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Applied of Multivariate Multilevel Modeling for Student Cognitive Achievement Analysis in AKSI 2019 Survey

Hadi Rachmat[a]*, Dr Budi Susetyo[b], Dr Indahwati[c], Dr Rahmawati[d]

[a,b,c]Department Statistics, IPB University, 16680 Bogor, Indonesia
[d]Center for Assessment and Learning, Ministry of Education and Culture, 10710 Jakarta, Indonesia
[a]Email: hadirachmat26@gmail.com, [b]Email: budisu@apps.ipb.ac.id, [c]Email: indahwati@apps.ipb.ac.id,
[d]Email: rahmawati@kemdikbud.go.id

Abstract

The Indonesian Student Competency Assessment (AKSI) is a national survey conducted by the Ministry of Education and Culture of the Republic of Indonesia which aims to monitor the quality of education. This survey measured students' cognitive abilities which included science, mathematics and reading literacy. Apart from that, this survey also collected a questionnaire of students to measure students' non cognitive abilities in ICT literacy. The sampling technique in the AKSI survey was conducted by multi-stage random sampling in which the first stage was randomly selected schools, then selected students sample in the selected schools. This article aims to identify the factors associated with students' ICT literacy on students cognitive achievement in the fields of science, mathematics and reading. AKSI has a hierarchical data structure with students are nested within school. In general, hierarchical data cause a violation of the assumption of independency of the residual between individual observations (students) and the homogeneity of variance between groups (school). The better statistical method for hierarchical data is multilevel modeling or hierarchical linear models. There are three correlated response variables in this study, so multivariate multilevel modeling is used. The results of this study conclude that the factors that affect the students cognitive achievement sorted according to their size are gender, perception index on the benefits of using ICT, accreditation, school ICT restriction index, father's education, ICT usage index for other school activities, ICT usage index for school activities, digital device availability index and school digital device usage index.

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* Corresponding author.

Apart from that, the results of the analysis concluded that there was an interaction effect between father's education and accreditation, meaning that the effect of parental education on students' cognitive achievement also depends on the school quality.

Keywords: Hierarchical data; MVMM; AKSI; ICT literacy.

1. Introduction

Social and economic research often involves problems that investigate the relationship between two or more variables. Linear regression is a statistical method that is widely used for investigating the relationship of two or more variables consisting of the response variable and the predictor variable. In general, the single response variable may be relate to several predictor variables, called multiple linear regression. In some studies, several response variables are often used to measure the characteristics of an observation that cannot be measured directly, such as students' cognitive abilities. This characteristic is often called as latent variable or unobserved variable. In that case, several response variable may be relate to the predictors. The multivariate regression is a modeling that consisting two or more correlated response variables and a single set of predictor variables [1]. The assumptions underlying the multivariate regression are the residual has multivariate normal distribution with expected value is zero, the residual variance is constant and independent each other. This assumption can generally fulfilled if the observation unit of a survey are independent. In a certain survey with multi-stage random sampling, for example the Indonesian Student Compentency Assessment (AKSI) survey, where the first stage was selecting school samples randomly, then selecting student samples from each selected school. If the analysis is conducted using classical multiple linear regression, it is likely that there will be violation of the assumption of independency and homogeneity of variance residual. Responses of student observation from the same school are dependent and variance between school are not constant due to the varying of school quality. Data obtained through sampling techniques such as in the AKSI survey above in statistics is called hierarchical data and the better statistical method for this data is multilevel modeling or hierarchical linear models. The multilevel modeling is analyzed based on several levels and indicates lower levels nested within higher levels [2]. Multilevel modeling can also accommodate the violation of assumption occurred in multiple linear regression due to hierarchial data structure [3]. The multilevel modeling only involves one response variable and explained by the predictor variables in each level. whereas more than one response variables can use a multivariate multilevel model (MVMM). The term "multivariate" refers to the response variable, there are assumed to be two or more correlated response variables [4]. Several studies have been conducted regarding MVMM. Leonardo and his colleagues [5] applied MVMM to determine the factors that affected student academic achievement in the 2011 TIMSS and PIRLS surveys. Reference [6] applied MVMM Logistics to analyze risk factors that affect the severity of cardiovascular disease and diabetes (CDD) and chronic respiratory conditions (CRC). The Indonesian Student Competency Assessment (AKSI) is a survey conducted by Center for Assessment and Learning (Pusmenjar) of Indonesian Ministry of Education and Culture of Republic of Indonesia to monitor the national and regional education quality that describes the achievement of student abilities. One objective of AKSI is determining the factors that affect the student achievement. The assessment contained cognitive and non-cognitive instruments. Cognitive instruments are used as benchmarks for the achievement of student competencies, consists of student assessments in science, mathematics and reading.

while non-cognitive instruments contained some test packages as one of which was about the ICT literacy. The ICT literacy questionnaire aims to measure students' noncognitive abilities in digital literacy and determine their effects on cognitive achievement. Varied school quality is thought to cause diversity and also affect the student cognitiveachievement. By noticing the hierarchial structure in AKSI data with students nested within schools, thereby a multivariate multilevel modeling (MVMM) was used in this study to determine the factors that affect the student cognitive achievement. MVMM is also used because there are three assessment that are correlated each other.

2. Material and Methods

The data used in this study are the 2019 AKSI survey data conducted by Center for Assessment and Learning (Pusmenjar) and school accreditation data from BAN-S/M. Variables used consist of the student level and school level. Variables from each level can be shown in Table 1. Accreditation is used at school level variables to determine the effect of school quality on student achievement. The data used in the analysis were 16524 students from 1802 junior high schools (SMP).

Table 1: Variables used in the study

Variable	Note
Response	
Y1	Science Score (IPA
Y2	Mathematics Score (MAT)
Y3	Reading Score (BIN)
Predictor level student	
X1	Gender
X2	Mother educational period (year)
X3	Father educational period (year)
X4	Digital device availability index
X5	School digital device usage index
X6	ICT usage index for school activities
X7	ICT usage index for other school activities
X8	School ICT restriction index
X9	Behavior index on information and digital device
X10	Perception index on the benefits of using ICT
Predictor level school	
Z1	School accreditation score

AKSI survey was carried out using multistage random sampling technique where the first stage was the sample school selection and the second stage was the student sample selection. The statistical method used in this study is multivariate multilevel modeling. There are $p\ (1,2,..,P)$ response variable y and $k\ (1,2,..,K)$ predictor variable X at the student's level and $l\ (1,2,\dots,L)$ predictor variable Z at the school level. Let j denote schools, with different numbers of students n_j in each school. So in general the model can be written as follows.

Model level 1 (dummy response variable level) :

$$Y_{pij} = \pi_{1ij}d_{1ij} + \pi_{2ij}d_{2ij} + \cdots + \pi_{pij}d_{pij}$$

Model level 2 (student level) :

$$\begin{cases} \pi_{1ij} = Y_{1ij} = \beta_{10j} + \sum_{k=1}^{K} \beta_{1kj}X_{kij} + e_{1ij} \\ \pi_{2ij} = Y_{2ij} = \beta_{20j} + \sum_{k=1}^{K} \beta_{2kj}X_{kij} + e_{2ij} \\ \qquad\qquad \vdots \\ \pi_{pij} = Y_{pij} = \beta_{p0j} + \sum_{k=1}^{K} \beta_{pkj}X_{kij} + e_{pij} \end{cases}$$

The error term $e_{1ij}, e_{2ij}, \dots, e_{pij}$ has $E(e) = \mathbf{0}$ and $Var(e) = \boldsymbol{\Omega_e}$

Model level 3 (school level) :

$$\begin{cases} \beta_{10j} = \gamma_{100} + \sum_{l=1}^{L} \gamma_{1l0}Z_{lj} + u_{10j} \\ \beta_{1kj} = \gamma_{10k} + \sum_{l=1}^{L} \gamma_{1lk}Z_{lj} + u_{1kj} \end{cases}$$

$$\vdots$$

$$\begin{cases} \beta_{p0j} = \gamma_{100} + \sum_{l=1}^{L} \gamma_{p0l}Z_{lj} + u_{p0j} \\ \beta_{pkj} = \gamma_{p0k} + \sum_{l=1}^{L} \gamma_{pkl}Z_{lj} + u_{pkj} \end{cases}$$

The error term $u_{10j}, \dots, u_{p0j}, u_{1kj} \dots, u_{pkj}$ has $E(u) = \mathbf{0}$ and $Var(u) = \boldsymbol{\Omega_u}$

The parameter estimation method used in the model is the maximum likelihood estimation (MLE). Data analysis was conducted using SAS 9.4 and R version 4.0.0 (2020-04-24) software with the following steps:.

1. Checking the correlation among response and predictor variables.
2. Modeling one level multivariate regression and assumption test.
3. Forming the multivariate random intercept models, containing:
   a. Random intercept model without predictor variables or intercept only model (Model M0)
   b. Random intercept model with the predictors at student level only (Model M1.1)
   c. Random intercept model with the predictor at student level and school level (Model M1.2)
   d. Calculating the deviance value in each model and conducting the LRTs test to choose the best model fits
4. Forming the multivariate random coefficient models, containing:
   a. Random coefficient modeling without interaction (Model M2.1)
   b. Random coefficient modeling with the variable interaction between levels or cross-level interaction model (Model M2.2)

c. Calculating the deviance value in each model and conducting the LRTs test to choose the best model fits

5. Selecting the best model based on on LRTs test and making its interpretation.

3. Result and Discussion

3.1. Data Eksploration

Based on AKSI data in 2019, the percentage of female students in the study was more than male students, which was around 51.07%. Description of each response variable and predictor variable can be seen through descriptive statistics in Table 2. The highest average score of student achievement was found in reading with 48.12 and a standard deviance of 8.39. The average of parents education period was 10 years or equivalent to senior high school (SMA). The digital device usage of school component had the highest average index with 0.61, which means that the digital device owned by school is quietly utilized by students. The ICT usage for school activities component had the lowest index with 0.31, which means that the student intensity in using ICT tools for learning is still low.

Table 2: Descriptive statistics of each variable

Variable	Mean	SD	Min	Max
Response				
Science Score (SCIE)	42.74	5.96	12.16	71.86
Mathematics Score (MATH)	39.49	6.84	14.79	73.51
Reading Score (READ)	48.12	8.39	20.98	80.49
Predictor Student Level				
Gender	-	-	-	-
Mother educational period (year)	10.36	3.85	3	19
Father educational period (year)	10.50	3.93	3	19
Digital device availability index	0.41	0.05	0	1
School digital device usage index	0.62	0.03	0	1
ICT usage index for school activities	0.31	0.04	0	1
ICT usage index for other school activities	0.39	0.06	0	1
School ICT restriction index	0.45	0.05	0	1
Behavior index on information and digital device	0.52	0.03	0	1
Opinions index on the benefits of using ICT	0.57	0.04	0	1
Predisctor School Level				
School accreditation score	88.21	6.63	57.00	99.71

The linear correlation between each students achievement score and the components in ICT literacy was conducted by the pearson correlation. The coefficient correlation among response variable had positive values and was significant at 5% degree. This indicates that among subject outcome score was correlated so that a multivariate analysis can be carried out. Mother (X2) and father (X3) education period had a quite great correlation (0.671), which indicates the two variables are not independent. To overcome the correlation between these variables, therefore this study only used father education period (X3) to describe the student parent educational backgrounds.

3.2. Multivariate Regression Modeling

The multivariate regression modeling was performed in student level to determine the factors that affected the student cognitive achievement in general and to test the assumptions of the model obtained. The parameter estimation was performed by the least square estimation method with the results as in the following equation:

$$\widehat{Y_1} = 26.953 - 0.453X_1 + 0.226X_3 + 1.130X_4 - 1.878X_5 + 5.328X_6 + 5.182X_7 + 4.135X_8 - 1.684X_9 + 16.988X_{10}$$

$$\widehat{Y_2} = 22.320 - 0.160X_1 + 0.308X_3 + 3.184X_4 - 3.917X_5 + 8.714X_6 + 5.252X_7 + 3.203X_8 - 5.344X_9 + 20.614X_{10}$$

$$\widehat{Y_3} = 22.471 - 2.078X_1 + 0.373X_3 + 3.939X_4 + 2.373X_5 + 7.837X_6 + 6.825X_7 + 6.457X_8 - 1.071X_9 + 21.433X_{10}$$

Assumption testing is carried out on the residual of the regression model in the equation above. The first assumption is residual has the multivariate normal distribution. A test performed to check the multivariate normal distribution was by determining *q-q plot* and calculating the observation quadratic distance (d_i^2) [1]. Residual can be said to distribute multivariate normally as the value of nilai $d_i^2 \leq \chi^2_{(0.5;p)}$ is more than or as same as 50%. The calculation obtained 55.126% of d_i^2 value was less than $\chi^2_{(0.5;3)}$ (2.336), which means that the residual of model has multivariate normal distribution. The second assumption was homogeneity covariance matrix of residual. This assumption was carried out through Box's M test [7]. The number of groups used in this test was 34 and resulted a statistical test of 412.42 with the p-value of $< 2.2\ x\ 10^{-16}$. The p-value obtained was less than the significant level used, i.e 5%, therefore can be concluded that the covariance matrix is not homogen. The third assumption was residual independent, the assumption test was performed using Bartlett Sphericity test. The result obtained χ^2_{hitung} was 7150.529 or more than $\chi^2_{(0.05;3)}$ (7.815), therefore can be concluded that the residual of multivariate regression model is not independent. Based on the assumption test above, there are two assumptions violations that occur, that are the residual is not independent and the residual covariance matrix is not homogen. The AKSI data has a hierarchical structure data so it is not appropriate if the method used is one-level multivariate regression. Next, we will discuss several models of the multivariate multilevel model used in this study.

3.3. Multivariate Multilevel Modeling (MVMM)

3.3.1. Multivariate Random Intercept Model

The random intercept model indicates that the intercept coefficient or the intersection point in the model is random at each school. This model is used to calculate the intraclass correlation coefficient (ICC). When in the model without predictor variables, fixed effect was the mean score of student achievement in science, mathematics, and reading with 42,643, 39,374 and 47,988, respectively, random effect is a residual covariance matrix in school and student level. Based on the covariance matrix, the intraclass correlation coefficient (ICC) can be calculated for each response variable [8], with the ICC estimation result in science was 0.211, mathematics was 0.260, and reading was 0.212. This means that the expected correlation between two students taken randomly in the same school in science is 0.211, mathematics is 0.260, and reading is 0.212. The next is modeling by involving predictor variables at the student level (Model M1.1) and is modeling by involving predictor variables at the student level and the school level (Model M1.2). Model M1.1 and M1.2 are used to see the explanatory variables at the student level and the school level that have an influence on students cognitive achievement. The significance test on model M1.1 showed that school digital device usage index (X5) and behavior index on information and digital device (X9) were not significant for two subjects. Based on the backward elimination procedure, X9 variable was eliminated from the model due to having the smallest contribution. Next step is calculating the deviance on each model and test the goodness of fit of the model as presented in Table 3..

Table 3: Deviance comparison value and LRTs test of random intercept model

Model	df	deviance	LRTs	p-value
M0	15	320885.5		
M1.1	39	319938.9	946.5	0.000
M1.2	42	319614.7	324.2	0.000

Based on Table 3, Model M1.2 has the smallest deviance and best model in this step. thus the addition of explanatory variables at the student level and at the school level has an effect on student achievement.

3.3.2. Multivariate Random Coefficient Model

The random coefficient model indicates that the intercept coefficient and slope are random at each school. This model is also used to identify the interaction effect between predictor variables at different levels (cross-level interaction). The predictor variables used are derived from the best model results in the previous modeling. The first step was determining the predictor variables of student level that had a random slope effect (M2.1 model). The estimation results of model M2.1 obtained that the gender variable (X1) and the father education period (X3) had a random slope effect, which means that student gender and father education period have a different effect on the student cognitive achievement. The next step is developing a random coefficient model by adding interaction between gender and school accreditation and father education and school accreditation (model M2.2). The significance test results showed that no interaction between gender and accreditation, so that variable was eliminated fom the model. The next step was calculating the deviance in each model and testing the goodness of fits of the models as presented in Table 4.

Table 4: Deviance value comparison and random coefficient LRTs test

Model	df	deviance	LRTs	p-value
M1.2	42	319614.7		
M2.1	64	319500.5	114.2	0.000
M2.2	67	319473.1	27.4	0.000

In Table 4, the difference in M1.2 and M2.1 model was significant at 5% degree, which means that the random coefficient model is better than random intercept model. The difference in M2.1 and M2.2 model also significant, then model with interaction was the best model used in this study. The fixed effect and random effect estimation of model M2.2 are presented in Table 5 and Table 6.

Table 5: Fixed effect estimation of the best model

	SCIE		**MATH**		**READ**		**F test**
	Coef.	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**	**p-value**
Intersept	23.265	<.0001	23.429	<.0001	19.540	<.0001	<.0001
X1	-0.353	0.000	-0.029	0.764	-1.929	<.0001	<.0001
X3	-0.194	0.207	-0.713	<.0001	-0.495	0.021	0.001
X4	-3.286	0.000	-3.120	0.002	-2.106	0.097	0.001
X5	-3.715	0.015	-6.010	0.000	0.108	0.959	0.001
X6	2.033	0.069	4.401	0.001	3.319	0.033	0.003
X7	2.798	0.001	2.190	0.021	3.649	0.002	0.001
X8	4.389	<.0001	3.478	0.002	6.847	<.0001	<.0001
X10	10.973	<.0001	12.128	<.0001	13.831	<.0001	<.0001
Z1	0.135	<.0001	0.096	<.0001	0.154	<.0001	<.0001
X3*Z1	0.003	0.046	0.010	<.0001	0.008	0.001	<.0001

The regression equation formed based on the best model in Table 5 is:

<u>Student Level :</u>

$$\begin{cases} \hat{Y}_{1ij} = \hat{\beta}_{10j} + \hat{\beta}_{11j}X_{1(1)ij} + \hat{\beta}_{13j}X_{3ij} - 3.286X_{4ij} - 3.715X_{5ij} + 2.033X_{6ij} + 2.798X_{7ij} \\ \qquad +4.389X_{8ij} + 10.973X_{10ij} \\ \hat{Y}_{2ij} = \hat{\beta}_{20j} + \hat{\beta}_{21j}X_{1(1)ij} + \hat{\beta}_{23j}X_{3ij} - 3.120X_{4ij} - 6.010X_{5ij} + 4.401X_{6ij} + 2.190X_{7ij} \\ \qquad +3.478X_{8ij} + 12.128X_{10ij} \\ \hat{Y}_{3ij} = \hat{\beta}_{30j} + \hat{\beta}_{31j}X_{1(1)ij} + \hat{\beta}_{23j}X_{3ij} - 2.106X_{4ij} + 0.108X_{5ij} + 3.319X_{6ij} + 3.649X_{7ij} \\ \qquad +6.847X_{8ij} + 13.831X_{10ij} \end{cases}$$

<u>School Level :</u>

$$\begin{cases} \hat{\beta}_{10j} = 23.265 + 0.135Z_{1j} + u_{10j} \\ \hat{\beta}_{11j} = -0.353 + u_{11j} \\ \hat{\beta}_{13j} = -0.194 + 0.003Z_{1j} \end{cases} \qquad \begin{cases} \hat{\beta}_{20j} = 23.429 + 0.096Z_{1j} + u_{20j} \\ \hat{\beta}_{21j} = -0.029 + u_{21j} \\ \hat{\beta}_{23j} = -0.713 + 0.010Z_{1j} + u_{23j} \end{cases}$$

$$\begin{cases} \hat{\beta}_{30j} = 19.540 + 0.154Z_{1j} + u_{30j} \\ \hat{\beta}_{31j} = -1.929 + u_{31j} \\ \hat{\beta}_{33j} = -0.495 + 0.008Z_{1j} \end{cases}$$

The F-test in Table 5 shows that the p-value of all student and school level variables are significant at 5% degree, which means that gender (X1), digital device availability index (X4), school digital device usage index (X5), ICT usage index for school activities (X6), ICT usage index for other school activities (X7), school ICT restriction index (X8), index of opinions on the benefits of using ICT (X10), school accreditation score (Z1), and interaction between father education and accreditation score (X3*Z1) had an effect on student cognitive achievement. Effect on these variables are different for each subject. Gender variable (X1) significantly affected the science and reading achievement. The negative sign on gender showed that girls have higher average score than boys. Other studies involving gender variables on student learning outcomes have drawn mixed conclusions in several countries. Leonardo and his colleagues [5] concluded that male students tend to have higher achievement scores in the scores on mathematics and science in Italy, whereas Melchor [9] in their study concluded that female students in Melilla, Spain consistently have higher achievement scores in mathematics than male students. It should also be noted that the estimated variation in random effects on gender variables is significant on science and reading scores (Table 5), meaning that the gender have a different effect on each school's for science and reading achievement scores. Father education period (X3) affected the mathematics and reading. The variable X3 cannot be interpreted directly because there is a significant interaction between the father education and the school accreditation score. Digital device usage availability index (X4) and school digital device usage index (X5) affected the science and mathematics. The negative sign on this variables means that the higher the index of these variables, the student's average achievement will decrease. This result is also supported by research conducted by Joyce and his colleagues [10], Bryce and his colleagues [11] and Melchor and his colleagues [9]. Joyce and his colleagues [10] concluded that the use of ICT in schools had a negative effect on reading scores, besides that students who reported having many digital devices and the internet at home had lower reading scores compared to students who had limited devices in the Netherlands. Bryce and his colleagues [11] concluded that the use of ICT and the availability of ICT at home and at school can lead to a decrease in the science scores of Bulgarian and Finnish students. Melchor and his colleagues [9] concluded that there is a negative relationship between the availability of digital devices at home and the use of digital school devices on students' math abilities in Memilla, Spain. According to Joyce and his colleagues [10] the negative relationship between ICT availability and reading scores could be due to students accessing more digital devices to play games and explore social media. According to Steffans in Joyce and his colleagues [10] also shows that the use of game consoles has a negative effect on cognitive scores, especially in achieving PISA. The explanation of the relationship between the use of ICT in schools and the availability of ICT devices with lower science scores according to Melchor and his colleagues [9] can be due to the fact that students use ICT for personal gain more than it is used to support their learning process. ICT usage index for school activities (X6) affected the mathematics and reading. This variable has a positive effect on student achievement scores, meaning that the higher the intensity of students in making presentations, doing school work, collecting and analyzing data, accessing digital learning content, the student achievement scores will also increase. The ICT usage index for other school activities (X7), school ICT restriction index (X8), and opinions index of ICT usage benefir (X10) affected all subjects. These three variables have a positive effect on student achievement scores, it shows students who often use ICT for fun such as using the internet, looking for practical information online, creating or editing digital content, then schools that limit and supervise the use of ICT, and students who have a positive perception of the benefits of ICT literacy have an effect on increasing student achievement scores. Digital device usage availability index (X4) and school digital device usage index (X5) affected the science and mathematics. The ICT usage index for other school activities (X7), school ICT restriction index (X8), and opinions index of ICT usage benefir (X10) affected all subjects. Among these variables, X10 and X8 has the bigest influence. This means that students who have a positive perception of the benefits of ICT literacy and restrictions on digital devices in schools have a major effect on improving students' score. The school accreditation score (Z1) obtained a positive effect on student achievement, which indicates that the average score of science, mathematics and reading increases with increasing school accreditation score. The interaction between father education and accreditation (X3*Z1) indicates that the effect of parental education on students' cognitive achievement also depends on the school quality. Based on Table 6, the variance estimation of student achievement between schools with predictor variable in science was 5.101, mathematics was 4.196, and reading was 9.085. The variance slope estimation of gender between schools in science was 2.387, mathematics was 0.915, and reading was 3.777. The slope variance of father education period between schools was only estimated from mathematics with 0.007 due to convergence problems. Moreover, there are residual variations between the subjects as seen in Table 6.

Table 6: Random effect estimation of the best model

	SCIE		**MATH**		**READ**	
Random effect	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
Between school cov. matrix						
$\mathrm{var}(u_{h0j})$	5.101	<.0001	4.196	<.0001	9.085	<.0001
$\mathrm{cov}(u_{10j}, u_{20j})$	4.156	<.0001				
$\mathrm{cov}(u_{20j}, u_{30j})$			5.463	<.0001		
$\mathrm{cov}(u_{10j}, u_{30j})$					6.698	<.0001
$\mathrm{var}(u_{h1j})$	2.387	<.0001	0.915	0.053	3.777	<.0001
$\mathrm{cov}(u_{11j}, u_{21j})$	1.216	0.002				
$\mathrm{cov}(u_{21j}, u_{31j})$			1.081	0.045		
$\mathrm{cov}(u_{11j}, u_{31j})$					2.009	<.0001
$\mathrm{var}(u_{23j})$			0.007	0.173		
Within school cov. matrix						
$\mathrm{var}(e_{hij})$	27.157	<.0001	33.932	<.0001	53.041	<.0001
$\mathrm{cov}(e_{1ij}, e_{2ij})$	8.241	<.0001				
$\mathrm{cov}(e_{2ij}, e_{3ij})$			11.398	<.0001		
$\mathrm{cov}(e_{1ij}, e_{3ij})$					10.095	<.0001

4. Conclusion

Multivariate multilevel model (MVMM) is used for hierarchial data with two or more correlated response variables. The best model used in this study was the random coefficient model with interaction (cross-level interaction model). Based on the significance test results, behavior index on information and digital device (X9) had the smallest contribution in the model, therefore eliminated in the model. Girls students were reported to have a higher score than boys. The digital device availability index (X4) and school digital device usage index (X5) had a negative effect, while other variables had a positive effect on the student cognitive achievement. There is a variance residual that occur between schools and within schools. The variance residual between schools in general can be caused by differences in the school quality, while the student variance in the same school can be caused by differences in student backgrounds and economic conditions, as well as differences in student perception in digital literacy usage (ICT literacy).

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