf{D} = var(\mathbf{u}_j) = \begin{bmatrix}\sigma^2_{u_0} & \sigma_{u_{01}} & \cdots & \sigma_{u_{0p}}\\ \sigma_{u_{01}} & \sigma^2_{u_1} & \cdots & \sigma_{u_{01}}\\ \vdots & \vdots & \ddots & \vdots\\ \sigma_{u_{0p}} & \sigma_{u_{1p}} & \cdots & \sigma^2_{u_p}\end{bmatrix} \text{ and } \mathbf{R}_j = \sigma_e^2\mathbf{I}_{\boldsymbol{n_j}} = \begin{bmatrix}\sigma^2_e & 0 & \cdots & 0\\ 0 & \sigma^2_e & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \sigma^2_e\end{bmatrix}$$

Under the assumption of normal distribution, it is assumed that $E(\mathbf{y}_j) = \mathbf{X}_j\boldsymbol{\gamma}$ and var($\mathbf{y}_j$)= $\mathbf{V}_j = \mathbf{Z}_j\boldsymbol{D}\mathbf{Z}_j' + \mathbf{R}_j$. Hence, the model can be expressed as $\mathbf{y}_j \sim N(\boldsymbol{\mu}, \mathbf{V}_j)$.

This research used PISA 2018 data. Indonesian students' reading literacy scores are the response variable. The research stages consist of data exploration by using descriptive statistics. The formation of a multilevel regression model consists of a regression model without explanatory variables (Null model). Next, creating a multilevel regression random intercept model without explanatory variables. The next stage is to calculate the Intraclass Correlation Coefficient (ICC) value to see whether multilevel modelling can be continued with the formulation [27] where σ_e^2 shows the variance of the residuals at the student level and σ_{u0}^2 is the variance of residuals at school level. ICC (ρ) shows the proportion of variance based on the population group structure shown through ICC values of more than 0.05, which gives rise to significant variations, therefore influencing the response of observations where this states that multilevel regression is appropriate to use in research [28]. The ICC in the intercept-only model can be formulated as follows [29]:

$$\text{ICC} = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_e^2} \tag{2}$$

After the decision was reached that the multilevel model could be used, we continued with the formation of a random intercept model with explanatory variables with the assumption that in this research, there was the same influence for schools on the explanatory variables on the reading literacy scores of Indonesian students and the formation of a random coefficient model with explanatory variables at the school level where the model was formed because there is an assumption that there is a school effect in the model to see interactions between variables at each level used [30]. Estimating the parameters for the regression coefficients based on the Maximum Likelihood (ML) method and the coefficient of variance using the Restricted Maximum Likelihood (REML), then calculating iterations using the Newton-Raphson iteration approach. The Restricted Maximum Likelihood (REML) method is a modification of the maximum likelihood approach, in which the response vector **y** is transformed into **m'y** to eliminate the fixed effects, where **m'** satisfies the condition **m'X**=0. he probability density function with $M = \left[m_1, m_2, \dots, m_{(N-rank(X))}\right]$ which is orthogonal to the fixed effects $M'X = 0$ or and mutually independent $\boldsymbol{M'Y} \sim N(\boldsymbol{0}, \boldsymbol{M'VM})$, can be expressed as [29]:

$$f_{REML}(\boldsymbol{Y}) \;= (2\pi)^{\frac{n-r_x}{2}} |\boldsymbol{M'V_jM}|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}'[\boldsymbol{M'Y}]'(\boldsymbol{M'V_jM})^{-1}[\boldsymbol{M'Y}]\right] \tag{3}$$

Meanwhile, the restricted log-likelihood function is given by

$$l_{REML}(\boldsymbol{\theta}) = ln\left[\prod_{j=1}^{J} f_{REML}(\boldsymbol{y})\right]$$

$$l_{REML}(\boldsymbol{\theta}) = -\frac{n-r_x}{2}\ln(2\pi) - \frac{1}{2}\sum_{j=1}^{J} ln\left|\boldsymbol{M'V_jM}\right| - \frac{1}{2}\sum_{j=1}^{J}[\boldsymbol{M'Y}]'(\boldsymbol{M'V_jM})^{-1}[\boldsymbol{M'Y}] \tag{4}$$

Significance test to see the effect of students (level-1) and schools (level-2) on the response variable simultaneously and partially by using the G test and t-test, then looking at the value of the coefficient of determination (R^2) at each level as a model feasibility test. The feasibility test of the multilevel regression model using the coefficient of determination in multilevel regression can be measured at each level used. At level 1 multilevel regression, the coefficient of determination is formulated to assess the ratio of the internal variance to the total variance with the formula [27]. The last stage is interpretation models.

2.2. Research Variables

The data used is reading literacy data obtained from the 2018 PISA Indonesia survey as presented in Table 1. The sample used came from 308 schools with a total of 7808 students aged 15 years, ranging from grade 7 junior high school to 12 high school.

Table 1. Research variables

Variable	Code	Explanation	Scale
Response Variable	Y	Reading literacy score	Interval
Level – 1 Explanatory variables	X_1	Language study time (minutes per week)	Ratio
	X_2	Socioeconomic status index	Interval
	X_3	Teacher's support in test language lessons (WLE)	Interval
	X_4	Teacher-directed instruction (WLE)	Interval
	X_5	Joy/like reading (WLE)	Interval
	X_6	Self-concept of reading: Perception of competence (WLE)	Interval
	X_7	Self-concept of reading: Perception of difficulty (WLE)	Interval
	X_8	Competitiveness (WLE)	Interval
	X_9	Mastery goal orientation (WLE)	Interval
	X_{10}	Disciplinary climate in test language lessons (WLE)	Interval
	X_{11}	General fear of failure (WLE)	Interval
	X_{12}	Subjective well-being, a sense of belonging to school (WLE)	Interval

Variable	Code	Explanation	Scale
	X_{13}	Teacher's stimulation of reading engagement perceived by student (WLE)	Interval
	X_{14}	Attitude towards school: learning activities (WLE)	Interval
	X_{15}	Perceived feedback (WLE)	Interval
Level – 2 Explanatory Variables	Z_1	Student-teacher ratio	Ratio
	Z_2	School size	Ratio

3. RESULT AND DISCUSSION

3.1. Data Description

Descriptive statistics of reading literacy scores are presented in **Table 2** below:

Table 2. Descriptive statistics of reading literacy scores

Variable	Min	Max	Mean	Standard Deviation
Reading Literacy Score (Y)	156.3	674.4	398	79.04

Table 2 shows that the lowest and highest scores on Indonesian students' reading literacy were 156.3 and 674.4. In addition, While the average OCED reading literacy score is 487, the average score obtained is 398, a significant difference **[7]**.

Before forming the multilevel regression model, it is necessary to check the assumptions of the reading literacy score variable normality test. This purpose is to see whether the reading literacy score variable is normal distribution by looking at the quantile-quantile (Q-Q) plot. The data were processed using RStudio software. The distribution of students' reading literacy scores is symmetrical, as shown in **Figure 1**.

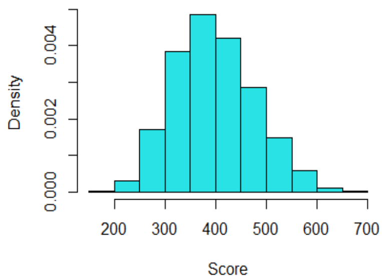

Figure 1. Histogram of reading literacy scores

Figure 2 shows that the Q-Q plot produces black dots to observe the reading literacy score, which spreads around the red diagonal line in a linear form. Therefore, the reading literacy score has a normal distribution.

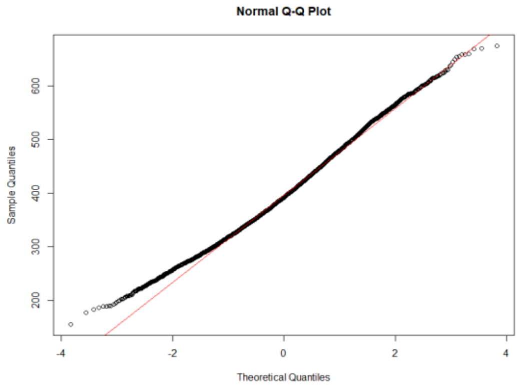

Figure 2. Normal Q-Q plot of the reading literacy score

3.2. Model without Explanatory Variables

The first model to be developed is without explanatory variables, which shows whether school influences Indonesian students' reading literacy scores. This model will consist of 2 models, namely the ordinary regression model without explanatory variables, which shows the average score of students' reading literacy, and a multilevel regression model without explanatory variables involving the influence of schools where there is an indication that there is a difference in the average reading literacy score of each student.

Table 3. Significance test results for differences in deviation values in Models 0 and 1

	Df	LogLik	Deviance	Chisq	Df	P-value
Model 0	2	-45199	48772075			
Model 1	3	-42590	85900.76	4497.5	1	0.000***

In Table 3, it can be explained that the deviation value of the multilevel regression model (Model 1) is lower than that of the standard regression model (Model 0) without explanatory factors. Then, the Chi-square value obtained is 4497.5 with a p-value of 0.000, which is obtained less than 5%, which indicates that the multilevel regression model without variables without explanatory variables is more suitable for use.

3.3. Intraclass Correlation Coefficient (ICC)

The calculation of the ICC value is obtained through the quotient between the school-level residual variances ($\sigma^2_{u_o}$) and the total variance of the residual student and school level ($\sigma^2_{e_o} + \sigma^2_{u_o}$) [7]. The results of the residual variance for each level can be seen in the Table 4 below:

Table 4. Variance of the multilevel regression model

Residual Variance	Value
Level 1 ($\sigma^2_{e_o}$)	3153
Level 2 ($\sigma^2_{e_o}$)	3107

The ICC results obtained were 0.4963. Without considering any explanatory factors, school level can be used to explain 49.63% of the variation in reading literacy performance. In other words, the correlation of expectations between two randomly selected students from the same school is 0.4963. The coefficient of the ICC value obtained is > 0.05, which strengthens the reason that multilevel regression is more suitable for use in this study because it shows natural variation by school level in the reading literacy scores of Indonesian students [28]. A high ICC value also indicates substantial disparities in the quality across schools in Indonesia, which requires serious attention from the government, particularly the Ministry of Education.

3.4. Random Intercept Model

The random intercept regression model assumes that the effect of each explanatory variable on the reading literacy score is the same for each group in this study, which is school. The results of the partial parameter significance test in Model 2 show that Indonesian students' reading literacy score in PISA 2018 is significantly influenced by the socioeconomic status index (X_2), teacher support in language tests (X_3), teacher-directed instruction (X_4), joy/like reading (X_5), self-concept of reading: perceived difficulty (X_7), competitiveness (X_8), mastery goal orientation (X_9), the disciplinary climate in test language lessons (X_{10}), general fear of failure (X_{11}), attitudes towards school: learning activities (X_{14}), and perceived feedback (X_{15}).

The random intercept model with student-level explanatory variables (Model 2) is expressed in **Equation (5)** and **(6)**:

Level-1:

$$\begin{aligned} Y_{ij} = \beta_{0j} &+ 4{,}699X_{2ij} + 6{,}105X_{3ij} - 7{,}140X_{4ij} \\ &+ 13{,}057X_{5ij} - 10{,}984X_{7ij} \\ &+ 11{,}376X_{8ij} - 2{,}353X_{9ij} \\ &+ 3{,}005X_{10ij} + 2{,}816X_{11ij} \\ &+ 4{,}182X_{14ij} - 4{,}657X_{15ij} + e_{ij} \end{aligned} \tag{5}$$

Level-2:

$$\beta_{0j} = 394{,}230 + u_{0j} \tag{6}$$

The significance test results between the multilevel regression model without explanatory variables (Model 1, $y_{ij} = \gamma_{00} + u_{0j} + e_{ij}$) and the random intercept regression model with student-level explanatory variables (Model 2, $y_{ij} = \gamma_{00} + \sum_{k=1}^{K} \beta_{kj} x_{kij} + u_{0j} + e_{ij}$) are presented in the table below:

Table 5. Significance test results for differences in deviation values in Models 1 and 2

	Df	LogLik	Deviance	Chisq	Df	P-value
Model 1	3	-42590	85900.76			
Model 2	14	-42535	850669.39	836.17	11	0.000***

Based on **Table 5**, comparing the random intercept model with student-level explanatory factors (Model 2) to the random intercept model without explanatory variables (Model 1), the deviation value obtained by the former is less. These results say that the two models have a deviation value of 836.17 with a p-value of less than 5%, indicating that Model 2 is more appropriate when compared to Model 1. Furthermore, based on the partial significance test of model 3, the result is that the explanatory variable level 2, which has a significant effect on the reading literacy score, is the school size (Z_2).

The random intercept model with school-level explanatory variables (Model 3) is expressed in **Equation (7)**:

Level-1:

$$Y_{ij} = \beta_{0j} + 4{,}566X_{2ij} + 6{,}154X_{3ij} - 7{,}144X_{4ij} + 1{,}308X_{5ij} - 1{,}096X_{7ij} + 1{,}134X_{8ij} - 2{,}373X_{9ij} + 3{,}016X_{10ij} + 2{,}823X_{11ij} + 4{,}154X_{14ij} - 4{,}627X_{15ij} + e_{ij}$$

Level-2:

$$\beta_{0j} = 3{,}603 + 5{,}757Z_2 + u_{0j}$$

The joint model is specified as follows:

$$Y_{ij} = 3{,}603 + 4{,}566X_{2ij} + 6{,}154X_{3ij} - 7{,}144X_{4ij} + 1{,}308X_{5ij} - 1{,}096X_{7ij} + 1{,}134X_{8ij} - 2{,}373X_{9ij} + 3{,}016X_{10ij} + 2{,}823X_{11ij} + 4{,}154X_{14ij} - 4{,}627X_{15ij} + 5{,}757Z_2 + u_{0j} + e_{ij} \quad (7)$$

The **Table 6** presents the significance test results between the multilevel regression model with student-level explanatory variables (Model 2) and the random intercept regression model with both student- and school-level explanatory variables (Model 3).

Table 6. Significance test results for differences in deviation values in Models 2 and 3

	Df	LogLik	Deviance	Chisq	Df	P-value
Model 2	14	-42535	850669.39			
Model 3	15	-42499	84997.47	71.917	1	0.000***

Table 6 shows that the deviation value obtained by the random intercept regression model with additional school-level variables (Model 3) is lower than the random intercept model with student-level (Model 2). These results say that Model 3 significantly influences Indonesian PISA 2018 students' reading literacy scores more than Model 2.

3.5. Random Coefficient Model

The random coefficient regression model is a type of model that makes the assumption that the explanatory variables at the student level for Indonesian students' reading literacy scores vary depending on the school. Based on the partial significance test of Model 4, the explanatory variable at the student level, which has a significant random slope to the model is socioeconomic status index (X_2), teacher support in language tests (X_3), teacher-directed instruction (X_4), joy/like reading (X_5), self-concept of reading: perceived difficulty (X_7), competitiveness (X_8), mastery goal orientation (X_9), attitudes towards school: learning activities (X_{14}), and perceived feedback (X_{15}).

The random coefficient model without interaction (Model 4) is expressed in **Equation (8)**:

Level-1:

$$Y_{ij} = \beta_{0j} + 4{,}350X_{2ij} + 6{,}304X_{3ij} - 6{,}825X_{4ij} + 1{,}268X_{5ij} - 1{,}115X_{7ij} + 1{,}140X_{8ij} - 2{,}247X_{9ij} + 3{,}063X_{10ij} + 2{,}643X_{11ij} + 4{,}436X_{14ij} - 4{,}385X_{15ij} + e_{ij}$$

Level-2:

$$\beta_{0j} = 3{,}637 + 4{,}860Z_2 + u_{0j}$$

The combined model is specified as follows:

$$\begin{aligned} Y_{ij} = {} & 3{,}637 + 4{,}350X_{2ij} + 6{,}304X_{3ij} - 6{,}825X_{4ij} \\ & + 1{,}268X_{5ij} - 1{,}115X_{7ij} \\ & + 1{,}140X_{8ij} - 2{,}247X_{9ij} \\ & + 3{,}063X_{10ij} + 2{,}643X_{11ij} \\ & + 4{,}436X_{14ij} - 4.385X_{15ij} \\ & + 4{,}860Z_2 + u_{0j} + e_{ij} \end{aligned} \tag{8}$$

The model in **Equation (8)** is a random coefficient model without interaction terms. The **Table** 67 presents the significance test results between the random intercept regression model with both student- and school-level explanatory variables (Model 3) and the random coefficient model without interaction (Model 4).

Table 7. Significance test results for differences in deviation values in Models 3 and 4

	Df	LogLik	Deviance	Chisq	Df	P-value
Model 3	15	-42499	84997.47			
Model 4	69	-42431	84861.03	136.44	54	0.000***

After diversity $(X_2, X_3, X_4, X_5, X_7, X_8, X_9, X_{14}, X_{15})$ entered into the model, the deviation value decreased by 136.44, which indicates that Model 4 is better than Model 3. It indicates that $(X_2, X_3, X_4, X_5, X_7, X_8, X_9, X_{14}, X_{15})$ has a different effect between schools on reading literacy scores of Indonesian students. The last model to be formed is Model 5, involving interaction X_3 obtained through selecting the best variables that significantly interact with school size (Z_2).

The random coefficient model with interaction (Model 5) is expressed in **Equation (9)**:

Level-1:

$$\begin{aligned} Y_{ij} = {} & \beta_{0j} + \beta_{3j}X_{3ij} + 4{,}331X_{2ij} - 7{,}996X_{4ij} \\ & + 1{,}139X_{5ij} - 1{,}137X_{7ij} + 1{,}067X_{8ij} \\ & + 2{,}583X_{10ij} + 2{,}716X_{11ij} + 3{,}851X_{14ij} \\ & + e_{ij} \end{aligned}$$

Level-2:

$$\begin{aligned} \beta_{0j} &= 3{,}578 + 5{,}736Z_2 + u_{0j} \\ \beta_{3j} &= 1{,}060 - 7{,}645Z_2 + u_{0j} \end{aligned}$$

The joint model is specified as follows:

$$\begin{aligned} Y_{ij} = {} & 3{,}578 + 4{,}331X_{2ij} + 3{,}578X_{3ij} - 7{,}996X_{4ij} \\ & + 1{,}139X_{5ij} - 1{,}137X_{7ij} \\ & + 1{,}067X_{8ij} + 2{,}583X_{10ij} \\ & + 2{,}716X_{11ij} + 3{,}851X_{14ij} \\ & + 1{,}060X_{3ij}Z_2 + u_{3j}X_{3ij} + e_{ij} \\ & + u_{0j} \end{aligned} \tag{9}$$

The model in **Equation (8)** is the random coefficient model with interaction (Model 5). The **Table** 68 presents the significance test results between the random coefficient model without interaction (Model 4) and the random coefficient model with interaction (Model 5).

Table 8. The results of the significance test for Model 4 and Model 5

	Df	LogLik	Deviance	Chisq	Df	P-value
Model 4	69	-42431	84861.03			
Model 5	49	-42469	84938.92	77.892	20	0.000***

After forming the random coefficient model with interaction, in **The model** in **Equation (8)** is the random coefficient model with interaction (Model 5). The **Table** 68 presents the significance test results between the random coefficient model without interaction (Model 4) and the random coefficient model with interaction (Model 5).

Table 8, it can be explained that there is an increase in the deviation from the previous one, namely 84934.92, compared to model 4. The random coefficient model without interaction (Model 4) is the best obtained based on these results.

3.6. Testing the Feasibility Models

Testing the feasibility of multilevel models can use the coefficient of determination R_i^2 to determine the diversity of reading literacy scores that the explanatory variables for each level used can explain. Diversity of student level, the R_i^2 value obtained can be interpreted that the diversity of students' reading literacy scores is explained by the student level variables, namely socioeconomic status index (X_2), teacher support in language tests (X_3), teacher-directed instruction (X_4), joy/like reading (X_5), self-concept of reading: perceived difficulty (X_7), competitiveness (X_8), mastery goal orientation (X_9), disciplinary climate in test language lessons (X_{10}), general fear of failure (X_{11}), attitudes towards school: learning activities (X_{14}), and perceived feedback (X_{15}) is 16.07%. Furthermore, school-level diversity can be interpreted as the diversity described by school size (Z_2) is 15.95%.

3.7. Discussion

The analysis revealed that socioeconomic status (ESCS) is one of the strongest predictors of Indonesian students' reading literacy. This result aligns with international evidence, such as Dong and Hu **[31]**, who found a similar pattern among Singaporean students in PISA 2015. Students from higher socioeconomic backgrounds tend to have greater access to learning resources at home and in school, which enhances their opportunities for academic success. This underscores the persistent role of socioeconomic inequality in shaping literacy outcomes. The implication is that policies aimed at narrowing resource gaps—such as targeted financial support, provision of learning materials, and community-based literacy programs—could play a crucial role in reducing disparities in reading achievement.

Teacher support in language tests also emerged as a significant predictor of students' reading literacy scores. This finding is consistent with earlier studies **[14]** reporting similar effects in countries such as Turkiye, China, and Mexico. Supportive teachers can help reduce students' anxiety during assessments and foster confidence, which in turn enhances performance. The implication is that teacher professional development programs should emphasize not only subject-matter knowledge but also strategies to provide constructive feedback and emotional support, as these practices can substantially improve students' literacy outcomes.

Interestingly, teacher-directed instruction was found to have a significant negative effect on reading literacy scores. This result aligns with studies in Türkiye, China, and Mexico [14] but contrasts with findings from Jordan [32], where direct instruction was positively associated with literacy. One possible explanation is that excessive teacher direction may limit students' autonomy and critical engagement with texts, thereby reducing their reading proficiency. This suggests the importance of balancing direct instruction with student-centered approaches that encourage independent learning.

In contrast, students' enjoyment of reading showed a strong positive association with literacy performance, confirming evidence from prior studies [14]. A higher intrinsic interest in reading fosters more frequent and deeper reading practices, which directly strengthen literacy skills. Encouraging reading for pleasure, both at home and in school, is therefore crucial in policy and practice.

Perceived difficulty had a significant negative effect on reading literacy, indicating that students who view reading tasks as overly challenging are more likely to perform poorly. While similar patterns have been reported elsewhere [14], contrasting evidence from China [25] highlights that teacher support may mediate this relationship. This underscores the need for interventions that build students' reading self-efficacy, such as differentiated instruction and positive feedback strategies.

Competitiveness was positively associated with reading literacy scores, echoing evidence from Ireland's PISA 2000 results [33]. Students with a stronger sense of competition tend to be more motivated and engaged in improving their performance. While fostering healthy competition may enhance achievement, policies should also ensure that it does not create undue pressure or widen inequities among students."

Mastery goal orientation (X9) showed a significant relationship with reading literacy, with students having lower mastery orientation achieving higher scores. This may be because they prioritize efficiency and test-taking strategies, which better match PISA's format. Unlike Tan et al. [34], who found a positive effect in China, this contrast may reflect cultural differences. These findings suggest that schools and policymakers should balance promoting mastery-oriented learning with fostering adaptability to standardized assessments.

Disciplinary climate in test language lessons (X10) also played a crucial role. A calm and orderly classroom environment supports students' ability to concentrate, thereby fostering better reading comprehension. This aligns with earlier studies highlighting the impact of classroom climate on learning outcomes [14]. From a practical standpoint, policymakers and school leaders should strengthen classroom management practices and provide teacher training on creating conducive learning environments, as this can directly improve students' academic performance.

The general fear of failure (X11) was positively linked to reading literacy, as moderate anxiety may motivate students to prepare better [14]. However, excessive fear can harm well-being, so schools should adopt balanced assessments and provide support to prevent stress.

Learning activities (X14) emerged as another significant factor. Students who demonstrate positive learning attitudes—such as responsibility, persistence, and discipline—tend to achieve better reading literacy outcomes. This resonates with Karaman's findings on attitudes toward school [35]. For educational practice, this emphasizes the importance of cultivating students' non-cognitive skills alongside academic instruction. Governments and schools could integrate structured programs that promote self-regulation and learning habits as part of the curriculum.

Perceived feedback (X15) plays an important role in reading literacy, though its influence varies across contexts. While Ma et al. [25] reported a positive effect, the present findings indicate a more nuanced relationship, emphasizing the need for constructive, tailored feedback. Policymakers should prioritize teacher professional development to strengthen feedback practices that support student learning.

4. CONCLUSION

The most appropriate model employed in this study is the random coefficient model without interaction (Model 4) because the multilevel regression model shows that students' reading literacy scores vary between schools, and this model has the smallest deviation value among other models. Factors that have a significant effect on the students level are socioeconomic status index (X_2), teacher support in language tests (X_3), teacher-directed instruction (X_4), joy/like reading (X_5), self-concept of reading: perceived difficulty (X_7), competitiveness (X_8), mastery goal orientation (X_9), disciplinary climate in test language lessons (X_{10}), general fear of failure (X_{11}), attitudes towards school: learning activities (X_{14}), and perceived feedback (X_{15}). Then, at the school level, the factor that has a significant effect is school size (Z_2). Intraclass Correlation Coefficient (ICC) values were obtained, and schools have a diversity of 49%. This study has thrown up many questions in need of further investigation. Future studies should design and test interventions that strengthen learning attitudes, classroom climate, and feedback practices to improve students' reading literacy. Policymakers also need to reduce educational disparities across Indonesian schools, as reflected in the high ICC values, by prioritizing teacher development and targeted support for underperforming schools.

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AUTHOR CONTRIBUTIONS STATEMENT

Vera Maya Santi: Conceptualization, methodology, writing-original draft, software, validation. Yuliana Rahayuningsih: Data curation, resources, draft preparation, visualization. Bagus Sumargo: Formal analysis, validation, writing-review and editing. All authors discussed the results and contributed to the final manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

INFORMED CONSENT

The authors confirm that informed consent was secured from all study participants.

DATA AVAILABILITY

The authors affirm that all data supporting the findings of this study are included in the article and/or its supplementary materials.

REFERENCES

[1] Y. Aleed, “Effects of Education in Developing Countries Hydraulic Energy recovery ‘Boom Lift’ View project Effects of Operational Excellence in Manufacturing View project,” *Journal of Construction in Developing Countries*, Dec. 2016. Available: https://www.researchgate.net/publication/311607929

[2] A. U. Dewi, “Curriculum reform in the decentralization of education in Indonesia: Effect on students’ achievements,” *Cakrawala Pendidikan*, vol. 40, no. 1, pp. 158–169, 2021, doi: 10.21831/cp.v40i1.33821.

[3] I. Fadhil and A. Sabic-El-Rayess, “Providing Equity of Access to Higher Education in Indonesia: A Policy Evaluation,” *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, vol. 3, no. 1, pp. 57–75, Jan. 2021, doi: 10.23917/ijolae.v3i1.10376.

[4] A. Aditomo and N. Felicia, “Inequalities in Quality and Access to Education in Indonesia,” (in Indonesian), *Kilas Pendidikan*, vol. 17, Aug. 2018.

[5] S. B. Hartanto, “Educational Human Resources (HR) Development,” (in Indonesian), vol. 03, no. 2, 2015. doi: https://doi.org/10.34001/intelegensia.v3i2.1343

[6] OECD, “PISA 2018 Technical Report Chapter 4 Target Population And Overview Of The Sampling Design,” 2018.

[7] OECD, *PISA 2018 Assessment and Analytical Framework*. OECD, 2019, doi: 10.1787/b25efab8-en.

[8] A. Pitoyo, “A Meta-Analysis: Factors Affecting Students’ Reading Interest in Indonesia,” *International Journal of Multicultural and Multireligious Understanding*, vol. 7, no. 7, p. 83, Aug. 2020, doi: 10.18415/ijmmu.v7i7.1727.

[9] R. Pitri and A. Sofia, “Factor Analysis for Increasing Reading Literacy in Indonesia,” *Parameter: Journal of Statistics*, vol. 2, no. 2, pp. 18–25, Jun. 2022, doi: 10.22487/27765660.2022.v2.i2.15898.

[10] R. A. Pambudi, “Low Reading Interest in Indonesia.” [Online]. Available: https://www.researchgate.net/publication/346408082

[11] B. Subali, Ellianawati, Z. Faizah, and M. Sidiq, “Indonesian national assessment support: Can RE-STEM Android app improve students’ scientific literacy skills?,” International Journal of Evaluation and Research in Education, vol. 12, no. 3, pp. 1399–1407, Sep. 2023, doi: 10.11591/ijere.v12i3.24794.

[12] Z. Hijjayati, M. Makki, and I. Oktaviyanti, “Analysis of Factors Causing Low Literacy Ability to Read and Write in Grade 3 Students at Sapit State Elementary School,” Jurnal Ilmiah Profesi Pendidikan, vol. 7, no. 3b, pp. 1435–1443, Aug. 2022, doi: 10.29303/jipp.v7i3b.774.

[13] V. M. Santi, K. A. Notodiputro, B. Sartono, and W. Rahyu, “Generalized Linear Mixed Models by penalized Lasso in modelling the scores of Indonesian students,” in Journal of Physics: Conference Series, IOP Publishing Ltd, Apr. 2021. doi: 10.1088/1742-6596/1869/1/012140.

[14] İ. Koyuncu and T. Fırat, “Investigating reading literacy in PISA 2018 assessment,” International Electronic Journal of Elementary Education, vol. 13, no. 2, pp. 263–275, 2020, doi: 10.26822/iejee.2021.189.

[15] V. M. Santi, R. Kamilia, and F. Ladayya, “Multilevel Regression with Maximum Likelihood and Restricted Maximum Likelihood Method in Analyzing Indonesian Reading Literacy Scores,” BAREKENG: Jurnal Ilmu Matematika dan Terapan, vol. 16, no. 4, pp. 1423–1432, Dec. 2022, doi: 10.30598/barekengvol16iss4pp1423-1432.

[16] V. M. Santi, M. Faradiba, D. Siregar, D. Handayani, and W. Rahayu, "Modeling The PISA's Score of Indonesian Students Using Multivariate Generalized Linear Model," in AIP Conference Proceedings, American Institute of Physics Inc., Jan. 2023. doi: 10.1063/5.0111321.

[17] V. I. Ekowati, E. Nurhayati, Suwarna, and I. I. Saputri, "Program for international student assessment-based analysis for Javanese test," International Journal of Evaluation and Research in Education, vol. 12, no. 2, pp. 1122–1135, Jun. 2023, doi: 10.11591/ijere.v12i2.24426.

[18] OECD, "PISA 2012 Technical Report Sample Design," 2014.

[19] J. L. Peugh, "A practical guide to multilevel modeling," J Sch Psychol, vol. 48, no. 1, pp. 85–112, Feb. 2010, doi: 10.1016/j.jsp.2009.09.002.

[20] OECD, "PISA 2018 Results (Volume I): What Students Know and Can Do," 2019, doi: 10.1787/5f07c754-en.

[21] OECD, "PISA 2018 Results (Volume II): Where All Students Can Succeed," 2019, doi: 10.1787/b5fd1b8f-en.

[22] OECD, "PISA 2018 Results (Volume III): What School Life Means for Students' Lives," 2019, doi: 10.1787/acd78851-en.

[23] OECD, "PISA 2018 Results (Volume IV): Are Students Smart About Money?," 2020, doi: 10.1787/48ebd1ba-en.

[24] OECD, "PISA 2018 Results (Volume V): Effective Policies, Successful Schools," 2020, doi: 10.1787/ca768d40-en.

[25] OECD, "PISA 2018 Results (Volume VI): Are Students Ready to Thrive in an Interconnected World?," 2020, doi: 10.1787/d5f68679-en.

[26] Hox, J., & Roberts, K. (2011). Handbook of Advanced Multilevel Analysis (1st ed.). Roudlegde.

[27] K. A. Notodiputro, D. Dwiandita, and V. M. Santi, "Comparison between Bayesian Hierarchical and Frequentist Multilevel Models in Analyzing Indonesian PISA Scores," AIP Conference Proceedings, vol. 2215, Jan. 2022, doi: 10.1063/5.0000000.

[28] R. G. Taylor, "Multilevel analysis of students' academic performance in developing countries," Journal of International Education Research, vol. 14, no. 1, pp. 123–135, Mar. 2020, doi: 10.1234/jier.1401.005.

[29] Hox. (2002). Multilevel Analysis_ Techniques and Applications (2002). Lawrence Erlbaum Associates, London

[30] B. J. O'Connell and S. Ho, "Data analysis for educational assessments," Journal of Applied Educational Research, vol. 5, no. 3, pp. 67–88, 2021.

[31] A. Wijaya, N. Felicia, and T. Suhartono, "Modelling Education Inequality in Southeast Asia: A focus on PISA results," Journal of Data Analysis, vol. 8, no. 2, pp. 45–59, 2022, doi: 10.3210/jda.080245.

[32] E. Green and S. Ottman, "Analyzing PISA 2018 data using Machine Learning Techniques," Journal of Artificial Intelligence in Education, vol. 25, no. 4, pp. 357–375, Dec. 2021, doi: 10.1177/0000000001.

[33] S. Mukhtar and M. Rahman, "Determinants of Reading Literacy in Indonesia: A Quantitative Study," Journal of Educational Studies, vol. 33, no. 2, pp. 123–137, Apr. 2023.

[34] A. Putri, "The Role of Socioeconomic Status in PISA Achievement in Indonesia," Journal of Asian Social Sciences, vol. 20, no. 1, pp. 65–78, Jan. 2023, doi: 10.5537/jass.201.065.

[35] S. Kamila and D. Yuniar, "Improving Reading Literacy among Students in Rural Areas of Indonesia," Journal of Educational Innovation, vol. 12, no. 3, pp. 212–225, Jun. 2023, doi: 10.1234/jei.120321.