JSDS: JOURNAL OF STATISTICS AND DATA SCIENCE
VOLUME 4, No 2, October 2025
e-ISSN: 2828-9986
https://ejournal.unib.ac.id/index.php/jsds/index

APPLICATION OF STRUCTURAL EQUATION MODELING (SEM) IN ANALYZING ACADEMIC PERFORMANCE

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Article Info

Article History:
Received: 10 04 2024
Revised: 03 25 2025
Accepted: 12 29 2025
Available Online: 12 30 2025

Key Words:
Academic Stress
Academic Performance
Academic Resilience
Factor Analysis
Structural Equation Modeling (SEM)

Abstract

Academic performance is one of the ways to determine whether one has had a good education. There are multiple factors that can influence student's academic performance. Structural Equation Modeling (SEM) is used to determine the relationship between level of stress, level of resilience, and academic performance. The data for this study is collected using Google Forms, distributed to active students of Prasetiya Mulya University. The SEM model in this study is a combination of multivariate regression analysis and confirmatory factor analysis called structural regression model. There are three hypotheses made in this study. The modelled hypotheses will then be evaluated using a chi-square test, Root Mean Square Error of Approximation (RMSEA), Tucker-Lewis Index (TLI), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The chi square test shows that two of the three models are significant with the first model being the best one out of the three. The first model, which states that resilience and stress affect students' academic performance, but stress and resilience have no correlation with one another, shows minimal discrepancy between the data and model estimation, shown by the chi square p-value of 0.454, RMSEA of 0.005, and TLI of 1.

1. INTRODUCTION

Education is a pertinent aspect in developing the minds of children. An environment that facilitates and provides students with learning opportunities is key in achieving great academic prospects [1]. According to International Student Evaluation Program oleh Organization for Economic Co-operation and Development (OECD), academic performance in Indonesia is in the 10th lowest spot in all of Southeast Asia. This is of course concerning to say the least [2]. There are several factors that could influence students' academic performance, some of those factors are stress and resilience. A common stress factor amongst students is the number of tests and workload they must face [3]. When high level of stress is remained untreated, it can cause mental exhaustion and in result affect students' academic performance [4]. On the other hand, resilience plays an important role in keeping their performance intact and despite of adversities [5]. The ability to rise above these adversities and maintain their stress level to improve and maintain their academic performance is important to ensure their academic prowess [6]. Therefore, through analyzing these three factors in a single model, a better understanding about these factors and their relations can be achieved. There have been studies conducted in analyzing the factors separately, but it is important to analyze them together for a better understanding. This study will do exactly that. The method that will be used is structural equation modeling (SEM) because of its flexibility in multivariate modeling of latent variables and its common practice in behavioral science studies. In SEM, relationship between latent and observed variables are evaluated in a single model [7].

2. METHOD

The research method contains a description of the method and the steps used to solve the problem in the research that is written completely, briefly, and clearly. If there is a design used in the study, it must be included in the method along with the details. The method must also be able to explain how to obtain supporting data for research results. The content in the method is made in such a way that the research can be repeated again with the same results.

The focus of the research is to prove hypothesis about the causal relations between latent variables of academic performance, stress, and resilience. The relations between these latent variables and their respective indicators are also evaluated. The data for this research are primary data collected through Google Forms survey and distributed among students at Prasetiya Mulya University. The method to analyse these causal relations is structural equation modeling (SEM) which is a common method used in psychometry because of its flexibility in analysing multivariate latent variables.

2.1 Latent and Observed Variables

Analyzing concepts such as climate, stress level, satisfaction, and resilience can be a challenge since it is a construct with no quantifiable value. These concepts are called latent variables. Latent variables can't be directly observed in a dataset, but it reflects an unquantifiable dimension. In SEM, the latent variables are measured by the indicators or observed variables. Observed variables are measurable variables that reflects the corresponding factors, then factor analysis is implemented to measure the relations between a latent variable and their corresponding observed variables.

There are exogenous latent variables with exogenous observed variables as their indicators and endogenous latent variables with endogenous observed variables as their indicators. Exogenous latent variables are also known as independent variables or the cause that affect fluctuation in value of the other latent variables, while the variables that are affected is called the endogenous variables [8].

2.2 Measurement and Structural Model

Measurement model is the relation between a latent variable and observed variables. In SEM, all latent variables are modeled as a factor that affects the indicators. The relation between the two variables is called a loading factor notated by λ [7]. The measurement models have the following equations:

$$\boldsymbol{x} = \boldsymbol{\Lambda_x \xi} + \boldsymbol{\delta} \tag{1}$$

$$\boldsymbol{y} = \boldsymbol{\Lambda_y \eta} + \boldsymbol{\epsilon} \tag{2}$$

where $\boldsymbol{x}$: vector exogenous observed variables, $\boldsymbol{y}$: vector endogenous observed variables, $\boldsymbol{\eta}$: vector endogenous latent variables, $\boldsymbol{\xi}$: vector exogenous latent variables, $\boldsymbol{\Lambda_x}$: matrix for *loading factor* (λ) or coefficient between $\boldsymbol{\xi}$ and $\boldsymbol{x}$, $\boldsymbol{\Lambda_y}$: matrix for *loading factor* (λ) or coefficient between $\boldsymbol{\eta}$ and $\boldsymbol{y}$, $\boldsymbol{\epsilon}$: vector error measurement model for $\boldsymbol{y}$, and $\boldsymbol{\delta}$: vector error measurement model for $\boldsymbol{x}$.

The structural model are the relations between latent variables. These relations are expressed by a linear equation as followed [8]:

$$\boldsymbol{\eta} = \boldsymbol{B\eta} + \boldsymbol{\Gamma\xi} + \boldsymbol{\zeta} \tag{3}$$

The vector $\boldsymbol{\xi}$ is assumed to be independent with $\boldsymbol{\zeta}$ and $\boldsymbol{I} - \boldsymbol{B}$ is *nonsingular.* Therefore, the above equation can also be written as:

$$\boldsymbol{\eta} = (\boldsymbol{I} - \boldsymbol{B})^{-1}(\boldsymbol{\Gamma\xi} + \boldsymbol{\zeta}) \tag{4}$$

with $\boldsymbol{\eta}$: vector for endogenous latent variables, $\boldsymbol{\xi}$: vector for exogenous latent variables, $\boldsymbol{B}$: matrix of coefficient between endogenous latent variables, $\boldsymbol{\Gamma}$: matrix of coefficient between exogenous and endogenous latent variables, and $\boldsymbol{\zeta}$: vector *error* in the structural model.

2.3 Model Evaluation

A model can be considered good if it represents the data and reflects the underlying theory. This is measured by evaluation metrics that assess the model fit. It is important for researchers to use various fit indices techniques to determine whether a particular model fits the data. Here are some examples of evaluation methods used in this study:

1. Chi-Square ($\boldsymbol{\chi^2}$)

This method measures how well the model fits the data and assesses the degree of discrepancy between the sample and the covariance matrix. Chi-square examines how closely the data fit the sample covariance matrix S and the model covariance matrix $\Sigma(\theta)$. Thus, the null hypothesis can be written as followed:

$$H_0 : S = \Sigma(\theta)$$

$$H_1 : S \neq \Sigma(\theta)$$

The formula for the chi square test is as followed:

$$\chi^2 = (N-1)F(S, \Sigma(\theta)) \tag{5}$$

The chi square distribution with the degree of freedom of $\mathbf{p}^* - \boldsymbol{q}$:

$$p^* = \frac{p(p+1)}{2} \tag{6}$$

where $F(S, \Sigma(\theta))$: discrepancies between S and $\Sigma(\theta)$, p^*: non-redundant variable, p: number of observed variables, q: estimated parameter, and N: sample size,

Chi-square is a measure of fit or misfit, where a higher chi-square value indicates that the model does not fit well. Conversely, a lower chi-square value indicates that the model fits well. The chi-square is expected to yield a low value with a p-value above 0.05 because this indicates that the predicted and actual input metrics are not significantly different statistically.

2. Root Mean Square Error of Approximation (RMSEA)

This method evaluates the model's performance in estimating unknown parameters that align with the population covariance matrix, making it optimal. The Root Mean Square Error of Approximation (RMSEA) can calculate the surrounding confidence interval because the distribution of the statistic is known, making the null hypothesis testing more precise. This is possible due to the known distribution values of the statistic, which facilitate more accurate null hypothesis testing. The formula for calculating RMSEA is as follows:

$$RMSEA = \sqrt{\frac{\chi^2 - df}{df(N-1)}} \tag{7}$$

where χ^2 : chi-square value and df : $p^* - q$.

An RMSEA value of less than 0.05 indicates an excellent fit between the model and the data. When the value is in the range of 0.05 to 0.08, it indicates a good fit. Meanwhile, RMSEA values in the range of 0.08 to 0.10 suggest a mediocre fit, but still acceptable. However, RMSEA values above 0.10 indicate that the model does not fit the data well and should be rejected.

3. Tucker-Lewis Index (TLI)

The Tucker Lewis Index (TLI) indicates the extent to which the hypothesized model improves over the baseline model. The baseline model is the worst model without any correlations between variables and has the worst evaluation results. This index was initially used for factor analysis but is now often used for SEM as well. The formula for this method is as follows:

$$NNFI/TLI = \frac{\frac{\chi_i^2}{df_i} - \frac{\chi_h^2}{df_h}}{\frac{\chi_i^2}{df_i} - 1} \tag{8}$$

where χ_i^2 : chi-square of baseline, χ_h^2 : chi-square of hypothesized model, df_i : degree of freedom of baseline, and df_h : degree of freedom of hypothesized model.

The recommended minimum value for TLI/NNFI is 0.80 as the proposed threshold, but the best fit is indicated when NNFI $\geq$ 0.95.

4. Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is used in the model selection process as a metric to evaluate how well a model fits the data compared to other models. The smaller the relative distance, the less information is expected [9]. AIC selects the model that minimizes the negative likelihood penalized by the number of parameters, as described in the equation. The formula for AIC is as follows:

$$\mathrm{AIC} = -2 \times \log(\mathrm{L}) + 2\mathrm{p} \tag{9}$$

where p : model parameter and L : likelihood of fitted model.

5. Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) is one of the criteria in the class of criteria that uses consistency or dimension consistency as an approach for model selection. Unlike AIC, BIC aims to find the model that is truly capable of fitting the observed data. In addition to penalizing the number of parameters, BIC also penalizes the sample size [9]. The formula for BIC is as follows:

$$\mathrm{BIC} = -2 \times \log(\mathrm{L}) + \mathrm{p}\log(\mathrm{n}) \tag{10}$$

where p : model parameter, L: likelihood of fitted model, and n: sample size.

When analyzing very large data sets, AIC is recommended because the penalty for additional parameters imposed by AIC tends to be much smaller than the penalty for additional parameters imposed by BIC [10].

2.4 Model Hypothesis

The SEM model in this research is a structural regression model, where measurement and structural model are combined in a single model. There will be 3 hypotheses made in this research which are:

1. Modeling of Hypothesis I

The first model is based on research amongst Korean students which states that there is a negative effect of stress towards academic performance, but in can be reduced by resilience [11]. Based on the statement in the research, it is hypothesized that resilience and stress have effect towards academic performance but the two has no effect towards each other. The hypothesis model is as followed:

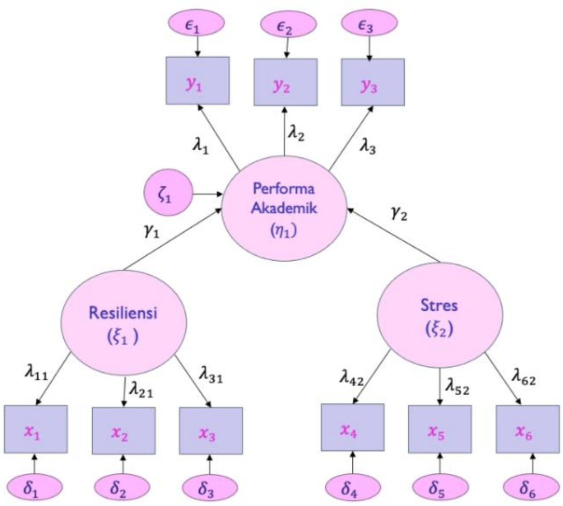

Figure 1. Model Illustration for Hypothesis I

The model above shows that resilience and stress acts as the exogenous latent variables, while academic performance is the endogenous latent variable. Therefore, the measurement and structural equation that is formed is as follow:

Table 1. Equations in Hypothesis I

Observed Endogenous Variables	Observed Exogenous Variables	Latent Endogenous Variable
$\boldsymbol{y_1 = \lambda_1\eta_1 + \epsilon_1}$	$x_1 = \lambda_{11}\xi_1 + \delta_1$	$\eta_1 = \gamma_1\xi_1 + \gamma_2\xi_2 + \zeta_1$
$\boldsymbol{y_2 = \lambda_2\eta_1 + \epsilon_2}$	$x_2 = \lambda_{21}\xi_1 + \delta_2$	
$\boldsymbol{y_3 = \lambda_3\eta_1 + \epsilon_3}$	$x_3 = \lambda_{31}\xi_1 + \delta_3$	
	$x_4 = \lambda_{42}\xi_2 + \delta_4$	
	$x_5 = \lambda_{52}\xi_2 + \delta_5$	
	$x_6 = \lambda_{62}\xi_2 + \delta_6$	

2. Modeling of Hypothesis II

The second model is based on research among business undergraduate college student which states that continuous stress can lead to a decline in academic performance, while resilience is imperative in reducing the effect of stress [12]. Based on the statement in the research, it is hypothesized that stress has a direct effect on academic performance, while resilience has an indirect effect towards academic performance through its mediator stress. The hypothesis model is as followed:

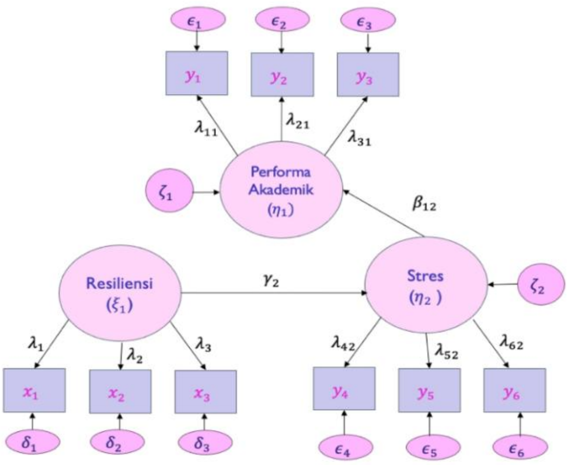

Figure 2. Model Illustration for Hypothesis II

The model above shows that resilience acts as the exogenous latent variable, while academic performance and stress are the endogenous latent variables. Therefore, the measurement and structural equation that is formed is as follow:

Table 2. Equations in Hypothesis II

Observed Endogenous Variables	Observed Exogenous Variables	Latent Endogenous Variable
$\mathbf{y_1 = \lambda_{11}\eta_1 + \epsilon_1}$	$x_1 = \lambda_1\xi_1 + \delta_1$	$\eta_2 = \gamma_2\xi_1 + \zeta_2$
$\mathbf{y_2 = \lambda_{21}\eta_1 + \epsilon_2}$	$x_2 = \lambda_2\xi_1 + \delta_2$	$\eta_1 = \beta_{12}\eta_2 + \zeta_1$
$\mathbf{y_3 = \lambda_{31}\eta_1 + \epsilon_3}$	$x_3 = \lambda_3\xi_1 + \delta_3$	$\eta_1 = \beta_{12}(\gamma_2\xi_1 + \zeta_2) + \zeta_1$
$\mathbf{y_4 = \lambda_{42}\eta_2 + \epsilon_4}$		
$\mathbf{y_5 = \lambda_{52}\eta_2 + \epsilon_5}$		
$\mathbf{y_6 = \lambda_{62}\eta_2 + \epsilon_6}$		

3. Modeling of Hypothesis III

The third and last hypothesis is an explorative hypothesis, which concise of several hypothesis combined. The studies used in this explorative hypothesis states that resilience level has a positive effect on courage and optimism in handling stress and maintaining academic performance, while stress level is affected by one's academic performance [13],[14],[15]. Based on the statement in that research, it is hypothesized that resilience has a direct effect on academic performance and stress, academic performance has direct effect on stress, and resilience also has an indirect effect towards stress through academic performance:

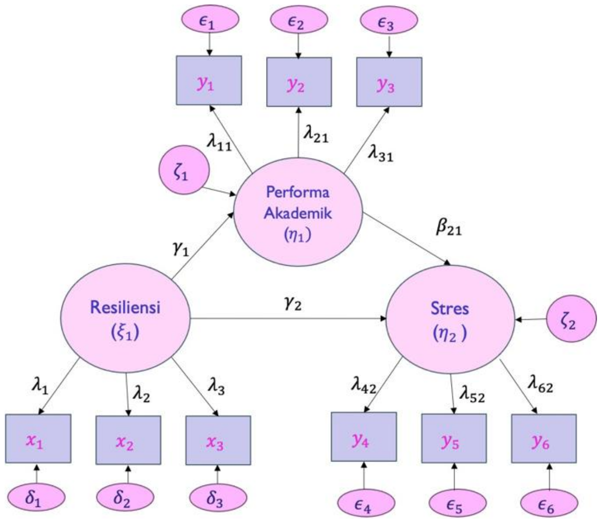

Figure 3. Model Illustration for Hypothesis III

The model above shows that resilience acts as the exogenous latent variable, while academic performance and stress are the endogenous latent variables. Therefore, the measurement and structural equation that is formed is as follow:

Table 3. Equations in Hypothesis III

Observed Endogenous Variables	Observed Exogenous Variables	Latent Endogenous Variable
$\mathbf{y_1 = \lambda_{11}\eta_1 + \epsilon_1}$	$x_1 = \lambda_1\xi_1 + \delta_1$	$\eta_1 = \gamma_1\xi_1 + \zeta_1$
$\mathbf{y_2 = \lambda_{21}\eta_1 + \epsilon_2}$	$x_2 = \lambda_2\xi_1 + \delta_2$	$\eta_2 = \gamma_2\xi_1 + \beta_{21}\eta_1 + \zeta_2$
$\mathbf{y_3 = \lambda_{31}\eta_1 + \epsilon_3}$	$x_3 = \lambda_3\xi_1 + \delta_3$	$\eta_2 = \gamma_2\xi_1 + \beta_{21}(\gamma_1\xi_1 + \zeta_1) + \zeta_2$
$\mathbf{y_4 = \lambda_{42}\eta_2 + \epsilon_4}$		
$\mathbf{y_5 = \lambda_{52}\eta_2 + \epsilon_5}$		
$\mathbf{y_6 = \lambda_{62}\eta_2 + \epsilon_6}$		

3. RESULTS AND DISCUSSION

An Exploratory Factor Analysis (EFA) model is also explored along with the three CFA model which are stated before. In this section, the best model will be discussed thoroughly, here are the result from the best model in EFA and CFA:

3.1 Confirmatory Factor Analysis

In confirmatory factor analysis, models are hypothesized based on the previous studies as stated before. Based on the evaluation metrics, the first hypothesis which states that resilience and stress have effect towards academic performance but the two has no effect towards each other has shown the best result, signifying it as the best model out of the three. This first model has the following result:

Table 4. Result for Model of Hypothesis I

		Measurement Model			
Latent Variabels	**Symbol**	***Loadings***	***z-value***	***p-value***	
Resilience (x_1)	λ_{11}	0.766	12.347	0.000	
Resilience (x_2)	λ_{21}	0.644	10.092	0.000	
Resilience (x_3)	λ_{31}	0.719	11.480	0.000	
Stress (y_4)	λ_{42}	0.620	9.069	0.000	
Stress (y_5)	λ_{52}	0.761	10.822	0.000	
Stress (y_6)	λ_{62}	0.681	9.851	0.000	
Performance (y_1)	λ_1	0.726	10.349	0.000	
Performance (y_2)	λ_2	0.868	11.407	0.000	
Performance (y_3)	λ_3	0.695	9.948	0.000	
		Structural Model			
Regression	**Symbol**	**Koefisien**	***z-value***	***p-value***	
Performance ~ Resilience	γ_1	0.667	6.895	0.000	
Performance ~ Stress	γ_2	0.180	2.578	0.010	
		Evaluation Metrics			
Chi – Square	25.151	df	25	*p-value*	0.454
RMSEA	0.005		90% CI = [0.000, 0.051]		
TLI			1.000		
AIC			4328.079		
BIC			4398.509		

The table above shows that all the measurement models are all significant, meaning all factors are significant in measuring the indicators. The loadings for the model have a minimum loading of 0.6, therefore it can be concluded that for each indicator, at least 36% of the variance of that item is explained by the corresponding latent variable. For example, take the performance indicator 3 (y_3), which is an indicator for Emotional Engagement defined in this study as how satisfied students are with their GPA, their ability to follow classes, and their willingness to help their classmates in group studies. Therefore, based on the positive loadings result of 0.695, it can be concluded that for every 1-unit standard deviation increase in academic performance, behavioral engagement will increase by 0.695 standard deviations of emotional engagement, and 48.3% of the variance in emotional engagement behavior is due to high academic performance. This represents the direct effect between the latent variable and its indicator.

The structural model, which shows the regression between latent variables are also significant, meaning stress and resilience are significant predictors for academic performance (η_1). The regressions show that both stress (ξ_2) and resilience (ξ_1) have positive relations towards academic performance. Resilience has a bigger influence towards academic performance than stress. The coefficient shows that a 1-unit increase in resilience will increase performance by $0.667(\gamma_1)$, while a 1-unit increase in stress level will increase academic performance by $0.18(\gamma_2)$. Which from table one, the regression equation results as $\eta_1 = 0.667\xi_1 + 0.18\xi_2 + \zeta_1$ showing direct positive effect between the two. The higher resilience level someone has, they will have more motivation and determination in achieving academic excellence. It may seem queer that stress and academic performance has a positive relation, but it can be explained by the effort and care one puts in their studies. Indicators for academic performance are defined by the care one shows in an academic setting, therefore those that shows carelessness would realistically be less stressful.

Looking at the regression, higher levels of stress are associated with higher or better academic performance. This does not imply that an increase in stress is a positive thing because it can improve academic performance. Instead, it indicates that individuals with good academic performance often have higher levels of stress because two of the academic performance indicators the first indicator (Behavioral Engagement) and the second indicator (Cognitive Engagement) reflect how much a student cares about their academic performance. The first indicator measures concern for regularly attending and following the material presented, while the second indicator is defined by the level of effort they put into projects and material comprehension. Therefore, students who do not care about their academic performance are unlikely to experience stress since there is no effort required.

On the other hand, high resilience can encourage a person to desire it. With high resilience, an individual will be more motivated to engage with the material (cognitive engagement and behavioral engagement), be more satisfied with their performance, and want to help/contribute to group discussions (emotional engagement). This is because high resilience motivates a person to strive harder while still appreciating themselves and valuing their classmates in discussions.

To delve further into this through indirect effects, taking the example of the first performance indicator (behavioral engagement). The equation from table 1, resulted in $y_1 = 0.726\eta_1 + \epsilon_1$ can also be written as $y_1 = 0.726(0.667\xi_1 + 0.18\xi_2 + \zeta_1) + \epsilon_1$. Thus, there are two indirect effects in this indicator:

- Through the indirect effect, each 1-unit increase in stress will increase academic performance by 0.18, which causes the loadings between stress and the behavioral engagement indicator to be 0.13 ($\lambda_1 * \gamma_2$). This shows that for every 1-unit standard deviation increase in stress, the standard deviation of the behavioral engagement indicator will increase by 0.13 or 1.69% of the variance in behavioral engagement, such as concern for attendance and class participation, where stress is the factor. Therefore, stress, in improving academic performance, encourages individuals to be more active in class.
- Through the indirect effect, each 1-unit increase in resilience will increase academic performance by 0.667, which causes the loadings between resilience and the behavioral engagement indicator to be 0.484 ($\lambda_1 * \gamma_1$). This shows that for every 1-unit standard deviation increase in resilience, the standard deviation of the behavioral engagement indicator will increase by 0.484 or 23.04% of the variance in behavioral engagement, such as concern for attendance and class participation, where resilience is the factor. Therefore, the nature of resilience or the desire to improve academic performance encourages individuals to be more active in class.

This also applies to other performance indicators, while observed variables from exogenous latent variables only have direct effects influencing them.

The evaluation metrics shown by the table above proves that the model is significant in representing the data. The chi-square test concludes that the null hypothesis which states that estimations are equal to data is accepted, meaning the first model is well fitted. This is also reflected by the small RMSEA or error value of 0.005, it can be 90% confidently said that the error value lies between 0 and 0.05. The model is also has been 100% improved from the baseline model based on the TLI result, which is quite a high improvement. Furthermore, the AIC and BIC both shows the lowest value amongst the other two hypothesis, showing that this first model is the one that is closest to its true model.

3.2 Exploratory Factor Analysis

In exploratory factor analysis, there are no restriction set in the model. The number of factors or latent variables are not determined before modeling and every variable can be freely corelated with each other. In this study, EFA is used to validate the model in CFA by proving the indicators has been correlated correctly with the latent variables. It will also show which of the latent variables are highly correlated. In EFA, the number of factors in a dataset can be determined from a scree plot. The data in this study shows that the ideal number of factors are between three or four. Based on the variances and communalities shown, it is concluded that the three-factor model is better than the four-factor model. The table below is the EFA result of a three-factor model extracted with maximum likelihood estimation and the factors are rotated with oblique Promax rotations:

Table 8. Result EFA with 3 Factors

	Loadings		
Indicators	**Factor 1**	**Factor 2**	**Factor 3**
S1	0.016	0.095	0.609
S2	0.012	-0.052	0.760
S3	-0.006	-0.050	0.694
R1	-0.042	0.827	-0.030
R2	-0.025	0.665	0.007
R3	0.128	0.602	-0.039
P1	0.651	0.080	0.079
P2	0.839	0.022	0.050
P3	0.779	-0.065	-0.114
	Variances		
	Factor 1	**Factor 2**	**Factor 3**
SS Loadings	1.753	1.514	1.453

Proportion Var	0.195	0.168	0.161
Cumulative Var	0.195	0.363	0.524
Factor Correlations			
	Factor 1	**Factor 2**	**Factor 3**
Factor 1	1.000	-0.1455	-0.641
Factor 2	-0.145	1.000	0.0207
Factor 3	-0.641	0.0207	1.000
Chi-Square **8.02** ***on*** **12** ***degree of freedom***, ***p-value*** **= 0.783**			

The rotated loadings of the model shows that each observed variables have been categorized exactly as how it is hypothesized in the CFA model. It is shown that the three corresponding indicators for stress have formed a factor, the same can be said for the indicators of resilience and academic performance.

The variance and communalities in the model show that three factors are the ideal number of factors, proven by the SS loadings. The result shows that all three factors have a value of above 1, signifying that all three factors are strong enough. The proportion variance shows how much of the dataset variance is explained by each factor. Each factor explains 16%-19% of the variance in the dataset. While the cumulative proportion result shows that 52.4% of the variance in the dataset can be explained by the three factors.

The factor correlations shows that the factor with the strongest correlations is the one between the first factor and the third factor. This shows that the factor stress and academic performance are the two factors with the highest correlation. The two has a negative correlation, meaning the more stressed a student will affect negatively on their academic performance and vice versa. Which differentiates from the structural regression result in the CFA model.

4. CONCLUSION

The evaluation results from the CFA show that the first and third hypotheses are the models that passed the chi-square test, with the first model being the best model, while the second model is the worst. This is evident from the chi-square test statistic values, where the first model has the lowest value, followed by the third model, and the second model has the highest value. This indicates that the first model has the smallest difference between the data and the estimated results compared to the other models. Additionally, the first model also shows the smallest RMSEA, AIC, and BIC values, indicating the least error. The TLI results show that the first model has the highest improvement from the baseline model. The first model hypothesis states that resilience and stress directly affect academic performance but are not related to each other. The regression results of the first model show that resilience has a greater impact on academic performance than stress. However, all three hypothesized models still failed the chi-square test with p-values less than alpha.

The EFA results indicate that the appropriate number of factors according to the scree plot is between 3 or 4. Although both models passed the statistical test with chi-square, after further analysis, the loadings and proportion variance values show that the model with 3 factors is better. The EFA results with 3 factors show that each factor has 3 indicators that correspond to the hypotheses conducted in the CFA for each factor. These results reinforce the CFA results in the measurement model section for the previous three models. Additionally, the correlation between factors through EFA with 3 factors shows that the largest correlation is between the resilience factor and the performance factor, followed by the stress factor and the performance factor, while the correlation between the stress factor and the performance factor is the smallest with a value below 0.1. This also strengthens the CFA results in the structural model section for the three hypotheses and proves that the first hypothesis is the most appropriate among the three.

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