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STRUCTURAL EQUATION MODELING FOR ANALYZING THE TECHNOLOGY ACCEPTANCE MODEL OF STUDENTS IN ONLINE TEACHING DURING THE COVID-19 PANDEMIC

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Abstract: Online teaching can be a solution in the learning process during the pandemic to stop the spreading of the Covid-19 infection. Universitas Negeri Makassar (UNM) as an educational institution provided a Learning Management System (LMS) to support the online teaching and learning process with the platform name SYAM-OK. In this research, we examine the behavioral model of a student's acceptance of the use of an information system SYAM-OK in online teaching. 120 students in the sample used online teaching fully during the pandemic. The data was obtained from an online questionnaire using a google form whose contents were based on Technology Acceptance Model (TAM). The variable of TAM consists of Perceived Ease of Use, Perceived Usefulness, Attitude Towards, Behavioral Intention, and Actual Use. The Structural Equation Modeling (SEM) PLS method was used in this research for modeling the relationship between TAM variables. Based on the results of the SEM we obtained that Perceived Usefulness significantly affects the Attitude Towards and Attitude Towards significantly affects the behavioral intention. By using the bootstrapping and T statistics, we conclude that SEM has identified the significant effects between variables of TAM.

1. INTRODUCTION

The Covid-19 pandemic since December 2019 has had a major impact on various fields, including the education sector. This pandemic forced countries all over the world to adopt emergency management mechanisms (Annas et al., 2020). The covid-19 pandemic motivated academic institutions and schools to online learning. Some researchers have developed a model of online teaching at the time of the Covid-19 Pandemic including lockdown (Sangeeta &Tandon, 2021; Yilmaz, 2022). The Indonesian government sets regulations to limit community activities that have the potential to make direct contacts, such as work from home (WFH), and online teaching. The letter with law number 4 of 2020 by the Ministry of Education and Culture (MOEC) explains that universities should not carry out face-to-face learning.

The existence of online teaching helps the learning process without the need for direct interaction so that it is effective learning (Hussein, 2017; Rahman, 2014). Some researchers have discussed the use of online teaching and how to adapt to new and different scenarios in normal or emergencies (Bao, 2018; Flores & Gago, 2020) and developing strategies for successful online teaching and learning (Burd et al., 2009; Pasch & Stewart, 2002).

Over time, technology in the world of education began to develop learning media. Indonesia has developed its educational technology as an innovation in increasing effectiveness in the teaching and learning process. A device used to carry out administrative purposes in teaching and learning activities is also called a Learning Management System (LMS). LMS is software that is used to create online learning materials and manage learning activities and results, which also has features that can meet the needs of users in terms of learning (Purwandari & Susena, 2022). Each educational institution can create and develop its own LMS with the desired facilities that can provide easy access to teaching and learning, as well as packaged in the form of multimedia. Since 2006, UNM Makassar has released an online learning system under the name learning.unm.ac.id. and August 19, 2020, UNM launched its LMS under the name "System Application Management of Open Knowledge" (SYAM-OK). SYAM-OK is a learning system that can be used online, blended, or fully online equipped with features for class creation, class management, material management, assessment activity management, and monitoring. These features are expected to provide convenience for students and lecturers in the lecture process.

The establishment of a new information system in an organization will affect the entire organization, especially its human resources. SYAM-OK as a new information system especially in online learning systems brings big hope for the convenience of students and lecturers in the learning process as expected. The success of the development of this information system including SYAM-OK is dependent on the level of user acceptance of the information system, in this research case students. One of the models to analyze the factors that influence the behavior of information technology users towards information technology is the Theory of Acceptance Model (TAM). TAM was first introduced by Fred D. Davis in 1986 which is an adaptation of the Theory of Reasoned Actional (TRA). Some researchers have expanded to find the progress of TAM (Aggorowati et al., 2012; Samat et al., 2020). TAM aims to explain the external factors of the behavior of information technology users on the acceptance of information technology itself. TAM is one of the models that analyze user behavior to accept and use new technology (Aggorowati *et al.*, 2012). TAM explains the development of technology from two main factors, namely perceived usefulness and perceived ease of use, and both will affect other variables in stages to actual use.

The previous research has discussed TAM in online teaching using SEM, but they have not implemented bootstrapping SEM PLS to model latent variables in TAM. This research aims to measure the accuracy of the indicators of TAM variables and examine the behavioral model of a student's acceptance of online teaching.

2. LITERATURE REVIEW

2.1. Technology Acceptance Model (TAM) and Online Learning

Technology Acceptance Model (TAM) was first introduced by Davis in 1989 which is an adaptation of the Theory of Reasoned Actional (TRA) which was made specifically for modeling the acceptance behavior of an individual towards the use of information. TAM aims to explain the factors of the behavior of information technology users on the acceptance of information technology itself. TAM explains the acceptance of information technology using certain dimensions that can affect whether or not the information technology is accepted by users. According to Davis (1989) TAM aims to explain and predict the level of use of users in accepting a technology. TAM is considered capable of predicting user acceptance of technology based on the impact of two factors, namely perceived usefulness and perceived ease of use.

The original constructs of TAM formulated by Davis (1989) are perceived usefulness and perceived ease of use, attitudes, behavioral intentions, actual usage, and there are external factors, namely experience and complexity. Perceived usefulness describes the level of someone who believes that the use of the system will improve its performance, in other words, being able to provide the users use when used it can be functioning under the goal. The Benchmark of this perception is seen from the frequency or how often someone is using the system (Davis, 1989). According to Venkatesh & Davis (2000), the Perception of ease of use describes a person's confidence level that the use of information systems is a thing easy and does not require a hard effort from the wearer. Attitude toward use is a tendency of early response to the condition fun and unpleasant on a certain object. Behavioral intent is a tendency to behave to apply technology and the real use of a system is a real condition application system.

Research related to TAM in online learning has been widely carried out by previous researchers, including (Al-Adwan *et al.*, 2013) using the technology acceptance model (TAM) to predict the acceptance of e-learning by Jordanian students. The result of their research is usefulness had no significant influence on students' attitudes, also perceived ease of use significantly influenced both attitude and perceived usefulness. (Marandu & Makudza, 2019) found that there is a direct and strong relationship between the intention to behave and actual behavior. Research conducted by (Ngabiyanto *et al.*, 2021) the results provide that perceived usefulness has a positive influence on e-learning intention, also that teachers' perceived usefulness, experience, and gender do not influence e-learning intentions.

E-learning is a form of information technology that is applied in the field of education in the form of a virtual world, with learning using electronic media or certain devices as intermediaries to deliver learning materials. E-learning is generally a website where users interact with each other like social media sites. The existence of e-learning helps the learning process without the need for direct interaction between lecturers or lecturers' students so that learning effectiveness can be further enhanced by the existence of a question and answer forum and easy access to learning materials (Hussein, 2017).

Learning achievement is the result that has been achieved by someone after attending the education and training program. Learning achievement is the maximum result that has been achieved by someone after carrying out learning efforts. Learning achievement is the result of all activities carried out by students, both from learning, experience, and training from an activity. The evaluation of learning outcomes for each subject programmed by students in one semester must be given value as an evaluation of learning outcomes, which is carried out periodically and can take the form of exams, assignments, and direct observation by lecturers. The exams are conducted in the form of semester exams and final exams for study programs, and learning outcomes are a reflection of aspects of knowledge, attitudes, and skills.

2.2. Structural Equation Modeling (SEM)

Structural equation modeling (SEM) is a multivariate analysis technique that combines factor analysis methods, regression analysis, and path analysis to measure the relationship between variables simultaneously (Bollen *et al.*, 2014; Hair *et al.*, 2010). SEM consists of two parts, namely: a measurement model section that describes the relationship between indicator variables and latent variables, and a structural model section that describes the relationship between latent variables by using the regression analysis concept (Isnayanti & Abdurakhman, 2019; Annas *et al*., 2022). As an alternative, SEM is developed with a variance or component approach, which is sometimes called the PLS approach or known as component-based SEM. Covariance-based SEM is more oriented to the model building which is intended to explain the covariance of all observed indicators, while component-based SEM can analyze as well as variables formed with reflective and formative indicators. The PLS approach began to be used in path modeling in 1980 (Wold, 1980)

The first component of SEM is the structural model, Bollen & Lennox (1991) wrote the structural model as follows:

$$\boldsymbol{\eta} = \boldsymbol{B\eta} + \boldsymbol{\Gamma\xi} + \boldsymbol{\zeta} \tag{1}$$

where $\boldsymbol{\eta}$ is the endogenous latent variable of size, $\boldsymbol{\xi}$ is the exogenous latent variable, $\mathbf{B}$ is the coefficient matrix that shows the influence between endogenous latent variables, and $\boldsymbol{\zeta}$ is a random error that has an expected value equal to zero. Given two equations as follows:

$$\boldsymbol{\eta_1} = \boldsymbol{\alpha_{12}\eta_2} + \boldsymbol{\beta_{11}\xi_1} + \boldsymbol{\zeta_1} \tag{2}$$

$$\boldsymbol{\eta_2} = \boldsymbol{\alpha_{21}\eta_1} + \boldsymbol{\beta_{22}\xi_2} + \boldsymbol{\zeta_2} \tag{3}$$

From Equation (2) and Equation (3) we can write in matrix form as follows:

$$\begin{bmatrix} \boldsymbol{\eta_1} \\ \boldsymbol{\eta_2} \end{bmatrix} = \begin{bmatrix} \mathbf{0} & \boldsymbol{\alpha_{12}} \\ \boldsymbol{\alpha_{21}} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\eta_1} \\ \boldsymbol{\eta_2} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\beta_{11}} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\beta_{22}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\xi_1} \\ \boldsymbol{\xi_2} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\zeta_1} \\ \boldsymbol{\zeta_2} \end{bmatrix} \tag{4}$$

To evaluation of the structural model is done by looking at the R-Square. Structural models can be evaluated by observing the significance of the relationship between latent variables. This can be seen from the path coefficient which describes the relationship between latent variables. These results can be obtained from the bootstrapping process.

The second component of SEM is the measurement model which is written as follows:

$$\boldsymbol{x} = \boldsymbol{\Lambda_x\xi} + \boldsymbol{\delta} \tag{5}$$

$$\boldsymbol{y} = \boldsymbol{\Lambda_y\eta} + \boldsymbol{\varepsilon} \tag{6}$$

where $\mathbf{x}$ with size $p\times1$ and $\mathbf{y}$ with size $q\times1$ are vectors of observed variables. $\mathbf{\Lambda_x}$ with a size of $p\times m$ and $\mathbf{\Lambda_y}$ with a size of $q\times n$ respectively are a coefficient matrix that shows the relation from x to $\boldsymbol{\xi}$ and y to $\boldsymbol{\eta}$. Sequentially $\boldsymbol{\delta}$ with size $p\times1$ and $\boldsymbol{\varepsilon}$ with size $q\times1$ are the measurement errors of $\mathbf{y}$ and $\mathbf{x}$. A measurement model or outer model is used to present the relationship between the latent variable construct and its indicator. There are two methods to evaluate the measurement model, namely the convergent validity of the indicators and composite reliability. Convergent validity is a test that aims to determine the ability of an indicator to measure latent variables. Convergent validity can be seen from the standardized loading factor value for each construct indicator. The indicator variable is said to be significant as an indicator that measures the construct if the loading factor value is more than 0.7 for confirmatory research, and 0.6 for explanatory research. However, loading factor values above 0.5 are acceptable, and values below 0.5 are excluded from the model (Chin, 2014). Composite reliability is a test carried out to prove the accuracy, consistency, and accuracy of an instrument in measuring the construct. To measure whether an indicator can reliably measure a construct, the variance-based structural equation can be done by measuring the reliability of the composite or construct. An indicator is said to be a good constructor (reliable) if it has a correlation value of more than 0.7 (Chin, 2014).

3. MATERIAL AND METHOD

3.1. Data

This study used primary data. Data were collected through an online questionnaire survey by using google form with the content about TAM in online learning with SYAM-OK. The population in this study were students of the Statistics Study Program, Faculty of Mathematics and Natural Sciences UNM Makassar, with the sample being 120 students in the Even Semester of 2020/2021. Samples were selected by purposive sampling. These students were chosen for reason that they were considered students of the Statistics Study Program, FMIPA UNM, who had conducted offline learning before the Covid-19 Pandemic, and then in the Even Semester of 2020/2021 became using online teaching.

3.2. Research Model

This study uses a quantitative approach. The type of research used is ex-post facto. The research model (Figure 1) was adopted from TAM, which has five factors namely perceived usefulness, perceived ease of use, attitude towards use, behavioral intention to use, and actual use. The questionnaire has been filled out by 120 students of the Statistics Study Program FMIPA UNM.

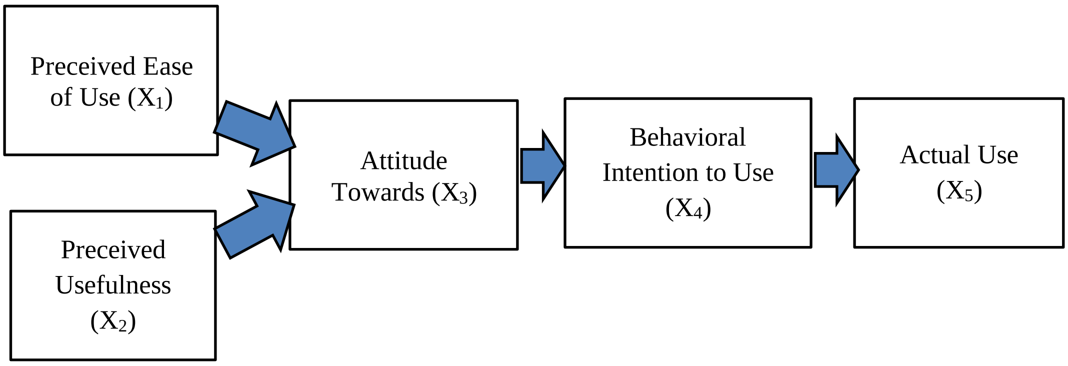

Figure 1. Research Model

3.3. Analysis Method

An observable random vector $\boldsymbol{x}$ with the size$p_1 + p_2$ is the component that has a vector mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. $\boldsymbol{x}$ linearly dependent on some unobserved random variable ξ_1, ξ_2,…,ξ_m which is called the latent variable. The source of variation $\delta_1, \delta_2, \ldots \delta_{(p_1+p_2)}$ is called error which is sometimes also called a special factor. Here is the model of exploratory factor analysis in Equation (7).

$$\begin{aligned} x_{11} &= \lambda_{11}\xi_1 + \lambda_{12}\xi_2 + \cdots + \lambda_{1m}\xi_m + \delta_{11} \\ &\vdots \\ x_{p1} &= \lambda_{p1}\xi_1 + \lambda_{p2}\xi_2 + \ldots + \lambda_{pm}\xi_m + \delta_{p1} \end{aligned} \tag{7}$$

The Equation (7) can be written in matrix form as follows:

$$\boldsymbol{x} = [\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\boldsymbol{\xi} + \boldsymbol{\delta}_{(p_1+p_2)x1} \tag{8}$$

The coefficient λ_{ij} is a loading factor of the *i*-th variable on the *j* factor. Some assumptions about random variables and those that affect the covariance structure are: $E(\boldsymbol{\xi}) = \mathbf{0}$, $\mathrm{Cov}(\boldsymbol{\xi}) = E(\boldsymbol{\xi}\boldsymbol{\xi}') = \boldsymbol{I}$,$E(\boldsymbol{\delta}) = \mathbf{0}$

The covariance variance matrix for the exogenous latent variable indicator is:

$$\begin{aligned}
\boldsymbol{\Sigma}_{xx}(\boldsymbol{\theta}) &= E(\boldsymbol{x}\boldsymbol{x}') \\
&= E\left(\left([\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\boldsymbol{\xi} + \boldsymbol{\delta}_{(p_1+p_2)x1}\right)\right. \\
&\quad \left.\left([\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\boldsymbol{\xi} + \boldsymbol{\delta}_{(p_1+p_2)x1}\right)'\right) \\
&= [\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\boldsymbol{\Phi}[\boldsymbol{\Lambda}'_x]_{2x(p_1+p_2)} + [\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\mathbf{0} \\
&\quad + [\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\mathbf{0} + \boldsymbol{\Theta} \\
E(\boldsymbol{x}\boldsymbol{x}') &= [\boldsymbol{\Lambda}_x]_{(p_1+p_2)x2}\boldsymbol{\Phi}[\boldsymbol{\Lambda}'_x]_{2x(p_1+p_2)} + \boldsymbol{\Theta}
\end{aligned} \tag{9}$$

Confirmatory Factor Analysis (CFA) in SEM is used because there is already theoretical information on the general structure of the pattern data and wants to match or deny a structure that has been hypothesized. (Ruliana et al., 2015) the measurement model in CFA for the exogenous latent variable is:

$$\boldsymbol{x} = [\boldsymbol{\Lambda}_x]_{(p_1+p_2)\times m}\boldsymbol{\xi} + \boldsymbol{\delta}_{(p_1+p_2)\times 1} \tag{10}$$

where $\boldsymbol{x}$ is a vector of size $(p_1 + p_2) \times 1$ from observation score, $\boldsymbol{\xi}$ is a vector of size $m \times 1$ of latent factor score. The point in confirmatory factor analysis is a relevant theory that allows researchers to determine the data structure before the process of estimating parameters $\mathbf{B}$, $\boldsymbol{\Phi}$**,** and $\boldsymbol{\Psi}$. Given the measurement model of the exogenous latent variable as follows:

$$\boldsymbol{x} = \boldsymbol{\Lambda}_x\boldsymbol{\xi} + \boldsymbol{\delta} \tag{11}$$

where

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}, \boldsymbol{\Lambda}_x = \begin{bmatrix} \lambda_{11} \\ \lambda_{21} \\ \vdots \\ \lambda_{p1} \end{bmatrix}, \boldsymbol{\xi} = [\xi_1], \boldsymbol{\delta} = \begin{bmatrix} \delta_{11} \\ \delta_{21} \\ \vdots \\ \delta_{p1} \end{bmatrix}, \boldsymbol{\delta} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\Sigma})$$

with $E(\boldsymbol{\xi}\boldsymbol{\xi}') = \boldsymbol{\Phi}_\delta$, $E(\boldsymbol{\delta}\boldsymbol{\delta}') = \boldsymbol{\Theta}_\delta$, $cov(\boldsymbol{\xi}, \boldsymbol{\delta}) = \mathbf{0}$

Given the measurement model of the endogenous latent variable as follows (Ruliana et al., 2015). Equation (13) can be denoted in the form of a matrix which is written as:

$$\begin{gathered}
\boldsymbol{y} = \boldsymbol{\Lambda}_y\boldsymbol{\eta} + \boldsymbol{\varepsilon} \\
\boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_q \end{bmatrix}, \boldsymbol{\Lambda}_y = \begin{bmatrix} \lambda_{12} \\ \lambda_{22} \\ \vdots \\ \lambda_{q2} \end{bmatrix}, \boldsymbol{\eta} = [\eta_1], \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{p1} \end{bmatrix} \\
\boldsymbol{\varepsilon} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\Sigma})
\end{gathered} \tag{12}$$

with $E(\boldsymbol{\xi}\boldsymbol{\xi}') = \boldsymbol{\Phi}_\delta$, $E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \boldsymbol{\Theta}$, $cov(\boldsymbol{\xi}, \boldsymbol{\varepsilon}) = \mathbf{0}$

In the structural equation model, there is a coefficient that connects the latent variable to its indicator. It is the loading coefficient which notation "lambda" (λ). Lambda for exogenous latent is:

$$\hat{\lambda}_{jk}^{g} = \frac{cov(x_{jk}^{g}, \xi_{j}^{g})}{var(\xi_{j}^{g})^{2}} \tag{13}$$

and for endogenous latent is:

$$\hat{\lambda}_{jk}^{g} = \frac{cov(y_{jk}^{g}, \eta_{j}^{g})}{var(\eta_{j}^{g})^{2}} \tag{14}$$

The step of analysis are:

a. Describing the TAM variable: Perceived Ease of Use (X_1), Perceived Usefulness (X_2), Attitude toward to use (X_3), Behavioral Intention (X_4), and Actual Use (X_5)
b. Testing the validity of the TAM variable indicator with the provision: if loading factor $> 0{,}5$ then the indicator is valid to measure the latent variable. If cross-loading of the indicator with their latent variable has a loading factor greater than the loading factor of another latent variable, then the indicator is accurate to measure the variable
c. Testing the structural model by using bootstrap and statistic T
d. Estimate the parameter structural model
e. Evaluated the performance model.

4. RESULTS AND DISCUSSION

Descriptive Statistics of Student's Score TAM in Online Teaching is given in Table 1.

Table 1. Descriptive Statistics of Student's Score TAM in Online Teaching

Variable	Statistics				
	Minimum	Maximum	Mean	SD	Variance
Perceived Ease of Use (X_1)	12	30	22.950	3.100	9.611
Perceived Usefulness (X_2)	11	30	21.190	3.699	13.686
Attitude toward to use (X_3)	4	12	9.630	1.251	1.564
Behavioral Intention (X_4)	8	24	15.830	3.218	10.359
Actual Usage (X_5)	3	10	7.210	1.499	2.009

Table 1 presents the result of a descriptive analysis of Student's Score TAM in online teaching. The student's responses to the perceived ease of use (mean 22.950 with ideal score 6 to 30), Perceived usefulness (mean 21.190 with ideal score 6 to 30), attitude toward use (mean 9.630 with ideal score 3 to 15), behavioral intention (mean 15.830 with ideal score 5 to 25) and actual usage (mean 7.210 with ideal score 2 to 10). These results explain that students' responses to the Technology Acceptance Model in using SYAM-OK are very satisfactory. This shows that using online teaching during the pandemic outbreak is the right strategy to maintain the safety of students and lecturers and ensure that all lecture schedules are carried out properly over zoom, or other virtual class options.

By using Software SmartPLS 3.0, we get the result of SEM Model and factor loading values. The result are shown in Figure 2 and Table 2.

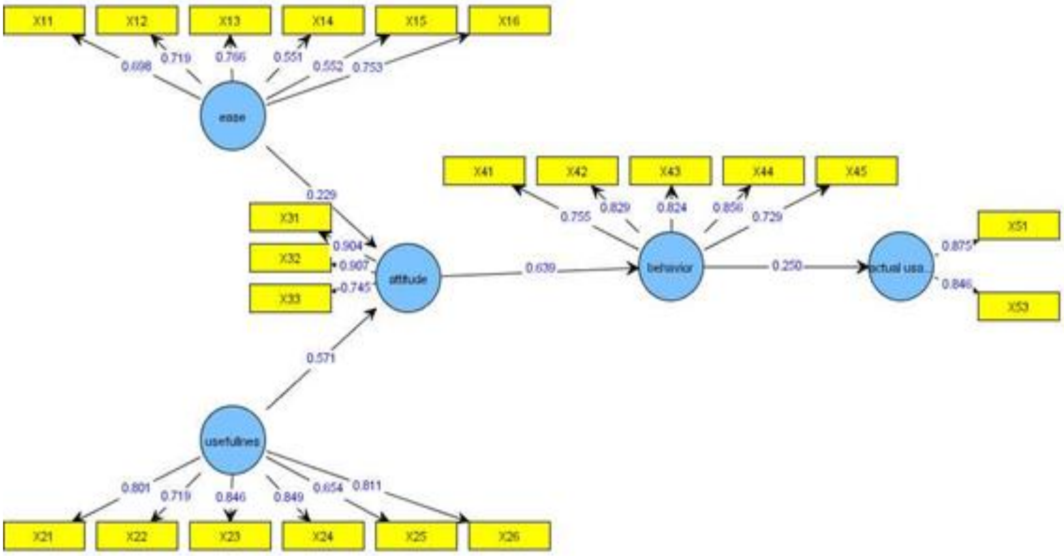

Figure 2. Result of Structural Equation Modeling for Calculating Loading Factor and Parameter Coefficient of TAM Variable

Table 2. The Value of Outer loading SEM-PLS

Variable	Indicator	Outer loadings	Conclusion
(X1)	X11	0.698	Valid
	X12	0.719	Valid
	X13	0.766	Valid
	X14	0.551	Valid
	X15	0.552	Valid
	X16	0.753	Valid
(X2)	X21	0.801	Valid
	X22	0.719	Valid
	X23	0.846	Valid
	X24	0.849	Valid
	X25	0.654	Valid
	X26	0.811	Valid
(X3)	X31	0.904	Valid
	X32	0.907	Valid
	X33	-0.745	Valid
(X4)	X41	0.755	Valid
	X42	0.829	Valid
	X43	0.824	Valid
	X44	0.856	Valid
	X45	0.730	Valid
(X5)	X51	0.843	Valid
	X53	0.873	Valid

We use CFA to measure the accuracy of the latent variables of Perceived Ease of Use (six indicators), Perceived Usefulness (six indicators), Attitude to Use (three indicators), Behavioral Intention (five indicators), and Actual Usage (two indicators). The result of SEM PLS indicated the assumption for the five latent variables holds outer loading >0.5 and composite reliability >0.5 (see Table 2 and Table 3). Both outer loading and composite reliability are consistent with the accuracy criteria recommended by Trujillo (2009), which suggests that all the indicators are accurate in measuring the latent variable.

Table 3. The Result of Composite Reliability Testing

Variable	Composite Reliability
Perceived Ease of Use (X_1)	0.835
Perceived Usefulness (X_2)	0.904
Attitude Toward to Use (X_3)	0.586
Behavioral Intention (X_4)	0.899
Actual Usage (X_5)	0.851

To model the latent variables of TAM and the Semester Achievement Index (Y) we used the regression analysis concept, and the result is shown in Table 4.

Table 4. Structural Model SEM of TAM Variable

Path Connection	Parameters estimates	Standard deviation	T statistics
X_1-> X_3	0.229	0.132	1.742
X_2-> X_3	0.571	0.122	4.689
X_3-> X_4	0.639	0.092	6.916
X_4-> X_5	0.249	0.159	1.564
X_5-> Y	0.026	0.174	0.152

From Table 4, it is known that the latent variable's perceived ease of use (X_1) does not significantly affect the latent variable attitude toward use (X_3). Meanwhile, the latent variable perceived usefulness (X_2) significantly affects the attitude towards, besides that attitude toward (X_3) effect on X_4. Variable actual usage (X_5) not significantly affects Y. This result explains that perceived usefulness by students can build a positive attitude towards and drive their behavioral intention to adopt online teaching during the pandemic outbreak. This finding is consistent with the previous studies (Dwivedi et al, 2019; Mosunmola et al, 2018) and (Nikou & Economides, 2019) about attitude emerging as a significant construct having a direct effect on behavioral intention. The findings of this research provide significant implications to the policymakers of the University to encourage online teaching at the time of the pandemic outbreak. This is a strategy for the university to keep the safety of students and lecturers while still ensuring that all lecture schedules are carried out properly. This finding is vital as it underlines the significance of individual characteristics in the adoption of any technology (Dwivedi et al., 2019). This research only uses a linear model between latent variables. It is acknowledged that the relationship between latent variables maybe nonlinear model.

5. CONCLUSION

Based on the results, we conclude that in the measurement model all the indicators are accurate in measuring the latent variable of TAM. SEM Model has identified the significant effects between variables of TAM. The findings of this research suggest that Perceived Usefulness significantly affects the Attitude Towards and Attitude Towards students drives their Behavioral Intention to conduct online teaching during the pandemic outbreak. The results of the study indicate that the Universitas Negeri Makassar should improve performance of the SYAM-OK as a Learning Management System to support online teaching.

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