IJSA (2021), Vol. 6, No. 1, 63-76
DOI: https://doi.org/10.29244/ijsa.v6i1p63-76

Indonesian Journal of Statistics and Its Applications
Available at https://ijsa.stats.id
e-ISSN: 2599-0802

Bayesian-Structural Equation Modeling on Learning Motivation of Undergraduate Students During Covid-19 Outbreak*

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Abstract

The aim of this study is to explore the relationship model between e-learning readiness, self-directed learning readiness, and learning motivation of the students at STMIK Sumedang during the COVID-19 outbreak. Bayesian-Structural Equation Modeling and Markov Chain Monte Carlo Algorithm are used in the estimation of the parameters. The posterior distribution is formed using informative prior i.e., inverse-Gamma distribution on variance parameters, inverse-Wishart distribution on residual covariance, and normal distribution on other parameters of the model. The calculation is performed using the blavaan package on R-Software version 4.1.0 with 19000 iteration and 9000 samples of burn-in period. Data were taken from 214 samples of the students at STMIK Sumedang. The outcome from the calculation showed there is a significant effect from self-directed learning readiness to motivation learning of students and there is no significant effect from e-learning readiness to learning motivation. The direct effect on learning motivation is 7.25 from self-directed learning readiness and 0.045 from e-learning readiness.

Keywords: Bayesian-SEM, e-learning readiness, learning motivation, MCMC, self-directed learning readiness.

* Received: Jul 2021; Reviewed: Nov 2021; Published: May 2022

1. Introduction

Structural Equation Modeling (SEM) is a multivariate technique that is widely applied to analyze relationships amongst latent variables. Latent variables in SEM are not directly observable, these variables are observed through each construct and often correspond to hypothetical constructs that represent a wide range of phenomena (Marliana and Nurhayati, 2020). An indirect measure of a construct is called an indicator which is an observed variable. There are three latent variables in this study i.e., self-directed learning readiness, e-learning readiness, and learning motivation of undergraduate students at STMIK Sumedang. Indicators of e-learning readiness (Al-araibi et al., 2019), self-directed learning readiness (Akkilagunta et al., 2019), and learning motivation (Law and Geng, 2019) can be seen at Table 1.

During the COVID-19 outbreak, to help bend the curve of the COVID-19 cases, the Ministry of Education and Cultural of the Republic of Indonesia insists Higher Education provide online learning using a platform such as website, Google classrooms, learning management system (LMS), e-learning, etc. With this strict policy, students are forced to use online platforms that they just discovered and learned but have to immediately comprehend. This phenomenon is one of the factors that caused student's stress levels (Irawan et al., 2020). One consequence of using technology as learning media is giving high pressure on students who do not have enough technology skills (Widyanti et al., 2020). Therefore, the ability to use computers and the internet are fundamentals skills of students for e-learning applications or other platforms. The measurement of this ability in this study is called e-learning readiness. We assume that high e-learning readiness can affect student's motivation in learning. Based on Irawan, Dwisona and Lestari (2020), after the first two weeks of online learning, students feel bored and had emotional disturbances. It is likely their learning motivation depends on the psychological impact on students. Furthermore, Saeid and Eslaminejad (2016) showed that 21,1% variance of self-directed learning readiness affects the learning motivation significantly. In self-directed learning, students take initiative and the responsibility to select, manage, and assess their learning activities during online learning with or without assistance (Saeid and Eslaminejad, 2016). Therefore, in this study, we tried to explore and studied the relationship amongst learning motivation, e-learning readiness, and self-directed learning readiness using SEM.

SEM proposes two-approach i.e. Partial Least Squares-SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM) (Marliana and Nurhayati, 2020). Parameter estimation methods that are often used in CB-SEM are Weighted Least Squares (WLS), Generalized Least Squares (GLS), and Maximum Likelihood (ML). These estimation methods have similar asymptotic properties and generate estimates which converge to the similar optimum points if the data are multivariate normally distributed with the correct model specification (Olsson et al., 2000). ML tends to be more stable and shows higher accuracy regarding theoretical and empirical fit than WLS and GLS (Olsson et al., 2000). ML and GLS estimation methods require large sample sizes and the assumption of multivariate normality. Statistical power ends up an issue in itself when sample size gets bigger, with a very big sample, not only trivial level of model misfit has no importance or substantive meaning but also can lead to statistical refusal of the model and standard errors of the estimations of parameter incline to be a quite small (Raykov and Widaman, 1995). In addition, non-normality also can affect the significance tests caused by underestimated standard errors (Olsson et al., 2000). WLS allows a small sample size, and it is suggested when data are non-normally distributed. If data are multivariate normally distributed with a miss-specified model, GLS and WLS will produce equivalent estimators which are different from ML estimator (Olsson et al., 2000). In consequence of the strictness of model criteria with exact zero cross-loadings besides zero residual correlations, ML-based estimator analysis is probably experience hardship from model misspecification (Noudoostbeni et al., 2018).

Similar to the WLS, PLS-SEM allows small sample size and can be used when the violation of multivariate normality is found (Marliana and Nurhayati, 2019). Data with non-multivariate normally distributed transformed by PLS-SEM algorithm using the central limit theorem (Hair, 2014; Marliana and Nurhayati, 2020). The parameter of the PLS-SEM is estimated based on Ordinary Least Square (OLS) method. PLS-SEM also called as a variance-based approach to SEM (Hair, 2014). Compared to the CB-SEM, PLS-SEM performs elevated efficiency in the estimation of the parameter that leads to higher statistical power (Hair, 2014). Different from CB-SEM, even as sample sizes increase to infinity, PLS-SEM generates biased estimates of parameters of the model due to the method focus on composite which does not fully put measurement error in and is only viewed as the supposition of factors. (Kock, 2019; Marliana and Nurhayati, 2020).

ML, GLS, WLS and OLS method (frequentist) treat parameters of the model are fixed but unknown (Ong et al., 2018). When the parameters of the model are viewed as random with a certain probability distribution, the parameter estimation methods called Bayesian method. Due to the method does not depend on multivariate normality assumption, for a smaller sample size, the Bayesian not only more precise than ML but also provides the flexibility to incorporate the uncertainty of the model and to assess too tricky model or too computationally requiring for frequentist (Smid et al., 2020). The Bayesian enable to estimate all cross-loadings and residual correlation simultaneously in a certain model which is not possible if the ML estimation method on CB-SEM or OLS on PLS-SEM applied (Hair, 2014; Noudoostbeni et al., 2018). Dissimilar from CB-SEM with sample covariance matrix, and sample variance on PLS-SEM, the Bayesian methods build upon raw observation random data (Anggorowati, 2014; Yanuar, 2014). The utilization of raw individual random observation gives several benefits such as the expansion statistical methods that build upon its traits, leads to an estimation of latent variables directly, and gives a more direct interpretation. (Anggorowati, 2014).

2. Bayesian Structural Equation Modeling (BSEM)

ML yields estimates by maximizing a likelihood calculated for data, meanwhile Bayesian affiliates prior distributions of parameters with a likelihood of data to establish a posterior distribution for the parameter estimation (Muthen and Asparouhov, 2010).

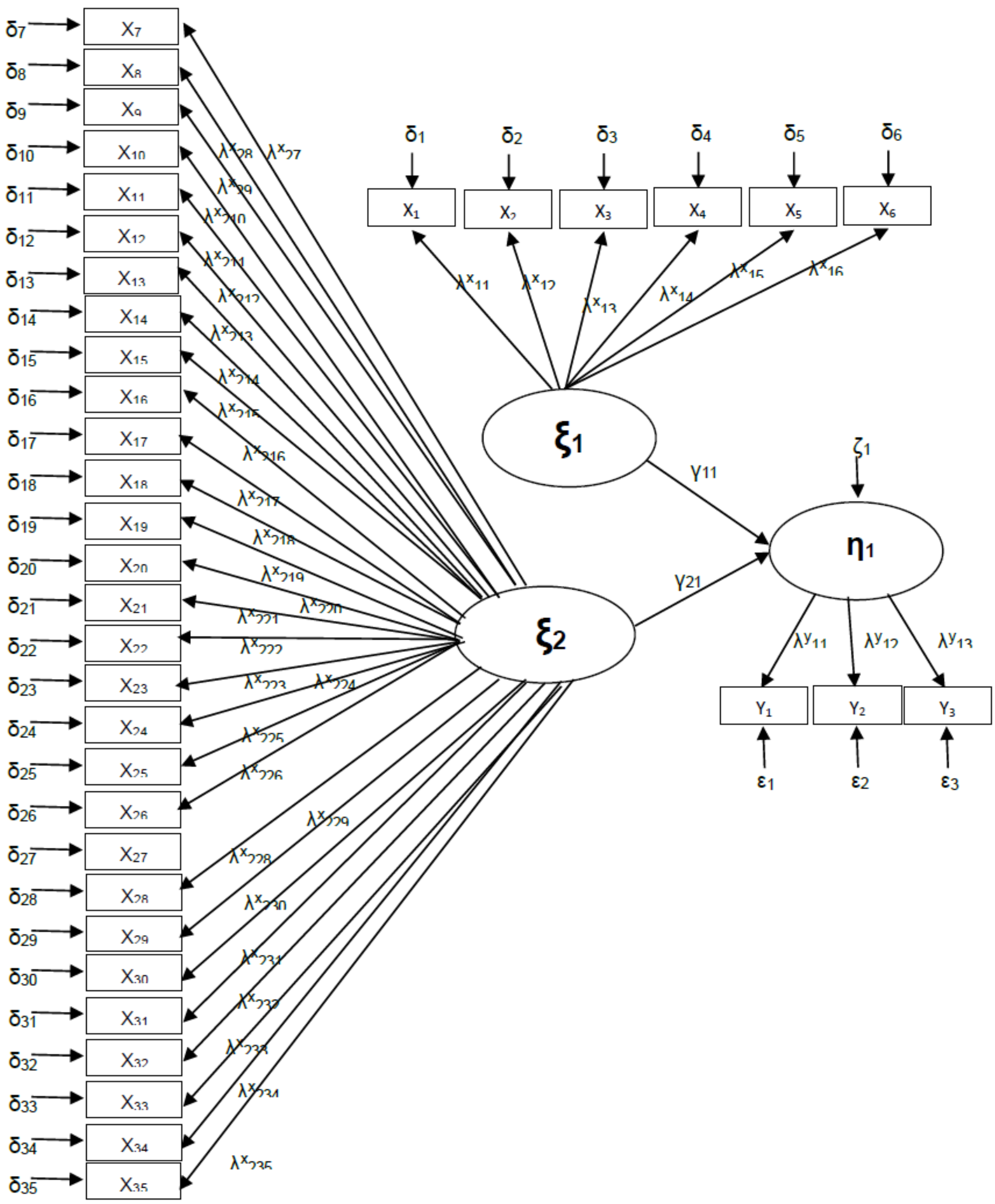

Figure 1: Model Specification

2.1 Model Specification

We build a path diagram (Figure 1) using Indicators of e-learning readiness based on Al-araibi *et al.* (2019), Indicator of self-directed learning readiness are formed based on Abridged 29-item self-directed learning readiness scale (Akkilagunta et al., 2019) , and indicators learning motivation based on Law and Geng (2019). Moreover, relationship between self-directed learning readiness and learning motivation is formed based on Saeid and Eslaminejad (2016); Geng, Law and Niu (2019). Meanwhile the relationship between e-learning readiness and learning motivation is formed based on Harandi (2015).

Table 1: List of Construct's Indicators

Construct	No	Indicator	Notation
E-Learning Readiness (ξ_1)	1	I like the idea to receipt instruction and deliver assignment using e-learning	X_1
	2	I like to attempt new learning media or technology associated with e-learning	X_2
	3	I feel convinced with my competence to use e-learning	X_3
	4	I can learn on my own how to use e-learning and to discover most of things about it.	X_4
	5	If I knew more about how to operate e-learning, I will feel better to utilizing it.	X_5
	6	I consider e-learning as appliance to help me studying my courses.	X_6
Self-Directed Learning Readiness (ξ_2)		**Self-Control**	
	1	I like to solve problem of the questions	X_7
	2	I capable to see the focal point on a problem	X_8
	3	I have to know the reasons	X_9
	4	I assess new ideas critically	X_{10}
	5	I have high confidence in my abilities	X_{11}
	6	I believe in my ability to looking for information	X_{12}
	7	I take pleasure in the challenge	X_{13}
	8	I am keen on studying new information	X_{14}
	9	I relish studying new information	X_{15}
	10	I think with logic	X_{16}
	11	To assess my performance, I prefer to set my own criteria	X_{17}
	12	I can discover information for me	X_{18}
	13	I need small favor to discover the information	X_{19}
	14	I like to establish decisions for myself	X_{20}
		Self-Management	
	15	I put first my duties as student	X_{21}
	16	I am good at organizing my time	X_{22}
	17	I set a stringent time plan	X_{23}
	18	I am studying systematically	X_{24}
	19	I am liable	X_{25}
	20	I am studying at specific times set	X_{26}
	21	I discipline myself	X_{27}
	22	I am an organized person	X_{28}
	23	I am a methodical person	X_{29}
		Desire For Learning	
	24	I prepared to alter my idea	X_{30}
	25	When it is necessary, I will seek help in my study	X_{31}
	26	I am ready to get advice from lectures, friends, others	X_{32}
	27	I am not closed to new precious learning opportunities	X_{33}
	28	I am widely open to new concepts and ideas	X_{34}
	29	I will seek help when I meet a problem, I cannot solve	X_{35}
Learning Motivation (η_1)	1	Clear goals in study	Y_1
	2	Willingness to perform task with good quality	Y_2
	3	Willingness to participate in learning	Y_3

The model specification is an *over-identified* model with *df*=662. An *over-identified* model has less unknown information than known information, which is probable to assess all the parameters estimation using equations of the known information. Further, an over-identified model used fit statistics to assess the fit of the overall model (Marliana & Nurhayati, 2020).

Based on the model specification (Table 1 and Figure 1), with *i*= 1,2,…,35, and *j*=1,2 we get the measurement model for E-Learning Readiness (ξ_1) and Self-Directed Learning Readiness (ξ_2) which can be defined as follows:

$$x_i = \lambda_{ji}^{X}\xi_j + \delta_i \quad (1)$$

At the same time with *k*=1,2,3 the measurement model for Learning Motivation can be defined as follows:

$$Y_k = \lambda_{1k}^{y}\eta_1 + \varepsilon_k \quad (2)$$

Equation (1) and (2) can be rewrite become:

$$\boldsymbol{x} = \boldsymbol{\Lambda_x}\boldsymbol{\xi} + \boldsymbol{\delta} \quad (3)$$

$$\boldsymbol{y} = \boldsymbol{\Lambda_y}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \quad (4)$$

Where $\boldsymbol{x}$ is an $i \times 1$ vector of indicators depicting the $j \times 1$ vector $\boldsymbol{\xi}$ containing exogenous variables and $\boldsymbol{\delta}$ is an $i \times 1$ vector of residuals. While $\boldsymbol{y}$ is an $k \times 1$ vector of indicators depicting the 1×1 vector $\boldsymbol{\eta}$ containing endogenous variable and $\boldsymbol{\varepsilon}$ is an $k \times 1$ vector of residuals. Furthermore $\boldsymbol{\Lambda_x}$ and $\boldsymbol{\Lambda_y}$ are matrix of factor loadings. It is assumed that $\boldsymbol{\delta} \sim N_{\boldsymbol{i}}(\boldsymbol{0}, \boldsymbol{\psi_\delta})$ and $\boldsymbol{\varepsilon} \sim N_{\boldsymbol{k}}(\boldsymbol{0}, \boldsymbol{\psi_\varepsilon})$ (Anggorowati, 2014; Merkle & Rosseel, 2018; Yanuar, 2014; Yum Lee, 2007). It is also assumed that $\boldsymbol{\xi} \sim N_{\boldsymbol{i}}(\boldsymbol{0}, \boldsymbol{\Theta_\xi})$ and $\boldsymbol{\eta} \sim N_{\boldsymbol{i}}(\boldsymbol{0}, \boldsymbol{\Theta_\eta})$ (Yum Lee, 2007; Muthen and Asparouhov, 2010; Song *et al.*, 2011; Anggorowati, 2014; Yanuar, 2014; Liu and Song, 2018)**.**

In addition, the structural model can be defined as:

$$\eta_1 = \gamma_{11}\xi_1 + \gamma_{21}\xi_2 + \zeta_1 \quad (5)$$

Also, we can rewrite equation (5) become:

$$\boldsymbol{\eta} = \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{Z} \quad (6)$$

Where $\boldsymbol{\Gamma}$ is an $1 \times j$ regression parameter matrix to connect endogenous variables and exogenous variables, and $\boldsymbol{Z}$ the 1×1 vector of disturbance. While $\boldsymbol{Z}$ is assumed $N(\boldsymbol{0}, \boldsymbol{\psi_Z})$ and uncorrelated with $\boldsymbol{\xi}$ (Yanuar, 2014)**.**

2.2 Prior Specification

We consider $\boldsymbol{X} = (\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \dots, \boldsymbol{x_{35}})$, and $\boldsymbol{Y} = (\boldsymbol{y_1}, \boldsymbol{y_2}, \boldsymbol{y_3})$ be data matrix and let $\Omega = (\xi_1, \xi_2, \eta_1)$ be the matrix of exogenous and endogenous variables and parameter $\boldsymbol{\theta}$, a vector which accommodate all the unknown parameters in $\boldsymbol{\Theta_\xi}, \boldsymbol{\Theta_\eta}, \boldsymbol{\psi_\delta}, \boldsymbol{\psi_\varepsilon}, \boldsymbol{\psi_Z}, \boldsymbol{\Lambda_x}, \boldsymbol{\Lambda_Y}, \boldsymbol{\Gamma}$

and $\boldsymbol{Z}$. The prior distribution of the parameter $\boldsymbol{\theta}$ personifies the distribution of probable parameter values, from where parameter $\boldsymbol{\theta}$ has been picked up (Yum Lee, 2007). There are noninformative prior and informative prior. Noninformative prior well-known as a vague or a diffuse prior with a large variance which contains a big quantity of ambiguity about the population parameter while informative prior in the opposite (Yum Lee, 2007; Muthen and Asparouhov, 2010; Kaplan and Depaoli, 2012; Önen, 2019). Using informative prior based on Yum Lee (2007), Muthen and Asparouhov (2010), Song *et al.* (2011), Muthén and Asparouhov (2012), Kaplan and Depaoli (2012), Anggorowati (2014), De Bondt and Van Petegem (2015), Merkle and Rosseel (2018), Liu and Song (2018), Önen (2019), Guo *et al.* (2019), and Smid *et al.* (2020), we specified inverse-Wishart distributions on residual covariances, inverse-Gamma distributions on variance parameters, and normal distributions on other parameters as the prior distribution. Parameters of the informative prior are called hyperparameters. Furthermore, we define the prior distribution for variance parameter as follows:

$$\boldsymbol{\Theta}_{\xi} \sim InvGamma(\alpha_{0\xi}, \beta_{0\xi}) \tag{7}$$
$$\boldsymbol{\Theta}_{\boldsymbol{\eta}} \sim InvGamma(\alpha_{0\boldsymbol{\eta}}, \beta_{0\boldsymbol{\eta}}) \tag{8}$$

Where $\alpha_{0\xi}, \beta_{0\xi}, \alpha_{0\boldsymbol{\eta}}, \beta_{0\boldsymbol{\eta}}$ are hyperparameters of the inverted Gamma as prior distribution for variance parameters. At the same time, we assign the prior distribution for residual covariances as follows:

$$\boldsymbol{\psi}_{\boldsymbol{\delta}} \sim InvWishart(\boldsymbol{R}_{0\boldsymbol{\delta}}, \rho_{0\boldsymbol{\delta}}) \tag{9}$$
$$\boldsymbol{\psi}_{\boldsymbol{\varepsilon}} \sim InvWishart(\boldsymbol{R}_{0\varepsilon}, \rho_{0\boldsymbol{\varepsilon}}) \tag{10}$$
$$\boldsymbol{\psi}_{\boldsymbol{Z}} \sim InvWishart(\boldsymbol{R}_{0Z}, \rho_{0\boldsymbol{Z}}) \tag{11}$$

Where $InvWishart(\boldsymbol{R}_{0\boldsymbol{\delta}}, \rho_{0\boldsymbol{\delta}})$, $InvWishart(\boldsymbol{R}_{0\boldsymbol{\varepsilon}}, \rho_{0\boldsymbol{\varepsilon}})$, $\boldsymbol{Inv}\, Wishart(\boldsymbol{R}_{0\boldsymbol{Z}}, \rho_{0\boldsymbol{Z}})$ are *q*-dimensional inverted Wishart distribution with hyperparameter $\rho_{0\boldsymbol{\delta}}, \rho_{0\boldsymbol{\varepsilon}}, \rho_{0\boldsymbol{Z}}$ and positive definite matrix $\boldsymbol{R}_{0\boldsymbol{\delta}}, \boldsymbol{R}_{0\boldsymbol{\varepsilon}}$ and $\boldsymbol{R}_{0\boldsymbol{Z}}$. Meanwhile we set the prior distribution on other parameters as follows:

$$\boldsymbol{\Lambda}_{\boldsymbol{x}} | \boldsymbol{\Theta}_{\xi} \sim N(\boldsymbol{\Lambda}_{0x,} \boldsymbol{\Theta}_{\xi} \boldsymbol{H}_{0\xi}) \tag{12}$$
$$\boldsymbol{\Lambda}_{\boldsymbol{Y}} | \boldsymbol{\Theta}_{\boldsymbol{\eta}} \sim N(\boldsymbol{\Lambda}_{0Y,} \boldsymbol{\Theta}_{\boldsymbol{\eta}} \boldsymbol{H}_{0\boldsymbol{\eta}}) \tag{13}$$

$$\boldsymbol{\Gamma} \sim N(\mu_{\boldsymbol{\Gamma}}, \boldsymbol{\Sigma}_{\boldsymbol{\Gamma}}) \tag{14}$$
$$\boldsymbol{Z} \sim N(\mu_{\mathbf{Z}}, \boldsymbol{\Sigma}_{\mathbf{Z}}) \tag{15}$$

Where elements in $\boldsymbol{\Lambda}_{0x,}, \boldsymbol{\Lambda}_{0Y,} \mu_{\boldsymbol{\Gamma}}, \mu_{\mathbf{Z},}, \boldsymbol{H}_{0\xi}, \boldsymbol{H}_{0\eta}, \boldsymbol{\Sigma}_{\boldsymbol{\Gamma}}$, and $\boldsymbol{\Sigma}_{\mathbf{Z}}$ are hyperparameters, and $\boldsymbol{H}_{0\xi}, \boldsymbol{H}_{0\boldsymbol{\eta}}, \boldsymbol{\Sigma}_{\boldsymbol{\Gamma}}$, and $\boldsymbol{\Sigma}_{\mathbf{Z}}$ are positive definite matrix

2.3 Posterior Distribution

Dissimilar with classical statistics or frequentist that present no distributional information, the posterior distribution produce maximum information about the parameter provided the data (De Bondt and Van Petegem, 2015). Basically, we present the posterior distribution as follows:

$$p(\boldsymbol{\theta}, \Omega|\boldsymbol{Y}, \boldsymbol{X}) \propto p(\boldsymbol{Y}|\boldsymbol{\theta})p(\boldsymbol{\theta}) \quad (16)$$

Where $p(\boldsymbol{\theta}|\boldsymbol{Y}, \boldsymbol{X})$ is posterior distribution, $p(\boldsymbol{Y}|\boldsymbol{\theta})$ is data likelihood of conditional distribution and $p(\boldsymbol{\theta})$ is prior distribution of unknown parameters (see the equation 7 to 15). The most popular algorithm which usually use for Bayesian estimation is build upon MCMC sampling. The MCMC takes particularly built samples based on the posterior distribution $p(\boldsymbol{\theta}|\boldsymbol{Y}, \boldsymbol{X})$ of the parameters (Kaplan and Depaoli, 2012). To calculate posterior distribution, we used MCMC algorithm as follows:

1. Set the initial value of each hyperparameters of parameters based on specified prior distribution.
2. Set the number ot iteration *T*
3. For *t*=1,2,….,*T*, at the (*t*+1)th iteration with current value of $\Omega^{(t)}$ and $\boldsymbol{\theta}^{(t)}$
   a) Generate $\Omega^{(j+1)}$ from $p\left(\Omega\middle|\boldsymbol{\theta}^{(j)}, \boldsymbol{Y}, \boldsymbol{X}\right)$
   b) Generate $\boldsymbol{\theta}^{(j+1)}$ from $p\left(\boldsymbol{\theta}\middle|\Omega^{(j)}, \boldsymbol{Y}, \boldsymbol{X}\right)$
4. Check the convergence of the algorithm using trace plot
5. Determine burn in period
6. Calculated posterior predictive model check to assess the global or local fit.

3. Results and Discussion

This study took data from 214 observation from undergraduate student at STMIK Sumedang. Calculation the posterior distribution and analysis are performed using blavaan package on R-Software version 4.1.0. MCMC algorithm used with 19000 iteration and burn in period at 9000 samples. This model took more than 7 hours to compute.

To save the space, we only provide a trace plot (Figure 2) which depict a tight and horizontal band for λ^x_{12}, λ^x_{13}, λ^x_{14} and λ^x_{15}. This plot does not shows a fluctuation or jump in the chain, it's likely λ^x_{12}, λ^x_{13}, λ^x_{14} and λ^x_{15} have reached convergence (De Bondt and Van Petegem, 2015; Kaplan and Depaoli, 2012). Not only λ^x_{12}, λ^x_{13}, λ^x_{14} and λ^x_{15}, but also all the parameters on Figure 1 have reached the convergence. At the same time, all the standardized loading of E-Learning (Table 2), Self-Directed Learning Readiness (Table 3), and Learning Motivation (Table 4) are lies between 0.52 to 0.79 and indicate a validity of all indicators except λ^x_{27} (X_7 on Table 3). Even though the standardized loading of λ^x_{27} quite small (0,1091), we tend to keep this important indicator (see Table 1). Saeid and Eslaminejad (2016) pointed out that skill of studying and problem solving are the most important predictor of achievement motivation of students. Furthemore, all the composite reliability values are greater than 0.6 and the AVE values are greater than 0.5 except for Self-Directed Learning Readiness (0.419) with a small gap (Table 5).

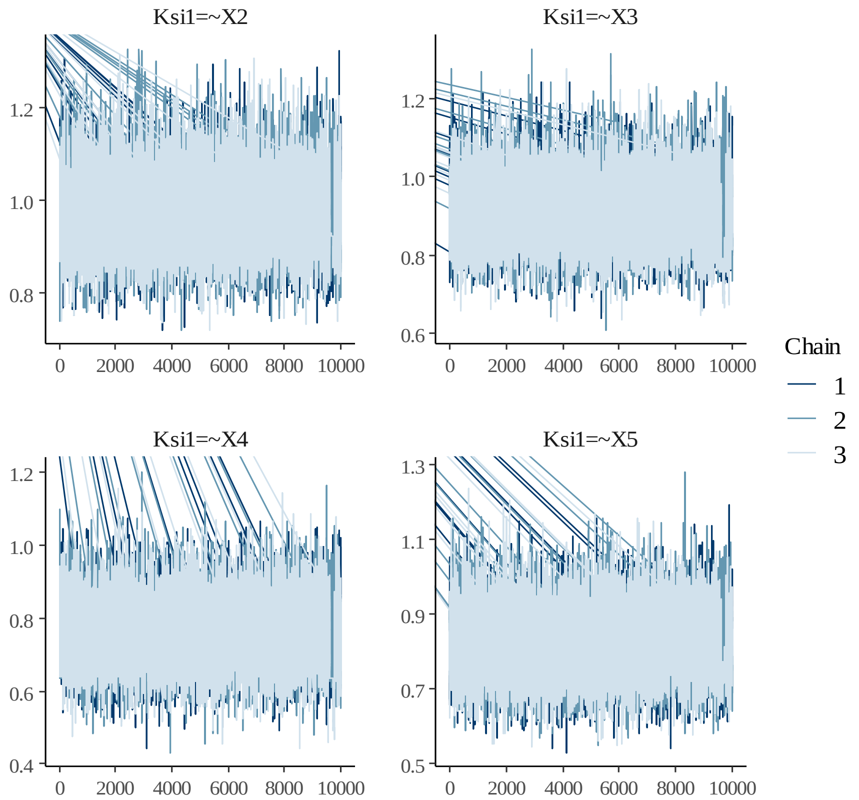

Figure 2: Trace Plot

Table 2: Standardized Loading of E-Learning Readiness

Indicator	Standardized Loading
X_1	0.7855
X_2	0.7956
X_3	0.7585
X_4	0.6215
X_5	0.6663
X_6	0.7975

Table 3: Standardized Loading of Self-Directed Learning Readiness

Indicator	Standardized Loading	Indicator	Standardized Loading	Indicator	Standardized Loading
X_7	0.1091	X_{17}	0.7173	X_{27}	0.6872
X_8	0.5976	X_{18}	0.6491	X_{28}	0.7038
X_9	0.5586	X_{19}	0.4710	X_{29}	0.6433
X_{10}	0.5903	X_{20}	0.6716	X_{30}	0.5961
X_{11}	0.6509	X_{21}	0.6678	X_{31}	0.6131
X_{12}	0.6920	X_{22}	0.6966	X_{32}	0.6513
X_{13}	0.6882	X_{23}	0.6315	X_{33}	0.7293
X_{14}	0.7302	X_{24}	0.6322	X_{34}	0.6895
X_{15}	0.6998	X_{25}	0.7443	X_{35}	0.6036
X_{16}	0.6673	X_{26}	0.6920		

Table 4: Standardized Loading of Learning Motivation

Indicator	Standardized Loading
Y_1	0.8257
Y_2	0.7858
Y_3	0.8265

Table 5: Composite Reliability and AVE

Variable	Composite Reliability	AVE
E-Learning Readiness	0.8785	0.5486
Self-Directed Learning Readiness	0.9530	0.4191
Learning Motivation	0.8538	0.6608

The well-known method for model animadversion in BSEM entangles posterior predictive model checking (PPMC). In hypothesis testing, PPMC used to define the posterior predictive *p*-value (p_{post}), where an upper-tailed (two-tailed) test with significant level *α* is undertaken by rejecting the null hypothesis if data-model fit if p_{post} less than α (Levy, 2011). Moreover, a low p_{post} (<0.05) exhibit poor model fit and a good fit if p_{post} around 0.5 (De Bondt & Van Petegem, 2015; Guo et al., 2019; Hoofs et al., 2018). Rather than treated as the model fit assessment, others treat PPMC as diagnostic tool that aims to ensure weaknesses and strengths of the model, where p_{post} solely sum up the calculation numerically, and has slight influence with the possibility of refusing a model which already known to be erroneous circumstances where the model is true (Levy, 2011). In addition, if the value nearby 1 or 0 denote substantiation which the model is overpredicts or underpredicts. From the calculation, we get the value of p_{post} is 0.00 (Table 6) which is less than of the significant level *α* (0.05) and close to 0. It means the model is misfit or underpredicts (Kaplan & Depaoli, 2012). According to Hoofs *et al.*, (2018), p_{post} is robust for model fit assessment within small samples and becomes sensitive for large samples. Based on Levy (2011) and Hoofs *et al.*, (2018), we tend to assume that the model is weak or poor but still acceptable. Moreover, we got the Bayesian Information Criterion (BIC) and Deviance Information Criterion (DIC) values with small differences (Table 6). These values usually used to compare two model or more (Guo et al., 2019; Kaplan and Depaoli, 2012; Yum Lee, 2007).

Table 6: Posterior Predictive Model Checking

P_{post}	BIC	DIC
0.00	17695.619	17261.908

Table 7: Structural Model Assessment

Variable	Estimate	Post.SD	T-Value
E-Learning Readiness	0.045	0.063	0.7143
Self-Directed Learning Readiness	7.250	1.894	3.8279

Further analysis exhibits a significant effect from Self-Directed Learning Readiness to Learning Motivation with a high direct effect 7.25 (Table 7). We got t-values of Self-Directed Learning Readiness higher than 1.96 (Table 7). This significant relationship represent the same outcome which obtained by Saeid and Eslaminejad (2016). Saeid and Eslaminejad (2016) used bivariate linear regression to investigate the relationship between achievement motivation and self-direct learning readiness of Payam Noor University students. In the meantime, we got t-values of E-Learning Readiness is 0.7143 (less than 1.96) which be an indication of no significant relationship between E-Learning Readiness and Learning Motivation with a small direct effect 0.045. Lastly, to save the space we could only present the estimate of the structural model (see equation 5) as follows:

$$\eta_1 = 0.045\xi_1 + 7.250\xi_2 + 0.098$$

4. Conclussion

The outcome of the posterior distribution calculation which performed based on the prior specification and the MCMC algorithm above exhibit a significant effect of self-directed learning readiness on student motivation at STMIK Sumedang with 7.25 direct effect. In contrast, the same results depict there is not a significant effect of e-learning readiness to learning motivation. This outcome is reinforced by very small direct effect value which is 0.045. For further analysis we need to compare the model in this study with the model with different prior distribution. We also suggest using different algorithm with better time complexity

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