

Application of PLS-SEM in analyzing Mathematical Statistics II course online learning

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Abstract. The impact of the COVID-19 pandemic on the education sector includes the learning system that cannot be conducted offline. With the change in the learning system, it is necessary to analyze whether the implemented online learning system can run well and provide the expected results. The level of student satisfaction is one of the factors that can be used to analyze online learning. This study analyzed the student satisfaction level with online learning for the Mathematical Statistics II course at the Mathematics Department, Andalas University, related to the quality of lecture services and the level of student understanding. Data analysis was performed using causal a model, namely Partial Least Square Structural Equation Modeling (PLS-SEM). By using The PLS-SEM, it is known that there is a significant and positive effect between service quality on student satisfaction in the Mathematical Statistics II course. In addition, the service quality also affects the understanding level significantly and positively. However, the level of student understanding has no significant effect on the level of student satisfaction. The coefficient of determination (R^2) of the structural model of student satisfaction with online learning for the Mathematical Statistics II course is 0.774. This value indicates that the resulting model is good because it has relatively high accuracy.

Keywords: Mathematical Statistics II, PLS-SEM, Student satisfaction level

INTRODUCTION

Education is one sector of human life that has been dramatically affected by the COVID-19 pandemic. To prevent the spread of COVID-19, educational institutions are expected to no longer carry out the usual learning process. Online learning methods replace every teaching and learning activity [1,2]. This is in line with the letter of the Minister of Education and Culture of the Republic of Indonesia number 3 of 2020 regarding the prevention of Corona Virus Disease (COVID-19) by working from home and studying online [3].

Online learning is highly dependent on various components of learning, such as students, educators, resources, and technology support [4]. At the university level, the collaboration between lecturers and students is very important to optimize online learning. With the change in the learning system, it is necessary to analyze whether the online

learning system applied can run well and provide the expected results. This can be done by analyzing student satisfaction with the online learning that they take [5].

Student satisfaction can be defined as a function of the relative level of experiences and perceived performance of educational service during the study period [6]. Student satisfaction is one of the benchmarks for the quality of online learning. In addition, the level of satisfaction can indicate whether students enjoy the online learning process [7]. The factors influencing student satisfaction are the student understanding level and the service quality provided by the lecturer. Student Understanding Level is a form of a statement of learning outcomes [8]. Students' understanding of new information is actually integrated into the student's existing knowledge schemes [9]. Service quality is the result of a comparison between expectations and perceptions of performance [10]. Service quality is very important for universities to be able to provide a good service performance system. The role of service quality on student satisfaction must be considered as part of public service [11]. Good service quality will have a positive impact on student satisfaction and be able to improve

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student performance in the learning process [5]. As stated in [12] and [13], the high service quality will result in a high level of consumer satisfaction as well. Thus, student satisfaction as consumers is influenced by the quality of services provided by higher education institutions (universities), especially lecturers as service providers.

The level of satisfaction is difficult to measure because it is abstract, complex, and cannot be observed directly. However, the Structural Equation Modeling (SEM) analysis method allows us to measure the satisfaction level indirectly through indicators that can represent it [14].

There are two approaches to SEM analysis. Covariance Based Structural Equation Modeling (CB-SEM) and Partial Least Square Structural Equation Modeling (PLS-SEM). The CB-SEM approach requires some assumptions on the data, such as a large sample size (minimum 200) [15]. As an alternative to the CB-SEM approach, the PLS-SEM approach tends to be more flexible. This approach can be used on data with small sample sizes (less than 100) and can be used on not normally distributed data [14].

This study analyzes student satisfaction in the Mathematical Statistics course as one of the fields of the Undergraduate Mathematics Study Program. Mathematical Statistics is an interesting subject where students will be able to apply statistical probability inference and mathematical theory. However, students often see this subject as one of the most challenging subjects [16].

In the Undergraduate Mathematics Study Program at Andalas University, Mathematical Statistics is divided into two courses, Mathematical Statistics I and Mathematical Statistics II. Mathematical Statistics I is a compulsory subject in the fourth semester. Initially, it was done offline in the even semester of 2019/2020, but due to the COVID-19 pandemic since March 2020, it was done online. Furthermore, the Mathematical Statistics II course is a compulsory subject for fifth semester students. In the odd semester 2020/2021, it was carried out thoroughly with an online system. This study is focused on Student Satisfaction Analysis. In this study, the number of observations used is quite small (< 100) with data that is not normally distributed, so the PLS-SEM method will be used to analyze student satisfaction with online learning for the Mathematical Statistics II course.

METHODOLOGY

Data

The data in this study are primary data obtained by distributing questionnaires to students of the Mathematics Department of Andalas University who took the Mathematical Statistics II course in the odd semester of 2020/2021. The questionnaire was submitted via google form to 98 students as respondents.

Variables and Hypothetical Model

There are two types of variables used in this study, namely latent variables and indicator variables. Each indicator variable in this study was measured through several questions with a Likert scale of 1-5. This study contains one exogenous latent variable, namely Service Quality and two endogenous latent variables, namely the Understanding Level and the Student Satisfaction Level.

The latent variable of Service Quality is the quality of services provided by lecturers. The latent variable of Service Quality (Y1) measured using the four following indicators :

- Service Time (X1), this variable is formed based on student's assessments of the lecture time, the time provided by the lecturer for discussion (scheduled or not) and the time provided by the lecturer to collect assignments.
- Learning Media (X2), this variable is formed based on student assessments of the lecture quality held by lecturers through WhatsApp/telegram/iLearning discussion forums, both synchronously and asynchronously, online meetings and discussions as well as assessments related to the media used.
- Learning Materials (X3), this variable is formed based on student assessments of the learning materials quality provided by lecturers during online learning in textbooks, modules/handouts, presentation slides, audio, and video.
- Lecturers Readiness and Mastery (X4), This variable is formed based on student assessments of the lecturers quality in preparing and delivering materials and the quality of assignments given by lecturers.

The latent variable Understanding Level is how well new information is actually integrated into the student's existing knowledge schemes. The latent variable Understanding Level (Y2) is measured using the two following indicators:

- Understanding of the learning materials (X5)
- Understanding of the lecturer's explanations (X6)

The latent variable of Satisfaction Level is student experiences and ability to enjoy the educational service during the study period. The latent variable of Satisfaction Level (Y3) is measured using the three following indicators :

- The satisfaction level with the lecturer's explanation (X7)
- The satisfaction level with the task discussion (X8)
- The satisfaction level with learning feedback/grading (X9)

Based on the latent variables and indicators used, the hypothetical model in this study can be seen in Figure 1.

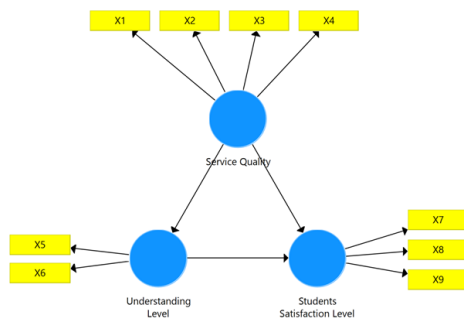


Figure 1. Hypothetical model of students satisfaction level

Structural Equation Modeling (SEM)

SEM is a multivariate analysis method that describes the simultaneous linear relationship between observed variables (indicators) and variables that cannot be observed directly (latent variables), as well as the relationship between latent variables and other latent variables [17]. SEM plays a variety of important roles, including simultaneous equation system, linear causal analysis, path analysis, covariance structure analysis, and structural equation modeling. There are several things that distinguish SEM from other multivariate analysis. SEM requires more than just a statistical tool that is based on ordinary regression and analysis of variance. Data analysis using SEM serves to explain the relationship between variables in the research as a whole [18].

SEM is a combination of two statistical methods, factor analysis and simultaneous equation modeling. The most obvious difference between SEM and other multivariate techniques is the separate relationship in the use of each set of independent variables.

There are two approaches in SEM, namely Covariance Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). CB-SEM can be used when the sample size is large, and the data has a normal distribution. In contrast, PLS-SEM can be used when the sample size is small, and the data are not normally distributed [19].

There are two types of variables in SEM, namely indicator variables and latent variables. Indicator variables are variables that can be observed directly. This variable is used as a measure of the latent variable. Latent variables are variables that cannot be observed directly. There are two types of latent variables, namely exogenous latent variables and endogenous latent variables. Exogenous latent variables are latent variables that affect a latent variable in the model and are not influenced by other latent variables in the model. Endogenous latent variables are latent variables that are influenced by other latent variables in the model. This variable can also affect other endogenous latent variables in the model [14].

There are two kinds of models in SEM. The measurement model and the structural model [14]. The measurement model is a model that describes the relationship between latent variables and indicator variables. The measurement model is generally written as in the equations (1) and (2) [18].

$$x = \lambda_x \zeta + \delta \quad (1)$$

$$y = \lambda_y \eta + \varepsilon \quad (2)$$

Where :

x : vector of indicator variables of exogenous latent variables

y : vector of indicator variables of endogenous latent variables

λ_x : outer loadings matrix of exogenous latent variables and the corresponding indicators

λ_y : outer loadings matrix of endogenous latent variables and the corresponding indicators

ζ : exogenous latent variable vector

η : endogenous latent variable vector

δ : indicator variable error vector of exogenous latent variable

ε : indicator variable error vector of endogenous latent variable

Structural model is a model that describes the relationship between latent variables. In general, the structural model equations can be seen in equation (3) [18].

$$\eta = B\eta + \Gamma\zeta + \zeta \quad (3)$$

Where :

η : endogenous latent variable vector

B : endogenous latent variable coefficient matrix
 ζ : exogenous latent variable vector
 I : exogenous latent variable coefficient matrix
 ζ : error vector

Partial Least Squares Structural Equation Modeling (PLS-SEM)

PLS-SEM is a SEM approach that aims to test the predictive relationship between latent variables by looking at the relationship between the latent variables [14]. In PLS-SEM, the latent variable is denoted by Y , and the indicator variable is denoted by X . Illustration of the PLS-SEM components is shown in Figure 2.

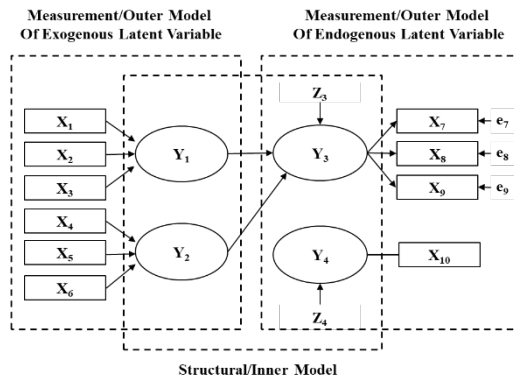


Figure 2. PLS-SEM Path Diagram

In Figure 2, an oval represents the latent variable (Y_1 to Y_4), and a square represents the indicator variable (X_1 to X_{10}). Y_1 and Y_2 are exogenous latent variables, Y_3 and Y_4 are endogenous latent variables, and X_1 to X_{10} are indicator variables. In PLS-SEM, the latent variables and indicator variables are linked by single-headed arrows [14].

PLS-SEM Model Estimation

There are two stages of estimation in PLS-SEM. Stage 1 estimates the value of the latent variable, and stage 2 estimates the outer loading and path coefficient [20].

Stage 1 : Estimating the value of the latent variable. The value of the latent variable will be estimated through iteration. One iteration consists of four steps. The iteration is running until it reaches the convergence limit.

Step 1.1: Outer Approximation

$$Y_j = \sum_{h=1}^k x_{jh} \tilde{w}_{jh} \quad (4)$$

Where :

Y_j : initial estimation value vector of j -th latent variable

x_{jh} : matrix that contains column vector of k indicator of j -th latent variable

$\tilde{w}_{jh}$: outer weight estimation value vector of the j -th latent variable with k indicator (for the first iteration, $\tilde{w}_{jh}$ initialized as a column vector with entries of 1)

Step 1.2: Inner Approximation

$$Z_j = \sum_{i=1}^m Y_i e_{ij} \quad (5)$$

Where :

Z_j : initial estimation value vector of latent variable Y_i that related with latent variable Y_j

e_{ij} : inner weight value vector, which a correlation of related Y_i and Y_j

m : the number of Y_i that related to Y_j

Step 1.3: Updating Outer Weight

Outer weight ($\tilde{w}_{jh}$) estimation consists of two, outer weight estimation for reflective models in equation (6) and outer weight estimation for formative models in equation (7).

$$\tilde{w}_{jh} = \text{cor}(X_{jh}, Z_j) \quad (6)$$

$$\tilde{w}_{jh} = (X_{jh}^T X_{jh})^{-1} X_{jh}^T Z_j \quad (7)$$

Step 1.4: Convergence Examination

$$|\tilde{w}_{jh}^s - \tilde{w}_{jh}^{s-1}| < 10^{-7} \quad (8)$$

$\tilde{w}_{jh}^s$ and $\tilde{w}_{jh}^{s-1}$ is the outer weight estimation of h -th indicator on the j -th latent variable at the s -th and $(s-1)$ -th iteration. If the outer weight value has met the convergence limit as in equation (8), the iteration is stopped. Furthermore, the estimated value of each latent variable is obtained as in equation (9).

$$Y_j = \sum_{h=1}^k X_{jh} \tilde{w}_{jh} \quad (9)$$

If it does not meet the convergence limit, the iteration is repeated from Step 1.1 to Step 1.4 until it meets the convergence limit.

Stage 2 : Estimating the outer loading value and the path coefficient. Estimating the outer loading value of the h -indicator on the j -latent variable is done by looking for the correlation of latent variables and indicators as in equation (10).

$$\hat{\lambda}_{jh} = \text{cor}(Y_j, X_{jh}) \quad (10)$$

In the structural model, the path coefficient value is estimated using Ordinary Least Squares (OLS) by minimizing the sum squares of the residuals. The general equation of the structural model with the endogenous latent variable Y_j

and the exogenous latent variable Y_i is written as in equation (11).

$$Y_j = Y_i\beta + \zeta \quad (11)$$

where β is the path coefficient vector, and ζ is the residual vector. Path coefficient estimation for Y_j is presented in equation (12).

$$\beta = (Y_i^T Y_i)^{-1} Y_i^T Y_j \quad (12)$$

provided $(Y_i^T Y_i)^{-1}$ exists.

RESULTS AND DISCUSSION

Respondent Characteristics

Respondents in this study were students of the Mathematics Department of Andalas University who took the Mathematical Statistics II course in the odd semester of 2020/2021. Figure 3 shows the characteristics of the respondents based on the year of entry.

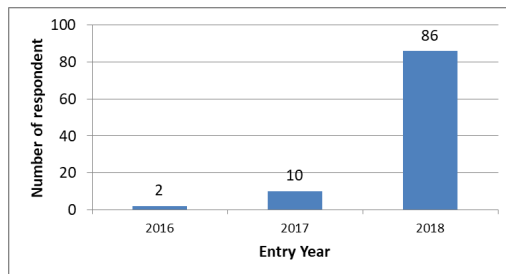


Figure 3. Description of respondents by entry year.

Based on Figure 3, it can be seen that most of the respondents in this course were from the class of 2018 with 86 respondents, followed by the class of 2017 with 10 respondents, and the class of 2016 with 2 respondents. This happened because the Mathematical Statistics II course is a mandatory course that must be taken by the class of 2018 students in the odd semester of 2020/2021. Meanwhile, for other respondents, their participation in the Mathematical Statistics II course in 2020/2021 odd semester was the second or more.

Descriptive Statistics of Service Quality Indicators

The latent variable Service Quality is measured by four indicators that are Service Time (X1), Learning Media (X2), Learning Materials (X3), Lecturers Readiness and Mastery (X4). The descriptive statistics for each indicator of service quality is presented in Table 1.

Based on Table 1, it can be seen the student's rating of each Service Quality indicator is good on average. Learning Media (X2) and Learning Materials (X3) have the lowest average value of the four indicators. This is understandable because it is necessary to adapt

to the learning media and teaching materials used in the online learning system.

Table 1: Descriptive Statistics of Service Quality Indicators

	Indicator			
	X1	X2	X3	X4
Minimum Value	2	1.8	2	2
Maximum Value	5	5	5	5
Average	4.3	4.3	4.3	4.4
Standard Deviation	3	1	1	3
	0.5	0.5	0.6	0.5
	9	7	0	6

Descriptive Statistics Indicator Level of Understanding

The latent variable Understanding Level (Y2) is measured using the two indicators, Understanding of the learning materials (X5) and Understanding of the lecturer's explanations (X6). The descriptive statistics of each indicator are presented in Table 2.

Table 2: Descriptive Statistics Indicator Level of Understanding

	Indicator	
	X5	X6
Minimum Value	2.4	3
Maximum Value	5	5
Average	3.98	4.24
Standard Deviation	0.54	0.58

Based on Table 2, it can be seen that, on average, the student's rating of each indicator of the Understanding Level is lower than the indicator of Service Quality. Thus, it is suspected that the student understanding level of the online learning system is lower than the face-to-face learning system.

Descriptive Statistics of Student Satisfaction Level Indicators

The satisfaction level with the lecturer's explanation (X7), the satisfaction level with the task discussion (X8), the satisfaction level with learning feedback/grading (X9) are indicators that are used to measure the latent variable Students Satisfaction Level. Table 3 presents

descriptive statistics for each of these indicators.

Table 3: Descriptive Statistics of Student Satisfaction Level Indicators

	Indicator		
	X7	X8	X9
Minimum Value	2	2	2
Maximum Value	5	5	5
Average	4.46	4.09	4.18
Standard Deviation	0.66	0.80	0.76

Based on Table 3, it can be seen that the indicator satisfaction level with the task discussion (X8) has the lowest average. This may be caused by the limitations in online learning that the lecturer's performance is less optimal in providing discussions on the tasks given.

Parameters Estimation

At the initial stage, parameters estimation of the student satisfaction model is made based on the hypothetical model that has been formed. In Figure 4, the path diagram with coefficient values and outer loading are obtained using the student version of SmartPLS 3 v.3.2.9 software (open source).

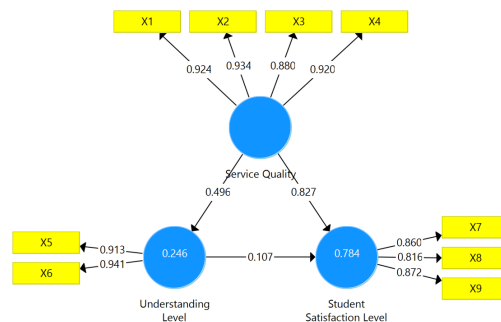


Figure 4. Student Satisfaction Level Model Path Diagram

Based on Figure 4, it is assumed that the variable student satisfaction level with online learning (Y3) is influenced by Service Quality (Y1) and Level of Understanding (Y2). The three latent variables are measured by the corresponding indicators as previously described. This model will be evaluated based on the measurement and the structural model evaluation.

Measurement Model Evaluation

In this study, the measurement model (outer model) is reflective in connecting the indicator

variable with the latent variable. In the reflective measurement model, the evaluation is carried out based on the criteria of convergent validity, internal consistency reliability, and discriminant validity.

a. Internal Consistency Reliability

Internal consistency reliability shows the indicator reliability in measuring its latent variables. In this study, the internal consistency reliability was tested using Cronbach alpha and composite reliability criteria. The latent variable is said to have good internal consistency reliability if it has a Cronbach alpha value of 0.80 and composite reliability value of 0.70 [14]. Table 4 represents the Cronbach alpha and composite reliability values for each latent variable.

Table 4: Cronbach Alpha and Composite Reliability

Latent Variable	Cronbach Alpha	Composite Reliability
Service Quality (Y1)	0.935	0.954
Understanding Level (Y2)	0.837	0.924
Student Satisfaction Level (Y3)	0.807	0.886

Table 4 shows that each latent variable in the model has a Cronbach alpha of more than 0.80 and composite reliability of more than 0.70. Based on the value of Cronbach alpha and composite reliability, it can be concluded that the latent variable has good internal consistency reliability.

b. Convergent Validity

The convergent validity test aims to show how well the results from a measurement with the theories used to define a latent variable. An indicator variable is said to have good convergent validity if the outer loading (λ) is more than 0.7 so that the variable can be maintained in the model. On the other hand, indicators that have an outer loading (λ) between 0.40 and 0.70 can be considered whether or not to be removed from the model. If the composite reliability value (ρ_c) and the extracted average value (AVE) have reached the recommended limits ($\rho_c \geq 0.7$ and $AVE \geq 0.5$), then the indicator with an outer loading value between 0.40 and 0.70 can be maintained in the model [14]. Outer loading for each latent variable is presented in Table 5.

Table 5: Outer Loading

Latent Variable	Indicator	Y1	Y2	Y3	Validity
Service Quality (Y1)	X1	0.924			Valid
	X2	0.934			Valid
	X3	0.880			Valid
	X4	0.920			Valid
Understanding Level (Y2)	X5		0.913		Valid
	X6		0.941		Valid
Student Satisfaction Level (Y3)	X7			0.860	Valid
	X8			0.816	Valid
	X9			0.872	Valid

Based on Table 5, it can be seen that all indicator variables have an outer loading of more than 0.7. This means that the variable has good convergent validity, and the variable can be maintained in the model.

c. Discriminant Validity

A discriminant validity test is conducted to test whether the latent variable is unique/single and able to explain all phenomena that cannot be explained by other latent variables in the model. Suppose the outer loading between the latent variable and the indicator is greater than the other latent variables. In that case, it indicates that the indicator variable is better at measuring the latent variable [14]. The cross loading of latent variables with each indicator is presented in Table 6.

Table 6: Cross Loading

Latent Variable	Indicator	Y1	Y2	Y3	Validity
Service Quality (Y1)	X1	0.924	0.442	0.777	Valid
	X2	0.934	0.419	0.773	Valid
	X3	0.880	0.465	0.812	Valid
	X4	0.920	0.484	0.852	Valid
Understanding Level (Y2)	X5	0.408	0.913	0.437	Valid
	X6	0.503	0.941	0.516	Valid
Student Satisfaction Level (Y3)	X7	0.827	0.447	0.860	Valid
	X8	0.668	0.430	0.816	Valid
	X9	0.736	0.441	0.872	Valid

In Table 6, the outer loading of the Service Quality (Y1) with the X1 indicator is 0.924, which is greater than the outer loading of X1 with the Understanding Level (Y2) and Student Satisfaction Level (Y3). This also applies to the other latent variable and its corresponding indicator. This means that the outer loading of the latent variable and the

corresponding indicator is greater than the other latent variables, which indicates that the latent variable is better at measuring the block/indicator.

From the measurement model analysis, the equation of the measurement model is obtained as follows:

$$X1 = 0.924Y1 + e_1$$

$$X2 = 0.934Y1 + e_2$$

$$X3 = 0.880Y1 + e_3$$

$$X4 = 0.920Y1 + e_4$$

$$X5 = 0.913Y2 + e_5$$

$$X6 = 0.941Y2 + e_6$$

$$X7 = 0.860Y3 + e_7$$

$$X8 = 0.816Y3 + e_8$$

$$X9 = 0.872Y3 + e_9$$

Structural Model Evaluation

This evaluation aims to develop the relationship model between latent variables. The criteria in this evaluation are path coefficient, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

a. Path Coefficient

The path coefficient has a standardized value that ranges between -1 and +1 (the value can be smaller or larger but usually revolves around this value). The path coefficient close to +1 indicates a strong positive relationship, and if the value close to -1 indicates a robust negative relationship which is usually statistically significant. The closer to 0 it indicates the weak relationship in the construct [14].

The significance of the path coefficient between latent variables can be seen from the p-value and |t-empirical| value obtained through the bootstrapping procedure. The path coefficient is assumed to be significant if the p-value ≤ 0.05 and the |t-empirical| ≥ 1.96 at the significant level $\alpha = 0.05$. In Table 7, the path coefficient values, p-values, and |t-empirical| values from the bootstrapping procedure are presented.

Table 7: Path Coefficient Significance Analysis

Path	Path Coefficient	p-values	t-empirical	Significance
Y1 → Y2	0.496	0.001	3.447	Significant
Y1 → Y3	0.827	0.000	15.369	Significant
Y2 → Y3	0.107	0.064	1.856	Nonsignificant

From Table 7, it can be seen that the path of the Understanding Level (Y2) to the Student Satisfaction Level (Y3) has a p-value of 0.064

≥ 0.05 and $|t\text{-empirical}|$ of $1.856 < 1.96$. This path is not statistically significant, so it will be eliminated as in Figure 5.

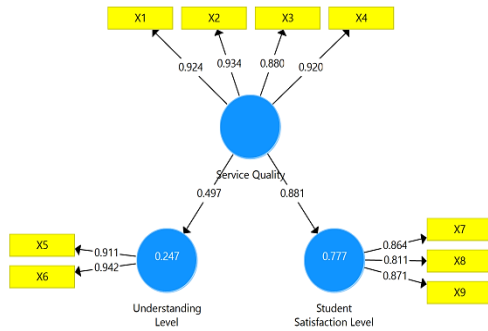


Figure 5: Path Diagram after Path Elimination

In Table 8, the path coefficient values, p-values, and $|t\text{-empirical}|$ values after eliminating nonsignificant paths are presented.

Table 8: Path Coefficient Significance Analysis after Path Elimination

Path	Path Coefficient	p-values	$ t\text{-empirical} $	Significance
Y1 $\rightarrow$ Y2	0.497	0.000	3.676	Significant
Y1 $\rightarrow$ Y3	0.881	0.000	34.977	Significant

From Table 8, it can be seen that the path coefficient from the path of the Service Quality variable (Y1) and the Student Satisfaction Level (Y3) is 0.881 with a p-value of $0.000 \leq 0.05$ and $|t\text{-empirical}|$ of $34.977 \geq 1.96$ at significance level $\alpha = 0.05$. It can be concluded that there is a significant effect of the Service Quality (Y1) on the Student Satisfaction Level (Y3). The two variables have a positive relationship which indicates the better the Service Quality (Y1), the higher the Student Satisfaction Level (Y3).

The path coefficient of the Service Quality (Y1) and the Understanding Level (Y2) is 0.497 with a p-value of $0.000 \leq 0.05$ and $|t\text{-empirical}|$ of $3.676 \geq 1.96$. It can be concluded that there is a significant effect of the Service Quality (Y1) on the Understanding Level (Y2), and it has a positive relationship which indicates the better the Service Quality (Y1), the higher the Understanding Level (Y2).

b. Coefficient of Determination (R^2)

This coefficient measures the model's ability to predict the correlation between certain endogenous latent variables and the predicted values. The value of R^2 ranges from 0 to 1. A higher value indicates a higher predictive

accuracy of structural models [14]. Table 9 presents the coefficient of determination (R^2) for each endogenous latent variable in the model.

Table 9: Coefficient of Determination

Endogenous Latent Variable	R^2
Y2 (Understanding level)	0.247
Y3 (Satisfaction Level)	0.777

Based on Table 9, the value of R^2 for the Student Satisfaction Level (Y3) is 0.777. This means that the 77.7% Student Satisfaction Level (Y3) variance can be explained by the Service Quality (Y1). This value indicates that Service Quality can explain Satisfaction Level well. The value of R^2 for the Understanding Level (Y2) is 0.247. This means that the 24.7% Understanding level (Y2) variance can be explained by the Service Quality (Y1). This value is relatively low, so it can be said that Service Quality does not have a good performance to explain the Understanding Level. It is suspected that there are other things outside of service quality that can also affect the understanding level, including the level of student adaptation to the online learning system.

c. Effect Size (f^2)

Effect Size (f^2) is used to observe the relationship effect of each exogenous latent variable on the endogenous latent variable in the model. The greater the f^2 the greater the effect [20]. In Table 10, the f^2 value of each exogenous latent variable on its endogenous latent variable is presented.

Table 10: Effect Size

Endogenous Latent Variable	f^2
Y1 $\rightarrow$ Y2	0.327
Y1 $\rightarrow$ Y3	3.483

From Table 10, it can be seen that the f^2 of the causal relationship of the Service Quality variable (Y1) to the Student Satisfaction Level (Y3) is $3.483 \geq 0.35$. Based on the effect size criteria, it can be concluded that Service Quality (Y1) has a large effect on the Student Satisfaction Level (Y3). The causal relationship of the Service Quality (Y1) to the Understanding Level (Y2) has f^2 of 0.327, which is in the interval of 0.15 and 0.35. Based on the effect size criteria, the Service Quality (Y1) has a moderate effect on the latent variable Understanding Level (Y2).

d. Predictive Relevance (Q^2)

Predictive relevance (Q^2) is used to measure how well the model and the parameter estimates produce the observed values. The value of Q^2 ranges from 0 to 1, where the closer to 1, the better the model and has good predictive relevance. On the other hand, the value of Q^2 , close to 0, indicates that the model does not have a good predictive relevance [14].

Because there is only one endogenous latent variable in the structural model between the Student Satisfaction Level (Y3) and the Service Quality (Y1), the (Q^2) is the same as the (R^2), which is 0.777. This value is close to 1, which means that the structural model has good predictive relevance.

Based on the results of the analysis, the structural model equations are obtained as in equations (13) and (14).

$$Y2 = 0.497Y1 + Z_1 \quad (13)$$

$$Y3 = 0.881Y1 + Z_3 \quad (14)$$

From equation (13), the latent variable of Service Quality (Y1) has a positive effect on the latent variable of Understanding Level (Y2). The better the Service Quality (Y1), the higher the Understanding Level (Y2) of students in the Mathematical Statistics II course. Furthermore, from equation (14), the Service Quality (Y1) has a positive effect on the Student Satisfaction Level (Y3), which indicates that the better the Service Quality (Y1), the higher the Student Satisfaction Level (Y3).

CONCLUSION

This study analyzed the level of satisfaction of students of the Mathematics Department of Andalas University who took the Mathematical Statistics II course in the odd semester of 2020/2021. This course is implemented using an online learning system as the impact of the COVID-19 pandemic.

Data analysis was conducted using PLS-SEM. Based on the structural model, it can be concluded that the latent variable of Service Quality has a positive effect of 0.497 on the Understanding Level. Furthermore, it is known that Service Quality has a positive effect of 0.881 on the Student Satisfaction Level. However, the level of student understanding has no significant effect on the level of student satisfaction. It can be used as material for further study because it is suspected that understanding the material is

not an important orientation for some students with this online learning system.

Based on these results, the service quality in online learning needs to be continuously improved to increase the level of student understanding and student satisfaction. The coefficient of determination (R^2) from the structural model in the Mathematical Statistics II course is 0.777. This value indicates that the resulting model is good because it has a fairly high level of accuracy.

Andalas University and lecturers can prioritize making improvements to the quality of services provided to students and their indicators so as to increase the level of student satisfaction with online learning. For further research, the authors suggest defining other latent variables that have a more significant effect on the student satisfaction level with online learning.

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