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Abstract

Multilevel Structural Equation Modeling (MSEM) is claimed to address hierarchical data structures and latent response variables, but it is still unstable with an increasing number of levels. N-Level SEM (nSEM) is an SEM framework that can handle the increasing number of levels in the model. The nSEM framework uses the Maximum Likelihood Estimation (MLE) method for parameter estimation, therefore requiring a large sample size and correct model specification. Therefore, it is important to pay attention to the required minimal sample size so that the results of parameter estimation in the nSEM model are accurate and efficient. This study examined how sample size affects the performance of parameter estimators in nSEM models. The application of the results of this study was then applied to student mathematics learning motivation data in Depok. The findings show that neither the number of environments nor the size of the environment affects the performance of fixed parameter estimation in the nSEM model. NSEM shows very good performance in estimating environmental variance at level 2, when the number of environments is getting bigger. Conversely, increasing the size of the environment makes the performance of estimating individual variance parameters worse. Overall, the nSEM framework for the latent random-intercept (LatenRI) model shows quite good performance for increasing sample sizes. The application data on LatenRI models show almost similar estimation results.
Keywords: hierarchical data; latent random intercept model; multilevel structural equation modeling; n-level structural equation modeling.

Abstrak

Multilevel Structural Equation Model (MSEM) diklaim untuk mengatasi struktur data hirarki dan peubah respon laten, namun masih belum stabil dalam jumlah level yang semakin banyak. N-Level SEM (nSEM) merupakan kerangka SEM yang dapat mengatasi meningkatnya jumlah level dalam model. Kerangka nSEM menggunakan metode *Maximum Likelihood Estimation* (*MLE*) dalam pendugaan parameternya, sehingga ini memerlukan ukuran contoh yang besar dan spesifikasi model yang akurat. Oleh karena itu, pentingnya memperhatikan ukuran contoh minimal yang diperlukan agar hasil pendugaan parameter pada model nSEM akurat dan efisien. Penelitian ini menguji bagaimana ukuran contoh mempengaruhi kinerja penduga parameter bagi nSEM. Aplikasi dari hasil penelitian ini kemudian diaplikasikan pada data motivasi belajar matematika siswa di Depok. Temuan menunjukkan bahwa jumlah lingkungan maupun ukuran lingkungan tidak mempengaruhi kinerja pendugaan parameter tetap pada model nSEM. NSEM menunjukkan kinerja yang sangat baik pada pendugaan ragam lingkungan di level 2, ketika jumlah lingkungan semakin besar. Sebaliknya ukuran lingkungan yang membesar membuat kinerja pendugaan parameter ragam individu semakin memburuk. Secara keseluruhan kerangka nSEM untuk model Latent variable random intersep (LatenRI) menunjukkan performa yang cukup baik untuk ukuran contoh yang semakin membesar. Data aplikasi pada kedua model LatenRI menunjukkan hasil pendugaan yang hampir mirip.
Kata kunci: *data hirarki; model intersep acak laten; model persamaan structural multilevel; model persamaan structural n-level*.

2020MSC: XXXXX

1. INTRODUCTION

Researchers are often interested in examining the relationship between a response variable and several explanatory variables. The simplest analysis to see the relationship between the two is multiple regression analysis with a linear model approach, where there is only one continuous response variable. However, this analysis cannot handle the complex structure of the response variable. For example, in educational studies, where the response variable is latent or cannot be measured directly and has a hierarchical structure. If the data has a hierarchical structure, then to overcome the random effect on the response variable, namely with a linear mixed model. However, if the response variable cannot be observed directly, the linear mixed model and SEM cannot yet handle both of these response variable structures. If one of these two response variable structures is ignored, then not only are the parameter estimates and standard errors biased, but important information about the phenomenon being observed can also be lost. In addition, [1] also revealed that serious inferential errors can occur due to complex data analysis if it is assumed that the data was obtained based on a simple random sampling scheme.

The multilevel model (MLM) or Hierarchical Linear Modeling (HLM) is proposed to analyze hierarchical data, where observations at the lowest level (eg, students) are nested within units at another level (eg, classes). MLM addresses aggregation bias, standard error estimation errors, and heterogeneity in least squares regression [2]. MLM allows researchers to separate individual and environmental influences [3], [4], understand intergroup diversity [5], [6], and consider hierarchical data structures [7]. The development of multilevel models continues to follow developments in methodological work that result in complex data structures. The integration of the multilevel model with SEM was developed by Muthen [5], [8] who proposed hierarchical constraints that link the parameters of the SEM model at the lowest level and the highest level. The MSEM model can become very complex, especially if it involves many levels of hierarchy, variables, or relationships between variables. Some software for MSEM analysis has limitations on the number of levels and how to connect those levels. [9] overcomes the limitations of the MSEM model with the nSEM framework. This framework is claimed to be flexible with a large number of levels and complex relationships between variables [10], [11], [12]. The Latent Variable Random-Intercept Model (LatenRI) is one of the MSEM models in the nSEM framework. This model includes the influence of environmental random intercepts at level 2 that affect individual latent factors at level 1.

LatenRI is a model with a fairly complex complexity that affects the determination of the minimum sample size required. LatenRI in the nSEM framework uses the Maximum Likelihood Estimation (MLE) method in parameter estimation, so it needs a large sample size and the right model specification [13], [14]. This study examined how sample size affects the performance of parameter estimators in nSEM models. The model built in this study has a split plot variance structure with a complexity that is still simple, namely the model only includes random intercepts. The sample size at the lowest level (n) and the highest level (m) provides different performance. [15] revealed that the consideration in choosing the sample size is the type and complexity of the model. The determination of the sample size of the multilevel model needs to pay attention to the total sample size for each level [16], [17]. The results of this study provide recommendations for determining the sample size that optimizes the performance of the nSEM model.

2. METHODS

2.1. NSEM: Latent Variable Random-Intercept (LatentRI)

NSEM is an alternative framework that combined the SEM approach for cluster data and longitudinal data [9]. nSEM is also a general approach to formulate and estimate complex data relationships in a simple way, such as model specifications that include multiple levels, cross-classified [11], or multiple membership [18], coupled with complex nested structures such as partially nested, and multivariate outcomes [19]. The equations used in nSEM to represent the model are quite complex, so in modeling it uses superscripts and subscripts [9]. Superscripts indicate the level for each variable and parameter, while subscripts are as usual to reflect the variable, with provisions. The modeling framework allows observed variables and latent variables at any level to be influenced by observed variables and latent variables at that level as well as variables at higher levels.

The LatenRI model is a 2-level hierarchical model that only includes random intercepts at level 2. The random intercepts in the multilevel model are considered as latent variables within the SEM framework, namely latent random intercept variables or single latent variables at level 2. This model addresses the problem of non-independence in individual observations, as individuals can be influenced by their environment or group. Figure 1 shows the path diagram of the latent variable random-intercept model (LatenRI). This model includes individual factors at level 1 which are measured by *p* observed variables and influenced by environmental factors at level 2.

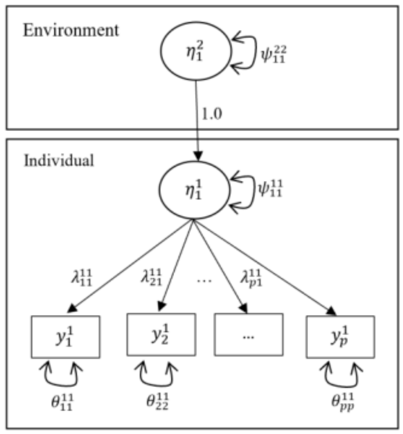


Figure 1. Path diagram of LatentRI model

The scalar model from Figure 1 is expressed in the following equations:

Level 1 : $y_{pij}^1 = v_p^1 + \lambda_{p1}^{1,1}\eta_{1ij}^1 + \varepsilon_{pij}^1$

Level 2 → Level 1 : $\eta_{1ij}^1 = \beta_{11}^{1,2}\eta_{1j}^2 + \xi_{1ij}^1 = 1 \cdot \eta_{1j}^2 + \xi_{1ij}^1.$

Both models can be simplified to:

$$y_{pij}^1 = v_p^1 + \lambda_{p1}^{1,1}\eta_{1j}^2 + \lambda_{p1}^{1,1}\xi_{1ij}^1 + \varepsilon_{pij}^1. \quad (1)$$

Equation (1) can also be expressed in matrix notation, namely:

$$\mathbf{y}^1 = \mathbf{1}_{mn} \otimes \boldsymbol{\nu}^1 + (\mathbf{I}_m \otimes \mathbf{1}_n \otimes \boldsymbol{\Lambda}^{1,1})\boldsymbol{\eta}_1^2 + (\mathbf{I}_{mn} \otimes \boldsymbol{\Lambda}^{1,1})\boldsymbol{\xi}^1 + \boldsymbol{\varepsilon}^1 \quad (2)$$

η_{1ij}^1 represents the individual latent factor at level 1, while η_{1j}^2 represents the level-2 teacher random intercept for the individual latent factor with $\eta_{1j}^2 \sim N(0, \psi^{2,2})$. The level-1 latent residual ξ_{1ij}^1 for the individual latent factor is the deviation between individuals in each environment with the assumption $\xi_{1ij}^1 \sim N(0, \psi^{1,1})$. The ICC in the LatenIA model indicates the proportion of variance in the individual latent factor at level 1 that is explained by the random intercept of the single latent factor at level 2, namely ([20]):

$$ICC = \frac{\psi^{2,2}}{\psi^{2,2} + \psi^{1,1}} \quad (3)$$

Equation (3) also indicates that individual variance in the underlying latent factor causes variance in each observation.

Model fit indices are crucial in model selection, especially when determining the appropriate variance structure. The selection of the variance-covariance structure is vital in fields such as psycholinguistics, genetics, and medical research. Various studies highlight the importance of choosing the most suitable variance structure for the model under analysis [21], [22], [23]. Commonly used indices are Deviance [24], Akaike's Information Criterion, and Schwartz's Bayesian Information Criterion (BIC). Deviance is expressed as -2LL or -2 Log Likelihood, while AIC is [25]:

$$AIC = -2LL + 2p, \tag{4}$$

p is the number of parameters estimated by Maximum Likelihood Estimation (MLE). Schwartz's BIC is given by [23]:

$$BIC = -2LL + p\ln(N) \tag{5}$$

N is the sample size at level 1. AIC and BIC give a penalty on the number of covariance parameters estimated. These three criteria are used to select a model with better fit, which is the model with the smallest value even close to zero.

2.2. Simulation Data

The simulation data in this study was generated from the LatenRI model, which is a model that only includes the random effect of the latent intercept at level 2. A 2-level model was used to examine how stable the model is against the sample size and the correlation between the observed variables. The response variables in this model were six observed variables. The following is the data simulation procedure that was carried out:

1. Specify the nSEM model on the data to be generated, namely with the *p*-th observed response variable (p = 1, 2, …, 6) on the *i*-th individual (1, 2, ..., n) for each *j*-th environment (1, 2, …, m). The nSEM model specification is expressed in graphical form and in scalar form, namely in Figure 1 and Equation (1).
2. Determine the values of the parameters to be estimated, namely:
   A. Level-1 Single factor: Level-1 factor loadings and intercepts

$$\mathbf{\Lambda}^{1,1} = \begin{bmatrix} \lambda_{1,1}^{1,1} \\ \lambda_{2,1}^{1,1} \\ \lambda_{3,1}^{1,1} \\ \lambda_{4,1}^{1,1} \\ \lambda_{5,1}^{1,1} \\ \lambda_{6,1}^{1,1} \end{bmatrix} = \begin{bmatrix} 1 \\ 1,5 \\ 1,0 \\ 1,0 \\ 0,8 \\ 0,7 \end{bmatrix} \text{ and } \mathbf{v}^{1} = \begin{bmatrix} 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 \end{bmatrix}$$

   B. The structural error variance of the i(j)-th latent factor at level-1: $\boldsymbol{\xi}_{i(j)}^{1} \sim N(0, \psi^{1,1})$, with $\mathbf{\Psi}^{1,1} = \psi_{1,1}^{1,1} = 25$.
   C. The variance-covariance matrix of the observed residuals at level-1: $\boldsymbol{\varepsilon}^{1} \sim \mathbf{N}(\mathbf{0}, \mathbf{\Theta}^{1,1})$

$$\mathbf{\Theta}^{1,1} = \begin{bmatrix} \theta_{1,1}^{1,1} & \theta_{1,2}^{1,1} & \theta_{1,3}^{1,1} & \theta_{1,4}^{1,1} & \theta_{1,5}^{1,1} & \theta_{1,6}^{1,1} \\ \theta_{2,1}^{1,1} & \theta_{2,2}^{1,1} & \theta_{2,3}^{1,1} & \theta_{2,4}^{1,1} & \theta_{2,5}^{1,1} & \theta_{2,6}^{1,1} \\ \theta_{3,1}^{1,1} & \theta_{3,2}^{1,1} & \theta_{3,3}^{1,1} & \theta_{3,4}^{1,1} & \theta_{3,5}^{1,1} & \theta_{3,6}^{1,1} \\ \theta_{4,1}^{1,1} & \theta_{4,2}^{1,1} & \theta_{4,3}^{1,1} & \theta_{4,4}^{1,1} & \theta_{4,5}^{1,1} & \theta_{4,6}^{1,1} \\ \theta_{5,1}^{1,1} & \theta_{5,2}^{1,1} & \theta_{5,3}^{1,1} & \theta_{5,4}^{1,1} & \theta_{5,5}^{1,1} & \theta_{5,6}^{1,1} \\ \theta_{6,1}^{1,1} & \theta_{6,2}^{1,1} & \theta_{6,3}^{1,1} & \theta_{6,4}^{1,1} & \theta_{6,5}^{1,1} & \theta_{6,6}^{1,1} \end{bmatrix}$$

$$= \begin{bmatrix} 20 & 5 & 5 & 5 & 5 & 5 \\ 5 & 20 & 5 & 5 & 5 & 5 \\ 5 & 5 & 20 & 5 & 5 & 5 \\ 5 & 5 & 5 & 20 & 5 & 5 \\ 5 & 5 & 5 & 5 & 20 & 5 \\ 5 & 5 & 5 & 5 & 5 & 20 \end{bmatrix}$$

D. Across-Level Model (level 2 → level 1): Latent factor regression coefficients

$$\mathbf{\Gamma}^{1,2} = \left[\gamma_{1,1}^{1,2}\right] = [1]$$

E. The variance of the latent environmental factors at level 2: $\mathbf{\Psi}^{2,2} = \psi_{1,1}^{2,2} = 30$

3. Generate a single latent factor at level 2 $\mathbf{\eta}_1^2 \sim N\left(0, \psi_{1,1}^{2,2}\right)$, m times.
4. Generate a single latent factor error $\mathbf{\xi}^1 \sim N\left(0, \psi_{1,1}^{1,1}\right)$ at level 1, $m \times n$ times.
5. Generate measurement errors at level 1, $\mathbf{\varepsilon}^1 \sim \mathbf{N}(0, \mathbf{\Theta}^{1,1})$ for p variables, p = 1, 2, …, 6, $m \times n$ times.
6. From steps 2 to 5, substitute into the observed response variable $\mathbf{y}^1$ in Equation (2).

2.3. Simulation Design

Simulation design to study the LatenRI Model on Complex Data. The simulation design aimed to investigate the LatenRI model on complex data, where the model includes random components from both individuals and environments. The specific objectives of this simulation were:

1. To determine whether the number of environments (m) affects the estimation results of factor loadings and environmental variance produced by the model.
2. To determine Whether the environment size (n) affects the estimation results of factor loadings and individual variance.

The steps to be carried out in this study were:

1. Generate sample data, namely steps 3-6 (sub-chapter 2.3) on both models with *m* environments and *n* sample size per environment for 300 data clusters.
2. Generate simulation data using several variations to investigate the effect of increasing sample size. At this stage, there are 4 combinations of *m* (10, 25) and *n* (30, 100).
3. Perform nSEM analysis that includes random components on each simulated data, resulting in 300 sets of parameter estimates.
4. Evaluate the performance of the nSEM model to determine the goodness of the model's performance. Evaluation is done by looking at the bias value and Mean Square Error (MSE) as follows:

$$\text{Bias} = \text{E}(\theta - \hat{\theta}) = \frac{1}{S}\sum_{s=1}^{300}(\theta - \hat{\theta}_s) \tag{4}$$

dan

$$\text{MSE} = \text{E}(\theta - \hat{\theta})^2 = \frac{1}{S}\sum_{s=1}^{300}(\theta - \hat{\theta}_s)^2 \tag{5}$$

2.4. Real Data Example

Real data was used as an illustration of the LatentRI model, specifically focusing on the motivation of mathematics students in Depok. The data had previously been analyzed by [26] to investigate the random effects of teachers on students' mathematics learning motivation. The data analysis employed the LatentRI model, which included the influence of random intercepts only, and LatentRI which encompassed both random intercepts and coefficients. The study involved three key variables: the teachers' ability factor (a single endogenous variable), teacher competence (an exogenous variable at the teacher level), and student motivation (another endogenous variable). Two questionnaires were utilized as research instruments to evaluate teachers' competence and students' learning motivation. The study employed a stratified random sampling technique in three specific districts in Depok, namely Sawangan, Bojong Sari, and Limo, encompassing 11, 7, and 6 schools, respectively. The research utilized this sampling method to ensure that the selected sample was representative of the population. Out of the 24 schools selected, a total of 32 math teachers and 768 students participated as respondents.

3. RESULTS

Model identification in nSEM is similar to SEM in general, that is, it is based on applicable theory. nSEM modeling also requires initial values that affect the convergence of the resulting model. If the initial values we input are far from the actual parameters, then the resulting parameter estimates may not converge. Thus, the determination of initial values is very important in this case. In addition to determining the initial value, the sample size also needs to be considered. So it is very important to study the appropriate sample size used in estimating the parameters of the nSEM model.

Sample size can affect the goodness of the resulting model. The results of the goodness of the nSEM model with various sample sizes are presented in Table 1.

Tabel 1. *Deviance* model nSEM ditinjau dari variasi ukuran contoh

Sample Size	Deviance
300	10803.335
750	27041.469
1000	36006.145
2500	90049.843

It can be seen that the deviance value is getting bigger if the sample size is getting bigger. This is because the calculation of deviance depends on the sample size.

3.1. Fixed Effect Parameter

The bias and MSE for the nSEM fixed parameter estimator are presented in Figure 6. Both bias and MSE for all fixed parameters were quite small or close to 0. Most of the biases produce negative values (underestimates). The range of bias in the parameter estimates produced was quite large for small numbers of observations (nj = 30) in both numbers of environments. However, the differences between the four sample sizes were not significant and only range from -0.0056 to 0.0008. In addition, there was a decrease in MSE as the sample size increases for each parameter estimator. At each environment size, it showed good performance as the number of environments increases. This finding indicated that nSEM was very good at estimating fixed parameters of the model.

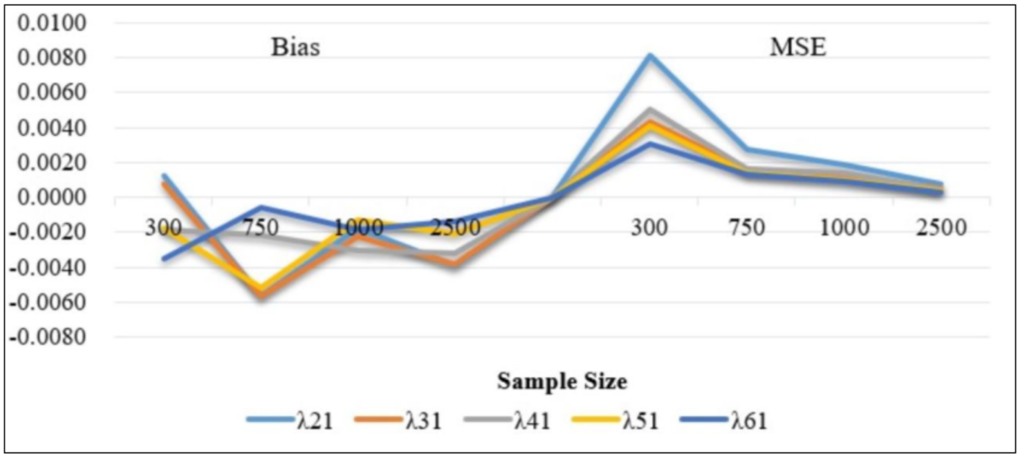
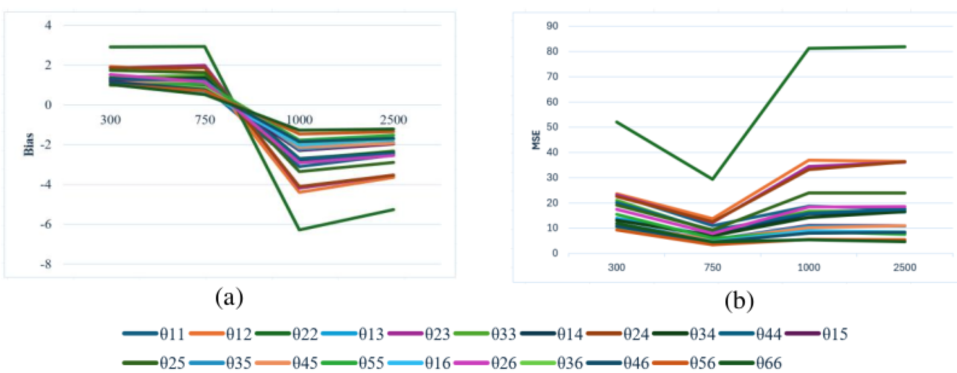


Figure 2. Graph of bias and MSE for the nSEM fixed estimator

3.2. Random Effect Parameter

The performance of random parameter estimation in the nSEM model was studied based on bias and MSE values. Both values were presented in Figure 7. There were 21 random measurement error parameters and two random structural error parameters studied in this section. The comparison of bias and MSE results for each random parameter estimate showed different results than the previous fixed parameter estimates. The magnitude of the bias produced for all measurement error parameters was negative at environment size $n = 100$, while for $n = 30$ the bias was positive. The trend pattern of bias and MSE was illustrated in Figure 7(a-d).



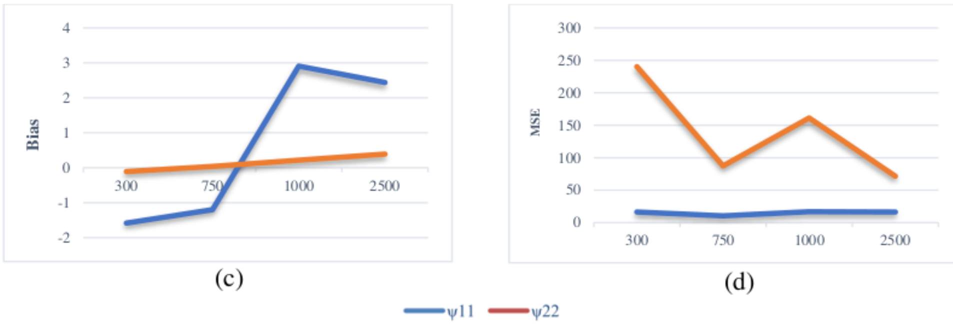


Figure 3. Bias dan MSE penduga parameter acak nSEM (a) Bias galat pengukuran (b) MSE galat pengukuran (c) Bias galat sturktural. dan (d) MSE galat struktural

Figure 7 (a-b) showed that the variance-covariance matrix of measurement errors for the observed variable produces a larger bias and MSE compared to other variance-covariance matrices of measurement errors. In addition, the MSE for a sample size of 750 (n = 25 and m = 30) had the smallest value among other sample sizes, while the bias was relatively the same. Smaller bias and MSE indicated better estimation performance. Therefore, this sample size could be said to be quite optimal in estimating the variance-covariance matrix of measurement errors. In addition, the larger the sample, the better the performance of nSEM in estimating measurement errors.

The structural error variance of the second level latent variable was also important to examine. Table 1 showed that the bias of these two parameters was quite small, ranging from -1.5837 to 2.9066 for all sample sizes (Figure 7 (c)). The structural variance parameter at level 2 showed a more stable bias pattern than the structural variance at level 1. Conversely, the structural variance parameter at level 1 showed a more stable MSE graph than the structural variance at level 2 (Figure 7 (d)). The structural variance at level 2 was quite large, ranging from 16.5418 to 240.2847. A large individual sample size (n = 100) produced a superior MSE compared to n = 30.

3.3. Real Data Example

The results of the analysis using both models were:

Table 1. random effect estimator for LatenRI model

Parameter	LatentRI Model		LatenRI Model with random coefficient	
	Estimate	Confidence interval (CI) 95%	Estimate	Confidence interval (CI) 95%
Fixed Effects				
Student				
Relevance $(\lambda_{2;1}^{1;1})$	1.360*	[1.218; 1.523]	1.358*	[1.216; 1.521]
Confidence $(\lambda_{3;1}^{1;1})$	1.666*	[1.483; 1.875]	1.669*	[1.486; 1.879]
Satisfaction $(\lambda_{4;1}^{1;1})$	0.743*	[0.588; 0.908]	0.744*	[0.589; 0.909]
Teacher				
Personality $(\lambda_{2;1}^{2;2})$	-	-	0.477*	[0.120; 0.861]
Social $(\lambda_{2;1}^{2;2})$	-	-	1.003*	[0.649; 1.417]
Professional $(\lambda_{2;1}^{2;2})$	-	-	1.132*	[0.8165; 1.5146]
Competence (β_{12}^{22})	-	-	-0.070	[-0.0697; 0.0296]

Random Effects				
Motivation (ψ_{55}^{11})	0.0598	[0.049; 0.072]	00597	[0.049; 0.072]
Teacher (ψ_{11}^{22})	0.0030	[0.001; 0.007]	0.0027	[0.001; 0.007]
Teacher comp. (ψ_{22}^{22})	-	-	0.0943	[0.052; 0.170]
Goodness of fit				
Latent-ICC	4.77%			
Deviance	2985.744		3017.808	
AIC	3011.744		3069.808	
BIC	3090.135		3227.652	

The application of the LatenRI model to student mathematics learning motivation data used a sample size of 768 with m = 32 (unbalanced environment sizes). Based on the simulation results, this sample size is still quite accurate in estimating both fixed and random parameters. Both models produced relatively similar and significant analysis results for both fixed and random effect parameters, except for the random coefficient estimator of teacher competence (95% confidence interval includes 0). Furthermore, the LatenRI model produced a smaller goodness-of-fit measure than the LatenRI with random coefficients. An ICC of 4.77% was quite good in measuring Education.

4. DISCUSSION

In SEM research, the focus is typically on fixed effect parameters (factor loadings) to see how observed variables contribute to building latent factors. The contribution of observed variables also reflects the measurement method used to generate observed data [27]. The chosen sample size does not specifically affect the performance of nSEM factor loadings. This meant that the fixed parameter estimators produced by nSEM were accurate and efficient for various sample size variations. However, observed variables with factor loadings greater than 1.0 tend to have poorer performance in estimating the variance-covariance matrix of measurement errors at the individual level.

The bias performance was quite small, as shown in the estimation of random parameters of the model at both the lowest and highest levels. However, MSE was quite strict in assessing the accuracy of the model. This was seen in the poor performance of nSEM under conditions of small sample sizes at both levels. The nSEM parameter estimation process becomes more sensitive if the sample size was larger. The larger the number of environments, the greater the computing power required. Setting the initial value in nSEM which was further away from the actual parameter tends to make the model parameter estimation not converge. Therefore, nSEM computing still needs to be developed, one of which is determining the initial value in its modeling.

The sample size in LatenRI was divided into two categories, namely the number of environments and the size of the environment. The larger the number of environments, the more accurate it was in distinguishing between individuals and environments. However, with a large number of environments, most of the measurement error parameter estimators perform poorly as the size of the environment increases. In addition, the size of the environment gave different results on the performance of the model in distinguishing between individuals and environments. The larger the size of the environment, the more accurate it was in distinguishing the environment, but on the contrary, it was less accurate in distinguishing individuals.

LatenRI was used to distinguish groups accurately. The limitation in this study was that the number of environments evaluated was moderate. But these findings provided enough information that a sufficiently large number of environments or 25 gives more accurate results in distinguishing groups. This was because the size of the environment has a greater influence on the performance of the nSEM model. The nSEM model with a large environment size showed better performance. This was also revealed by [5] who showed that the effect of sample size at the individual level was generally greater than the effect of sample size at the environmental level. This meant that increasing the individual sample size has a greater impact on the accuracy of estimation, detection power, and generalization of results compared to increasing the group sample size. With a larger sample size, nSEM was better able to detect smaller effects with higher precision. [28] revealed the main problem with between-group models is producing inaccurate and inefficient parameter estimates and this occurs when the number of environments was small (<50) while the ICC is low. This problem was overcome at least with the number of environments 100. [29] revealed that a relatively simple MSEM, at least 60 environments were needed to detect structural influences at the highest level.

5. CONCLUSIONS

Both the number of environments and the size of the environment did not affect the performance of fixed parameter estimation in the nSEM model, because the bias and MSE of the fixed parameter estimator were close to 0. However, if the factor loading was quite large or > 1.0, the model performance deteriorated in estimating the variance-covariance matrix of measurement errors at the lowest level. In estimating environmental variance, nSEM showed very good performance when the number of environments was getting bigger. Conversely, increasing the size of the environment made the performance of estimating individual variance parameters worse.

The study of MSEM in the nSEM framework still needs to be evaluated for a large number of environments, at least more than 50, while the size of the environment was more than 100. The nSEM framework for simple models (LatenRI) shows quite good performance for increasing sample sizes. For further research, it is seen how nSEM performs for models that are not simple or complex.

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