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Multigroup Analysis on Partial Least Square-Structural Equation Modeling in Modeling College Students' Saving Behavior

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ABSTRACT

This study aims to determine the factors that influence college students' saving behavior, with gender as a moderating variable. The analysis used is Partial Least Square-Structural Equation Modeling (PLS-SEM) with Multigroup Analysis. This study was conducted on 200 college students in City X who were selected by purposive sampling. Data collection was carried out using a structured questionnaire that measures Perceived Benefits, Perceived Ease of Use, Saving Intentions, and Saving Behavior. Confirmatory Factor Analysis (CFA) and Bootstrapping were used to validate the measurement model and structural relationships. The results showed that Perceived Benefits and Perceived Ease had a significant effect on Saving Intentions and Saving Behavior. In addition, Saving Intentions had a significant effect on Saving Behavior. This relationship applies to both male and female groups, with a determination coefficient of 86.2% for males and 86.7% for females. Moderation analysis shows that gender moderates the relationship between Perceived Benefits and Saving Behavior, as well as between Perceived Ease and Saving Behavior. These findings highlight the importance of considering gender differences in efforts to improve students' savings behavior.

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A. INTRODUCTION

Structural Equation Modelling (SEM) is a statistical technique used to analyze complex relationships between exogenous and endogenous variables, while simultaneously incorporating indicator models (Solimun et al., 2017). According to Hair et al. (2019), SEM data analysis provides a comprehensive explanation of the study's variable relationships. For a set of distinct multiple regression equations calculated concurrently, SEM offers the most suitable and effective estimation method. It consists of two primary components: the structural model, which represents the relationships between latent constructs, and the measurement model, which links latent constructs to their indicators. One type of SEM approach is Partial Least Square SEM (PLS-SEM).

Partial Least Squares SEM (PLS-SEM) is a variance-based approach to SEM, particularly suitable for exploratory research and prediction-oriented studies (Henseler et al., 2016). The goal of PLS-SEM is to predict latent variables using observed data (Hair et al., 2017). Unlike covariance-based SEM, PLS-SEM is advantageous because it does not require strict distributional assumptions and accommodating small sample sizes or complex models (Hanafiah, 2020). Because of its flexibility, PLS-SEM is particularly useful for research in social and economic fields, where the relationships between variables often involve perceptions and behaviors, such as the saving behavior of university students.

University or college students are in a distinct period of their lives where when they begin managing their own finances without parental guidance, who start to deal with monetary challenges such as paying bills, keeping a budget, or having a credit card to their own names for the first time (Akben-Selcuk, 2015). Saving is one of the most common financial practices among college students, a crucial habit that reflects their ability to balance short-term expenses with long-term financial goals. Given the importance of saving behavior in this context, understanding its determinants through a robust analytical approach such as PLS-SEM is both practical and necessary.

The driving factors of college students' savings behavior are based on Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM). Ajzen and Fishbein in 1975 developed the Theory of Reasoned Action (TRA) and its extension, the Theory of Planned Behavior (TPB) that provide a theoretical framework for understanding human behavior. TPB posits that behavior is influenced by intentions, which are shaped by attitudes, subjective norms, and perceived behavioral control (Kashif et al., 2018). Similarly, the Technology Acceptance Model (TAM) emphasizes two key factors, such as perceived benefits or percieved usefulness and perceived ease of use (Wicaksono & Maharani, 2020).

In testing the influence between variables, there are times when the influence of exogenous variables on endogenous variables is also strengthened or weakened by moderating variables. Moderation occurs when the relationship between an independent variable and a dependent variable changes based on the value of the moderating variable (Dawson, 2014). A moderating variable refers to a variable that influences the nature of the effects of antecedents on outcomes (Aguinis et al. 2017). Moderating variables are crucial for understanding how relationships between variables differ across groups (Memon et al., 2019). There are two types of moderating variables: non-metric (categorical data) and metric (continuous data) moderating variables. Multigroup Analysis is a suitable approach to examine these moderating effects when the moderator has distinct categories, such as gender (Rigdon et al. 2017). For this study, gender serves as a moderator to analyze differences in saving behavior between male and female students, providing insights into how perceived benefits and ease of use affect saving intentions and behavior across these groups.

This study aims to determine the effect of perceived benefits and perceived ease of use on college students' saving behavior through saving intentions, with gender as a moderating variable. The analysis used is Partial Least Squares SEM (PLS-SEM) with a multigroup analysis approach. This research was conducted on 200 college students in City X who were selected by purposive sampling technique. Bootstrapping resampling and Confirmatory Factor Analysis (CFA) were applied to ensure the validity and reliability of the measurement model. This study provides insights into the factors that influence saving behavior and how these factors differ based on gender (male and female), which is further useful for the government and financial institutions, especially banks in designing effective strategies to increase college students' saving behavior. The findings also contribute to the academic field by demonstrating the applicability of Multigroup Analysis within the PLS-SEM framework, particularly in using moderating variables with categorical data types. This enriches the understanding of advanced statistical methods for analyzing complex data.

B. METHODS

1. Data and Variables

This study used secondary data obtained from a questionnaire survey on college students' saving behavior in X City. The sample consisted of 200 respondents obtained through purposive sampling, divided into male and female groups. The data were collected using a Summated Rating Scale (Likert scale, 1-5). The variables used in this study consist of two exogenous variables, namely Perceived Benefits (X1) and Perceived Ease (X2), one moderating variable, namely Gender (X3), one intervening variable, namely Saving Intention (Y1), and one pure endogenous variable, namely Saving Behavior (Y2). All the variables mentioned above have been tested for validity and reliability by the researcher, with the results showing that all questionnaire items are valid. Additionally, all questionnaire items are reliable, making them suitable for analysis. The indicators used in latent variables are reflective. The variables and indicators in this study are shown in Table 1.

Table 1. Variables and Indicators

Variable	Indicator
Perceived Benefits (X1)	Economic Sector(X_{11})
	Future Vision(X_{12})
Perceived Ease (X2)	Ease of Access(X_{21})
	Ease of Application Use(X_{22})
	Ease of Finding Information(X_{23})
	Ease of Interaction with Service Units(X_{24})
Saving Intention (Y1)	Desire(Y_{11})
	Prioritization(Y_{12})
Saving Behavior (Y2)	Saving Decision(Y_{21})
	Savings Action(Y_{22})
	Opportunities(Y_{23})

2. Structural Equation Modeling (SEM)

Structural equation modelling (SEM) a powerful multivariate technique that allows simultaneous examination of both measurement models and structural models (Fan et al., 2016). SEM allows for simultaneous examination of both measurement models (relationships between latent constructs and their indicators) and structural models (relationships between latent constructs) (Albahri et al., 2021). In SEM, latent variable models can be specified to estimate the relationships between latent constructs and observed indicators, and a set of linear relationships with more than one dependent variable can be estimated simultaneously (Ryu, 2014). This study employed the Partial Least Squares SEM (PLS-SEM) approach, which is suitable for prediction-oriented objectives, handling non-normal data distributions, and accommodating small sample sizes (Hanafiah, 2020). The goal of PLS-SEM is to predict latent variables using observed data (Hair et al., 2017). In the context of this research, PLS-SEM was used to examine the relationships between Perceived Benefits (X1), Perceived Ease (X2), Saving

Intention (Y1), and Saving Behavior (Y2), with Gender (X3) as a moderating variable. The analysis includes designing path diagrams, estimating the parameters of the inner (structural) and outer (measurement) models, and testing the significance of these relationships. The path diagram as research model is depicted in Figure 1 below:

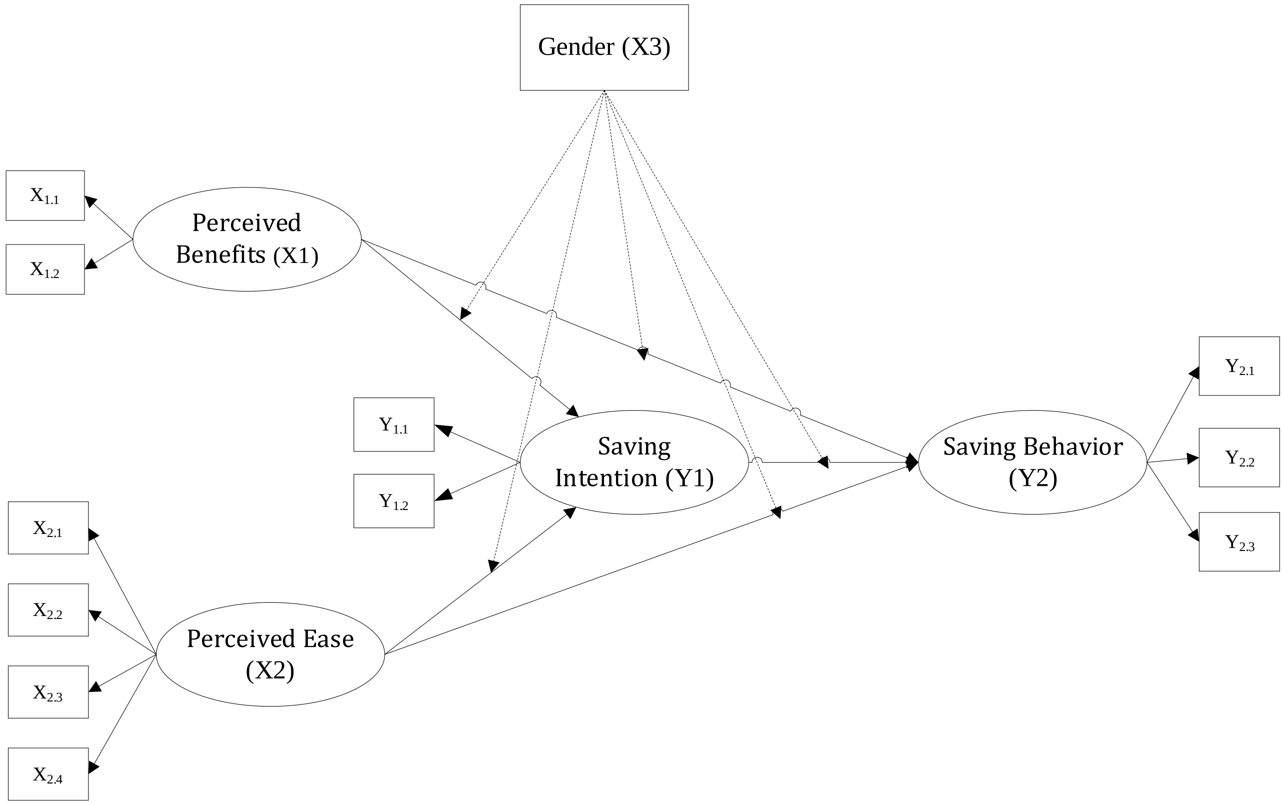

Figure 1. Research Model

3. Linearity Assumption Test with Ramsey's RESET Test

Ramsey's Regression Specification Error Test (RESET) was used to test the assumption of linearity in the relationships between predictor variables and the response variable (Pandis, 2016). One method to test the linearity assumption is the Regression Specification Error Test or RESET which was first introduced in 1969 by Ramsey. According to Fernandes et al. (2021), the steps to apply RESET are as follows:

a. Regress X_1 on Y_i. The equation of $\hat{Y}_i$ as an endogenous variable in the model is presented in the form of equation (1).

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} \tag{1}$$

b. Compute the coefficient of determination, R_1^2 which is presented in the equation (2).

$$R_1^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \tag{2}$$

c. Regress X_1 on Y_i nd two additional predictor variables $\hat{Y}_i^2$ and $\hat{Y}_i^3$. Furthermore Y_i^* as the response variable is presented in equation (3).

$$Y_i^* = \beta_0^* + \beta_1^* X_{1i} + \beta_2 \hat{Y}_i^2 + \beta_3 \hat{Y}_i^3 + \varepsilon_i^* \tag{3}$$

d. Then, compute $\hat{Y}_i^*$ as per the model in equation (4).

$$\hat{Y}_i^* = \hat{\beta}_0^* + \hat{\beta}_1^* X_{1i} + \hat{\beta}_2 \hat{Y}_i^2 + \hat{\beta}_3 \hat{Y}_i^3 \tag{4}$$

e. Calculate the coefficient of determination according to equation (4) as R_2^2 presented in equation (5).

$$R_2^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i^*)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \tag{5}$$

f. Testing the linearity between predictor variables and the response with the following hypothesis.
$H_0 : \beta_2 = \beta_3 = 0$
$H_1 : \textit{there is at least one } \beta_j \neq 0; j = 2,3$

g. with test statistics following the F distribution according to equation (6).

$$F_{value} = \frac{(R_2^2 - R_1^2)/m}{(1 - R_2^2)/(n - k - 1 - m)} \sim F_{m,n-k-1-m} \tag{6}$$

Information: n is number of observations; k is the number of initial predictor variables; and m is number of additional predictor variables.

h. Conduct the RESET test using the F-statistic in Equation (6). If the test statistic $F_{value} > F_{(\alpha,m,n-k-1-m)}$ or $p - value < \alpha$ then Reject H_0. Thus, it can be concluded that there is a nonlinear relationship between variables. Conversely, if Accept then the relationship between variables is linear.

4. Measurement Model with Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) assesses the relationship between latent variables and their observed indicators. CFA evaluates whether an assumed relationship between manifest indicators and latent factors is in line with the empirical data (Goretzko et al., 2024). In this study, CFA is used to validate the measurement model and ensure that the observed indicators accurately represent the latent constructs (Roos & Bauldry, 2022). The reflective measurement model is applied, meaning the indicators are assumed to reflect the underlying latent variable (Hair et al., 2019).

5. Structural Model Testing with Resampling Bootstrap

Hypothesis testing in PLS-SEM is conducted using bootstrap resampling to estimate standard errors and confidence intervals (Efron & Tibshirani, 1994). The bootstrap method involves repeatedly resampling the original dataset with replacement to create multiple pseudo-samples. This process helps assess the stability and significance of the estimated path coefficients (Horowitz, 2019). In this study, 5,000 bootstrap samples are used to generate reliable estimates. Bootstrap uses a resampling algorithm with a number of samples that can be selected by the user randomly or known as the "resampling with replacement" method. It means that a large number of samples with replacement are then taken from the original sample and the statistic of interest is calculated from this pseudo-population as an estimate of the corresponding parameter of the population (Theodorsson, 2015). Suppose there is a sample containing a data set $\{x_{12}, \dots, x_{1n}, x_{21,}x_{22}, \dots x_{2n}, y_{11}, y_{12}, \dots y_{1n}, y_{21,}y_{22}, \dots y_{2n}\}$ and $\hat{\theta} = s(xy)$ is an estimator for a parameter. The steps to estimate the standard error of the bootstrap are as follows (Efron & Tibshirani, 1994).

a. Determines the number B of bootstrap samples $(\boldsymbol{xy}_{\boldsymbol{1}}^{*}, \boldsymbol{xy}_{\boldsymbol{2}}^{*}, \dots, \boldsymbol{xy}_{\boldsymbol{B}}^{*})$ obtained from random sampling with the replacement of n elements from the initial sample.
b. Calculate the statistic of interest ($\hat{\theta}^*$) for each bootstrap sample using Equation (7).

$$\hat{\theta}^*_{(b)} = s(xy^*_{(b)}); b = 1, 2, \dots, B \tag{7}$$

with,

$$\hat{\theta}^{*T} = \left[\hat{\lambda}^*_{X_{11}} \quad \hat{\lambda}^*_{X_{12}} \quad \cdots \quad \hat{\lambda}^*_{X_{ij}} \quad \hat{\lambda}^*_{Y_{11}} \quad \hat{\lambda}^*_{Y_{12}} \quad \cdots \quad \hat{\lambda}^*_{Y_{gk}} \quad \hat{\beta}^*_1 \quad \hat{\beta}^*_2 \quad \cdots \quad \hat{\beta}^*_5 \right] \tag{8}$$

c. Compute the standard error using the standard deviation of the B bootstrap replications, as shown in Equation (9).

$$SE_{\hat{\theta}^*} = \sqrt{\frac{\sum_{b=1}^{B} \left(\hat{\theta}^*_{(b)} - \bar{\hat{\theta}}^*_{(.)} \right)^2}{B}} \tag{9}$$

with

$$\bar{\hat{\theta}}^*_{(.)} = \sum_{b=1}^{B} \frac{\hat{\theta}^*_{(b)}}{B} \tag{10}$$

6. Moderation Variable Test

An intergroup difference test was conducted using Fisher's Z-test to determine the moderating effect of Gender (X3) (Solimun et al., 2017). The test statistic is calculated using Equation (11).

$$\frac{b_{jG1} - b_{jG2}}{SE_{b_{jG1} - b_{jG2}}} \sim \mathrm{N}(0,1) \tag{11}$$

The standard error for small and large samples is computed using Equations (12) and (13), respectively. A significant difference indicates a moderating effect, suggesting that gender influences the relationship between the independent and dependent variables.

$$SE_{b_{jG1}-b_{jG2}} = \sqrt{\frac{\left(df_{b_{jG1}} SE_{b_{jG1}}{}^{2}\right)+\left(df_{b_{jG2}} SE_{b_{jG2}}{}^{2}\right)}{df_{b_{jG1}} + df_{b_{jG2}}}} \tag{12}$$

$$SE_{b_{jG1}-b_{jG2}} = \sqrt{SE_{b_{jG1}}{}^{2} + SE_{b_{jG2}}{}^{2}} \tag{13}$$

C. RESULT AND DISCUSSION

1. SEM Model Specifications

Structural models and measurement models will be easier to understand if expressed in the form of path diagrams. The path diagram resulting from the design of the structural model (inner model) and measurement model (outer model) can be seen in Figure 2.

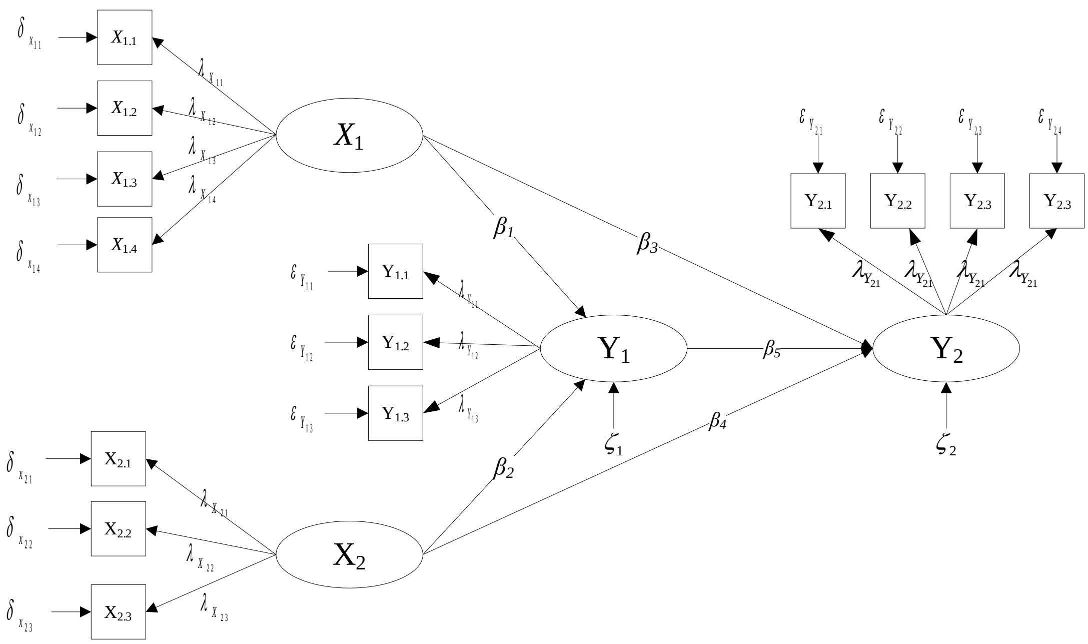

Figure 2. SEM Path Diagram

Information: X_i is exogenous latent variable to-*i*; Y_g is endogenous latent variable to-*g*; X_{ij} is exogenous variable to-*i* indicator to-*j*; Y_{gk} is endogenous variable to-g indicator to-*k*; λ_{xij} is coefficient loading exogenous variable to-*i* indicator to-*j*; λ_{ygk} is coefficient loading endogenous variable to-g indicator to-*k*; β is coefficient of influence of latent variables; δ_{X_i} is error measurement on manifest variables for exogenous latent variables; ε_{Y_g} is measurement error on manifest variables for endogenous latent variables; ζ_g is error g-model. Based on the SEM model, an inner model or structural model is formed as follows:

$$Y_{1i} = \beta_{01} + \beta_1 X_{1i} + \beta_2 X_{2i} + \zeta_{1i} \tag{14}$$

$$Y_{2i} = \beta_{02} + \beta_3 X_{1i} + \beta_4 X_{2i} + \beta_5 Y_{1i} + \zeta_{2i} \tag{15}$$

Which can be described in matrix form as follows:

$$\begin{bmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{1n} \\ Y_{21} \\ Y_{22} \\ \vdots \\ Y_{2n} \end{bmatrix}_{2n\times 1} = \begin{bmatrix} 1 & X_{11} & X_{21} & 0 & 0 & 0 & 0 \\ 1 & X_{12} & X_{22} & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{1n} & X_{2n} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & X_{11} & X_{21} & Y_{11} \\ 0 & 0 & 0 & 1 & X_{12} & X_{22} & Y_{12} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 1 & X_{1n} & X_{2n} & Y_{1n} \end{bmatrix}_{2n\times 7} \begin{bmatrix} \beta_{01} \\ \beta_1 \\ \beta_2 \\ \beta_{02} \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix}_{7\times 1} + \begin{bmatrix} \zeta_{11} \\ \zeta_{12} \\ \vdots \\ \zeta_{1n} \\ \zeta_{21} \\ \zeta_{22} \\ \vdots \\ \zeta_{2n} \end{bmatrix}_{2n\times 1}$$

or it can be written in matrix notation, as in equation (16):

$$\underset{\sim}{Y}_{2n\times 1} = \underset{\sim}{X}_{2n\times 7}\,\underset{\sim}{\beta}_{7\times 1} + \underset{\sim}{\zeta}_{2n\times 1} \qquad (16)$$

Meanwhile, in the outer model, the indicator model can be written with equation (17) and equation (18).

$$X_{ij} = \lambda_{X_{ij}} X_i + \delta_{X_{ij}} \qquad (17)$$

$$Y_{gk} = \lambda_{Y_{gk}} Y_g + \varepsilon_{Y_{gk}} \qquad (18)$$

2. Linearity Assumption Test Results

Assumptions in SEM analysis are only related to structural modeling, where the relationship between latent variables in the structural model is linear. The linearity assumption test is carried out using RESET with the help of Rstudio software. The results of the linearity test can be seen in Table 2.

Table 2. Linearity Test Results

Group	Variable	F-Statistic	P-value	Relationship
Male	X1 with Y1	1,4465	0,2363	Linier
	X1 with Y2	0,0054	0,9414	Linier
	X2 with Y1	0,0697	0,7931	Linier
	X2 with Y2	0,2001	0,6571	Linier
	Y1 with Y2	0,3228	0,5732	Linier
Female	X1 with Y1	3,3826	0,0721	Linier
	X1 with Y2	0,1734	0,6789	Linier
	X2 with Y1	0,2574	0,6142	Linier
	X2 with Y2	0,1295	0,7205	Linier
	Y1 with Y2	0,9871	0,3254	Linier

Based on Table 2, it can be seen that the relationship between latent variables produces a p-value> α (5%), so it is decided that H0 is accepted and it is concluded that all relationships between latent variables in this study are linear.

3. Measurement Model Testing with CFA

The measurement model was analyzed using CFA which is shown in Table 3.

Table 3. Outer Model Testing

Variable	Indicator	Loading	P-Value
Perceived Benefits (X1)	Economic Sector	0.924	<0.001
	Future Vision	0.924	<0.001
Perceived Ease (X2)	Ease of Access	0.805	<0.001
	Ease of Application Use	0.848	<0.001
	Ease of Finding Information	0.832	<0.001
	Ease of Interaction with Service Units	0.801	<0.001
Saving Intention (Y1)	Desire	0.829	<0.001
	Prioritization	0.829	<0.001
Saving Behavior (Y2)	Saving Decision	0.788	<0.001
	Savings Action	0.833	<0.001
	Opportunities	0.878	<0.001

Based on the Table 3, it can be seen that the p-value of each indicator < α , so it is concluded that all indicators can reflect the variables of Perceived Ease, Perceived Benefits, Saving Intention and Saving Behavior. In some variables that have more than two indicators, we can see the most dominant indicator to reflect the variable based on the highest outer loading value. Indicators of economic aspects and future vision are equally large in reflecting the Perceived Benefits variable with an outer loading of 0.924. The most dominant indicator reflecting the Ease variable is the ease of use of the application with an outer loading of 0.848. The desire and priority indicators are equal in reflecting the intention to save variable with an outer loading of 0.829. Meanwhile, the most dominant indicator in reflecting the Saving Behavior variable is the opportunity with an outer loading of 0.878.

4. Structural Model Testing

Inner relation or often called inner model is a specification for the relationship between latent variables. The following is a path diagram of the SEM model shown in Table 4 and Figure 3 below.

Table 4. Results of Inner Model Hypothesis Testing

Group	Relationship Between Variables	Path Coefficient	P-value	Information
Male	X1→Y1	0.634	<0.001	Significant
	X2→Y1	0.245	0.026	Significant
	X1→Y2	0.332	0.007	Significant
	X2→Y2	0.243	0.034	Significant
	Y1→Y2	0.349	0.004	Significant
Female	X1→Y1	0.798	<0.001	Significant
	X2→Y1	0.216	0.048	Significant
	X1→Y2	0.439	<0.001	Significant
	X2→Y2	0.212	0.050	Significant
	Y1→Y2	0.247	0.029	Significant

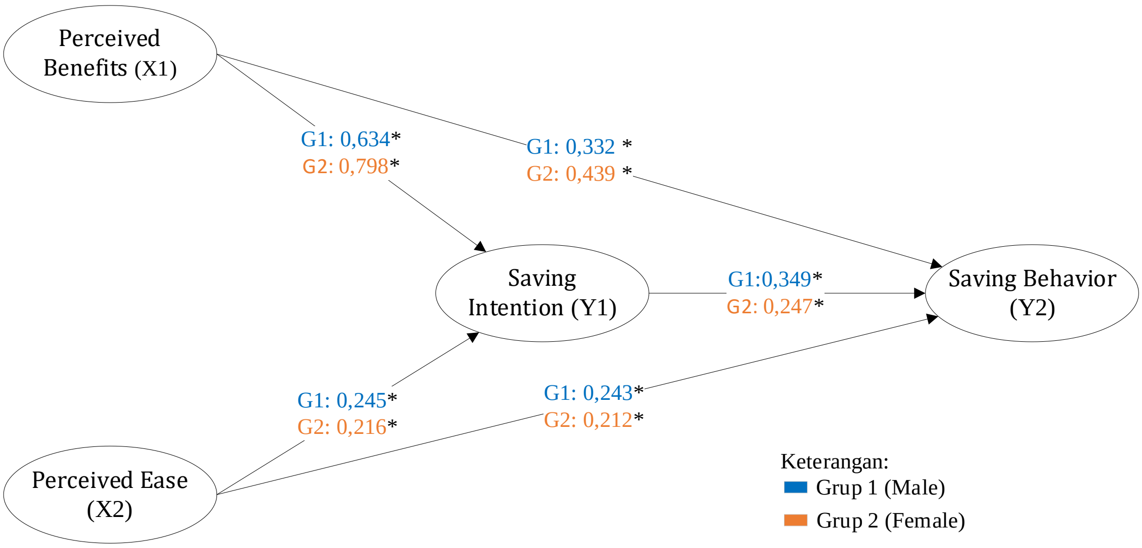

Figure 3. Results of testing the inner model hypothesis for group 1 and group 2.

Based on the inner model path coefficients on Table 4 and Figure 3, the function estimate is obtained through:

$$Y_{1i} = \beta_{01} + \beta_1 X_{1i} + \beta_2 X_{2i} + \zeta_{1i}$$
$$Y_{2i} = \beta_{02} + \beta_3 X_{1i} + \beta_4 X_{2i} + \beta_5 Y_{1i} + \zeta_{2i}$$

By performing standardization, the following equation is produced:

$$Z_{Y1} = \beta_1 Z_{X1} + \beta_2 Z_{X2} + \zeta_1$$
$$Z_{Y2} = \beta_3 Z_{X1} + \beta_4 Z_{X2} + \beta_5 Z_{Y1} + \zeta_2$$

So the function estimate for the Male Group is:

$$Z_{Y_1} = 0{,}634 Z_{X_1} + 0{,}245 Z_{X_2}$$
$$Z_{Y_2} = 0{,}332 Z_{X_1} + 0{,}243 Z_{X_2} + 0{,}349 Z_{Y_1}$$

So the function estimate for the Female Group is:

$$Z_{Y_1} = 0{,}798 Z_{X_1} + 0{,}216 Z_{X_2}$$
$$Z_{Y_2} = 0{,}439 Z_{X_1} + 0{,}212 Z_{X_2} + 0{,}247 Z_{Y_1}$$

Based on Table 4 and Figure 3, it can be concluded that in Male and Female students, the relationship between perceived benefits and saving intention is significant with a coefficient of 0.634. This indicates that, the higher the perceived benefits felt by students, the higher the college students' saving intention. This means that the higher the perceived economic sector and future vision benefits, the higher the college students' saving intention. This is felt more in the male group, characterized by a larger path coefficient in the male group. Then the relationship between perceived convenience and saving intention is significant characterized by the p-value of both groups < α, with a coefficient of 0.245 in the male group and 0.216 in the female group. This indicates that changes in perceived convenience have a significant effect on the saving intention of male and female college students in X City. The easier the access, ease of application use, ease of finding information, and ease of interaction with service units, the greater their intention to consider saving at institutions that offer these conveniences. This perceived convenience provides a positive impetus to foster saving intentions. Furthermore, the relationship between perceived benefits and saving behavior is significant with a coefficient of 0.332 in the male group and 0.439 in the female group. So it can be concluded that the higher the perceived benefits, the more college students' saving behavior in City X will increase. This is felt to be greater in female college students, with a larger path coefficient in the female group. Perceived benefits, both in terms of contribution to the economic sector and college students' future vision, play an important role in increasing their saving behavior. College students who feel that saving money can provide their benefits in the economic sector and achieve long-term goals are more likely to develop the habit of saving behavior.

In addition, the relationship between perceived convenience and saving behavior in both groups is significant with a coefficient of 0.243 for male college students and 0.212 for female college students. It can be concluded that the higher the perceived benefits, the higher the saving behavior of male and female college students. This indicates that perceived convenience plays an important role in shaping college students' saving behavior. When college students find it easy to access, use the application, search for information, and interact with the service unit, they tend to be more interested in building savings behavior. It is important for financial institutions to continue to improve this aspect of convenience in order to facilitate broader savings behavior among college students. And then the relationship between Saving Intention and Saving Behavior is significant in both groups with a p-value < alpha, with a coefficient of 0.349 in the male group and 0.247 in the female group. So that the higher the college students's Saving Intention, the higher the male college students' Saving Behavior. This shows that saving intention, which is reflected in college students' desires and priorities in saving, acts as the main driver in shaping their saving behavior. When college students have a strong desire and make saving a priority, they are more likely to translate their intention into real behavior, such as setting aside funds consistently. The role of saving intention is not only relevant for male college students, but also for female college students, although there are slight differences in the strength of the relationship. By strengthening saving intentions among college students, financial and educational institutions can help encourage more structured and responsible saving patterns among the younger generation. Evaluation of the structural model can be observed with the R-Square value or coefficient of determination of each endogenous variable in each model. The R-Square value of the endogenous variables is presented in the following Table 5.

Table 5. R-Square of Each Endogenous Variable

Group	Coefficient of DeterminationY_1	Coefficient of DeterminationY_2	Total Determination Coefficient
Man	0.569	0.681	1 – (1-0.569)(1-0.681) = 0.862
Woman	0.637	0.633	1 – (1-0.263)(1-0.569) = 0.867

Based on Table 5, it can be seen that the total determination coefficient value for Male College Students is 0.862, which means that the model can explain 86.2% of the data while the remaining 13.8% is explained by other variables outside the research model. On the other hand, for Female College Students, the total determination coefficient value is 0.867, which means that the model can explain 86.7% of the data while the remaining 13.3% is explained by other variables outside this research model.

5. Moderation Variable Test Results

The overall results of the multigroup moderation variable testing can be seen in Table 6 below.

Table 6. Results of Moderation Variable Testing

Connection	Coefficient		P-Value			Information
	Group 1	Group 2	Group 1	Group 2	Moderation	
X1→Y1	0.634	0.798	<0.001	<0.001	0.178	Not moderation
X2→Y1	0.245	0.216	0.026	0.048	0.185	Not moderation
X1→Y2	0.332	0.439	0.007	<0.001	0.040	Moderation
X2→Y2	0.243	0.212	0.034	0.050	0.046	Moderation
Y1→Y2	0.349	0.247	0.004	0.029	0.125	Not moderation

Based on Table 6, it can be seen that the p-value of testing the moderation variable of the relationship between Perceived Benefits (X1) and Saving Behavior (Y2) is significant, which is 0.04. So it can be concluded that the moderation variable, namely the gender variable, is a moderating variable in the relationship between Perceived Benefits and Saving Behavior. In addition, the moderation p-value of the relationship between Perceived Ease (X1) and Saving Behavior (Y2) is also significant, which is 0.046. This means that the Region variable moderates the relationship between Perceived Ease and Saving Behavior. While in other relationships, the p-value is not significant, so it can be concluded that the Region variable is not a moderating variable in the relationship between Perceived Benefits (X1) and Saving Intention (Y1), Perceived Ease (X2) and Saving Intention (Y1) and Saving Behavior (Y2).

D. CONCLUSION AND SUGGESTIONS

Based on the results and discussion of the PLS-SEM approach with multigroup analysis, it can be concluded that for both male and female college students, Perceived Benefits and Perceived Ease have a significant effect on Saving Intention and Saving Behavior, with Saving Intention also significantly affecting Saving Behavior. These results are significant, with a coefficient of determination of 86.2% for the male group and 86.7% for the female group. The statistical tests confirm that these relationships are valid and robust, with Gender acting as a moderating variable in the relationship between Perceived Benefits and Saving Behavior, as well as Perceived Ease and Saving Behavior. However, this study has limitations, such as the use of a college student sample, which may not be generalizable to a broader population, and the exclusion of other potential influencing variables like social or economic factors. Therefore, caution should be applied when interpreting and applying these results in different contexts.

These findings have practical implications, particularly for educational institutions and financial organizations, which can design programs that emphasize the benefits and ease of saving, tailored to gender-specific characteristics, to enhance college students' saving behaviors. Policies that encourage accessible savings programs with clear benefits could also positively impact college students' financial behaviors. For future research, it is suggested to consider more specific moderating variables, such as age, income level, or financial literacy, and to calculate indirect or total effects in multigroup moderation analysis to better understand complex relationships. Additionally, exploring the development of second-order indicator models in PLS-SEM with multigroup moderation analysis could provide a more comprehensive understanding of the variables involved.

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