Structural equation modeling on the post-flood regional public welfare in South Kalimantan

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Abstract. This research was conducted to know the structural equation model on public welfare in the post-flood region of South Kalimantan in early 2021. The method and analysis in this study used Structural Equation Model (SEM) with compared the Maximum Likelihood (ML) and Generalized Least Square (GLS) approach to test and estimate the suitability of the post-flood public welfare model in South Kalimantan. The data collection technique in this study used a questionnaire to the people in areas victims of floods in South Kalimantan. The result is GLS approach gave more fit data than MLE based on AGFI and GFI values. The validated models gave the structural equation model with the final interpretation is Economy condition gives the significant relationship to the post-flood public welfare in South Kalimantan.

1. Introduction
Structural Equation Modeling (SEM) is a statistical technique to test and estimate the causal relationships between variables based on statistical data and qualitative causal assumptions. SEM techniques can be considered the second generation of multivariate analysis because they can test the relationships among multiple independent and dependent constructs between several variables simultaneously. As a combination of factor analysis, path analysis, and regression analysis, SEM can be an efficient statistical tool in testing a theoretical model in various branches of science.

SEM can be used to provide an overview or prediction model of the relationship between observed variables (indicators) and unobserved variables (unobserved) directly. Due to its efficiency and wide scope in the analysis and description of the model, it is not wrong if it is widely used to test the theories in various fields of science. E.g., in the fields of social science, science, education, finance, and management.[1]

In the social field, SEM is used to explain the complex relations between several social conditions so that the structural model of the social theories that later occur can be known [2]. SEM is not only able to provide simultaneous analysis results on the relationship of complex variables, but also it can estimate a series of multiple regression equations. Therefore, social indicators can be tested against their relationship with the social construct to be studied [3].

Various events hit Indonesia in early 2021. The crisis caused by the COVID-19 pandemic that attacked almost all countries globally since 2020 had a social impact on health, economy, education and changed the way people live. Survive in the New Normal era must be faced. However, the spread of CoVid-19 and people who are not fully ready with the various rules and policies for the new normal period have to face various natural disasters that then hit several regions in Indonesia.
Based on data from Badan Nasional Penanggulangan Bencana (BNPB), into early 2021, hydrometeoro logical disasters dominate disaster events in Indonesia. Until January 31, 277 disaster events occurred, with 98% being hydrometeorological disasters. In January, the loss of life and damage to settlements due to several significant disasters included floods in South Kalimantan, the floods in Manado, the landslide in Sumedang, the earthquake in West Sulawesi. Compared to the previous year, the flood experienced a significant increase in the number of fatalities and damage to settlements[4].

As one of the provinces affected by the floods from 12 to 13 January 2021, South Kalimantan had thousands of homes submerged and thousands of residents evacuated. From 28 January to February 2021, at least 11 districts were affected by the flood disaster. There were 24 deaths, more than 100.000 people displaced, 600.000 people were affected and caused damage with material losses of IDR 1.127 trillion.[5]

Four districts were affected by the most severe floods in South Kalimantan, namely Banjar, Tanah Laut, South River Hulu, and Hulu Sungai Tengah. The flood disaster hit almost all of the people of South Kalimantan, not only impacted the environment and the economic condition of the community. However, it also has an impact on social conditions and public health. Most of the affected residents even had to lose their primary source of livelihood due to the floods.[4]

Currently, people in the post-flood areas are slowly starting to restore their order of life. The government's role is needed to restore the public's economic condition after the flood. Assistance from the central, provincial, regional and local governments can help the community so that at least the level of community welfare recovers as before the flood disaster. A study is needed to help the government determines what conditions are priorities in restoring public welfare. Structural Equation Modeling (SEM) can be used to analyze the indicators that should be prioritized for welfare recovery in the post-flood disaster area in South Kalimantan.

Various social studies based on SEM analysis are the reference of this research. The ability of SEM to estimate the relationship between variables that are multiple relationships and be able to describe the model of relationships between latent variables and their indicators is also the reason for using SEM in predicting the post-flood community welfare model. The use of SEM has the underlying assumption that is the normal multivariate and a large sample. Using a small sample can result in parameter estimates that are not good and even do not converge[6].

The structural equation model in this study aims to provide an overview of models and approaches that fit the data on related variables to the level of public welfare. The data is based on the feedback of the respondents who used to be the flood victims in 4 regions in South Kalimantan, i.e. Banjar Regency, Hulu Sungai Tengah Regency, Hulu Sungai Selatan Regency, and Tanah Laut Regency. Because the data used are from sample data, an estimation method is needed to estimate the parameters designed in SEM. One part of the estimation process is to compare the estimation of the population covariance matrix with the sample covariance matrix[7]. Several estimation methods can be used to estimate the parameters of the SEM models. Commonly used in SEM are Maximum Likelihood (ML) and Generalized Least Square (GLS)[8]. In this study, two-parameter estimation methods will be compared to test the model in the given case study.

2. Material and Methods

This study departs from Structural Equation Modeling (SEM) to analyze the relationship between variables, which consists of several interconnected equations in various social studies. One of the social studies that use SEM to predict factors that affect the quality of public construction projects is research[7]. In this research, Maximum Likelihood (ML) and Generalized Least Square (GLS) were used to analyze the objective model in two stages: the measurement model that determines the relationship between the indicator and its latent, and the structural model that determines the relationship between the latent variables.
2.1. Nature of Structural Equation Models

There are two types of latent variables in SEM, namely endogenous latent variables and exogenous latent variables. Endogenous latent variables are latent variables that act as dependent variables, while exogenous latent variables act as independent variables. Besides being able to provide an overview of the relationship between variables simultaneously, SEM is also able to represent the pattern of the relationship between a variable and its indicators [9]. As a statistical technique which is a development of multivariate analysis and regression analysis, SEM can provide models and analysis results that involve many variables as well as linear equations on latent variables. Structural equation model supports latent variables and manifest variables. Latent variables can be considered as hypothetical constructs invented by a scientist for the purpose of understanding a research area [10]. Since latent variables are unobservable and cannot be directly measured, researchers use observable and empirically measurable indicator variables (also referred to as manifest variables) to estimate latent variables in the model[11].

The structural equation model is divided into two models, namely the structural model and the measurement model. General representation of Structural equations with observed variables: [12]

\[ y = By + \Gamma x + \zeta \]  

where:
- \( B = m \times m \) coefficient matrix
- \( \Gamma = m \times n \) coefficient matrix
- \( y = p \times 1 \) vector of endogenous variables
- \( x = q \times 1 \) vector of exogenous variables

Disturbances \( \zeta \) represent random errors in the relationships between \( y' \)'s and \( x' \)'s these models are sometimes referred to as errors in the equation models. The standard assumption is that errors (\( \zeta \)) are uncorrelated with \( x \).

The implicit measurement model for structural equations with observed variables is

\[ y = \eta \]
\[ x = \xi \]

where
- \( y = p \times 1 \) vector of manifest (observed) variables
- \( x = q \times 1 \) vector of manifest (observed) variables

Simply put, \( x \) and \( y \) are assumes to exactly represent the latent \( \xi \) and \( \eta \) only one indicator is used for each latent variable. The number of \( y \) variables equals the number of \( \eta \) variables \((p = m)\) and the number of \( x \) variables equals the number of \( \xi \) variables \((q = n)\).

2.2. Structural Equation Model Approach

The primary statistical problem to analyze the structural equation model is the optimal estimation of the model’s parameters and the determination of the model’s goodness of fit to the sample data on the measured variables.

Based on Eq. (2), \( p \times 1 \) vector \( y \) that contains the of \( p \) repeated measures of \( y \) for individual \( i \). \( y \) can be expressed as an underlying confirmatory factor analytic model in which latent factors represent the latent curve components. In matrix terms, the general expression is

\[ y = \Lambda \eta + \epsilon \]  

Where \( y = p \times 1 \) vector repeated measures,
- \( \Lambda = p \times m \) matrix of factor loading,
- \( \eta = m \times 1 \) vector of \( m \) latent factors,
- \( \epsilon = p \times 1 \) vector pf residuals

For a simple linear trajectory model fit to \( p \) repeated measures, the elements of Eq.(3) are: [13]
\[
\begin{pmatrix}
Y_{i1} \\
Y_{i2} \\
\vdots \\
Y_{ip}
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 \\
1 & 1 \\
\vdots & \vdots \\
1 & p - 1
\end{pmatrix}
\begin{pmatrix}
\alpha_i \vline & \beta_i \\
\vline & \vline \\
\epsilon_i \vline & \epsilon_i
\end{pmatrix}
+ 
\begin{pmatrix}
\epsilon_{i1} \\
\epsilon_{i2} \\
\vdots \\
\epsilon_{iT}
\end{pmatrix}
\]  

(4)

Thus, each repeated observation of \( y \) for individual \( i \) at time \( t \) is a weighted combination of a random intercept and linear slope term plus an individual time-specific residual.

The most common estimator to estimate the parameters in SEM, is Maximum Likelihood and Generalized Least Square estimator.

### 2.3. Maximum Likelihood Estimation

Maximum likelihood (ML) function is the most widely used fitting function for general structural equation models. The fitting function that is minimized is

\[
F_{ML} = log|\Sigma(\theta)| + tr\left(SS^{-1}(\theta)\right) - log|S| - (p + q)
\]

(5)

Assume that \( \Sigma(\theta) \) and \( S \) are positive-definite (nonsingular). It would be possible for undefined log of zero to appear in \( F_{ML} \). When \( \hat{\Sigma} = S \) substitute \( \hat{\Sigma} \) for \( \Sigma(\theta) \) and \( \hat{\Sigma} = S \) in Eq. (5).

In this case

\[
F_{ML} = log|\Sigma(\theta)| + tr(1) - log|S| - (p + q)
\]

(6)

Where \( tr(1) = p + q \), and \( F_{ML} \) is zero. Thus the model perfectly predicts the values of the sample covariance matrix. A perfect fit is indicated by a zero.

ML estimators have several important properties. The properties of ML estimators are asymptotic, so that they hold in large samples. Although they may biased in small samples, ML estimators are asymptotically unbiased. The distribution of the estimator approximates a normal distribution as sample size increases. [12]

The ML method can provide valid results with a minimum recommended sample size of 100 to 150. Because this method uses an iterative approach to reach a solution, small sample size may lead to invalid results. However, a sample size that is too large (>400) makes this method more sensitive, resulting in poor model fit [8]

### 2.4. Generalized Least Squares

Like ML, GLS also uses an iterative procedure to reach an estimation solution. The resulting estimated value is based on the least-squares criterion. Solution in regression analysis is to employ generalized least squares (GLS) which weights to correct for the unequal variances or nonzero covariances of the disturbances. A general for, of the GLS fitting function is

\[
F_{GLS} = \left(\frac{1}{2}\right) tr\left((S - \Sigma(\theta)|W^{-1}\right)^{2})
\]

(7)

Where \( W^{-1} \) is a weight matrix for the residual matrix.

\( F_{GLS} \) is scale invariant and scale free. In \( F_{GLS} \), \( (N - 1)F_{GLS} \) evaluated at the final estimates has an asymptotic chi-square distribution when the model is correct. \( (N - 1)F_{GLS} \approx \) chi-square variate in large samples. If the model is valid, \( (N - 1)F_{GLS} \) are asymptotically equivalent so that in large samples these estimated chi-squares should be close. [14]

### 2.5. Conceptual Model

For the selection of latent and indicator variables, this study is based on previous research [15] which examined that the social and economic conditions of the citizens are the main objects to determine the public welfare. Furthermore, the researchers chose health conditions as one of the variables, because at this time, almost all levels of society are faced with COVID-19 which threatens public health.

Furthermore, for the factor of community welfare on this study is based on the results of research [16] on the factors that affect the level of community welfare. In this study, several factors that affect the welfare of the community can be seen based on the level of income, the fulfillment of the need for
clothing and food, and the level of nutritional adequacy of the community. Factor analysis using SEM has also been carried out by [14] to analyze the factors that affect the performance of Village-Owned Enterprises in Bali. The research provides an overview of the use of SEM and how to form the conceptual model to determine the factors related to people's welfare. The determination of manifest variables on exogenous and endogenous latent is also based on the results of the study [17], which places education as an exogenous variable. At the same time, objective welfare and subjective well-being are endogenous latent variables.

![Figure 1. Conceptual Model](image)

The conceptual model of the research has 3 hypotheses that interpretate the related factor of the public welfare based on the post flood condition in Kalimantan Selatan. The study hypotheses are as follows:

- **H₁**: Social Conditions have a significant effect on public welfare.
- **H₂**: Economy Conditions have a significant effect on public welfare.
- **H₃**: Healthy Conditions have a significant effect on public welfare.

2.6. **Data Sources**

Data was collected from 300 respondents of flood victims in Kab.Banjar, Kab.Hulu Sungai Tengah, Kab.Hulu Sungai Selatan, and Kab. Tanah Laut using a structured questionnaire which was derived from the literature. Non-probability purposive sampling was used to select the respondents who used to be the flood victims. The questionnaire consist of 14 items, with scale from 1 to 5. Scale 1 express a very negative, and Scale 5 express a very positive point of view about the statement related condition after being affected by floods of the selected responden.

2.7. **Preliminary List of Factors**

Based on the conceptual model on Figure 1, with the comprehensive and detailed literature review, the Latent and Manifest Variables was conducted the related factors of public welfare. These list of factor were used to know the condition of the flood victims in Kalimantan Selatan.
Table 1. The preliminary list of factors affecting Public Welfare

| Latent Variables               | Manifest Variables |
|--------------------------------|--------------------|
| Social Condition (ξ₁)          | Residence condition | X₁            |
|                                | Family productivity | X₂            |
|                                | Educational activities | X₃            |
| Economy Condition (ξ₂)         | Family income      | X₄            |
|                                | Source if income   | X₅            |
|                                | Possession of valuables | X₆            |
| Healthy Condition (ξ₃)         | Clean water availability | X₇            |
|                                | The use of toilet  | X₈            |
|                                | CoVid-19 patients  | X₉            |
|                                | JAMKESMAS services | X₁₀           |
| Public Welfare (η)             | Food purchasing power | Y₁           |
|                                | Family Nutrition Sufficiency | Y₂           |
|                                | The Use of clothing | Y₃           |
|                                | Provincial Minimum Wage | Y₄           |

3. Data Analysis

AMOS version 23.0 was used to analyze the model and hypotheses conducted. Because of using AMOS to estimate the conducted model, this research using the research framework by [11]. In this research, after problem definition and research design, then theoretical foundation was conducted. Data analysis on this research will follow the next step: (1) Model Construction (2) Data Collection (3) Model Validation (4) Interpretation

To analyze the data, structural equation model validation was applied in this research based on a two-step procedure as recommended by [18]. The first step, involves the evaluation of the outer measurement model, and then evaluation of the inner structural model.

3.1 Model Construction

Based on the conceptual model and the preliminary list of factors, we conducted the first model construction to estimate

Figure 2 The 1st model construction

with constructs:
ξ₁: Public Social condition
ξ₂: Public economic condition
ξ₃: Public health condition
η: Public welfare
The Path Diagram Model in Figure 2 then we conversed in Measurement and Structural Equation as follow:

$$\eta = \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_3 + \zeta$$  \hspace{1cm} (8)

with matrix as:

$$[\eta] = \begin{bmatrix} \gamma_1 \\
\gamma_2 \\
\gamma_3 \\
\end{bmatrix} [\xi_1 \\
\xi_2 \\
\xi_3] + [\zeta]$$  \hspace{1cm} (9)

where: $\eta$ = estimate parameter of endogenous construct; $\gamma_1, \gamma_2, \gamma_3$ = loading structural of exogenous construct to endogeneous construct; $\xi_1, \xi_2, \xi_3$ = random errors of the model.

**Endogenous Variable Measurement model**

\[
\begin{align*}
Y_1 &= \lambda_1 \eta + \varepsilon_1 \\
Y_2 &= \lambda_2 \eta + \varepsilon_2 \\
Y_3 &= \lambda_3 \eta + \varepsilon_3 \\
Y_4 &= \lambda_4 \eta + \varepsilon_4
\end{align*}
\]  \hspace{1cm} (10)

with matrix as:

$$\begin{bmatrix} Y_1 \\
Y_2 \\
Y_3 \\
Y_4 \\
\end{bmatrix} = \begin{bmatrix} \lambda_1 \\
\lambda_2 \\
\lambda_3 \\
\lambda_4 \\
\end{bmatrix} [\eta] + \begin{bmatrix} \varepsilon_1 \\
\varepsilon_2 \\
\varepsilon_3 \\
\varepsilon_4 \\
\end{bmatrix}$$  \hspace{1cm} (11)

where: $Y_1,Y_2,Y_3,Y_4$ = manifest variables of endogenous construct; $\lambda_1,\lambda_2,\lambda_3,\lambda_4$ = loading factor of endogenous construct, and $\varepsilon_1,\varepsilon_2,\varepsilon_3,\varepsilon_4$ = random errors of endogenous measurement model

**Exogenous Variable Measurement model**

\[
\begin{align*}
X_1 &= \lambda_{11} \xi_1 + \delta_1 \\
X_2 &= \lambda_{21} \xi_1 + \delta_2 \\
X_3 &= \lambda_{31} \xi_1 + \delta_3 \\
X_4 &= \lambda_{42} \xi_2 + \delta_4 \\
X_5 &= \lambda_{52} \xi_2 + \delta_5 \\
X_6 &= \lambda_{62} \xi_2 + \delta_6 \\
X_7 &= \lambda_{73} \xi_3 + \delta_7 \\
X_8 &= \lambda_{83} \xi_3 + \delta_8 \\
X_9 &= \lambda_{93} \xi_3 + \delta_9 \\
X_{10} &= \lambda_{103} \xi_3 + \delta_{10}
\end{align*}
\]  \hspace{1cm} (12)

with matrix as:

$$\begin{bmatrix} X_1 \\
X_2 \\
X_3 \\
X_4 \\
X_5 \\
X_6 \\
X_7 \\
X_8 \\
X_9 \\
X_{10} \\
\end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 & 0 \\
\lambda_{21} & 0 & 0 \\
\lambda_{31} & \lambda_{42} & 0 \\
0 & \lambda_{52} & 0 \\
0 & \lambda_{62} & 0 \\
0 & \lambda_{72} & \lambda_{83} \\
0 & 0 & \lambda_{93} \\
0 & 0 & \lambda_{103} \\
\end{bmatrix} [\xi_1 \\
\xi_2 \\
\xi_3] + \begin{bmatrix} \delta_1 \\
\delta_2 \\
\delta_3 \\
\delta_4 \\
\delta_5 \\
\delta_6 \\
\delta_7 \\
\delta_8 \\
\delta_9 \\
\delta_{10} \\
\end{bmatrix}$$  \hspace{1cm} (13)

where: $X_1,X_2,X_3,X_4,X_5,\ldots,X_{10}$ = manifest variables of exogenous construct; $\lambda_{11},\lambda_{21},\lambda_{31},\lambda_{42},\lambda_{52},\lambda_{62},\lambda_{72},\lambda_{83},\lambda_{93},\lambda_{103}$ = loading factor of endogenous construct, and $\varepsilon_1,\varepsilon_2,\varepsilon_3,\varepsilon_4$ = random errors of endogenous measurement model
3.2 Measurement Models

At the measurement models of exogenous variable on the 1st construction model, we tested the convergent validity and reliability models. According to [19], a composite reliability of 0.70 or above and an average variance extracted if more than 0.50, are deemed acceptable.

According to [20] the composite reliability and average variance can be obtained by the equation:

**Composite Reliability**

\[
CR = \frac{\left(\sum_{i=1}^{n} \lambda_i \right)^2}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} \epsilon_i}
\]

(10)

And

**Average Variance Extracted**

\[
AVE = \frac{\sum_{i=1}^{n} \lambda_i^2 \epsilon_i}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} \epsilon_i}
\]

(11)

with:

**Measurement Error**

\[
\epsilon_i = 1 - \lambda_i^2
\]

(12)

As can be seen from Table 2, Variables \(X_3, X_6, \text{and } X_7\) have the small values of estimated factor loadings. The composite reliability values are above 0.70 except for construct \(\xi_2\) (Economy) which is acceptable as there are only 2 measurement items. The average variance extracted is above 0.50 for the construct \(\xi_1\) (Social) and \(\eta\) (Welfare). We need to modify the models for this measurement models, because of the manifest variables aren’t a reflection of the construct variable especially for construct \(\xi_1\) (Social) and construct \(\xi_2\) (Economy).

**Table 2** The preliminary list of factors affecting Public Welfare

| Construct Variable | Manifested Variables | Convergent Validity |
|--------------------|----------------------|---------------------|
| \(\xi_1\) | \(X_1\) | 0.956 | 0.843 | 0.663 |
|                  | \(X_2\) | 0.946 |
|                  | \(X_3\) | 0.424 |
| \(\xi_2\) | \(X_4\) | 0.745 | 0.540 | 0.365 |
|                  | \(X_5\) | 0.734 |
|                  | \(X_6\) | 0.018 |
| \(\xi_3\) | \(X_7\) | 0.147 | 0.725 | 0.442 |
|                  | \(X_8\) | 0.802 |
|                  | \(X_9\) | 0.811 |
|                  | \(X_{10}\) | 0.667 |
| \(\eta\) | \(Y_1\) | 0.747 | 0.806 | 0.519 |
|                  | \(Y_2\) | 0.834 |
|                  | \(Y_3\) | 0.782 |
|                  | \(Y_4\) | 0.46 |

3.3 Structural Models

**Estimated Model using MLE**

The structural model was estimated using the maximum likelihood method (MLE). Fig. 1 presents the results. The fit statistics are presented in Table 3. All the fit measures from this study are below to the recommended values suggesting a good model fit. The result is the model doesn’t fit to data we used.
Table 3. The Estimated of Construction Model using MLE

| Fit Measures | Values  | Recommended Values |
|--------------|---------|--------------------|
| df           | 71      |                    |
| $x^2$        | 699.34  | $< x^2_{\text{table}}$ |
| $x^2/df$     | 9.85    | $\leq 3.00$        |
| GFI          | 0.70    | $\geq 0.90$        |
| AGFI         | 0.55    | $\geq 0.80$        |
| CFI          | 0.76    | $\geq 0.90$        |
| RMSEA        | 0.172   | $\leq 0.08$        |

Estimated Model using GLS

The structural model was estimated using the maximum Generalized Least Square. The fit statistics are presented in Table 4. Based on the GFI and AGFI, the model is fit, but we used to modify the models to get the more fit values of GFI and AGFI.

Let see, the model was given the fit values of GFI and AGFI with using GLS estimate instead of using MLE.

Table 4. The Estimated of Construction Model using GLS

| Fit Measures | Values  | Recommended Values |
|--------------|---------|--------------------|
| df           | 71      |                    |
| $x^2$        | 303.655 | $< x^2_{\text{table}}$ |
| $x^2/df$     | 4.277   | $\leq 3.00$        |
| GFI          | 0.9     | $\geq 0.90$        |
| AGFI         | 0.8     | $\geq 0.80$        |
| CFI          | 0.5     | $\geq 0.90$        |
| RMSEA        | 0.10    | $\leq 0.08$        |

We need to modify the models to testing the hypothesis about the relationship of the exogenous and endogenous variable.

4. Modification Models

Modification of the model is done by evaluating and reconstructing the model that has been made. Modification 1 eliminates the manifest variable with the lowest loading factor, namely X6. However, the model does not provide a better fit data value. Modification 2 is done by returning X6 and eliminating the manifest variable with the 2nd lowest loading factor, namely X7. However, the model does not provide a better fit for the data. The 3rd modification was carried out by returning X7, then abolishing X3. However, the model that was formed gave a low data fit value. Because the data fit is not better than the initial model, and the analysis in Amos suggests not reducing the observed variables.

Furthermore, modifications were made by giving a minimal constant value for the regression weight of the X6 variable. A better fit value was obtained, but it was not good enough for further hypothesis analysis. Thus, a covariant error matrix is formed on the manifest variables considered to have a relationship based on the obtained social theory.
Table 5. The Estimated Covariance Error

| e13 | e15 | 0.096 | 0.019 | 5.024 *** par_16 |
|-----|-----|-------|-------|-----------------|
| e12 | e16 | 0.034 | 0.040 | 0.851 0.395 par_17 |
| e10 | e16 | 0.080 | 0.036 | 2.251 0.024 par_18 |
| e10 | e15 | 0.056 | 0.019 | 3.002 0.003 par_19 |
| e10 | e11 | 0.065 | 0.027 | 2.408 0.016 par_20 |
| e9  | e11 | 0.017 | 0.032 | 0.510 0.610 par_21 |
| e8  | e11 | 0.129 | 0.036 | 3.543 *** par_22 |
| e7  | e13 | 0.182 | 0.036 | 5.115 *** par_23 |
| e7  | e16 | 0.062 | 0.055 | 1.139 0.255 par_24 |
| e6  | e15 | 0.077 | 0.024 | 3.245 0.001 par_25 |
| e6  | e16 | 0.163 | 0.060 | 2.694 0.007 par_26 |
| e6  | e7  | 0.264 | 0.058 | 4.589 *** par_27 |
| e6  | e13 | 0.155 | 0.039 | 3.961 *** par_28 |
| e4  | e12 | 0.082 | 0.023 | 3.507 *** par_29 |

Table 5 provides an overview of the modification of the covariant error manifest variable in the modified model.

5. Model Validation and Interpretation

After making modifications to the initial construction model, then a model with a better fit is obtained so that the following results are obtained:

Table 6. The Estimated of Modified Model using GLS

| Fit Measures | Values | Recommended Values |
|--------------|--------|--------------------|
| df           | 58     |                    |
| $x^2$        | 161.37 |                    |
| $x^2/df$     | 2.78   | $\leq 3.00$        |
| GFI          | 0.92   | $\geq 0.90$        |
| AGFI         | 0.86   | $\geq 0.80$        |
| CFI          | 0.76   | $\geq 0.90$        |
| RMSEA        | 0.07   | $\leq 0.08$        |

The structural model was estimated using the maximum Generalized Least Square. The fit statistics are presented in Table 6. All the fit measures are above the recommended values suggesting a good model fit. All the paths are significant at the 0.05 level. The modified models can be used to test the hypothesis about the relationship of the exogenous and endogenous variable. By Table 7, we obtained the structural equation modeling can be shown by the estimate regression weight as follow:

$$\eta = -8.02 \xi_1 + 1.88 \xi_2 - 1.44 \xi_3 + \xi$$

The modified model then we used to test the hypothesis. The results are the model accepted $H_2$: Economy Condition has a significant relationship with the public welfare, rejected $H_1$: Social Condition has a significant relationship with the public welfare and $H_3$: Healthy Condition has a significant relationship with the public welfare.

Table 7. The Estimated of Modified Model using GLS

| Estimate   | Social   | Healthy  | Economy |
|------------|----------|----------|---------|
| Welfare    | ---      | -0.802   | -1.40   |
| Welfare    | ---      |          | 1.882   |
| Welfare    | ---      |          |         |
It means Economy condition gives the significant relationship to the in the post-flood public welfare in South Kalimantan, at the significant level 0.05. The result of the hypotheses testing can be seen as follow.

| Hypothesis | C.R  | p value | Decision (α = 5%) |
|------------|------|---------|------------------|
| H1: Social Condition has a significant relationship with the public welfare | 1.553 | 0.12 | Not Supported |
| H2: Economy Condition has a significant relationship with the public welfare | 2.36 | 0.01 | Supported |
| H3: Healthy Condition has a significant relationship with the public welfare | 0.326 | 0.745 | Not Supported |

6. Conclusion

Structural Equation Modeling on The Post-Flood Regional Public Welfare in South Kalimantan was conducted with the general equation as $\eta = \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_3 + \zeta$. Comparing Maximum Likelihood Estimation (MLE) and Generalized Least Square (GLS) approach to test and estimate the suitability of the post-flood public welfare gave the result which GLS made the more fit data than MLE with a large sample data from 300 respondents. The validated models given the structural equation model as $\eta = -8.02 \xi_1 + 1.88 \xi_2 - 1.44 \xi_3 + \zeta$, with the final interpretation is Economy condition gives the significant relationship to the post-flood public welfare in South Kalimantan.

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