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Mixed Second Order Indicator Model: The First Order Using Principal Component Analysis and The Second Order Using Factor Analysis

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Abstract. The second order indicator model can be the first order having formative or reflective indicators of an underlying second order. The research used principal component analysis in the first order and factor analysis in the second order. The variable used in the research was *ihsan* behavior. This research aims to apply multivariate analysis, i.e. the principal component analysis in the first order and the factor analysis in the second order to obtain the latent variable data of *ihsan* behavior in the second order indicator model. The data used in this research were primary data by distributing questionnaires. Respondents of this research were lecturers of the Faculty of Economics and Business at the University of X. The research results generated latent variable data in the form of *ihsan* behavior. *Ihsan* behavior was reflected in six indicators, i.e. doing something perfectly, repaying goodness with more goodness, reducing optimally unpleasant consequences, as a solution when justice cannot be realized, as a logical consequence rather than faith, and as an investment in future success.
Keywords: Second Order Model, *Ihsan* Behavior

1. Introduction

In the current globalization era, working is an effort to meet needs. *Ihsan* behavior is highly recommended in working. *Ihsan* behavior literally means to do well or to do the best. *Ihsan* behavior includes work optimization as well as acting, working, and performing duties in accordance with good performance and high quality [8]. *Ihsan* behavior is defined as doing work perfectly, repaying kindness better, reducing optimally the unpleasant consequences, as a way out when optimal justice cannot be realized, and as a logical consequence on faith and investment in future success [7]. *Ihsan* behavior can be applied anywhere, including in the centers of education. One of the centers of education is Higher Education. The role of the lecturer is very important in building and developing student character in Higher Education.

Ihsan behavior is a variable that cannot be directly measured (a latent variable), so a research instrument is needed in the form of a questionnaire [11]. A latent variable can be modeled with reflective or formative indicators. The latent variable data with the formative indicator model is in the form of principal component scores while the latent variable data with the reflective indicator model is in the form of factor scores. The second order indicator model is derived from the fact that that the first order can have either formative or reflective indicators. The first order in the second order indicator model can be a reflective or formative indicator [9]. In this research, a measurement study of *ihsan* behavior variable was conducted on the lecturers of the Faculty of Economics and Business at the University of X using principal component analysis in the first order and factor analysis in the second order. This research aims to obtain the latent variable of *ihsan* behavior.

2. Literature Review

2.1. Formative Indicator Model

Latent variables with formative indicator models have composite properties that include error terms in the model, i.e. the error term placed on the latent variable is not on the indicator so that it does not allow to obtain measurement errors [12]. The characteristics of the formative indicator model, namely:

1. The direction of causality as if it were an indicator to a latent variable. It is as if PC_1 is affected by $X_1, X_2, ... X_p$, but PC_1 does not have data and the data will be searched so that it is not true that the indicator affects latent variables.
2. Between indicators are assumed to be uncorrelated.
3. Eliminating one indicator will causes changing the meaning of the latent variable.

2.2. Principal Component Analysis

Principal Component Analysis is an analytical method used in the formative indicator model. Principal Component Analysis basically aims to explain the various structures through linear combinations of variables [1]. The basic model of Principal Component Analysis is [2]:

$$PC_p = b_{p1}X_1 + b_{p2}X_2 + ... + b_{pp}X_p + \varepsilon_p \tag{1}$$

Determine the characteristic roots of existing characteristic roots to be used in the first main component as explained in the following equation.

$$\begin{aligned} \left(\mathbf{X}^T\mathbf{X} - \lambda_i\mathbf{I}\right)\mathbf{b}_i &= 0 \\ \mathbf{X}^T\mathbf{X}\mathbf{b}_i - \lambda_i\mathbf{I}\mathbf{b}_i &= 0 \\ \mathbf{X}^T\mathbf{X}\mathbf{b}_i &= \lambda_i\mathbf{I}\mathbf{b}_i \end{aligned} \tag{2}$$

2.2.1. The Role of Principal Component. Relative importance is the ratio between the various principal components to j with a total variety, because $\sum_{j=1}^{p}\lambda_j$ is total diversity, the role of the main components is explained as follows.

$$K_j = \frac{\lambda_j}{\sum_{j=1}^{p}\lambda_j} \times 100\% \tag{3}$$

2.2.2. Principal Component Weighting Coefficient. The principal component weighting is important in the principal component analysis [1]. Weighting the principal components as explained in the following equation.

$$K_j = b_{1j}X_1 + b_{2j}X_2 + ... + b_{pj}X_p \tag{4}$$

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Coefficient b_{ij} shows the contribution of the variable *i* to the principal component to *j* and the sign (positive and negative) shows the direction of influence.

2.2.3. Determination of the Main Components Used. Further interpretation and analysis is based on the main components that are meaningful [1]. The main components that mean certain criteria are as follows.

1. Choosing characteristic roots greater than 1 ($\lambda_j \geq 1$)
2. Selecting *k* main components as the biggest contributor to the diversity of data, as in the equation (5)

$$\frac{\sum_{j=1}^{k} \lambda_j}{\sum_{j=1}^{p} \lambda_j} > 0.75 \tag{5}$$

In this case *p* is the original number of variables or the sum of all the principal components produced.

2.2.4. Principal Component Score. If the main component has been obtained, the next step is to calculate the component scores of each individual that will be used for further analysis. Then the component score of the individual i as in the equation (6)

$$SK_{ij} = \mathbf{b}_j^T \left(\mathbf{X}_i - \bar{\mathbf{X}} \right) \tag{6}$$

2.3. Reflective Formative Indicator Model

The reflective indicator model is a model with attitude or behavior variables that are reflected, seen and reflected. This model was developed based on the classical test theory which assumes that the variation of the value of the latent variable is a function of the true score. So the latent variable seems to influence the indicator or as if the direction of causality from variable to indicator. The reflective model is also called the confirmatory factor model where the latent variable data is a factor score and is obtained using factor analysis.

2.4. Factor Analysis

The process of factor analysis tries to find a relationship between a number of mutually independent variables, so that one or several sets of variables can be made that are less than the initial number of variables [13]. Gifi introduced a form of measurement model on a mixed data scale (metric and non-metric) using linear factor analysis [4]. According to [1] random observation of vector $\mathbf{X}$ with *p* component, has an average of $\boldsymbol{\mu}$ and covariant variant matrix $\mathbf{\Sigma}$ or $\mathbf{X} \sim N_p(\boldsymbol{\mu}, \mathbf{\Sigma})$. The factor model states that *X* is directly proportional to some of the random variables observed $F_1, F_2, \ldots, F_m$ which are called general factors and $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p$ which are called errors or specific factors. The factor analysis model can be written as follows:

$$\underset{(p\times 1)}{\mathbf{X}-\boldsymbol{\mu}} = \underset{(p\times m)}{\mathbf{L}}\,\underset{(m\times 1)}{\mathbf{F}} + \underset{(p\times 1)}{\boldsymbol{\varepsilon}} \tag{7}$$

Where:
μ_p : average of *p*-variable
ε_p : *Specific factor p*
F_m : *Common factor m*
l_{pm} : *loading* from the *p*-variable on *m*-factor

2.4.1. Factor Analysis Assumptions. According to [5], there are several assumptions that must be fulfilled in factor analysis, namely:

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1. Sample Adequacy Testing

In testing the sample adequacy, a test can be used is *Kaiser Meyer Oikin* (*KMO*). This index compares the magnitude of the correlation coefficient between variables with the magnitude of the partial correlation coefficient. Small KMO values indicate that inter-pair correlations of variables cannot be explained by other variables and factor analysis may not be appropriate [14].

H_0 : Data size is not enough to be factored *vs.*
H_1 : Data size is sufficient to be factored

A group of data is said to fulfill the adequacy requirements for analysis of factors if the KMO value is greater than 0.5 [15]. According to Kaiser and Rice in [6], KMO testing uses the following formula.

$$K = \frac{\sum_i \sum_j r_{ij}^2}{\sum_i \sum_j r_{ij}^2 + \sum_i \sum_j q_{ij}^2}, (i \neq j) \tag{8}$$

where:

i : 1, 2, 3, ..., p
j : 1, 2, ..., n
r_{ij} : Correlation coefficient between i-variable and j-variable
q_{ij} : Partial correlation coefficient between i-variable and j-variable

The criteria for testing the adequacy of the sample is rejecting H_0 if the KMO value is greater than 0.5 which can be concluded that the size of the data is sufficiently factored [15].

2. Feasibility Test for Factor Analysis

Testing the feasibility of a factor analysis can be done with the Bartlett's test of sphericity. Bartlett's test of sphericity aims to test the correlation between variables. Correlation matrix is an identity matrix, where in the main diagonal the number of one and outside the main diagonal is zero, which means that between variables do not correlate with each other. The statistical test for sphericity is based on a transformation when the square of the correlation matrix determinant [13].

H_0 : $\mathbf{R} = \mathbf{I}$ (there is no correlation between variables) *vs.*
H_1 : $\mathbf{R} \neq \mathbf{I}$ (there is a correlation between variables)

$$BTS = -\left((n-1) - \frac{2p+5}{6} \right) \ln |\mathbf{R}| \sim \chi_v^2 \tag{9}$$

where:

$v = \frac{p^2 - p}{2}$, is a degree of freedom distribution χ^2
p : number of variables
n : number of observations
$\mathbf{R}$: correlation matrix between variables

If *p-value* < α then reject H_0 so it can be concluded that there is a correlation between variables and is feasible for factor analysis [3].

3. Measure of Sampling Adequency (MSA)

MSA testing has a purpose to find out whether variables can be used for factor analysis [15].

H_0 : Variables are not sufficient for further analysis vs.
H_1 : Variables are sufficient to be analyzed further

$$MSA_i = \frac{\sum_j r_{ij}^2}{\sum_j r_{ij}^2 + \sum_j q_{ij}^2}, (i \neq j) \tag{10}$$

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where:
i : 1, 2, 3, ..., p
j : 1, 2, ..., n
r_{ij} : Correlation coefficient between i-variable and j-variable
q_{ij} : Partial correlation coefficient between i-variable and j-variable
The criteria for MSA testing are reject H_0 if the value of MSA_i or diagonal Anti Image Correlation is > 0.5 so it can be concluded that the variables are sufficient to be analyzed further using factor analysis. [15].

2.4.2. Parameter Estimation Method. Principal component method is used for data transformation if there is a matrix of data size n×p with numerical scale variables. Input data for principal component methods are covariant (**S**) matrices or correlation (R) matrices. Covariance matrix (**S**) is used when the unit unit and scale of data from all variables to be analyzed are the same while the correlation matrix (**R**) is used if the unit and scale of data for each variable is different in a data. From the covariance matrix or correlation matrix, the eigenvalues (λ_j) and eigen vector ($\boldsymbol{e}_j$).

Before calculating the load with the principal component method, eigenvalues and eigenvectors are needed. From **X** data the covariance matrix (**S**) or the correlation matrix (R) is sought, then from the covariance matrix (correlation) which is a square matrix of size $p \times p$ there are scalar numbers λ and vector e (nonzero) so that they meet equation (11)

$$\mathbf{Ae} = \lambda\mathbf{e} \tag{11}$$

The number λ is called the eigenvalue of **A** and **e** called the eigenvector which is related to the eigenvalue λ where **A** is the input matrix in the form of a covariance matrix (**S**) or the correlation matrix (**R**). The eigenvalue (λ_j) and eigenvector ($\mathbf{e}_j$) is called the characteristic root. The main component method of the covariance matrix (**S**) and the correlation matrix (**R**) is obtained from pairs of eigenvalues and eigenvectors $(\hat{\lambda}_1, \hat{e}_1), (\hat{\lambda}_2, \hat{e}_2), \dots, (\hat{\lambda}_p, \hat{e}_p)$ dengan $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \cdots \geq \hat{\lambda}_p$.

$$\begin{aligned}\mathbf{\Sigma} &= \lambda_1\mathbf{e}_1\mathbf{e}_1' + \lambda_2\mathbf{e}_2\mathbf{e}_2' + \cdots + \lambda_p\mathbf{e}_p\mathbf{e}_p' \\ &= \left[\sqrt{\lambda_1}\mathbf{e}_1 \middle| \sqrt{\lambda_2}\mathbf{e}_2 \middle| \dots \middle| \sqrt{\lambda_p}\mathbf{e}_p\right] \begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1{}' \\ \sqrt{\lambda_2}\mathbf{e}_2{}' \\ \vdots \\ \sqrt{\lambda_p}\mathbf{e}_p{}' \end{bmatrix}\end{aligned} \tag{12}$$

Equation (12) corresponds to the covariance structure determined for the factor analysis of the number of common factors equal to the original factor (m=p) with *specific variances* $\psi_i = 0$ for all i, so that it can be written as equation (13).

$$\underset{(p \times p)}{\mathbf{\Sigma}} = \underset{(pxm)}{\mathbf{L}}\underset{(m \times p)}{\mathbf{L}'} + \underset{(p \times p)}{\mathbf{0}} = \mathbf{LL}' \tag{13}$$

Can be assumed that the number of common factors is less than the original factor (m<p), then the calculation of the matrix factors loading $\{l_{ij}\}$ with the principal component method as in equation (14) [10].

$$\tilde{\mathbf{L}} = \left(\sqrt{\hat{\lambda}_1}\hat{\mathbf{e}}_1 \middle| \sqrt{\hat{\lambda}_2}\hat{\mathbf{e}}_2 \middle| \dots \middle| \sqrt{\hat{\lambda}_\mathrm{m}}\hat{\mathbf{e}}_\mathrm{m}\right) \tag{14}$$

3. Methodology

In this research, the researchers used primary data by distributing questionnaires. Respondents in this research were lecturers of the Faculty of Economics and Business at the University of X. The number of respondents was 75 people. The methods used in this research were principal component analysis in the first order and factor analysis in the second order. Indicators of *Ihsan* behavior were doing something perfectly (X1), repaying goodness with more goodness (X2), reducing optimally unpleasant consequences (X3), as solution when justice cannot be realized (X4), as a logical consequence rather than faith (X5), and as an investment in future success (X6). The steps in this research included the first was determining the variables used in the research, i.e. behaviors, the second was designing the research instrument in the form of a questionnaire, the third was testing the questionnaire with qualitative pre-test and evaluation, the fourth was conducting pilot test by validity and reliability checks on the questionnaire, the fifth was data collection by distributing the questionnaire to the respondents, the sixth was transforming the data scale from scores into interval scales using the Summated Rating Scale (SRS) method, the seventh was creating a correlation matrix, the eighth was conducting principal component analysis, the ninth was obtaining principal component scores, the tenth was conducting examination and testing of factor analysis assumptions, the eleventh was conducting factor analysis, the eighteenth was obtaining factor scores, and the last was doing interpretation. The research location was the Faculty of Economics and Business at the University of X. The research was conducted from August 2018 to December 2018. The populations in this research were all lecturers of the Faculty of Economics and Business at the University of X. The sampling technique used was nonprobability sampling with saturation sampling. The sample of this research was 112 people because the number of lecturers in the Faculty of Economics and Business at the University of X was 112 people.

4. Result and Discussion

Scale calculation for item 1 using the SRS method can be seen in Table 1.

Table 1. Scale Calculation for Item 1

Category	1	2	3	4	5
Frequency	0	1	2	60	12
Proportion	0	0.01	0.03	0.80	0.16
Cumulative Proportion	0.00001	0.006667	0.02667	0.44	0.92
MPK	-4.26489	-2.47474	-1.93221	-0.15097	1.405072
Z	0	-2.5758	-1.5982	-0.4959	0.7063
Scale	0	1.790151	2.332679	4.113922	5.669962

Based on Table 1, the data transformation from scores into scales in item 1 changed a score of 1 to a scale of 0, a score of 2 to a scale of 1.790151, a score of 3 to a scale of 2.332679, a score of 4 to a scale of 4.113922, and a score of 5 to a scale of 5.669962.

A correlation matrix calculation should be done before conducting principal component analysis. The followings are the correlation matrices for each indicator.

$$\rho_{(X1)} = \begin{bmatrix} 1 & 0.385 & 0.443 & 0.188 \\ 0.385 & 1 & 0.316 & 0.793 \\ 0.443 & 0.316 & 1 & 0.037 \\ 0.188 & 0.793 & 0.037 & 1 \end{bmatrix}$$

$$\rho_{(X2)} = \begin{bmatrix} 1 & 0.304 & 0.355 \\ 0.304 & 1 & 0.610 \\ 0.355 & 0.610 & 1 \end{bmatrix}$$

$$\rho_{(X3)} = \begin{bmatrix} 1 & 0.586 & 0.732 \\ 0.586 & 1 & 0.551 \\ 0.732 & 0.551 & 1 \end{bmatrix}$$

$$\rho_{(X4)} = \begin{bmatrix} 1 & 0.571 & 0.086 \\ 0.571 & 1 & 0.495 \\ 0.086 & 0.495 & 1 \end{bmatrix}$$

$$\rho_{(X5)} = \begin{bmatrix} 1 & 0.614 & 0.170 \\ 0.614 & 1 & 0.353 \\ 0.170 & 0.353 & 1 \end{bmatrix}$$

$$\rho_{(X6)} = \begin{bmatrix} 1 & 0.249 & 0.405 \\ 0.249 & 1 & 0.527 \\ 0.405 & 0.527 & 1 \end{bmatrix}$$

Table 2 shows the eigenvalues, eigenvectors, and the proportion of variance of each item on the first indicator (X1).

Table 2. The Eigenvalues, Eigenvectors, and Variance Proportion of Each Item on the First Indicator (X1)

Item	**Eigenvector**			
	PC_1	**PC_2**	**PC_3**	**PC_4**
X1.1	0.445	0.477	-0.753	0.079
X1.2	0.625	-0.260	0.129	-0.725
X1.3	0.367	0.640	0.644	0.202
X1.4	0.526	-0.543	0.035	0.654
Eigenvalue	2.1280	1.1707	0.5468	0.1546
The Variance Proportion	0.532	0.293	0.137	0.039

Table 2. shows that the first principal component (PC_1) had the largest eigenvalue and the value was greater than one than the other eigenvalues. The variance explained by the first principal component (PC_1) to total variance was 53.2%, which meant that the information described in the first principal component (PC_1) was 53.2%. Table 3 shows the eigenvalues, eigenvectors, and the proportion of variance of each item on the second indicator (X2).

Table 3. The Eigenvalues, Eigenvectors, and Variance Proportion of Each Item on the Second Indicator (X2)

Item	**Eigenvector**		
	PC_1	**PC_2**	**PC_3**
X2.1	0.476	-0.876	-0.082
X2.2	0.614	0.398	-0.682
X2.3	0.630	0.274	0.727
Eigenvalue	1.8619	0.7509	0.3872
The Variance Proportion	0.621	0.250	0.129

Table 3 shows that there was one eigenvalue greater than one, i.e. PC_1. The variance explained by the first principal component (PC_1) to total variance was 62.1%, which meant that the information contained in the first main component (PC_1) was 62.1%. Table 4 shows the eigenvalues, eigenvectors, and the proportion of variance of each item on the third indicator (X3).

Table 4. The Eigenvalues, Eigenvectors, and Variance Proportion of Each Item on The Third Indicator (X3)

Item	Eigenvector		
	PC_1	PC_2	PC_3
X3.1	0.599	-0.314	-0.736
X3.2	0.541	0.837	0.083
X3.3	0.590	-0.448	0.672
Eigenvalue	2.2493	0.4848	0.2659
The Variance Proportion	0.750	0.162	0.089

Table 4 shows that there was one eigenvalue greater than one, i.e. PC_1. The variance explained by the first principal component (PC_1) to total variance was 75%, which meant that the information contained in the first principal component (PC_1) was 75%. Table 5 shows the eigenvalues, eigenvectors, and the proportion of variance of each item on the fourth indicator (X4).

Table 5. The Eigenvalues, Eigenvectors, and Variance Proportion of Each Item on the Fourth Indicator (X4)

Item	Eigenvector		
	PC_1	PC_2	PC_3
X4.1	0.543	0.653	-0.528
X4.2	0.687	0.017	0.727
X4.3	0.483	-0.757	-0.440
Eigenvalue	1.7998	0.9147	0.2855
The Variance Proportion	0.600	0.305	0.095

Table 5 shows that there was one eigenvalue greater than one, i.e. PC^1. The variance explained by the first principal component (PC_1) to total variance was 60%, which meant that the information contained in the first principal component (PC_1) was 60%. Table 6 shows the eigenvalues, eigenvectors, and the proportion of variance of each item on the fifth indicator (X5).

Table 6. The Eigenvalues, Eigenvectors, and Variance Proportion of Each Item on the Fifth Indicator (X5)

Item	Eigenvector		
	PC_1	PC_2	PC_3
X5.1	0.610	-0.471	0.637
X5.2	0.666	-0.131	-0.734
X5.3	0.429	0.872	0.234
Eigenvalue	1.7904	0.8551	0.3545
The Variance Proportion	0.597	0.285	0.118

Table 6 shows that there was one eigenvalue greater than one, i.e. PC_1. The variance explained by the first principal component (PC_1) to total variance was 59.7%, which meant that the information contained in the first principal component (PC_1) was 59.7%. Table 7 shows the eigenvalues, eigenvectors, and the proportion of variance of each item on the sixth indicator (X6).

Table 7. The Eigenvalues, Eigenvectors, and Variance Proportion of Each Item on the Sixth Indicator (X6)

Item	**Eigenvector**		
	PC_1	**PC_2**	**PC_3**
X6.1	0.505	-0.814	-0.287
X6.2	0.580	0.567	-0.585
X6.3	0.639	0.129	0.758
Eigenvalue	1.7979	0.7622	0.4399
The Variance Proportion	0.599	0.254	0.147

Table 7 shows that there was one eigenvalue greater than one, i.e. PC_1. The variance explained by the first principal component (PC_1) to total variance was 59.9%, which meant that the information contained in the first principal component (PC_1) was 59.9%. The KMO test showed the KMO value of 0.611. Thus, it can be concluded that the factor analysis was quite appropriate to use. The Barlett's Test of Sphericity obtained a p-value of 0.000 so it can be concluded that there was a correlation between variables. Therefore, the assumption of the correlation between variables was fulfilled. Table 8 presents the eigenvalues and the proportion of variance.

Table 8. The Eigenvalues and the Variance Proportion

Factor	**Eigenvalue**	**The Variance Proportion (%)**
F_1	2.480	41.339
F_2	1.711	28.513
F_3	0.867	14.450
F_4	0.405	6.746
F_5	0.282	4.701
F_6	0.255	4.253

Table 8 shows that the first factor (F_1) had the largest eigenvalue and the value was greater than one than the other eigenvalues. The variance explained by the first factor (F_1) to total variance was 41.339% which meant that the information contained in the first factor (F_1) was 41.339%. Table 9 shows the factor loadings of F1.

Table 9. Factor Loadings

Indicator	**Factor Loading**
	F_1
SK_1	0.773
SK_2	0.147
SK_3	0.388
SK_4	0.903
SK_5	0.388
SK_6	0.412

Table 9 shows that the first factor (F_1) was a latent variable of *ihsan* behavior. *Ihsan* behavior was reflected in six indicators, i.e. doing something perfectly (X1), repaying goodness with more goodness (X2), reducing optimally unpleasant consequences (X3), as solution when justice cannot be realized (X4), as a logical consequence rather than faith (X5) and as an investment in future success (X6). The strongest indicator to reflect the latent variables of *ihsan* behavior was the third indicator, which was reducing optimally unpleasant consequences.

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Table 10. Presents the Results of the Variance Proportion of Latent Variable Data of *Ihsan* Behavior.

Indicator	The Variance Proportion In the First Order	The Variance Proportion In the Second Order	Variable
X1	53.2%		
X2	62.1%		
X3	75.0%		
X4	60.0%	**41.339%**	**X**
X5	59.7%		
X6	59.9%		
Mean	**61.65%**		

Table 10 shows that the proportion of variance in the first order was 61.65% in the principal component analysis process. The average calculation in the proportion of variance in the first order did not reduce the information contained in the data. The proportion of variance in the second order was 41,339% in the factor analysis process. Information that can be explained by the overall data was 25.48% (41.393% x 61.65% = 25.48%), so that information loss was 74.52% (100% - 25.48% = 74.52%). One weakness of the second order model is a lot of information loss, causing the second order should as much as possible be avoided. However, the second order model has the advantages of providing information on the strongest indicator in measuring variables.

5. Conclusion

Principal component analysis in the first order and factor analysis in the second order generated latent variable data in the form of *ihsan* behavior. *Ihsan* behavior was reflected in six indicators, i.e. doing something perfectly, repaying goodness with more goodness, reducing optimally unpleasant consequences, as a solution when justice cannot be realized, as a logical consequence rather than faith, and as an investment in future success. The biggest contribution to the latent variable of *ihsan* behavior was the fourth indicator, which was as a solution when justice cannot be realized. The strongest indicator to reflect the latent variable of *ihsan* behavior was the third indicator, which was reducing optimally unpleasant consequences.

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