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MULTILEVEL REGRESSIONS FOR MODELING MEAN SCORES OF NATIONAL EXAMINATIONS

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ABSTRACT

The National Exam, known as the UN score, is the final evaluation to determine the achievement of national graduate competency standards in the school. The determinants of the achievement of the standards cannot be separated from the role of schools and local governments in which this regard is known as nested. In the field of statistics, this phenomenon can be described with a multilevel model, where level-1 is the school while level-2 is the district where the school is located. Several multilevel models are used to describe the phenomenon. The result shows that the two-level regression model without interaction is selected as the best model and the variables that affect the UN average scores significantly at level-1 are school status (X_1)*, the ratio between laboratories and students* (X_9)*, while the variable at level-2 is expenditure per capita of district/city* (Z_2)*. From this study, that educational institutions' steps in achieving a graduation standard can be right on the target.*

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1. INTRODUCTION

Regression analysis is a method to examine the relationship between one dependent variable, symbolized by Y, and one or more independent variables of X, both often shown in a linear nexus [1]. In the General Linear Regression model (GLR), each observation is assumed independently. However, this assumption is often violated if the observations are subjects from the same or nested group. For example, in the field of education [2], that the students are nested in the schools, and schools are nested, sometimes at the level above, such as area. Those data are violating the independent assumption. To solve the violation of the assumption, a multilevel regression is proposed. This multilevel regression is actually a development of a Linear Mixed Model (LMM) with two components composed of contextual analysis and mixed effects model [3]. The contextual analysis focuses on the influence of the social context on individual behaviors, whereas the mixed effects model emphasizes more on the variety of contributions given by the social context. Mathematically, the multilevel regression model can be written in Equation (1):

$$Y_{ij} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} Z_{qj} + \sum_{p=1}^{P} \gamma_{p0} X_{pij} + \sum_{q=1}^{Q} \sum_{p=1}^{P} \gamma_{pq} X_{pij} Z_{qj} + \sum_{p=1}^{P} u_{pj} X_{pij} + +u_{0j} + \varepsilon_{ij} \quad (1)$$

The multilevel regression model is a method for analyzing a data set with a hierarchical or clustered structure. Through multilevel regression, the complexity of estimation with GLR can be described by estimating γ_{00}, variance u_{0j}, pq-slope, variance ε_{ij}, and using the distribution assumptions of each error. The multilevel model can also capture the variability of each level through u_{0j}, ε_{ij}, variance u_p, and the interaction of variables between levels via γ_{pq}. Ignoring the variability at each level will result in invalid traditional statistical analysis [4]; therefore, some researchers suggest employing the multilevel model [5].

The application of the multilevel regression model is mostly developed in education, such as the value of the National Examination (hereinafter referred to as UN) of students in schools. The UN is the final evaluation of students' achievement within national graduate competency standards, carried out periodically by the government on specific subjects. This value becomes the basis for educational institutions to graduate students who meet the required competency standards. The factors that affect the achievement of graduate competency of students in a school are undoubtedly inseparable from the role of the school and local government. This regard is known as nested. In the context of statistics, this phenomenon can be described with a multilevel model, where level-1 is the school, while level-2 is the district/city where the school is located. Using a multilevel model, the magnitude of the influence of schools, districts/cities, and the variety of components of each level can be obtained, so that educational institutions' steps in achieving a graduation standard can be right on the target.

In the two-level multilevel model for UN scores, school-related attributes are defined at level-1, symbolized X_{pij} in Equation (1), while X_{pij} denotes factors that influence the UN scores, consisting of facilities and infrastructures. [6] A correlation value between school facilities and infrastructure on learning motivation is 43.20%. [7] Then, the UN's correlation value with learning motivation is obtained at 56.25%, which affects the UN score. Meanwhile, [8] prior study found that facilities and infrastructures significantly affect student learning outcomes. In addition, another factor used in modeling the average score of the UN is the quality of teachers. [9] It is obtained that the results of the study that teacher quality has a significant effect on UN scores. The number of study groups has become the determinant, and total graduates and laboratories [10], [11], as well as other factors, are also considered relevant to UN scores.

From level-1 to level-2, it is symbolized Z_{qj} as written in Equation (1). At this level, attributes related to districts/cities are defined, namely the value of the district/city's Gross Domestic Regional Product (GDRP) [12], components of the HDI include expenditure per capita and the average length of schooling. This study uses various multilevel modeling alternatives to see data trends. The selection of the best model uses the MSE, AIC values, and the smallest residual variance.

The multilevel regression model also uses a statistical measure of the intraclass correlation coefficient (ICC). It was first introduced by Fisher in 1921 and utilized to measure sibling resemblance between siblings [13]. Afterward, ICC is widely applied in various fields, such as reliability measurement areas. In the same way, they classify the ICC values into four levels, namely *poor*, *moderate*, *good*, and *excellent reliability* [14], [15]. The ICC is also utilized in other fields. For instance, in the health field, it is used to conduct DNA *microarray similarity experiments* [16]. Up to now, ICC values have been widely used in multilevel models to measure the proportion of total variance between groups [17].

2. RESEARCH METHODS

2.1 Data

One of the objectives of the multilevel model is to explore the influence of variables between levels so that explanatory variables are used at the school level and the district/city level. The data used in this study was secondary data obtained from the Ministry of Education and Culture for the school level, and the Central Bureau of Statistics for the district/city level. A total of 1597 observations were used in the study after cleaning the missing data. They were then divided into $\frac{2}{3}$ data training and $\frac{1}{3}$ data testing, so that in the model, 1064 observations were used for training. They are observations at level-1 or, in this case, it is at the school level. The level-1 variables used in this study were related to the mean scores of the UN for Junior High Schools in terms of school status, infrastructure, teacher quality, and other variables considered relevant to the UN mean scores.

Variables at level-2, there were 24 observations collected from BPS in the form of variables with respect to attributes in 24 districts/cities in South Sulawesi Province, namely Gross Regional Domestic Product, expenditure per capita, and average length of schooling. In a nutshell, the variables at level-1 and level-2, respectively, are presented in **Table 1** as follows.

Table. 1 Research Variables

Symbol	Variable	Variable Operational Definition
Level-1 Variable		
Y	Mean scores of national exams	The average scores of the UN for all subjects in English, Indonesian, Mathematics, Science
X_1	School Status	School status is either State or Private
X_2	Number of graduates	the number of graduating students in the school
X_3	The ratio of the number of students dropping out to the number of students	the number of dropout students in the school
X_4	Number of Study Groups	The number of study groups in the school
X_5	Percentage of certified teachers	Percentage of the number of certified teachers to the total number of teachers
X_6	Percentage of teachers with the educational background of Diploma (D4) and bachelor's degree (S1)	Percentage of teachers with the educational background of Diploma (D4) and bachelor's degree (S1) to the total number of teachers
X_7	Number of administrative staffs	Quantity of administrative staff
X_8	The ratio of the number of classrooms to the number of students	The ratio of the number of classrooms to the total number of students
X_9	The ratio of the number of laboratories to the number of students	The ratio of the number of laboratories to the total number of students
X_{10}	The ratio of the number of computers to the number of students	The ratio of the number of computers to the total number of students
X_{11}	Library availability	Availability of libraries in the school
X_{12}	Student council room availability	Availability of student council room at the school
X_{13}	The ratio of the number of toilets to the number of students	The ratio of the number of toilets to total number of students
Level-2 Variable		
Z_1	District/City GRDP	
Z_2	Expenditure per Capita	
Z_3	The average years of the school	

2.2 Research Methods

The modeling of the average score of the UN in Junior High School used stages adapted from **[18]** by employing a multilevel approach and is run from the simplest model to a more complex model recursively. M1 is the intercept only model. This is identified as the simplest model. Move up to the next model, that is M2, a two-level multilevel model with no independent variables at level-2. The next is M3, a two-level multilevel model with independent variables at level-1 and level-2, respectively, with random components at the intercept. M4, a two-level multilevel model with independent variables at level-1 and level-2 without considering the interaction between independent variables at both levels with random components at the intercept and slope, and the final model is M5, a two-level multilevel model with independent variables at level-1 and level-2, considering the interaction between independent variables at both levels. These stages are as follows:

a. Exploring the description of each variable to see the characteristic of every variable.

b. Identifying the multilevel regression model. The modeling was undertaken in 1.064 schools in 24 different districts/cities, so $i = 1,2,\cdots,1064; j = 1,2,\cdots,24$.

1) Model-1 (M1): *intercept-only model*. This is a model without involving independent variable elements both at the level-1 and at the level-2, with a mathematical model as follows:

$$Y_{ij} = \gamma_{00} + u_{0j} + \varepsilon_{ij} \quad (2)$$

with, $i = 1,2,\cdots,1064; j = 1,2,\cdots,24; u_{0j} \sim IIDN(0, \sigma^2_{u_{0j}})$; and $\varepsilon_{ij} \sim IIDN(0, \sigma^2_{\varepsilon_{ij}})$.

After obtaining the estimated model from M1, the next step is to calculate the ICC from the equation model as follows:

$$ICC = \frac{\tau^2}{\tau^2 + \sigma^2} \quad (3)$$

where, τ^2= variance $u_{0j}$and σ^2= variance ε_{ij}

2) Model-2 (M2): a two-level multilevel model with no independent variables at level-2. This model is analogous to the mixed linear model (MLC) with random components at level-2 called as *Variance Component Model (VCM).*

$$Y_{ij} = \gamma_{00} + \sum_{p=1}^{13} \gamma_{p0} X_{pij} + u_{0j} + \varepsilon_{ij} \quad (4)$$

with, $i = 1,2,\cdots,1064; j = 1,2,\cdots,24; u_{0j} \sim IIDN(0, \sigma^2_{u_{0j}})$; and $\varepsilon_{ij} \sim IIDN(0, \sigma^2_{\varepsilon_{ij}})$.

3) Model-3 (M3): a two-level multilevel model with independent variables at level-1 and level-2, respectively, with random components at the intercept. This model is similar to M2, but it adds variables at level-2. It is also referred to as the VCM.

$$Y_{ij} = \gamma_{00} + \sum_{q=1}^{3} \gamma_{0q} Z_{qj} + \sum_{p=1}^{13} \gamma_{p0} X_{pij} + u_{0j} + \varepsilon_{ij} \quad (5)$$

with, $i = 1,2,\cdots,1064; j = 1,2,\cdots,24; u_{0j} \sim IIDN(0, \sigma^2_{u_{0j}}); \varepsilon_{ij} \sim IIDN(0, \sigma^2_{\varepsilon_{ij}})$.

4) Model-4 (M4): A two-level multilevel model with independent variables at level-1 and level-2 without considering the interaction between independent variables at both levels with random components at the intercept and slope. This model is known as *the Random Coefficient Model (RCM).*

$$Y_{ij} = \gamma_{00} + \sum_{q=1}^{3} \gamma_{0q} Z_{qj} + \sum_{p=1}^{13} \gamma_{p0} X_{pij} + \sum_{p=1}^{13} u_{pj} X_{pij} + u_{0j} + \varepsilon_{ij} \quad (6)$$

with $i = 1,2,\cdots,1064; j = 1,2,\cdots,24; u_{0j} \sim IIDN(0, \sigma^2_{u_{0j}})$; and $\varepsilon_{ij} \sim IIDN(0, \sigma^2_{\varepsilon_{ij}})$

5) Model-5 (M5): A two-level multilevel model with independent variables at level-1 and level-2, considering the interaction between independent variables at both levels. This model is known as *the Full Multilevel Model.*

$$Y_{ij} = \gamma_{00} + \sum_{q=1}^{3} \gamma_{0q} Z_{qj} + \sum_{p=1}^{13} \gamma_{p0} X_{pij} + \sum_{q=1}^{3} \sum_{p=1}^{13} \gamma_{pq} X_{pij} Z_{qj} + \sum_{p=1}^{13} u_{pj} X_{pij} + + u_{0j} + \varepsilon_{ij} \quad (7)$$

with $i = 1,2,\cdots,1064; j = 1,2,\cdots,24; u_{0j} \sim IIDN(0, \sigma^2_{u_{0j}})$; and $\varepsilon_{ij} \sim IIDN(0, \sigma^2_{\varepsilon_{ij}})$.

c. Evaluating the goodness of fit model

After analyzing several approaches used in the modeling, the next step was the evaluation of the goodness of fit model from valued of MSE [19], AIC [20], and the smallest residual variance. Residual variance is the statistical indicator to know that the multilevel model works for the data. The smallest residual variance, the better the model [21]. The MSE value was generated from the *testing data*, which is $\frac{1}{3}$ from a total of observations so that as many as 532 observations were used to calculate the MSE from the five models used, $q = 1, 2, \cdots, 532; m = 1, 2, \cdots, 5$. Mathematically, the MSE and AIC models can be written as follows:

$$MSE_{M_m} = \frac{1}{Q}\sum_{q=1}^{Q}\left(Y_q - \hat{Y}_q\right)^2;\ q = 1, 2, \cdots, 532;\ m = 1, 2, \cdots, 5; \quad (8)$$

with,
Y_q = actual data;
$\hat{Y}_q$ = predictive data;

$$AIC_{M_m} = d + 2p; \quad (9)$$

d = deviance;
p = the number of estimated variables.

3. RESULTS AND DISCUSSION

3.1 Exploration of the Description of Each Variable

Before conducting a multilevel analysis, an exploration of each variable related to the descriptive value was carried out so that the distribution of variables is generally seen. The description for continuous variables is as follows.

Table 2. Descriptive Statistics

	Min	Q1	Average	Q3	Max
Y	32.83	42.61	48.68	52.77	83.33
X_2	0	25	82.93	105	816
X_3	0	0	0.088	0	9.4
X_4	2	3	9.476	13	48
X_5	0	21.43	42.34	63.64	100
X_6	33.33	94.44	95.83	100	100
X_7	0	2	4.681	7	31
X_8	0.009	0.037	0.051	0.056	0.4
X_9	0	0	0.007	0.009	0.19
X_{10}	0	0	0.028	0.029	0.8
X_{13}	0.001	0.01	0.028	0.035	0.4
Z_1	25.07	32.81	43.77	45.94	106.2
Z_2	7087	9291	10663	11834	16597
Z_3	6.21	9.29	7.797	7.97	11.1

Source: Output of data processing

Based on the results of data exploration, by looking at the minimum and maximum values of each variable, there is a large difference between variable values. Then, a transformation is carried out. As a consequence, the results of the transformation of these variables are then used in the subsequent analysis stage. Afterward, taking a closer look at the distribution of the mean score of the UN for every district/city. The figure is shown as follows.

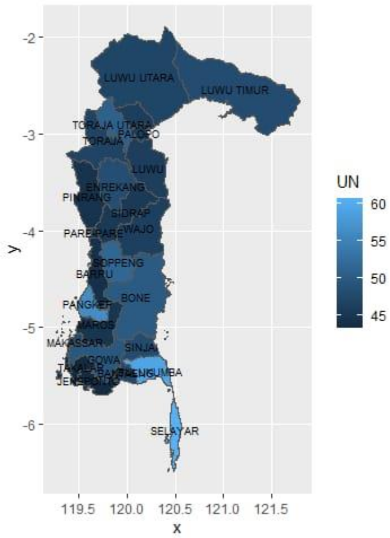

Figure 1. Mean Scores of the UN for Schools for Every Districts/Cities

Figure 1 is an illustration of the distribution of the average values of the UN for schools in every district/city. Based on **Figure 1**, every district/city has different mean values, so it indicates that there is an effect of the variable from each place resulting in the difference, and it is necessary to do further identification.

3.2 Identifying Multilevel Models

Random components:

Table 4. Random Model Component Values

	M1		M2		M3		M4		M5	
	Var.	St. Dev	Var.	St. Dev	Var	St. Dev	Var.	St. Dev	Var.	St. Dev
Intercept (district)	16.51	4,064	16.20	4,024	18.78	4,334	21.8	4,669	21,737	4,662
Residual	57.24	7,566	54.91	7,410	54.26	7,366	52.81	7,267	53,389	7,307

The estimation of random component parameters is shown in **Table 4**. It implies that the residual variance values of each model are 57.24 for M1, 54.91 for M2, 54.26 for M3, 52.81 for M4, and 53.389 for M5, respectively. Based on the result, it indicates that the smallest residual variance value is found in M4, which is a multilevel model without involving interactions between independent variables at each level. Afterward, the variance components of the variables in M4 are identified. They disclose how much diversity is given by each variable to the model.

Table 5. Fixed Model Component Values

	Coefficient of Model				
	M_1	M_2	M_3	M_4	M_5
Intercept	48.4*	47.37*	39.2*	42.109*	44.64*
X1	-	−2.949*	3,711*	3,592*	3,608*
X2	-	−0.092	-0.25	-	-
X3	-	−0.58	-0.58	-	-
X4	-	0.11	0.13	-	-
X5	-	−0.97*	-0.93*	-0.2	-
X6	-	0.47*	0.52*	-	-
X7	-	−0.6	-0.52	-	-
X8	-	11.48	11.8	-	-
X9	-	105.78*	100.2*	66.8*	-133.1
X10	-	8.08*	7,71*	1.44	-
X11		−0.67	-0.49	-	-
X12		0.71	0.68	-	-
X13		−20.571	-19.9		
Z1	-	-	0.03	-0.101*	-0.111*
Z2	-	-	5.98×10^{-4}*	0.001*	3.63×10^{-4}
Z3	-	-	2.5×10^{-2}	-	-
X1: Z2	-	-	-	-	3.29×10^{-4}
X9:Z2	-	-	-	-	1.46×10^{-2}

* statistically significant
Source: Output of data processing

a. M1

Hypotheses:

H_0:$\gamma_{00} = 0$

H_1:$\gamma_{00} \neq 0$

By using the CI values in **Table 5**, the interval values do not contain zero, so the model intercept is significant. Therefore, the equation of M1 can be written as follows:

$$\hat{Y} = 48{,}372 \quad (10)$$

After estimating the parameters from M1, the ICC value should be calculated as follows:

$$ICC = \frac{\tau^2}{\tau^2+\sigma^2} = \frac{16.51}{16.51+57.24} = 0.224 \quad (11)$$

One of the statistical measures used in the multilevel model is ICC. The ICC value of M1 shows 0.224 or 22.4%. This indicates that the proportion of variance from the average scores of the UN is 22.4%, which can be explained by districts/cities. Similarly, ICC values are generated by prior studies [22], [23]. This value is considered relatively small to be an indicator of the similarity of schools for each district/city. However, [18] they obtained the ICC value of 36% for the intercept-only model concerning student popularity data and concluded that the value is relatively large in the area of social studies. So that the ICC values obtained in this model are relatively fit in multilevel modeling.

b. M2

After conducting the analysis, the following results were obtained:

Hypothesis:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_{10} = 0$

By paying attention to the CI values in **Table 7**, it shows that the intervals that do not contain zero are the intercept, X_1, X_5, X_6, X_9, and X_{10}, respectively. So that the model can mathematically be written as follows.

$$\hat{Y} = 47.371 - 2.949X_1 - 0.973X_5 + 0.468X_6 + 105.776X_9 + 8.078X_{10} \quad (12)$$

Based on the results of the estimation, it is found that the significant variable is X_1, namely, school status, with a coefficient of -2.949, in this case, addressed to private or public schools. Frequently, the school status affects students' quality, so it also indirectly impacts the mean score of the UN. A private news portal published that private schools occupied the top 10 UN scores for Junior High School in Makassar. This result aligns with prior studies [24], [25]. Another significant variable relates to teacher quality generating X_5 with a coefficient of -0.973. This negative value means that if certified teachers go up 1%, the average scores of the UN decline by 0.973. Then, X_6 is the percentage of teachers with a minimum education of diploma and bachelor's degree. The result shows 0.468. This indicates that every increase in terms of teachers with the educational background of diploma and bachelor's degree is about 1%, and average scores of the UN tend to go up around 0.468. These results are in line with prior studies [9], [26]. In addition, other variables (X_9 and X_{10}) in relation to infrastructure are significant, X_9 and X_{10} variables respectively represent the ratio of the number of laboratories to the number of students [11] and the ratio of the number of computers to the number of students [27].

c. M3

After conducting the analysis, the following results were obtained:

Level-1 hypothesis:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_{10} = 0$

Level-2 hypothesis:

$H_0: \gamma_1 = \gamma_2 = \gamma_3 = 0$

The analysis results for M3 are similar to M2, where the significant variables in each model are not the same, namely X_1, X_5, X_6, X_9, X_{10}, and Z_2. The significant variables are further used in the modeling, namely M4 and M5.

Mathematically, M4 can be written as follows:

$$\hat{Y} = 39.14 + 5.984 \times 10^{-4} Z_2 - 2.813X_1 - 0.931X_5 + 0.518X_6 + 100.2X_9 + 7.709X_{10} \quad (13)$$

d. M4

Level-1 hypothesis:

$H_0: \beta_1 = \beta_5 = \beta_6 = \beta_9 = \beta_{10} = 0$

Level-2 hypothesis:

$H_0: \gamma_2 = 0$

As shown in **Table 5**, the estimated values of parameters of the variables that have been defined in the previous step are found that the intercept, variable coefficients X_1, X_9 and Z_2 are significant variable coefficients. Thus, the model can mathematically be written as follows.

$$\hat{Y} = 42.109 + 9.691 \times 10^{-4} Z_2 - 2.913 X_1 + 66.761 X_9 \quad (14)$$

In terms of M4, it denotes the RCM model. Variables used in this model are significant, as described in the previous model. Based on analysis results, significant variables that change from M2 to M4 are obtained. These variables include X_1, X_9 and Z_2, where Z_2 is expenditure per capita in the district/city over the period of 2018. The following model is M5. It is *a full multilevel model* with the same variables used in modeling as M4. After conducting analyses, the result is found that none of the variables have a significant effect on the UN average scores.

e. M5

After conducting the analysis, the following results were obtained.

Level-1 hypothesis:

$$H_0{:}\beta_1 = \beta_5 = \beta_6 = \beta_9 = \beta_{10} = 0$$

Level-2 hypothesis:

$$H_0{:}\gamma_2 = 0$$

Interaction hypothesis:

$$H_0{:}\gamma_{12} = \gamma_{92} = 0$$

Table 5 shows the estimated value for each parameter. It is found that only the intercept is significant, while other variables and interactions between variables also show insignificant. Mathematically, M5 can be written as follows.

$$\hat{Y} = 44.64 \quad (15)$$

3.3 Best Model Selection

After the modeling using five approaches, the next step is to select the best model with the criteria of the MSE, AIC, and the smallest residual variance. These values are presented in **Table 6** below.

Table 6. Criteria for the Goodness of the Model

Model	MSE	AIC	Residual Variance
M1	62,19	7383.66	57.24
M2	59,82	7303.87*	54.91
M3	58,89	7312.10	54.26
M4	57.96*	7308.32	52.81 *
M5	59,14	7345.82	53,389

Source: Output of data processing

Based on **Table 6**, the best model is M4, which is the RCM model without involving interactions between variables at each level. In addition to the interpretation of the variance components of the variables in M4, the variance component explains how much diversity is given by each variable to the model. The results show 1.97 (X_1)9.25 $\times 10^{-4}$, (X_5) 2.789 $\times 10^{-3}$(X_6) 76.09 (X_9) and 236.6(X_{10}).

4. CONCLUSIONS

Based on the result of data analysis, this study concludes that M4 is the best model for modeling mean scores of the UN for junior high school students in 24 districts/cities in South Sulawesi Province, where significant variables at the level-1 are school status (X_1), and the ratio of the number of laboratories to students (X_9), while at the level-2, the variable is the expenditure per capita of district/city (Z_2). The modeling method in this research for the mean score of the UN ignores the missing observations, in this case, it is eliminated. Meanwhile, the number of missing observations can reduce information on the actual data. So that, for further modeling, it is suggested to apply method by considering the values of the missing observations without eliminating initial observations. Furthermore, in the modeling, independent variables are mostly used, thereby providing opportunities for interactions or correlations between independent variables. As a suggestion for further additional modeling, the use of the method of reduction or selection of variables, such as multilevel factor analysis, multilevel analysis with LASSO, or other methods, should be taken into consideration.

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