Media Statistika

p-ISSN 1979 – 3693 e-ISSN 2477 – 0647
MEDIA STATISTIKA 13(2) 2020: 136-148
http://ejournal.undip.ac.id/index.php/media_statistika

STRUCTURAL EQUATION MODELING WITH GENERALIZED STRUCTURED COMPONENT ANALYSIS ON THE RELATIONSHIP BETWEEN RENUMERATION AND MOTIVATION ON EMPLOYEE PERFORMANCE AT UIN SUNAN KALIJAGA YOGYAKARTA

Epha Diana Supandi
Mathematics Study Program, State Islamic University, Sunan Kalijaga

e-mail: epha.supandi@uin-suka.ac.id

DOI: 10.14710/medstat.13.2.136-148

Article Info:
Received: 19 March 2020
Accepted: 21 October 2020
Available Online: 28 December 2020

Keywords:
Generalized Structured Component Analysis, Remuneration, Structural Equation Modeling
.

Abstract: Structural equation modeling (SEM) is a multivariate statistical analysis technique that is used to analyze the structural relationships between observed variables and latent constructs. SEM has several methods one of which is Generalized Structured Component Analysis (GSCA). An empirical application concerning the relationship between renumeration and work motivation on employee performance is presented to illustrate the usefulness of the GSCA method. Data were collected by a questionnaire distributed to lecturers and staffs at UIN Sunan Kalijaga Yogyakarta. The result showed that the remuneration variable had a significant and positive impact on work motivation. Also, the work motivation variable had a significant and positive effect on employee performance.

1. INTRODCUTION

Structural Equation Modeling (SEM) is a multivariate analysis technique which combines regression analysis, path analysis, factor analysis and structural models (Sarjono & Julianita, 2015). The strengths of SEM compared to other data analysis techniques are: it can be used to determine the indicators of a variable, test the validity and reliability of an instrument, confirm the accuracy of a model, and test the effect of a variable on other variables.

There are two approaches in the SEM model, namely Covariance-Based Structural Equation Modeling (CB-SEM) and Component-Based Structural Equation Modeling which is also known as Partial Least Square (PLS). PLS is a powerful analysis method because it can be applied to all data scales and requires neither many assumptions nor large sample size (Lohmöller, 1989; Wold, 1985).

According to (Hwang & Takane, 2004, 2014), one of the weaknesses of PLS model is its inability to resolve global optimization problems in parameter estimation. Therefore, the goodness of fit of PLS is only local, making it very difficult to determine how well the model fits the data.

(Hwang & Takane, 2004) proposed a new method to addrress the weaknesses of the PLS-SEM model, namely Generalized Structured Component Analysis (GSCA). GSCA is a part of variance-based SEM which offers benefits in calculating the overall goodness of fit. This way, the GSCA method can serve as an alternative to variance-based SEM modeling in addition to the PLS method. Several studies have applied the GSCA model, including (Kurniawan, 2017; Susanti, Tirta, & Dewi, 2014) as well as (Hwang, Takane, & Jung, 2017).

UIN Sunan Kalijaga Yogyakarta has approved to implement a remuneration system with the issuance of Decree of the Minister of Finance No. 1178 of 2015. The implementation of remuneration at UIN Sunan Kalijaga has started as of January 1, 2016 (Senjani, 2017).

Remuneration is a reward or compensation given to employees for their contributions to the organization (Sopiah, 2008). Remuneration policy is intended to motivate employees to give their best performance, encourage employee discipline in work, and promote employee job satisfaction.

Based on the abovementioned background, this study tried to apply Structural Equation Modeling using Generalized Structured Component Analysis to determine the relationship between remuneration and motivation on employee performance at UIN Sunan Kalijaga Yogyakarta.

2. LITERATURE REVIEW

2.1. *Generalized Component Structured Analysis*

Structural Equation Modeling (SEM) was first coined by Joreskorg in 1978. The SEM model is a multivariate analysis technique that is used to analyze the relationship between latent variables and observed variables (Bollen, 1989).

Latent variables are variables that cannot be observed and measured directly, so measuring them requires indicators. Observed variables are variables that serve as the indicators in the SEM model (Raykov & Marcoulides, 2000).

SEM contains two main components, namely measurement model and structural model. Measurement model is a model that links observed variables or indicators with latent variables. Meanwhile, structural model is the relationship between latent variables which is formed from observed variables (indicators).

Generalized Structured Component Analysis (GSCA) is a variance-based SEM model that was developed to complement the weaknesses of Partial Least Square (PLS). The GSCA model was first proposed by Hwang and Takane in 2004. This model is very powerful because it is not based on many assumptions and able to assess the overall goodness of fit mode.

Suppose latent variable $\boldsymbol{\gamma}' = (\gamma_1, \gamma_2, \cdots, \gamma_t)$ and observed variable (indicator) $\boldsymbol{z}' = \left(z_1, z_2, \cdots, z_j\right)$. Latent variable is a weighted component or composite of observed variables (the indicators), formulated as follows (Hwang & Takane, 2004):

$$\boldsymbol{\gamma_i} = \boldsymbol{W}'\boldsymbol{z_i} \tag{1}$$

Where $\boldsymbol{W}'$ is the weight matrix. Next, the equations of the measurement and structural models in GSCA are as follows:

$$\boldsymbol{z_i} = \boldsymbol{C'\gamma_i} + \boldsymbol{\varepsilon_i} \quad (2)$$

$$\boldsymbol{\gamma_i} = \boldsymbol{B'\gamma_i} + \boldsymbol{\xi_i} \quad (3)$$

Where $\boldsymbol{C'}$ is the loading matrix, $\boldsymbol{B'}$ is the path matrix, $\boldsymbol{\varepsilon}$ is the residual vector for observed variable and $\boldsymbol{\xi}$ the residual vector for latent variable. Equations (1), (2) and (3) can be written as follows:

$$\begin{bmatrix} \boldsymbol{I} \\ \boldsymbol{W'} \end{bmatrix} \boldsymbol{z_i} = \begin{bmatrix} \boldsymbol{C'} \\ \boldsymbol{B'} \end{bmatrix} \boldsymbol{W'z_i} + \begin{bmatrix} \boldsymbol{\varepsilon_i} \\ \boldsymbol{\xi_i} \end{bmatrix}$$

$$\boldsymbol{V'z_i} = \boldsymbol{A'W'z_i} + \boldsymbol{E} \quad (4)$$

Where $\boldsymbol{V'} = \begin{bmatrix} \boldsymbol{I} \\ \boldsymbol{W'} \end{bmatrix}$, $\boldsymbol{A'} = \begin{bmatrix} \boldsymbol{C'} \\ \boldsymbol{B'} \end{bmatrix}$, $\boldsymbol{E} = \begin{bmatrix} \boldsymbol{\varepsilon_i} \\ \boldsymbol{\xi_i} \end{bmatrix}$ and $\boldsymbol{I}$ is the identity matrix.

If all vectors $\boldsymbol{z_i}$ are combined into a matrix then transposed and represented by matrix $\boldsymbol{Z}$, then equation (4) can be written as

$$\boldsymbol{ZV} = \boldsymbol{ZWA} + \boldsymbol{E} \quad (5)$$

Suppose $\boldsymbol{\Psi} = \boldsymbol{ZV}$ and $\boldsymbol{\Gamma} = \boldsymbol{ZW}$ then **e**quation (5) becomes

$$\boldsymbol{\Psi} = \boldsymbol{\Gamma A} + \boldsymbol{E} \quad (6)$$

Equation (6) is the GSCA model (Hwang & Takane, 2004)

2.2. Estimasi model GCSA

The GSCA parameters were estimated using the Alternating Least Square (ALS) method, i.e. by minimizing the sum square (SS) of all the residuals ($\boldsymbol{E}$), namely:

$$\boldsymbol{f} = SS(\boldsymbol{ZV} - \boldsymbol{ZWA}) = SS(\boldsymbol{\Psi} - \boldsymbol{\Gamma A}) \quad (6)$$

The Alternating Least Square (ALS) method is a general approach to parameter estimation which involves subdividing the parameter into several subsets, then obtaining the least squares for one of the parameter subsets by assuming that all the remaining parameters are constant. GSCA consists of two subsets, namely $\boldsymbol{A}$ and $\boldsymbol{V}$**,** $\boldsymbol{W}$ (Hwang & Takane, 2004). The algorithms used to update $\boldsymbol{A}$ are (Hwang & Takane, 2004):

1. Initializing $\boldsymbol{V}$ and $\boldsymbol{W}$;
2. Creating matrix $\boldsymbol{I} \otimes \boldsymbol{\Gamma}$, where $\boldsymbol{I}$ is the identity matrix;
3. Creating matrix $\boldsymbol{\Omega}$ which is a matrix formed by deleting the column associated with the zero element in $vec(\boldsymbol{A})$;
4. Updating matrix $\boldsymbol{A}$ by using least square estimation as follows:

   $$\hat{a} = \boldsymbol{\Omega'\Omega} - 1\boldsymbol{\Omega'}vec(\boldsymbol{\Psi})$$

   Where

   $\boldsymbol{a}$: vector formed by deleting the zero element in $\boldsymbol{A}$

   $\boldsymbol{\Psi}$: matrix formed by deleting the column of $\boldsymbol{I} \otimes \boldsymbol{\Gamma}$ that is associated with the zero element in $vec(\boldsymbol{A})$
5. Creating new matrix $\boldsymbol{A}$ by inputing the updated value of $\boldsymbol{a}$. It is assumed that $\boldsymbol{\Omega'\Omega}$ is not singular.

The second step is to update $\boldsymbol{V}$ and $\boldsymbol{W}$ by constant $\boldsymbol{A}$. The algorithms are as follows:

1. Initializing $\boldsymbol{A}$ using the updated $\boldsymbol{A}$;
2. Creating matrix $\boldsymbol{S}$ which contains the weight parameters to be estimated;
3. Suppose the number of columns in matrix $\boldsymbol{V}$ is p columns and the number of columns in matrix $\boldsymbol{W}$ is q columns. Defining matrix $\boldsymbol{S}$ to contain k columns, in which each column is from any columns in matrices $\boldsymbol{W}$ and $\boldsymbol{V}$;
4. Defining$\boldsymbol{\Lambda} = \boldsymbol{WA}$;
5. Defining $\boldsymbol{\beta}'$ and $\boldsymbol{\Delta}$, with $\boldsymbol{\beta}' = \boldsymbol{e}_{(p)}' - \boldsymbol{a}_{(q)}'$ and $\boldsymbol{\Delta} = \boldsymbol{\Lambda}_{(-q)} - \boldsymbol{V}_{(-p)}$;

   Where:

   $_{(p)}'$: row vector of which all the elements are zero except for the p-th element

   $_{(q)}'$: the q-th row in matrix **A**

   $\boldsymbol{\Lambda}_{(-q)}$: matrix $\boldsymbol{\Lambda}$ of which the q-th column is zero vector

   $_{(-p)}$: matrix of which the p-th column is zero vector
6. Creating matrix $\boldsymbol{\beta} \otimes \boldsymbol{Z}$;
7. Suppose $\prod$ is matrix that deletes the columns in $\boldsymbol{\beta} \otimes \boldsymbol{Z}$ that correspond to the elements defined in matrix $\boldsymbol{S}$. Assume matrix $\prod'\prod$ is not singular, then the least square estimation of $\boldsymbol{\eta}$ is as follows:

   $$\boldsymbol{\eta} = (\boldsymbol{\Pi}'\boldsymbol{\Pi})^{-1}\boldsymbol{\Pi}' vec(\boldsymbol{Z\Delta})$$

   Where:

   $\boldsymbol{\eta}$ is vector formed by deleting a number of constant elements in matrix $\boldsymbol{S}$
8. Updating the old $\boldsymbol{S}$ with the new $\boldsymbol{S}$ that is obtained from $\boldsymbol{\eta}$. After that, inputing into appropriate columns in matrix $\boldsymbol{V}$ and/or $\boldsymbol{W}$ in which the updated matrices $\boldsymbol{V}$ and $\boldsymbol{W}$ are used to update $\boldsymbol{S}$ in other columns;
9. Repeating step 8 for k times;
10. Obtaining new matrices $\boldsymbol{V}$ and $\boldsymbol{W}$.

The calculation process in ALS is very complex, so the process of obtaining the minimum residuals is carried out iteratively. The process stops when the conditions is convergent, i.e. if the decrease in the value of the loss function has reached 0.0001.

2.3. Evaluasi model CGSA

There are three steps to evaluate the GSCA model, namely

a. Measurement model evaluation

Measurement model evaluation is used to test the reliability and validity of indicators towards latent variables. A variable is considered to be valid if the Convergent Validity (CV) is high, i.e. if the loading value is greater than 0.40. The significance of the measurement model can be determined from the Critical Ratio (CR) that is obtained. CR is a value obtained from a statistical test (t-test) which indicates a certain level of significance. If CR is greater than 1.96, then the significance has a 95% confidence level.

To determine the reliability of the research variables, Cronbach's Alpha is used. An instrument is considered to be reliable or have good reliability towards the model if the alpha value is greater than 0.70. Another reliability measurement that can be used is average variance extracted (AVE). A variable is said to be reliable if the AVE value is greater or equal to 0.50.

b. Structural model evaluation

Structural model evaluation aims to determine the accuracy of the structural model being formed. The extent of the effect of a relationship between latent variables is determined by the extent of the estimated path coefficient. The relationship between variables is considered to be quite significant if the path coefficient is greater than 0.50.

c. Overall goodness of fit model evaluation

Overall goodness of fit model is evaluated using the FIT, AFIT, GFI, and SRMR tests. In the FIT test, the value is recommended to be greater than or equal to 0.50; in the AFIT (Adjusted FIT) test, the value is recommended to be greater than or equal to 0.50; in the GFI (goodness of fit index) test, the value is recommended to be close to 1; in the SRMR (Standardized Root Mean Square Residual) test, the value is recommended to be close to 0.

3. RESEARCH METHOD

3.1. Data Source

The data used in this study were primary data. The data were obtained through questionnaires distributed to all the employees (lecturers and staffs) at UIN Sunan Kalijaga. Based on the Rector's annual report of 2017, this university had 571 lecturers and 428 educational staffs. Thus, the total population of this study consisted of 999 people.

Questionnaires regarding the effect of Remuneration and Work Motivation on the Employees at UIN Sunan Kalijaga were distributed online and offline (face to face) in August 2019. This process obtained 142 respondents.

3.2. Research Variables

The variables in this study consisted of one endogenous latent variable, i.e. Employee Performance, one exogenous latent variable, i.e. Remuneration, and one mediating variable, i.e. Work Motivation that served as an endogenous variable in the Remuneration variable and as an exogenous variable in the Employee Performance variable.

The Remuneration variable consisted of five dimensions with 10 indicators, namely z_1 - z_{10}. Table 1 presents all the indicators and symbols (Mangkunegara, 2005). The work motivation variable consisted of six dimensions with 13 indicators, namely $z_{11} - z_{23}$. The indicators forming the Work Motivation variable is presented in Table 2. The employee performance variable consisted of four dimensions with 12 indicators, namely $z_{24} - z_{35}$. Table 3 shows all the indicators on the Employee Performance variable.

The data collection of this study was carried out using questionnaires. The measurements of the questionnaires used a Likert scale, namely 1. Strongly Disagree 2. Disagree 3. Moderately Agree 4. Agree 5. Strongly Agree. The data collected were then processed using R software, i.e. the gesca package using the Alternating Least Square (ALS) algorithm and bootstrapping method (Kim, Cardwell, & Hwang, 2017).

Tabel 1. Remuneration Variables and its Indicators

Variables	Dimensions	Indicators	Symbols (Code)
Remuneration (Exogeneous Variable)	Merit System	– In accordance with workload	z_1
		– In accordance with performance	z_2
	Fair	– Workload is in accordance with remuneration	z_3
		– Skill is in accordance with remuneration	z_4
	Worthy	– Fulfilling life needs	z_5
		– Improving welfare	z_6
	Competitive	– Equivalent to private employees	z_7
		– Loyal to the company	z_8
	Transparent	– Receiving no other remuneration	z_9
		– Knowing the process of remuneration	z_{10}

Tabel 2. Work motivation variable and its indicators

Variables	**Dimensions**	**Indicators**	**Symbols (Code)**
Work Motivation (Exogeneous variable)	Responsible	– Job responsibilities	z_{11}
		– Personal responsibilities	z_{12}
	Identifying Risks	– Task risks	z_{13}
	Innovative Creative	– Overcoming obstacles	z_{14}
		– Work effectiveness	z_{15}
		– Work routine	z_{16}
	Feedback	– Accepting suggestions from others	z_{17}
		– Self reflection	z_{18}
	Task Completion Time	– Not delaying work	z_{19}
		– Being faster	z_{20}
	Willingness to Improve	– High performing	z_{21}
		– Hard working	z_{22}
		– Performance	z_{23}

Tabel 3. Employee Performance Variable and its Indicators

Variables	**Dimensions**	**Indicators**	**Symbols (Code)**
Employee Performance (Endogeneous variable)	Work quality	– Accuracy	z_{24}
		– Thoroughness	z_{25}
		– Competence	z_{26}
	Work Quantity	– More work	z_{27}
		– Faster	z_{28}
		– More dilligent	z_{29}
	Reliability	– Diligence	z_{30}
		– Initiative	z_{31}
		– Instrusif	z_{32}
	Attitude	– Attitudes towards fellow employees	z_{33}
		– Attitudes towards company	z_{34}
		– Attitudes towards tasks	z_{35}

3.3. Data Analysis Technique

In this study, the data analysis used the Structural Equation Modeling with Generalized Structured Component Analysis (GSCA). SEM or structural equation model is a hybrid technique which includes the confirmatory aspect of factor analysis, path analysis and regression analysis.

According to (Ghozali & Kusumadewi, 2013), the steps to perform SEM – GSCA are as follows:

1. Data conceptualization, i.e. designing the outer model or measurement model (the relationship between the latent variables with the indicators/variables) and inner model or structural model (the relationship between the latent variables)
2. Construction of path diagram
3. Conversion of path diagrams into simultaneous equation model
4. Parameter estimation
5. Model evaluation
6. Model modification

In this step, model modification was performed if model evaluation does not meet the predetermined standards. Then the SEM – GCSA was repeated by doing step 1 – 5 until the model was fit.

4. RESULTS AND DISCUSSION

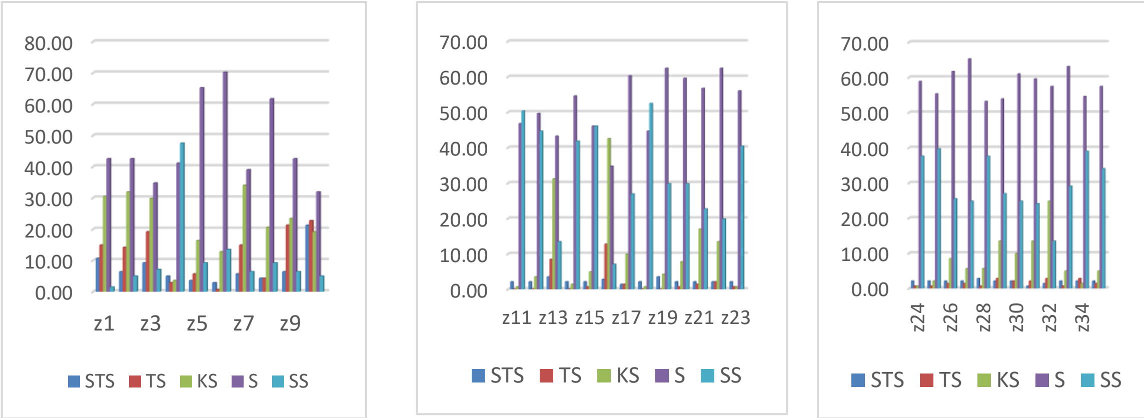
4.1 Data Description

The data obtained through the questionnaires showed that there were 142 respondents. Based on the sample, 55% of the respondents were lecturers and 45% were educational staffs. In terms of gender, 47.5% of them were male respondents and 52.8% were female respondents. Most of the respondents in this study had worked at UIN Sunan Kalijaga for 0 - 10 years (55.56%). In terms of level of education, there were 18.1% respondents who had doctoral degree, 62.5% who had master degree, 16.7% who had undergraduate degree, and 7.4% who graduated from senior high school or equivalent.

The results of the survey regarding the perceptions of remuneration, work motivation and employee performance are presented in Figures 2 panel (a), (b) and (c). The respondents' level of perceptions of the remuneration paid by UIN Sunan Kalijaga Yogyakarta can be seen in panel (a).

The respondents' (lecturers and staffs) perceptions on the Remuneration variable were good. This can be seen from the percentage of almost all the indicators, i.e. most of them (more than 50%) agreed. Indicator x_3 i.e. the variables of workload and remuneration should be improved because 40% of the respondents answered that they strongly disagreed and disagreed. In addition, indicator x_{10} i.e. regarding transparency in paying remuneration, should also be improved. There were 21.27% of the respondents whose perceptions were Strongly Disagree and 22.69% of Disagree.

Panel (b) shows the percentage of the respondents' perceptions of the indicators in the Work Motivation variable. It can be seen that the respondents' perception of work motivation was quite good. This is evident from the percentage of the respondents' responses to each indicator, starting from y_1 to y_{13}, i.e. most of them agreed and strongly agreed with them (more than 60%).



(a) The Remuneration Variable (b) The Work Motivation Variable (c) The Employee Performance Variable

Figure 3. Respondents' Perceptions of the the Remunertion Variable, the Work Motivation Variable and the Employee Performance Variable

Panel (c) shows that the respondents' perception of the indicators of the Employee Performance variable was good. This is evident from the percentage of the respondents' responses, i.e. there were more than 80% of the respondents who agreed and strongly agreed with all the indicators $z_1 - z_{12}$.

4.2 Analysis of GSCA Model

In this study, the relationship between remuneration and work motivation on employee performance was modeled using the Generalized Structured Component Analysis (GSCA) model. The GSCA model was solved using the Alternating Least Square (ALS) algorithms.

Table 4 shows the weights for all the observed variables (indicators) and the standard error obtained from the boostrap technique with 100x replications.

Table 4. Weight of Observed Variables (Indicators)

Remuneration Variable			Work Motivation Variable			Employee Performance Variable		
Indicator	***Estimate***	***Std.Error***	**Indicator**	***Estimate***	***Std.Error***	**Indicator**	***Estimate***	***Std.Error***
z_1	0.0859	0.0360	z_{11}	0.1030	0.0165	z_{24}	0.1073	0.0113
z_2	0.1852	0.0265	z_{12}	0.1167	0.0119	z_{25}	0.1149	0.0091
z_3	0.0975	0.0257	z_{13}	0.0782	0.0115	z_{26}	0.0900	0.0076
z_4	0.1931	0.0209	z_{14}	0.1176	0.0162	z_{27}	0.1072	0.0103
z_5	0.1695	0.0179	z_{15}	0.1021	0.0149	z_{28}	0.1053	0.0104
z_6	0.2204	0.0217	z_{16}	0.0374	0.0153	z_{29}	0.1037	0.0089
z_7	0.1496	0.0203	z_{17}	0.0815	0.0132	z_{30}	0.0935	0.0093
z_8	0.2031	0.0184	z_{18}	0.1237	0.0140	z_{31}	0.0919	0.0166
z_9	0.0902	0.0201	z_{19}	0.0953	0.0130	z_{32}	0.0912	0.0118
z_{10}	0.1128	0.0198	z_{20}	0.1138	0.0202	z_{33}	0.1115	0.0076
			z_{21}	0.1042	0.0187	z_{34}	0.1130	0.0108
			z_{22}	0.1030	0.0124	z_{35}	0.0938	0.0098
			z_{23}	0.1365	0.0155			

It can be seen that the estimated weights for each latent variable were significant and almost the same with each other. This indicates that all the indicators (observed variables) made equal contributions to explaining the latent variables.

The validity of the indicators towards the latent variable was tested using AVE and Cronbach's alpha. It can be seen that the AVE was 0.4100, indicating that the average variance of the indicators which could be explained by the latent variable was only 41%. Meanwhile, the Cronbach's alpha was 0.8331, meaning that the measurement model can be considered reliable.

Based on Table 5, it can be seen that there were three indicators with significant effect on the remuneration variable, namely z_5, z_6 and z_8. Indicator z_5 namely fulfilling life needs served as the dominant factor in the remuneration variable with a loading weight of 0.7943.

Table 5. Estimated Loading Weight, AVE and Cronbach's Alpha for Remuneration Variable

Indicator	Remuneration Variable		
	Estimate	***Std.Error***	***CR***
z_1	0.5735	0.0887	6.4656*
z_2	0.7032	0.0817	8.6070*
z_3	0.4154	0.1193	3.4819*
z_4	0.6841	0.0694	9.8573*
z_5	0.7943	0.0419	18.9570*
z_6	0.7529	0.0667	11.2878*
z_7	0.6682	0.0621	10.7600*
z_8	0.7794	0.0536	14.5410*
z_9	0.4367	0.0798	5.4724*
z_{10}	0.4405	0.0743	5.9286*
AVE = 0.4100			
Cronbach Alpha = 0.8331			

*Level of significance at $\alpha = 0.05$

The estimated loading weight for the Work Motivation variable is shown in Table 6. The loading value of all the indicators of the Work Motivation variable was similar, resulting in convergent validity (seen from the estimated loading value) greater than 0.40 except for variable z_{16} which only resulted in loading weight of 0.2283, but it was statistically significant (see CR 2.1931 > 1.96). It can be seen that the AVE was 0.5229, showing that the average variance of the indicators which could be explained by the latent variable was 52.29%. Meanwhile, the Cronbach's alpha was 0.9258, indicating that the measurement model can be considered reliable.

Based on Table 6, it can be seen that indicator z_{23} (willingness to improve work) had a significant effect on Work Motivation and became the dominant factor with a loading weight of 0.8537.

Meanwhile, the estimated loading weight for the Employee Performance variable is presented in Table 7. This table shows that the loading values of all the indicators of the Employee Performance variable resulted in convergent validity (seen from the estimated loading value) which was greater than 0 and statistically significant. The AVE value for the variable was 0.6610, indicating that the average variance of the indicators which could be explained by the latent variable was 66.10%. Meanwhile, the Cronbach's alpha was 0.9537, meaning that the measurement model can be considered reliable.

Table 6. Estimated Loading Weight, AVE and Cronbach's Alpha for Work Motivation Variable

Indicator	Work Motivation Variable		
	Estimate	***Std.Error***	***CR***
z_{11}	0.8332	0.0593	14.0506*
z_{12}	0.7812	0.0766	10.1984*
z_{13}	0.5437	0.0922	5.8970*
z_{14}	0.8336	0.0585	14.2496*
z_{15}	0.8008	0.0555	14.4288*
z_{16}	0.2283	0.1041	2.1931*
z_{17}	0.6594	0.0953	6.9192*
z_{18}	0.8228	0.0732	11.2404*
z_{19}	0.7311	0.0803	9.1046*
z_{20}	0.8451	0.0363	23.2810*
z_{21}	0.7684	0.051	15.0667*
z_{22}	0.7208	0.0719	10.0250*
z_{23}	0.8537	0.0468	18.2415*
AVE = 0.5229			
Cronbach's Alpha = 0.9258			

*Level of significance at $\alpha = 0.05$

Table 7. Estimated Loading Weight, AVE and Cronbach's Alpha for Employee Performance Variable

Indicator	Work Motivation Variable		
	Estimate	***Std.Error***	***CR***
z_{24}	0.8937	0.0342	26.1316*
z_{25}	0.8651	0.047	18.4064*
z_{26}	0.7546	0.0752	10.0346*
z_{27}	0.8768	0.0386	22.7150*
z_{28}	0.8074	0.0831	9.7160*
z_{29}	0.8015	0.0434	18.4677*
z_{30}	0.8658	0.0329	26.3161*
z_{31}	0.7300	0.0555	13.1532*
z_{32}	0.6899	0.0634	10.8817*
z_{33}	0.8190	0.0607	13.4926*
z_{34}	0.8482	0.0378	22.4392*
z_{35}	0.8153	0.0589	13.8421*
AVE = 0.661			
Cronbach's Alpha = 0.9537			

Table 7 shows that four indicators had a significant effect on Employee Performance, namely z_{24}, z_{25}, z_{27} and z_{30}. Indicator z_{24} namely accuracy of task completion had a significant effect on employee performance and became the dominant factor, i.e. 0.8937.

The estimated path coefficients for each of latent variables are tabulated in Table 8.

Table 8. Estimated Path Coefficient

	Estimate	*Std.Error*	*CR*
Remuneration → Work Motivation	0.5227	0.1533	3.409654
Remuneration → Employee Performance	-0.0486	0.0445	-1.092130
Work Motivation → Employee Performance	0.9037	0.0569	15.882250

Based on the table above, the path coefficient of remuneration to motivation was 0.5227, meaning that remuneration had a statistically significant and positive effect on motivation. The path coefficient of remuneration to employee performance was -0.0486, meaning that remuneration had a negative and not statistically significant effect on employee performance. The path coefficient of work motivation on employee performance was 0.9037, meaning that work motivation had a positive and statistically significant effect on employee performance. The results of the structural model analysis showed that the remuneration variable did not have an effect on employee performance. This way, the structural models should be revised.

The structural model outputs are presented in Table 9. As seen in Table 9, the path coefficient of remuneration to motivation was 0.5424, meaning that remuneration had a positive and statistically significant effect on motivation. The path coefficient of work motivation to employee performance was 0.8770, meaning that work motivation had a positive and statistically significant effect on employee performance.

Table 9. Estimated Path Coefficient o Revision

	Estimate	*Std.Error*	*CR*
Remuneration → Work Motivation	0.5424	0.1309	4.143621
Work Motivation → Employee Performance	0.8770	0.0529	16.57845

The mathematical structural equation model in this case can be formulated as follows:

Work Motivation = 0.5424 Remuneration + ξ

Employee Performance = 0.8770 Work Motivation + ξ

Regarding the fact that the evaluation results of the measurement and structural models were significant, the next step was to perform an overall goodness of fit test of the model. The summary of the goodness of fit test evaluation is shown in the following table.

Table 10. Results of Overall Goodness of Fit Test

Goodness of fit test	Measure	Conclusion
FIT	0.5839	Good
AFIT	0.5777	Good
GFI	0.9982	Good
SRMR	0.0954	Accepted

The above table displays the FIT value ≥ 0.5, the AFIT value ≥ 0.5, the GFI value ≥ 0.9 and the SRMR value ≤ 0.1. Thus, it can be said that the model created from the factors affecting the employee performance at UIN Sunan Kalijaga Yogyakarta was a good and acceptable model.

5. CONCLUSIONS

The results of the data analysis using the SEM – GSCA in this case showed that the effect of remuneration and work motivation on employee performance at UIN Sunan Kalijaga Yogyakarta is said to be fit. The evaluation of the model used the criteria FIT, AFIT, GFI and SRMR. Based on the results of the data analysis and hypothesis testing, the following conclusions can be drawn:

a. Paying remuneration has a positive effect on the work motivation of the employees at UIN Sunan Kalijaga Yogyakarta with a total effect of 0.5424. This means that employees who have a good perception of remuneration will have an increased work motivation.
b. Work motivation has a positive effect on the employee performance at UIN Sunan Kalijaga Yogyakarta with a total effect of 0.8770. This means that the remuneration paid so far can encourage or motivate employees to improve their performance.

ACKNOWLEDGEMENT

This study was a BOPTN Competitive Research Program for the lecturers at UIN Sunan Kalijaga 2019.

REFERENCES

Bollen, K. A. (1989). *Structural Equations with Latent Variables*. New York: John Wiley & Sons.

Ghozali, I., & Kusumadewi, K. A. (2013). *Generalized Structured Component Analysis (GeSCA) Model SEM Berbasis Komponen*. Semarang: Badan penerbit Universitas Diponegoro. Semarang.

Hwang, H., & Takane, Y. (2004). Generalized Structured Component Analysis. *Psychometrika*, *69*, 81–99. https://doi.org/10.1007/S11336-009-9119-Y

Hwang, H., & Takane, Y. (2014). *Generalized Structured Component Analysis: A Component Based Approach to Structural Equation Modeling*. Chapman and Hall/CRC.

Hwang, H., Takane, Y., & Jung, K. (2017). Generalized Structured Component Analysis with Uniqueness Terms for Accommodating Measurement Error. *Frontiers in Psychology*, *8*(DEC). https://doi.org/10.3389/fpsyg.2017.02137

Kim, S., Cardwell, R., & Hwang, H. (2017). Using R Package Gesca for Generalized Structured Component Analysis. *Behaviourmetrika*, *44*, 3–23.

Kurniawan, M. I. (2017). *Penerapan Structural Equation Modeling - Generalized Structured Component Analysis (SEM-GSCA) pada Kecerdasan Majemuk SMAN 1 Rumpin-Bogor*. IPB Bogor.

Lohmöller, J.-B. (1989). Latent Variable Path Modeling with Partial Least Squares. In *Latent Variable Path Modeling with Partial Least Squares*. Physica-Verlag. https://doi.org/10.1007/978-3-642-52512-4

Mangkunegara, A. P. (2005). *Manajemen Sumber Daya Manusia Perusahaan*. Bandung: PT Remaja Rosda.

Raykov, T., & Marcoulides, G. A. (2000). *A First Course in Structural Equation Modeling*. New Jersey: Lawrence Erlbaum Associates, Inc.

Sarjono, H., & Julianita, W. (2015). *Structural Equation Modeling (SEM) Sebuah Pengantar, Aplikasi untuk Penelitian Bisnis*. Jakarta: Salemba Empat.

Senjani, Y. P. (2017). Analisis Implementasi Remunerasi Blu (Studi Kasus Pada UIN Sunan Kalijaga Yogyakarta). *EkBis: Jurnal Ekonomi Dan Bisnis*, *1*(1), 12–33. https://doi.org/10.14421/ekbis.2017.1.1.993

Sopiah. (2008). *Perilaku Organisasional*. Yogyakarta: Andi Offset.

Susanti, N. I., Tirta, I. M., & Dewi, S. (2014). Approach Generalized Structured Component Analysis (GSCA) Method for Structural Equation Modeling Unidimensional. *Prosiding Seminar Nasional Matematika*, (November), 94–103.

Wold, H. (1985). *Partial Least Squares*. New York: John Wiley.