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Enacting Alternating Least Square Algorithm to Estimate Model Fit of Sem Generalized Structured Component Analysis

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Abstract Structural Equation Modeling (SEM) is a statistical modeling technique that combines three methods, namely factor analysis, path analysis and regression analysis to test a theoretical model in social science, psychology and management. Covariance-based SEM is a parametric SEM that must meet several parametric assumptions such as, multivariate normally distributed data, large sample sizes and independent observations, so that, variance-based SEM was developed to overcome the problem of covariance SEM, namely the Generalized Structured Component Analysis (GSCA) method.

This study aims to implement the GSCA method on factors data that are expected to have an effect on the level of behavioral intention towards online food delivery services and to examine the significance of the mediating variable on the structural relationship. The results of hypothesis testing with a 95% confidence level showed that the quality of convenience motivation, prior online purchase experience, and attitude towards online food delivery services had a significant effect on behavioral intentions towards online food delivery services. The fit value is above $0,523$ which indicates that the model is able to explain around $52,3\%$ of the variation of the data. Furthermore, the hedonic motivation variable has a significant effect on convenience motivation. Post usage usefulness and prior online purchase experience variables significantly affected the attitudes towards online food delivery services. The proposed model using GSCA achieves a much better result (good fit) compared with the previous model using Confirmatory Factor Analysis (CFA) with marginal fit.

Keywords Online Food Delivery Service, SEM, GSCA, Software R

1 Introduction

Structural Equation Modeling (SEM) consists of three methods, namely multiple regression analysis, path analysis, and factor analysis taken from econometrics and psychometrics which are able to describe latent variable (not directly measurable) and are measured directly based on manifest variable, so this analysis is often called as the second generation of multivariate analysis. Covariance-based SEM was first developed by Joreskog[14], Keesling[13], and Wiley[21] using the Maximum Likelihood (ML) function Ghozali[4]. CBSEM users are strongly influenced by parametric assumptions that must be met, such as the observed variables which have a multivariate normal distribution and the observations must be independent towards each other. A small "asymptotic" sample can give poor parameter estimation results and statistical models Chou and Bentler[3]. It can even generate a negative variance. Another alternative to overcome the problem of CBSEM is component-based SEM.

Component-based SEM is a better alternative and has two methods, namely Partial Least Square (PLS) and Generalized Structure Component Analysis (GSCA). Component-based SEM does not depend on the assumption of multivariate normal distribution Ghozali[5]. The first SEM-PLS was initiated by Wold[17]. PLS estimates the parameter model based on a fixed point algorithm. PLS cannot solve the problem by global optimization for parameter estimation so it does not provide a mechanism to assess the overall goodness-fit of the model and it is difficult to determine how well the model fits the data Ghozali[5]. As a solution to overcome PLS, GSCA; Hwang and Takane[7] proposed a new method called GSCA. GSCA is a powerful analytical method that measures the overall model fit. GSCA estimates the parameter model based on the alternating least squares algorithm. GSCA combines three sub-models, namely measurement, structural, and weighting relationship models into one formulation. It aims to minimize the global least squares optimization criteria, which are derived from a single formulation, to estimate all parameters simultaneously. Thus, unlike PLS, GSCA allows the calculation of an overall fit measure to evaluate how well a given model fits the overall data and to compare the competing models.

In this study, the researcher will implement the GSCA method in behavioral intention case study in an online food delivery service company. Online food delivery services are food delivery services that can be provided by restaurants, online delivery service sites, or online taxi bike. In Indonesia, the examples of food delivery application companies are Gofood and Grabfood id.techinasia.com[10]. Nielsen Singapore research in 2019 showed that around 58% of Indonesians bought fast food through online applications from smartphone. On average, people buy fast food through online food delivery application from their smartphone $2,6$ times per week. The percentage of internet users who use online food delivery applications in Indonesia, is $74,4\%$, which is considered as the highest in the world in 2020. The data is the result of monthly research/study by We Are Social katadata.co.id[12]. The trend of food delivery services during the new normal phase is predicted to be more competitive in the future. The reason is that these service features are not only available through applications created by Gojek and Grab, but other digital companies are also starting to follow these companies. As one of the trading industry fields, the key indicator of a food delivery company is how to maintain its existence by increasing consumer interest in the midst of many competitors for food delivery services that have sprung up or called as behavioral intention in online food delivery service companies. There are several key factors that significantly affect the level of behavioral intention in online food delivery services.

According to Yeo et.al[19], several previous studies conduct an analysis to examine the relationship between the factors that affect behavioral intention in online food delivery. In the existing model, there are factors such as hedonic motivation, prior online purchase experience, convenience motivation, post-usage usefulness, and attitude towards online food delivery services towards behavioral intentions. The modelling that can be used to measure the optimization of behavioral intention in a company's business process is Structural Equation Modelling (SEM).

Thus, based on the explanation of the background above, the researcher wants to apply the analysis using GSCA method for a case study on consumer interest in online food delivery service applications (behavioral intention toward online food delivery service).

2 LITERATURE REVIEW

GSCA (Generalized Structured Component Analysis) is a component-based SEM method, in which the latent variable is defined as component of indicator variable. The GSCA method includes component-based structural equation analysis with latent variable as the weighted component of the observed variable. The GSCA method was developed by Hwang in 2004 to avoid the main weakness of PLS-SEM, that is the goodness of fit Hwang and Takane[7].

The model in the GSCA consists of three sub-models, namely structural model, measurement model and weighting model. The structural model describes the relationship between latent variables, while the measurement model describes the relationship between latent variables and their indicators. In addition, a weighting model is used to estimate the value of latent variable. In general, the GSCA model can be written as follows.

1. Structural Model:

$$\boldsymbol{\gamma} = \boldsymbol{\gamma B} + \boldsymbol{\zeta} \tag{1}$$

Where B is the path coefficient matrix between latent variables measuring $t \times t$, and $\boldsymbol{\zeta}$ is the error vector for endogenous latent variables measuring $1 \times t$.

2. Measurement Model:
The measurement model in GSCA is mathematically written as follows:

$$\boldsymbol{z} = \boldsymbol{\gamma C} + \boldsymbol{\epsilon} \tag{2}$$

Where $\boldsymbol{z}$ is the indicator variable vector measuring $1 \times s$, $\boldsymbol{C}$ is the loading factor matrix between latent variables with indicator measuring $t \times s$, $\boldsymbol{\gamma}$ is the latent variable vector measuring $1 \times t$, and $\boldsymbol{\varepsilon}$ is the indicator error vector measuring $1 \times s$.

3. Weighting Model:
The weighting model in GSCA is mathematically written as follows:

$$\boldsymbol{\gamma} = \boldsymbol{zW} \tag{3}$$

$\boldsymbol{W}$ is the component weighting matrix from indicator variable to latent variable measuring $s \times t$.

GSCA integrates (1), (2), and (3) into a single equation written as follows.

$$[z, \gamma] = \gamma[C, B] + [\varepsilon, \zeta]$$
$$\boldsymbol{z[I, W]} = \boldsymbol{zW[C, B]} + [\boldsymbol{\varepsilon}, \boldsymbol{\zeta}] \tag{4}$$

I is the identity matrix measuring $s \times s$, $V = [I, W]$, $A = [C, B]$ and $e = [\varepsilon, \zeta]$. Thus, (4) can be written as follows.

$$\boldsymbol{zV} = \boldsymbol{zWA} + \boldsymbol{e} \tag{5}$$

3 MATERIAL AND METHOD

According to Hwang and Takane[7] in Kim, Cardwell, and Hwang[16], when the unknown GSCA parameter ($\boldsymbol{V}$, $\boldsymbol{W}$, and

$\boldsymbol{A}$) is estimated, the least square value of all error (e_i) becomes as small as possible to be observed, by minimizing the estimation of least square as follows.

$$\begin{aligned} \boldsymbol{g} &= \sum_{i=1}^{n} \boldsymbol{e_i' e_i} \\ &= \sum_{i=1}^{n} (\boldsymbol{V' z_i - A' W' z_i})(\boldsymbol{V' z_i - A' W' z_i}) \end{aligned} \quad (6)$$

Information:

- symbol $\boldsymbol{n}$ is the amount of observed data
- symbol $\boldsymbol{z}$ is the vector matrix of the size indicator variable $n \times 21$
- symbol $\boldsymbol{V}$ is a supermatrix of size 21×27 consisting of an identity matrix and a weight matrix.
- symbol $\boldsymbol{W}$ is a component weight matrix of size 21×6

The equation (6) can be summarized without summation and observation as follows.

$$\begin{aligned} \boldsymbol{g} &= \boldsymbol{SS(E)} \\ &= \boldsymbol{ZV - ZWA} \\ &= \boldsymbol{\Psi - \Gamma A} \end{aligned} \quad (7)$$

Information:

- $\boldsymbol{\Psi}$ is a matrix of indicator variables and their endogenous composite components measuring $n \times 27$.
- Γ is a matrix of indicator variables and composite components measuring $n \times 6$.
- **A** is a supermatrix of size 6×27 consisting of $A = [C, B]$ with C is a coefficient matrix factor loadings between latent variables and their indicators and the path coefficient matrix between latent variables denoted B.
- **e** is an error matrix of size $n \times 27$.

Hwang and Takane[7] in Kim, Cardwell, and Hwang[16] wrote that the Alternating Least Square (ALS) algorithm used in the GSCA consists of two steps. In the first step, $\boldsymbol{A}$ is updated with fixed $\boldsymbol{V}$ and $\boldsymbol{W}$. In the second step, $\boldsymbol{V}$ and $\boldsymbol{W}$ are updated with fixed $\boldsymbol{A}$. The following describes the two stages detail of ALS estimation in the GSCA. Any comments and suggestions are welcomed so that we can constantly improve this template to satisfy all authors' research needs.

- The algorithm used to update A is:
  In the first stage, the algorithm used to update A with matrix V and W fixed is as follows:
  1. Step 1: Initialize matrix V and W.
  2. Step 2: Form matrix $I \bigotimes \boldsymbol{\Gamma}$
  3. Step 3: Form matrix $\boldsymbol{\Omega} = I \bigotimes \boldsymbol{\Gamma}$
  4. Step 4: Update the estimation of least square of $\boldsymbol{\alpha}$ with constant $\boldsymbol{V}$ and $\boldsymbol{W}$ expressed as follows.
  $$\hat{\alpha} = (\Omega' \Omega)^{-1} \Omega' \text{vec}(\Psi) \quad (8)$$
  5. Step 5: To update A which is obtained from $\hat{\alpha}$ and assumed that $\Omega'\Omega$ is non-singular.
- The algorithm used to update V and W is: In the second stage, the matrix $\boldsymbol{V}$ and $\boldsymbol{W}$ are updated with fixed matrix $\boldsymbol{A}$. The algorithm used to update matrix $\boldsymbol{V}$ and $\boldsymbol{W}$ is as follows.
  1. Step 6: Initialize $\boldsymbol{A}$ from updated matrix $\boldsymbol{A}$.
  2. Step 7: Form matrix $\boldsymbol{S}$ which contain the estimated weight parameters.
  3. Step 8: Define $\boldsymbol{\Lambda = WA}$
  4. Step 9: Define β' **and** Δ
  5. Step 10: Form the matrix $\boldsymbol{\beta} \bigotimes \boldsymbol{Z}$
  6. Step 11: Form the matrix $\boldsymbol{\Pi}$
  Suppose P and Q be the number of columns containing the parameters to be estimated in the matrix $\boldsymbol{V}$ and $\boldsymbol{W}$. Suppose U have the same number of columns in the matrix $\boldsymbol{V}$ and $\boldsymbol{W}$. Suppose $K = P + Q - U$, to update all the parameters in $\boldsymbol{V}$ and $\boldsymbol{W}$ to be:
  $$g = \sum_{i=1}^{n} SS\big((\boldsymbol{\beta} \bigotimes \boldsymbol{Z})\boldsymbol{s_k} - \text{vec}(\boldsymbol{z}\Delta)\big) \quad (9)$$
  7. Step 12: Suppose:
  $\boldsymbol{\eta_k}$ is a vector formed by removing every element zero in $\boldsymbol{s_k}$.
  $\boldsymbol{\Pi}$ is a matrix formed by removing the column from $\boldsymbol{\beta} \bigotimes \boldsymbol{Z}$ which corresponds to element zero in $\boldsymbol{s_k}$.
  Thus, the estimation of least square from $\boldsymbol{\eta_k}$ is obtained as follows:
  $$\hat{\eta_k} = (\boldsymbol{\Pi' \Pi})^{-1} \boldsymbol{\Pi'} \text{vec}(\boldsymbol{Z}\Delta) \quad (10)$$
  8. Step 13: Update $\boldsymbol{s_k}$ obtained from $\boldsymbol{\eta_k}$. Then, insert it in the compatible matrix $\boldsymbol{V}$ and $\boldsymbol{W}$ column.
  9. Step 14 : Repeat step 12 and step 13 as much as K times (K column) or update $\boldsymbol{s_k}$ which is obtained from $\boldsymbol{\eta_k}$. Then, insert it in the compatible matrix $\boldsymbol{V}$ and $\boldsymbol{A}$ column.
  10. Step 15 :New $\boldsymbol{V}$ and $\boldsymbol{W}$are obtained.
  11. Step 16 : Check the convergence, if it is not convergent then repeat step 1.

The data set used in this study aims to analyze the factors that influence the proportion of consumer interest or behavioral intention to use online food delivery services in Indonesia. Respondents in this study were users of online food delivery service applications located in Indonesia, with a total of 188 respondents with 21 indicators, and 6 latent variables. The model has 3 exogenous variables, namely Hedonic Motivation (γ_1), Prior Online Purchase Experience (γ_2), and Post-Usage Usefulness (γ_3). Then, there are 3 endogenous variables, namely: Convenience Motivation (γ_4), Attitude Towards Online Food Delivery Services (γ_5), and Behavioral Intention Towards Online Food Delivery Services (γ_6). The latent variable exogenous Hedonic Motivation (γ_1), consists of three indicators, including: feeling of pleasure using Online Food Delivery (OFD) application (z_1), enjoyment of using OFD application (z_2), attractive OFD application interface (z_3). The exogenous Prior Online Purchase Experience (γ_2) variable contains three indicators, namely: the convenience in using OFD application (z_4), the experience in using OFD application (z_5), the knowledge in using OFD application (z_6). The third exogenous variable, namely Post-Usage Usefulness (γ_3) has 4 indicators, including: Using OFD services is faster and easier for users (z_7), increases effectiveness in ordering food (z_8), experience the benefit of using OFD applications (z_9), and benefit in transaction using the OFD application (z_{10}).

The first endogenous variable is Convenience Motivation (γ_4) which consists of 4 indicators, including: Ease of using OFD applications (z_{11}), OFD applications are clear and easy to understand (z_{12}), OFD applications are easy to be taught to others (z_{13}), OFD applications are easy to understand overall (z_{14}). The next endogenous variable is Attitude Towards Online Food Delivery Services (γ_5) which consists of four indicators, including: using OFD applications is a wise decision (z_{15}), using OFD application is the right decision (z_{16}), using all-digital OFD applications is a reasonable thing (z_{17}), OFD application is the best solution currently (z_{18}).

The last endogenous variable is Behavioral Intention Towards Online Food Delivery Services (γ_6) which consists of three indicators, including: plans to use additional services on the OFD application (z_{19}), try to use additional services on the OFD application (z_{20}), try to use additional services if needed on OFD application (z_{21}).

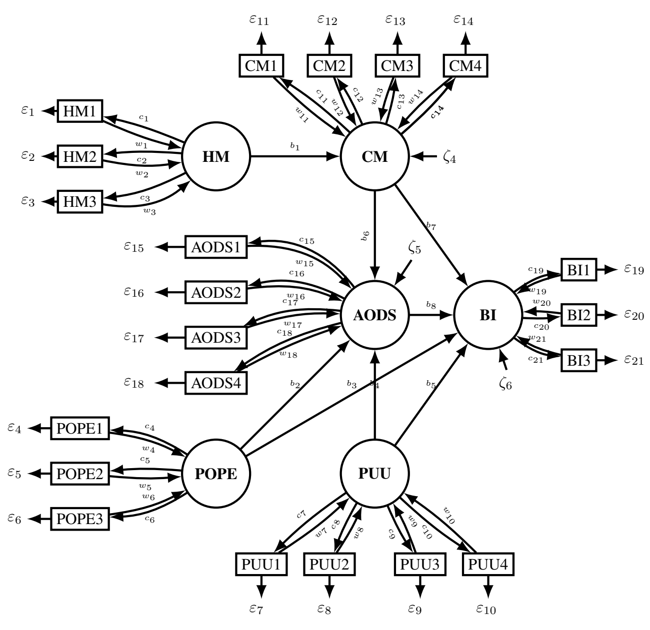

Figure 1. Research Path Diagram

Based on above model, 8 hypotheses can be proposed as follows:

$H1$: *Hedonic Motivations* (HM)) affect the *Convenience Motivation* (CM)
$H2$: *Prior Online Purchase Experience* (POPE) affect the *Attitude Towards Online Food Delivery Services*(AODS)
$H3$: *Prior Online Purchase Experience* (POPE) affect the *Behavioral Intention* (BI)
$H4$: *Post-Usage Usefulness* (PUU) affect the *Attitude Towards Online Food Delivery Services* (AODS)
$H5$: *Post-Usage Usefulness* (PUU) affect the *Behavioral Intention* (BI)
$H6$: *Convenience Motivation* (CM) affect the *Attitude Towards Online Food Delivery Services*(AODS)
$H7$: *Convenience Motivation* (CM) affect the *Behavioral Intention* (BI)
$H8$: *Attitude Towards Online Food Delivery Services* (AODS) affect the *Behavioral Intention* (BI)

The steps of SEM analysis with Generalized Structured Component Analysis are as follows:

a. Obtain concept and theory-based models to design structural models and measurement models.
b. Create a diagram path that explains the pattern of relationships between latent variables and their indicators.
c. Convert diagram path into equations.
d. Estimate the parameters, which consist of weight estimation, loading factor estimation, path coefficient estimation and bootstrap standard error estimation.
e. Determine the parameter coefficient (standard error) and the statistical t value by using the bootstrap method.
f. Evaluate the measurement model by selecting the loading factor that is more than 0.5.
g. Evaluate the structural model
h. Evaluate the overall model fit
i. Interpret and draw a conclusion.

4 RESULTS AND DISCUSSION

In this part, a case study will be conducted on the data that has been obtained and will explain the application of the GSCA method in real life. The case study taken in this research raised a theme related to the factors that affect the Behavioral Intention Towards Online Food Delivery Services conducted by Rachmawati[23].

4.1 Measurement Model Evaluation

The convergent validity of the measurement model with reflective indicators is assessed based on the loading factor value of each indicator forming the latent variable. A latent variable is considered to have a good convergent validity if the loading factor value is more than 0.5 Chin[2]. Based on data analysis with the help of GSCAPro and R software, a summary of the loading factor results is obtained and presented in table 1 as follows.

Table 1. The Estimation of Parameter in Measurement Model

Variable	Loading		
	Estimate	**SE**	**t-statistic***
HM	**AVE = 0.590, $\rho c(\alpha)$ = 0.637, ρ = 0.803**		
HM1	0.85	0.028	30.357
HM2	0.892	0.02	44.6
HM3	0.501	0.082	6.11
POPE	**AVE = 0.616, $\rho c(\alpha)$ = 0.672, ρ = 0.822**		
POPE1	0.544	0.085	6.4
POPE2	0.906	0.016	56.625
POPE3	0.856	0.024	35.667
PUU	**AVE = 0.562, $\rho c(\alpha)$ = 0.738, ρ = 0.837**		
PUU1	0.776	0.032	24.25
PUU2	0.812	0.029	28
PUU3	0.729	0.039	18.692
PUU4	0.675	0.059	11.441
CM	**AVE = 0.628, $\rho c(\alpha)$ = 0.803, ρ = 0.871**		
CM1	0.824	0.026	31.692
CM2	0.805	0.034	23.676
CM3	0.721	0.045	16.022
CM4	0.814	0.033	24.667
AODS	**AVE = 0.633, $\rho c(\alpha)$ = 0.803, ρ = 0.871**		
AODS1	0.852	0.021	40.571
AODS2	0.895	0.019	47.105
AODS3	0.632	0.062	10.194
AODS4	0.779	0.041	19
BI	**AVE = 0.797, $\rho c(\alpha)$ = 0.873, ρ = 0.922**		
BI1	0.893	0.019	47
BI2	0.904	0.023	39.304
BI3	0.881	0.021	41.952

Based on table 1 above, it can be seen that the convergent validity for latent modelling toward the factors that affect Behavioral Intention has a significant and good convergent validity above 0.5. The AVE value in a row is 0.590. 0.616, 0.562, 0.628, 0.633, and 0.797, in which these values are greater than 0.5. This indicates that the model has a good validity.

The latent composite reliability value can be measured from Cronbach alpha ($\rho c(\alpha)$) and Dillon-Goldstein's value (ρ). Composite reliability can be seen with ρc which is above 0.6. The Cronbach alpha ($\rho c(\alpha)$) values are 0.637, 0.672, 0.738, 0.803, 0.799, and 0.873. Then, the values of Dillon-Goldstein's (ρ) are 0.803, 0.822, 0.837, 0.871, 0.871, and 0.922. This study found that the Cronbach Alpha and Dillon-Goldstein's values for each construct exceeded 0.6, which are considered high and acceptable.

Validity can also be assessed by using discriminant validity, namely the measurement model with reflective indicators

Table 2. Fornell-Larcker criterion values

	HM	**POPE**	**PUU**	**CM**	**AODS**	**BI**
HM	0.768					
POPE	0.523	0.785				
PUU	0.398	0.285	0.75			
CM	0.544	0.507	0.378	0.792		
AODS	0.341	0.371	0.41	0.278	0.795	
BI	0.295	0.39	0.253	0.396	0.418	0.893

which are assessed by comparing the AVE square root of each latent with the correlation between the relevant latent and other latent in the model as shown in table 2 above. If the value of AVE square root of each latent is greater than the value of the latent correlation between other latent in the model, then it is said to have a good discriminant validity value Fornell and Larcker[22]. The AVE square root values respectively are 0.768, 0.785, 0.75, 0.792, 0.795, and 0.893, where these values are greater than the correlation value between latent variables and other latent variables. This shows that the model has a good discriminant validity.

4.2 Structural Model Evaluation

Then, the estimation and evaluation process for the structural model will be carried out again. Structural model evaluation aims to see the relationship path coefficient value between latent and the value of CR (Critical Ratio) to determine whether the path coefficient is significant. Based on table 3 below, it

Table 3. The Estimation of Parameter In Structural Model

Path Coefficients			
	Estimate	**SE**	**CR***
HM→CM	0.544	0.059	9.22
POPE→AODS	0.268	0.086	3.116
PUU→AODS	0.326	0.08	4.075
CM→AODS	0.019	0.089	0.213
POPE→BI	0.165	0.074	2.23
PUU→BI	−0.002	0.064	−0.031
CM→BI	0.231	0.092	2.511
AODS→BI	0.293	0.078	3.756

CR* = signifikan pada level 5%

can be seen that not all CR (Critical Ratio) values are statistically significant. The path coefficient between Convenience Motivation (CM) to Attitude Towards Online Food Delivery Services (AODS) and Post-Usage Usefulness (PUU) to Behavioral Intention (BI) is not statistically significant and the parameter coefficient values are sequentially very small (0.213, and −0.031). So that, the path between Convenience Motivation (CM) to Attitude Towards Online Food Delivery Services (AODS) and Post-Usage Usefulness (PUU) to Behavioral Intention (BI) is omitted from the model. The new model (model 2) is obtained by eliminating statistically insignificant paths, and then the estimation and evaluation process is carried out again for the structural model.

Furthermore, based on the output result of R and GSCAPro software, which includes the determination coefficient value (R^2) for each endogenous variable in the GSCA structural model, is shown in the following table. In the Table 4 above, it

Table 4. The Determination Coefficient in Structural Model

Latent Variable	R^2
Convenience Motivation	0.296
Attitude Towards Online Food Delivery Services	0.238
Behavioral Intention	0.278

Table 6. Model Fit Evaluation

Model Fit	
fit	**0.523**
Adjusted-fit	**0.517**
NPAR	**46**

shows the determination coefficient in the Behavioral Intention Towards Online Food Delivery Services variable has R^2 value of 0.278 which means that the Prior Online Purchase Experience, Post-Usage Usefulness, Convenience Motivation, and Attitude Towards Online Food Delivery Services variables can only explain the diversity of Behavioral Intention Towards Online Food Delivery Services by 27.8% and the rest is explained by other variables which are not included in the model. Meanwhile, the determination coefficient in the Convenience Motivation variable has the highest value of 0.296, which means the Hedonic Motivation variable and can only explain the Convenience Motivation diversity as of 29.6% and the rest is explained by other variables which are not included in the model.

Based on table 3 the structural equation model obtained from the model is as follows:

$$CM = 0.544HM + \zeta_4$$
$$AODS = 0.268POPE + 0.326PUU + 0.019CM + \zeta_5$$
$$BI = 0.165POPE - 0.002PUU + 0.231CM + 0.293AODS + \zeta_6$$

In the evaluation for the first model, there are 2 parameter estimations that are not significant, namely having a t-statistic value or Critical ratio (CR) in which both indicators are greater than 1.96. Then, it is excluded in the model, so that, the new measurement (model 2) does not have much change and for structural model evaluation, it can be seen that all path coefficients are statistically significant. The structural model evaluation for model 2 is shown in table 5 below.

Table 5. The Determination Coefficient in Structural Model

Path Coefficients			
	Estimate	SE	CR*
HM→CM	0.544	0.049	11.102
POPE→AODS	0.276	0.078	3.538
PUU→AODS	0.331	0.08	4.138
POPE→BI	0.165	0.08	2.063
CM→BI	0.231	0.078	2.962
AODS→BI	0.293	0.08	3.663

Based on table 5, the structural equation model 2 obtained from model 2 is as follows:

$$CM = 0.544HM + \zeta_4$$
$$AODS = 0.276POPE + 0.331PUU + \zeta_5$$
$$BI = 0.165POPE + 0.231CM + 0.293AODS + \zeta_6$$

4.3 Overall Model Evaluation

The final step in the GSCA analysis is to look at the overall model evaluation which can be summarized as the evaluation of overall model fit as it can be seen in table 6:

The overall model evaluation for model can be seen from the model fit test as shown in table 6 above. This study uses fit and Adjusted-fit, as it can be seen that the fit value is above 0.523 which indicates that the model is able to explain about 52.3% of the data variation. The corrected fit value (Adjusted-fit) obtained also shows results that are not much different, as much as 0.517, which indicates that the model is able to explain about 51.7%. The fit level of the resulting model is that there are 2 measurements which say that the model is good, so it can be concluded that the model used is good. In this model, there are 46 estimated parameters.

4.4 Post GSCA Analysis

To find out whether the best equation using the SEM-GSCA method has an indirect effect on the independent variable (X) to the dependent variable (Y) through the intervening variable (Z), it is necessary to test which includes the following test:

4.4.1 Mediation Test (Sobel Test)

The mediation test is used to determine whether there are significant independent variables that have an indirect effect on the dependent variable through the intermediate latent variable.

a. **Hypothesis Testing**

$$H_0 : \quad \rho X_j X_i \rho Y X_i = 0 \; (no\ mediation\ effect)$$
$$H_1 : \quad \rho X_j X_i \rho Y X_i \neq 0 \; (mediation\ effect\ is\ found)$$

b. Actual Level: $\alpha = 0.05$

c. Critical Area:
Reject H_0 if the value of $CR > 1.96$
Fail to Reject H_0 if the value of $CR < 1.96$

d. Result

Paths	Estimate	CR	SE	Result
HM → CM → AODS	0.01	0.046	0.22	Fail to Reject H_0
HM → CM → BI	0.126	0.05	2.52	Reject H_0
POPE → AODS → BI	0.079	0.035	2.257143	Reject H_0
PUU → AODS → BI	0.096	0.036	2.666667	Reject H_0

e. Conclusion:

- It can be concluded with 95% confidence level from the existing data, the result is fail to reject H_0 or it can be concluded that there is no indirect effect of HM on AODS through CM.
- It can be concluded with 95% confidence level from the existing data, the decision is reject H_0 or it can be concluded that there is an indirect effect of HM on BI through CM.
- It can be concluded with 95% confidence level from the existing data, the decision is reject H_0 or it can be concluded that there is an indirect effect of POPE and PUU on BI through AODS.

4.5 Comparison with Previous Research

There are two aspects that can be analyzed related to comparisons, with previous research, namely parameter estimation on structural model, and test the fit index to the model. Comparison of parameter estimates can be seen in the table 7.

Table 7. Comparison of Parameter Estimation Results in the Model Structural

	GSCA		CFA		Status
	Estimate	CR*	Estimate	CR*	
HM → CM	0.544	9.22	0.25	2.22	Significant
POPE → AODS	0.268	3.116	–	–	Significant
PUU → AODS	0.326	4.075	0.5	5.01	Significant
CM → AODS	0.019	0.213	0.08	0.96	Not Significant
POPE → BI	0.165	2.23	–	–	Significant
PUU → BI	−0.002	−0.031	0.18	1.52	Not Significant
CM → BI	0.231	2.511	0.33	3.49	Significant
AODS → BI	0.293	3.756	0.20	2.33	Significant
HM → PUU	–	–	0.01	0.15	Not Significant
POPE → CM	–	–	0.36	3.55	Significant
POPE → PUU	–	–	0.01	0.15	Not Significant

Based on table 7 above, it can be seen that the status for all relationships in this study (using SEM-GSCA) is the same as in the previous study (which used SEM-CFA). This shows that this study using a smaller dataset has been able to produce better decisions the same as research with a larger number of datasets. This means that the use of the SEM-GSCA method shows an improvement compared to previous studies, especially in terms of efficiency.

The results of the fit index test for the model in the study show a significant improvement compared to previous research, there is at least one value, namely Goodness of fit Index (GFI). The following is a comparison result.

Table 8. Comparison Results of Comparison Test Index

Method	GFI	Score *Cut-Off*	Description
SEM − CFA	0.87	Good fit if $GFI > 0.9$, and Marginal fit jika $0.8 \leq GFI \leq 0.9$	Marginal Fit
SEM − GSCA	0.99	Good fit if $GFI > 0.9$, and Marginal fit if $0.8 \leq GFI \leq 0.9$	Good Fit

Based on table 8 above, it can be seen that the SEM-CFA method used by Rachmawati[23] obtained a Goodness of value fit Index (GFI) of 0.87 or Marginal fit status. Whereas The SEM-GSCA method used in this study obtained Goodness of fit Index (GFI) value of 0.99 or Good fit status. So it can be concluded that based on the results of the fit index test using the GFI value to the model in this study showed a significant improvement compared to previous studies.

5 CONCLUSION

Based on the results of analysis and discussion that have been carried out, the following conclusions can be drawn as follows:

1. The path coefficients of convenience motivation, prior online purchase experience, and attitude towards online food delivery services significantly affect the behavioral intentions towards online food delivery services as much as 0.231, 0.16, and 0.293.

2. The fit value above is 0.523 which indicates that the model is able to explain around 52.3% of the data variation. The corrected fit value (Adjusted-fit) obtained also shows results that are not much different, namely 0.517, which shows that the model is able to explain around 51.7%. The fit level of the resulting model is that there are 2 measurements which claim that the model is good, so it can be concluded that the model used is good.

3. Hedonic Motivation has been identified as latent variable with the biggest indirect influence toward Behavioral Intention (via Convenience Motivation). In addition, Post Usage Usefulness and Prior Online Purchase Experience also have an indirect influence toward Behavioral Intention (via Attitude).

4. The proposed model (using GSCA) has proved much better compared with the previous model (using CFA). The proposed model achieved good fit status while the previous model has marginal fit status.

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