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To cite this article: Luthfatul Amaliana *et al* 2019 *IOP Conf. Ser.: Earth Environ. Sci.* **239** 012021

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# The Consistency of Bootstrap Resampling in Structural Model With PLS-PM Approach: Technology Acceptance Model in Green Marketing Management Strategy

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**Abstract.** Indonesia is one of the developing countries where information system technology is widely used in the field of management. One example is the use of Go-Food applications. Many problems and determinants of someone in using Go-Food. Not all problems can only be solved by looking at one exogenous variable alone. So that required a more complex modelling that is Partial Least Square - Path Modelling (PLS-PM). The PLS-PM process requires resampling in testing the hypothesis. so it is necessary to compare the bootstrap resampling and jackknife techniques as well as to determine how many replicas in each resampling technique to achieve convergent conditions. The analysis procedure is to collect the data, then proceed to make PLS-PM model which then tested by using bootstrap resampling and jackknife. Compare the best resampling and see convergent conditions on each resampling. In this study it is known that the results of PLS-PM relationship in accordance with the model where the relationship of benefits to the attitude becomes the most significant relationship. in the process of hypothesis testing obtained one path that is not significant ease of interest. In comparison the resampling results obtained jackknife more efficient than using bootstrap.

Keywords: Bootstrap Resampling, Jackknife Resampling, PLS-PM

## 1. Introduction

Structure Equation Model (SEM) is a statistical model that produces relationships between variables and indicator models simultaneously. A data analysis using SEM explains the relationship between variables in the study. SEM determines latent variables from indicators. SEM is based on the concept of covariant variant matrices, so latent variables can only be formed in a reflective format [1].

Partial Least Square (PLS) is a method for constructing models that can be used when there are too many factors. PLS was first developed by Wold as a general method for estimating path models that use latent variables with multiple indicators. PLS is also a powerful analytical method because it does



not assume data must be of a certain scale or small number of samples. Partial Least Square comes from social science, especially economics (Wold, 1996). This model is developed as an alternative to situations where the theoretical basis for designing models is weak or available indicators do not meet the reflexive measurement model. PLS, in addition to be used to confirm a theory, can also be used to build relationships that do not have a theoretical foundation or to test propositions.

Partial Least Square (PLS) does not require assumption that data is normally distributed. This happens because the data is resampling using the Bootstrap method, which is based on random sampling of new samples and original samples returned so they can be re-selected. The amount of replication does not always produce new samples suitable for the population, so it is necessary to see the consistency of the replication that it is sufficient to determine the number of replications.

Indonesia is one of the developing countries. Rapid development has caused intense competition in the world of economy. Competition in this era does not only depend on human resources and products but also includes technology. The sophisticated technology creates innovation that can dominate the economy that many people start doing business using technology. The technology widely used by the public is mobile phones—almost everyone has cell phones. This has led to the development of mobile-based applications of various benefits. One of the information system-based services that are widely used is Go-Food, which is part of the Go-Jek application. People love to use Go-Food application because it can deliver food without them having to go to a certain shop, restaurant, or place to eat.

This research was conducted in Malang City, as one of the education cities in Indonesia. Students also use Go-Food often. The Go-Food application becomes more useful, yet also more complex that not all people want to use it. This study uses Technological Acceptance Model (TAM) to explain how people perceive a system. The variables included are interests, attitudes, and ease and benefit of the application; all are measure using a Likert scale based questionnaire.

Based on existing explanations, the researcher will conduct research on the relationship between variables of interest, attitude, and ease and benefit of the Go-Food application using Partial Least Square (PLS) with the PLS-PM approach to reveal the consistency of Bootstrap resampling results.

## 2. Literature Review

The Technology Acceptance Model (TAM) adopted from the Theory of Reasoned Action (TRA) developed by [8] offers as a basis for obtaining a better understanding of user behaviour in the acceptance and use of Information Systems. This model places the additional factors of each user behaviour with two main variables, namely: The ease of use and usefulness variables, both of which have high determinants and validations that have been empirically tested [8].

There are several variables from the TAM model research including: Perceived Ease of Use (PEOU), perceptions of benefits (Perceived Usefulness / PU), Attitude Toward of Using / ATU, behaviour to keep using (Behavioural Intention to Use / ITU) [8]. This study uses Partial Least Square (PLS) with the PLS-PM approach to examine the relationship between variables of interest, attitude, ease and usefulness of using the Go-Food application. PLS-PM (Partial Least Square Path Modeling) is a development of SEM, where the manifest variable is formative and can also be reflective [2].

## 3. Research Method

This study collects primary data using research instruments in the form of questionnaires distributed to students of Brawijaya University, especially those in statistical study programs. The distribution of this questionnaire aims to determine the direct and indirect effect of the Technology Acceptance Model (TAM).

Proportional sampling is the technique of taking proportions to obtain a representative sample, taking balanced or comparable subjects from each strata or region [6]. Accidental sampling is a technique for determining samples based on chance, that is, anyone who accidentally meets the researcher and meets the criteria for being a respondent can be taken as a sample. The sample size can be calculated using the following Slovin formula [7]:

$$n = \frac{N}{1 + N(e^2)}$$

In which:

$n$  : sample size

$N$  : population size

$E$  : the level of inaccuracy that can be tolerated (in this study is 10%)

Based on Slovin calculation formula above, the minimum sample size in this study are:

$$\frac{401}{1 + 401(0.1^2)} = 80.27 \approx 81 \text{ students}$$

The analysis tools using Partial Least Square as follow:

### 3.1. Partial Least Square

PLS-PM is a powerful analytical method because it can be applied to all data scales, it does not require many assumptions, and it does not require a large sample size. It is also able to explain the relationship between variables with a weak or no theoretical basis; PLS-PM can also be used to confirm the theory. PLS-PM is a development of SEM, where the manifest variable is formative and can also be reflective [2].

Estimating parameters in PLS-PM includes three (3) things. The first is the weight estimate used to calculate the value of the latent variable. The second is the path estimate that connects between latent variables (path coefficients) and between latent variables with the manifest variable (loading). The third is the category related to means and location parameters (regression constant values) for manifest variables and latent variables.

The first stage is the essence of the PLS-PM algorithm, which contains an iterative step to produce a stable weight estimator. The estimator of component scores for each latent variable is obtained in two ways, namely outside approximation and inside approximation. To obtain the outside approximation weight, the inner model estimator is used, while to obtain the inside approximation weight, the estimator outer model is used. The iteration process will stop if convergent conditions have been reached. To check convergence in each iteration is by comparing the outer weight  $S$  with the outer weight  $S-1$ , where  $S$  is 1, 2, 3, ... with the following criteria [3]:

$$\left| \hat{w}_{k_i}^{S-1} - \hat{w}_{k_i}^S \right| < 10^{-5}$$

The PLS-PM algorithm can be written as follows [4]:

Stage 1: estimating iterations of weights and scores for latent variables (starting from step #4 then repeating back to step #1 and continuing with the next step) until convergent conditions are reached.

Stage 2: estimating the loading coefficient

Stage 3: estimating the path coefficient

#1 Inner weight with a centroid approach

$$v_{ji} = \begin{cases} \text{sign corr}(Y_j; Y_i), & \text{if } Y_j \text{ and } Y_i \text{ close} \\ 0, & \text{else} \end{cases}$$

#2 Inside approximation

$$Z_j = \sum_i v_{ji} Y_i$$

#3 Outer weight

$$y_{k_j} = \tilde{w}_{k_j} Z_j + u_{k_j} \quad \text{on the reflective model}$$

$$Z_j = \sum_{k_j} \tilde{w}_{k_j} y_{k_j} + d_j \quad \text{on the formative model}$$

#4 Outside approximation

$$Y_i = \sum_k \tilde{w}_{jk} X_{jk}$$

In which:

$Y_j$  : the latent variable of outside approximation

$Z_j$  : the latent variable of inside approximation

$y_{kj}$  : the manifest variable

$d$  : residual validity

$u$  : residual outer

$v$  : inner weight

$w$  : weight coefficient

$j=1, 2, 3, \dots, Q$  for the number of latent variables

$i=1, 2, 3, \dots, T$  for the number of neighbor latent variables

$kj=1, 2, 3, \dots, R$  for the number of relations of the manifest variable without  $j$

$n=1, 2, 3, \dots, N$  for the number of observations

### 3.2. Hypothesis Testing Using The Resampling Method

The application of the resampling method can be used to test hypotheses, on data that uses repeated sampling based on the original sample. There are several resampling methods, namely:

#### 3.2.1. Jackknifing

The resampling method used before the bootstrap method was found was resampling jackknife. According [9] jackknife can be used to build the variance of an estimator. The steps to estimate the standard error from Jackknife are as follows:

- 1) Resampling by deleting rows of data on each Jackknife sample.

$$x_{(i)} = x_1, x_2, \dots, x_{i-1}, x_{i+1}, \dots, x_n$$

For  $i = 1, 2, \dots, n$  called Jackknife samples.

- 2) Calculating the Jackknife replication related to each Jackknife sample.

$$\hat{\theta}(i) = s(x_i); i = 1, 2, \dots, n$$

- 3) Estimating the standard error by using the standard deviation for Jackknife which is replicated  $n$  times.

Suppose there are five samples on variable  $X$   $x = \{x_1, x_2, x_3, x_4, x_5\}$ . The following is the sampling process for the Jackknife delete- $d$  resampling method:

a. First take  $x_{(1)} = \{x_2, x_3, x_4, x_5\}$

b. Second take  $x_{(2)} = \{x_2, x_1, x_5, x_4\}$

#### 3.2.2. Bootstrapping

Bootstrap method was first introduced by [10] to predict standard errors and confidence intervals. The Bootstrap method depends on the suspicion of a Bootstrap sample. Bootstrap steps for standard error estimation are as follows [10]:

- 1) Determine the number of times  $B$  in the Bootstrap sample  $(x_1^*, x_2^*, \dots, x_B^*)$  obtained from random sampling with returns of  $n$  elements from the initial sample  $(x_1, x_2, \dots, x_n)$ .
- 2) The Bootstrap replication calculation related to each Bootstrap sample

$$\hat{\theta}^*(b) = s(x_b^*); b = 1, 2, \dots, B$$

- 3) Estimating the standard error by using the standard deviation for Bootstrap which is replicated  $B$  times.

Suppose there are five samples on variable  $X$ , that is  $X = \{x_1, x_2, x_3, x_4, x_5\}$ . The following is the sampling process in the Bootstrap resampling method:

- a. First take  $x_1^* = \{x_1, x_5, x_1, x_3, x_2\}$
- b. Second take  $x_2^* = \{x_4, x_2, x_3, x_4, x_5\}$

Based on the above process it can be seen that in each Bootstrap sample the same sample can be taken from the original sample.

### 3.3. Hypothesis Testing

Tests are carried out using the t test, with t test statistics as follows:

1. T test statistics for the outer model  $t = \frac{\hat{\lambda}}{SE(\hat{\lambda})}$
2. Test statistics for the inner model

The effect of exogenous latent variables on endogenous  $t = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$

The effect of endogenous latent variables on endogenous  $t = \frac{\hat{\beta}}{SE(\hat{\beta})}$

The statistical hypotheses are as follows:

1. For the outer model  $H_0 : \lambda_i = 0$  versus  $H_1 : \lambda_i \neq 0$
2. For the inner model

The effect of exogenous latent variables on endogenous  $H_0 : \gamma_i = 0$  versus  $H_1 : \gamma_i \neq 0$

The effect of endogenous latent variables on endogenous  $H_0 : \beta_i = 0$  versus  $H_1 : \beta_i \neq 0$

If  $t_{\text{count}} \geq t_{\text{table}} (1.96)$ , then  $H_0$  is rejected (significant). On the outer model, the result is significant, meaning that the manifest variable can be used as a measuring instrument for latent variables. On the inner model, the result is also significant meaning that there is a significant effect of latent variables on other latent variables.

### 3.4. Convergence

One method for estimating resampling parameters is to see the bias. The bias of  $\hat{\theta}$  is the difference from the estimation of  $\theta$  with the parameter value  $\theta$ , which can be written:

$$\text{bias}_F = \text{bias}_F(\hat{\theta}, \theta) = E_F[s(x)] - t(F)$$

Large bias is generally the most undesirable aspect. Many studies expect that the diversity of data is not too scattered. Ideal resampling results generally follow the approach of Monte Carlo simulations based on averages  $E_F[s(x)]$ .

$$\hat{\theta}^*(.) = \frac{\sum_{b=1}^B \hat{\theta}(b)}{B} = \sum_{b=1}^B s(x^{*b}) / B$$

The estimation of bias is based on the number of  $B$  replicas by substituting  $E_F[s(x)]$  with  $\hat{\theta}^*(.)$

Thus, becoming:

$$\text{bias}_B = \hat{\theta}^*(.) - t(\hat{F})$$

Many studies assume that  $B = 400$  is enough to get an estimator that is suitable for the standard error. To converge from the results of resampling, the following formula can be used:

$$\text{Prob}_{\hat{F}} \left\{ \left| \hat{\theta}^*(.) - E_F\{\hat{\theta}^*\} \right| < 2 \frac{se_B}{\sqrt{B}} \right\} = \text{Prob}_{\hat{F}} \left\{ \left| \text{bias}_B - \text{bias}_{\infty} \right| < 2 \frac{se_B}{\sqrt{B}} \right\} = 0.95$$

### 3.5. Relative Efficiency

To compare the resampling techniques used in this study, a measure is needed. Two estimators can be compared for efficiency using relative efficiency. The efficiency of two estimators  $\hat{\theta}_i$  relative toward  $\hat{\theta}_i^*$  can be defined as follows[5]:

$$eff(\hat{\theta}_i, \hat{\theta}_i^*) = \frac{V(\hat{\theta}_i^*)}{V(\hat{\theta}_i)}$$

In which

$V(\hat{\theta}_i^*)$  : Parameter estimation variance with Bootstrap resampling method

$V(\hat{\theta}_i)$  : Parameter estimation variance with Jackknife resampling method

If the results of the calculation are more than one, it can be stated that the estimator  $\hat{\theta}_i$  is an unbiased estimator that is better than  $\hat{\theta}_i^*$ .

## 4. Results And Discussion

### 4.1. Hypothesis Testing

At PLS-PM, hypothesis testing is done using the resampling method. In this study, the resampling method used is the Bootstrap and Jackknife method.

#### 4.1.1. Bootstrap

Outer model testing is done using the t test with the statistical hypothesis  $H_0 : \lambda_i = 0$  versus  $H_1 : \lambda_i \neq 0$ . The results of the calculation of the t test are summarized in Table 4.1.

Table 4.1 T-Test Statistical Value on Outer Model Bootstrap

Variable	Indicator	Loadings	T <sub>count</sub>
Benefit	X11	0.8595	22.5988
	X12	0.8891	24.7646
Ease	X21	0.8181	7.3586
	X22	0.8441	7.35868
Attitude	Y11	0.8958	40.2288
	Y12	0.8797	39.4921
	Y13	0.7311	9.15548
Interest	Y21	0.8531	22.5629
	Y22	0.8500	20.0670
	Y23	0.8779	26.2090

Table 4.1 shows that all indicators have  $t_{count} > 1.96$ , indicating that these indicators can be used as instruments for measuring latent variables.

Based on the test results of the outer model, it can be seen that:

- Indicators  $x_{11}$  and  $x_{12}$  reflect benefit at the 5% significance level
- Indicators  $x_{21}$  and  $x_{22}$  reflect ease at the 5% significance level
- Indicators  $y_{11}$ ,  $y_{12}$ , and  $y_{13}$  reflect attitude at the 5% significance level
- Indicators  $y_{21}$ ,  $y_{22}$ , and  $y_{23}$  reflect interest at the 5% significance level

Inner model testing is done using the t test, with the statistical hypothesis as follows:

- The effect of exogenous latent variables on endogenous  $H_0 : \gamma_i = 0$  versus  $H_1 : \gamma_i \neq 0$
- The effect of endogenous latent variables on endogenous  $H_0 : \beta_i = 0$  versus  $H_1 : \beta_i \neq 0$

The results of the calculation of t test statistic values can be presented in Table 4.2 below:

Table 4.2 shows three (3) relationships between latent variables having  $t_{count} > 1.96$  and two (2) relationships between variables that have  $t_{count} < 1.96$ , so it can be concluded that the relationship between ease and benefit towards interest is not significant.

Table 4.2: T-Test Statistical Value on Inner Model Bootstrap

Relationship	Path Coefficient	T <sub>count</sub>
Benefit to Attitude	0.3737	3.0576
Ease to Attitude	0.3046	2.8452
Benefit to Interest	0.1157	1.4045
Ease to Interest	-0.0718	-0.9223
Attitude to Interest	0.7724	11.9179

#### 4.1.2. Jackknife

Outer model testing is done using the t test with the statistical hypothesis  $H_0 : \lambda_i = 0$  versus  $H_1 : \lambda_i \neq 0$ . The results of the calculation of the t test are summarized in Table 4.3.

Table 4.3 T-Test Statistical Value on Outer Model Jackknife

Variable	Indicator	Loadings	T <sub>count</sub>
Benefit	X11	0.8595	10.7249
	X12	0.8892	10.6020
Ease	X21	0.8181	10.7139
	X22	0.8441	10.5631
Attitude	Y11	0.8958	7.8543
	Y12	0.8798	7.8515
	Y13	0.7312	8.1704
Interest	Y21	0.8532	7.9945
	Y22	0.8501	8.1686
	Y23	0.8780	7.9480

Table 4.3 shows that all indicators have  $t_{count} > 1.96$ , indicating that these indicators can be used as instruments for measuring latent variables.

Based on the test results of the outer model, it can be seen that:

- Indicators  $x_{11}$  and  $x_{12}$  reflect benefit at the 5% significance level
- Indicators  $x_{21}$  and  $x_{22}$  reflect ease at the 5% significance level
- Indicators  $y_{11}$ ,  $y_{12}$ , and  $y_{13}$  reflect attitude at the 5% significance level
- Indicators  $y_{21}$ ,  $y_{22}$ , and  $y_{23}$  reflect interest at the 5% significance level

Inner model testing is done using the t test, with the statistical hypothesis as follows:

- The effect of exogenous latent variables on endogenous  $H_0 : \gamma_i = 0$  versus  $H_1 : \gamma_i \neq 0$
- The effect of endogenous latent variables on endogenous  $H_0 : \beta_i = 0$  versus  $H_1 : \beta_i \neq 0$

The results of the calculation of t test statistic values can be presented in Table 4.4 below:

Table 4.4 T-Test Statistical Value on Inner Model Jackknife

Relationship	Path Coefficient	T <sub>count</sub>
Benefit to Attitude	0.3737	2.5401
Ease to Attitude	0.3046	2.5803
Benefit to Interest	0.1157	1.6337
Ease to Interest	-0.0718	1.7997
Attitude to Interest	0.7724	2.2973

Table 4.4 shows three (3) relationships between latent variables having  $t_{count} > 1.96$  and two (2) relationships between variables that have  $t_{count} < 1.96$ , so it can be concluded that the relationship between ease and benefit towards interest is not significant.



#### 4.2. Hypothesis Testing

Table 4.5 T-Test Statistical Value on Inner Model Bootstrap

Relationship	Path Coefficient	T <sub>count</sub>	p-value
Benefit to Attitude	0.3737	3.0576	0.0068
Ease to Attitude	0.3046	2.8452	0.0153
Benefit to Interest	0.1157	1.4045	0.1540
Ease to Interest	-0.0718	-0.9223	0.2467
Attitude to Interest	0.7724	11.9179	6.2806e-27

Table 4.5 shows three (3) relationships between latent variables having  $t_{\text{count}} > 1.96$  and two (2) relationships between variables that have  $t_{\text{count}} < 1.96$ , so it can be concluded that the relationship between ease and benefit towards interest is not significant.

Table 4.6 T-Test Statistical Value on Outer Model Bootstrap

Variable	Indicator	Loadings	T <sub>count</sub>	p-value
Benefit	X11	0.8595	22.5988	4.7092e-80
	X12	0.8891	24.7646	1.9336e-90
Ease	X21	0.8181	7.3586	6.98794e-13
	X22	0.8441	7.3586	6.28116e-14
Attitude	Y11	0.8958	40.2288	2.6407e-184
	Y12	0.8797	39.4921	1.4273e-191
	Y13	0.7311	9.1554	6.7163e-20
Interest	Y21	0.8531	22.5629	1.3767e-87
	Y22	0.8500	20.0670	1.9045e-65
	Y23	0.8779	26.2090	2.5087e-115

Table 4.6 shows four (4) relationships between latent variables having  $t_{\text{count}} > 1.96$  and one (1) relationship between variables that has  $t_{\text{count}} < 1.96$ , so it can be concluded that the relationship between ease towards interest is not significant.

#### 4.3. Relative Efficiency

The best resampling can be selected by looking at the relative efficiency value, the one that has the smallest variance as presented in Table 4.7. The table shows that Jackknife resampling has smaller variance value than using Bootstrap resampling. The relative efficiency value shows when the Jackknife variance value is divided by the Bootstrap variance value, the result is  $< 1$ , then Jackknife resampling is efficient than Bootstrap in this study.

#### 4.4. Resampling Convergence

Resampling convergence can be seen when the difference in the resampling parameters is not far from the original parameters, so each replication needs to be seen, tested 100 times, and searched for variance.

Bootstrap resampling with 20,40,60,80,100 and 200 replicas have a variance value that is still not consistent; this means that resampling has not reached convergence. In the replication of 500, 600, 800, and 1000, variance values are consistent, so resampling has reached convergence. Jackknife resampling on 20, 40, 60, 80, 100, and 200 replicas shows a variance value that is still not consistent; this means that resampling has not reached convergence. In 500, 600, 800, and 1000 replicas, it can be seen that the variance has been consistent, so resampling has reached convergence.

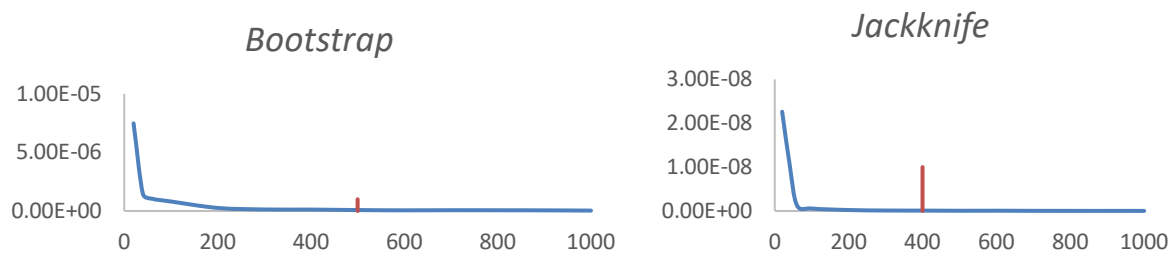


Figure 4.1 The Variance Value of Bootstrap and Jackknife Resampling

Table 4.7 Relative Efficiency Values

Parameter	Relationship	$Var\theta_B$	$Var\theta_J$	Relative Efficiency
$\gamma_1$	Benefit to Attitude	0.1208	0.0010	0.0082
$\gamma_2$	Ease to Attitude	0.1144	0.0009	0.0078
$\gamma_3$	Benefit to Interest	0.0806	0.0003	0.0037
$\gamma_4$	Ease to Interest	0.0747	0.0002	0.0026
$\beta_1$	Attitude to Interest	0.0645	0.0002	0.0031

#### 4.5. Discussion

This result is inline with the Technology Acceptance Model (TAM) adopted from the Theory of Reasoned Action (TRA) developed by [8] offers as a basis for obtaining a better understanding of user behaviour in the acceptance and use of Information Systems. This model places the additional factors of each user behaviour with two main variables, namely: The ease of use and usefulness variables, both of which have high determinants and validations that have been empirically tested [8]. Partial Least Square (PLS) with the PLS-PM approach to examine the relationship between variables of interest, attitude, ease and usefulness of using the Go-Food application. PLS-PM (Partial Least Square Path Modeling) is a development of SEM, where the manifest variable is formative and can also be reflective [2], by using jackknife resampling as the best method for hypothesis testing in PLS-PM. Benefit and ease of use are directly significant on attitude to use Go-Food application, and attitude as mediation variable in relationship between benefit and ease of use on interest of using Go-Food Application.

Based on the results of PLS-PM analysis on the bootstrap hypothesis test, it can be seen that the interest of statistical students is influenced by benefits and convenience indirectly through the attitude of the statistical students. Where the relationship between convenience and interest is not significant so that it cannot be directly connected. This is not in accordance with the existing theory, in this study good benefits do not fully influence students' interest in using the Go-Food application, this occurs because there are indicators or other variables that can explain more clearly. The PLS-PM results also show that the relationship between the ease of Go-Food applications and interest in using the Go-Food application does not fully influence, this supports the existing theory where convenience does not have a direct influence on interest. In bootstrap consistency experiments, convergent conditions were reached when the number of replicas used was more than 500 times which were tested 100 times for each replica, so when replicas were used as many as 20, 40, 60, 80, 100, or 200, 300 and 400 is still not enough to achieve consistent conditions.

## 5. Conclusions and Suggestions

### 5.1. Conclusions

Based on findings and discussion, the following conclusions are presented.

1. The results of the analysis using PLS-PM show a positive relationship of ease and benefit to attitude. In addition, attitude also has a positive effect on interest. Based on this relationship, the interest of students in using the Go-Food application is influenced directly by attitudes and benefits.
2. The parameter estimation results using Bootstrap and Jackknife resampling methods shows that Jackknife resampling is more efficient in this research. The convergence level of Jackknife resampling is reached when the number of replicas used is more than 400 times.

### 5.2. Suggestions

Based on the results of this study, it is advisable to conduct an analysis using items that are more valid and to understand deeply the factors that influence interest in using the application. It is recommended for the next study to clarify the use of language to be easily captured by respondents.

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