Structural Equation Modelling-Partial Least Square to Determine the Correlation of Factors Affecting Poverty in Indonesian Provinces

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Abstract. Structural Equation Modelling (SEM) is a multivariate statistical technique to analyze the pattern of relationships between latent variables (unobserved) with indicator variables (observed). One aspect that can be solved by SEM is poverty. Poverty is a major problem in economic development in developing countries like Indonesia. The problem of poverty can also be seen from the dimensions of education and health. This research uses SEM model with Partial Least Square (PLS) approach on poverty data in all provinces in Indonesia based on 2015-2017 Badan Pusat Statistik (BPS) data with latent variables of poverty, education, economy, and health. The results show that there is an indicator of latent educational variables that must be excluded from the model because it has a loading factor value > 0.5. The results of the outer model evaluation with Convergent Validity, Composite Reliability (CR), and Average Variance Extracted (AVE) show significant and reliable values that mean the indicators used can explain latent variables well. The SEM-PLS inner model evaluation results can be known from the value of R-Square ($R^2$) through the bootstrapping stage with 500 sample cases. R-square value for Economics is 0.751 means the model can explain variations of Economy in poverty cases in the Provinces of Indonesia at 75.1%, Education at 0.583 or 58.3% and the poverty model at 0.645 or 64.5%. The structural model for poverty cases in Indonesia in 2015-2017 is obtained Poverty = -0.548 Health - 0.085 Education + 0.128 Economy. The relationship of the poverty model shows that if poverty in Indonesia increases, the health of poor households and Education in Indonesia will decrease by 0.548 and 0.085 units respectively, whereas if poverty in Indonesia increases, the economy of poor households will increase by 0.128 assuming looking at the indicators that form latent economic variables.

1. Introduction
Poverty is a central issue for every country in the world, especially for developing countries, poverty alleviation and creating prosperity for the people is the final goal of a nation. According to Kunarjo [1] a country said to be poor is usually characterized by a low level of income per capita, has a high rate of population growth (more than 2 percent per year), most workers are engaged in the agricultural sector and are shackled in poverty circles. Poverty is also one of the problems faced by the Indonesian government. Poverty is not only related to the issue of a low level of income and consumption but also related to the low level of education, health, powerlessness to participate in the development and various problems on human development. Therefore, alleviating the problem of poverty must be a top priority in economic development, both short and long term.
Indonesia is a developing country consisting of 34 provinces. Based on data from the Central Statistics Agency (BPS), Indonesia's poverty conditions in March 2015, the number of poor people reached 28.59 million people or 11.22% of the total population of Indonesia. Entering March 2016, the sparse population recorded 28.01 million people or 10.86%. In March 2017, the poor community recorded 27.77 million people or 10.64%. Finally, in March 2018 the number of poor people was recorded at 25.95 million people or 9.82%. From the data also mentioned the number of poor people in urban areas in the 2018 period recorded 10.14 million people down 128.2 thousand people compared to the period September 2017 amounted to 10.27 million people.

Meanwhile, in rural areas, it fell by 505 thousand people (from 16.31 million in September 2017 to 15.81 million in March 2018). While in terms of the percentage of poor people in urban areas it was 7.02% lower than the September 2017 period of 7.26%. Meanwhile, the rate of poor people in rural areas in September 2017 was 13.47%, down to 13.20% in March 2018 [2].

The Indonesian government has always launched poverty reduction efforts from year to year. However, the number of poor people in Indonesia has not experienced a significant decrease, although the data in BPS shows a tendency to decrease the number of poor people, qualitatively it has not demonstrated the impact of real changes, but the condition is even more alarming each year [3]. Poor people often suffer from malnutrition, poor health, poor environment, and lack of access to infrastructure and adequate public services. Pockets of poverty spread throughout Indonesia from hamlets in the highlands, forest edge communities, poor small villages, fishing communities, farmers or slums in urban areas.

Factors that influence poverty levels cannot be measured directly because they are concepts (latent variables) such as inability to fulfill basic needs, limited human resource competence, inability to meet supporting needs, and limited access to infrastructure. Noting these factors, an indicator is needed to reflect the concept of poverty. Several statistical methods can be used to determine the relationship of these factors, one of which is Structural Equation Modeling (SEM). SEM analysis requires a strong theoretical foundation and clearly defined, covariance-based SEM method is more appropriate to be applied, but this method requires a large sample, assuming that the data must be a multivariate normal distribution. Real data in the field often show patterns of data that are spread abnormally, so we need a method that is free distribution [4].

A study that collided with small sample size and weak theoretical basis, then the fulfillment of the assumptions becomes difficult, we need an alternative SEM method that can accommodate the constraints of fulfilling the premises. The method is SEM based on variance or component (component-based SEM), which is the Structural Equation Modeling-Partial Least Square (SEM-PLS) method. SEM-PLS allows structural equation modeling with the assumption that the data used do not have to be normally distributed, can use a relatively small sample size, and the indicators used are reflective, formative, or a combination of both. PLS is an analytical method used to confirm theories and can also be used to explain the presence or absence of relationships between latent (unobserved) variables [5].

Until now, research related to poverty using the SEM method has been carried out by various parties. Fitriani and Otok (2013) in their research on developing indicators and determining poor households in East Java Province using Spatial Structural Equation Modeling using the dimensions of health, economy, human resources, in the analysis of poverty dimensions in East Java Province [6]. Afifah and Sunaryo (2013) made a grouping of regencies/cities in Central Java Province in 2011 based on the structure of the poverty model using the Finite Mixture Partial Least Square (FIMIX-PLS) method [7]. Anuraga and Otok (2013) conducted poverty modeling in East Java with Structural Equation Modeling Partial Least Square [8]. In this study, an analysis will be conducted related to the factors that influence poverty in Indonesian Provinces in 2015-2017 using the SEM-PLS method. This research is directed to address the issue of what factors are dominantly affecting poverty in Indonesian provinces. Analysis of the structure of poverty in this study wants to see whether there is a relationship, and how the relationship between the dimensions of poverty, the dimensions of
education, economic aspects, and health dimensions. This research can help the government to obtain information about the dominant factors that influence poverty in Indonesia so that in compiling programs to improve the welfare of the people in Indonesia can be done by the potential of each province.

2. Material and Methods
2.1. Data
The data used in this study is secondary data obtained from data from the Badan Pusat Statistik (BPS) in the Provinces of Indonesia in 2015-2017, which consists of 34 Provinces.

2.2. Research Variable
The following are the variables used in the study.

| Latent Variable | Code | Indicator Variable |
|-----------------|------|--------------------|
| Health          | X1   | Percentage of population that treats in a modern way for a month (Percent) |
|                 | X2   | Percentage of women aged 15-49 years old and married who are using birth control device (Percent) |
|                 | X3   | Percentage of women ever married aged 15-49 whose last birth process was assisted by Trained Nurses by Province (Percent) |
|                 | X4   | Percentage of households that use bottled drinking water (percent) |
| Poverty         | Y1   | Percentage of poor population (percent) |
|                 | Y2   | Poverty depth index (percent) |
|                 | Y3   | Poverty severity index (percent) |
| Education       | Y4   | Percentage of literacy numbers (percent) |
|                 | Y5   | The average length of school (percent) |
|                 | Y6   | Percentage of young people (15-24 years) who do not attend school, work or training (percent) |
| Economy         | Y7   | Percentage of people in the farming sector (percent) |
|                 | Y8   | Percentage of Households Using Wood-based as Main Fuel for Cooking (percent) |

Based on Table 1. Health latent variables consist of 4 indicator variables namely X1, X2, X3, X4, poverty latent variables comprise 3 indicator variables namely Y1, Y2, Y3, latent educational variables consist of 3 indicator variables namely Y4, Y5, Y6, and economic variables contain 2 indicator variables namely Y7, Y8.

2.3. Poverty
Poverty is a situation or condition experienced by a person or group of people who are unable to carry out their lives to a level that is considered humane [3]. There are four patterns of poverty, persistent poverty, namely poverty that has been chronic or hereditary. The second pattern is cyclical poverty, which is poverty that follows the model of the whole economic cycle. The third pattern is seasonal poverty, which is annual as found in the case of fishermen and food crop farmers. The fourth pattern is accidental poverty, namely poverty, due to natural disasters or the impact of a particular policy that causes a decrease in the welfare level of a community [9].

2.4. Structural Equation Modelling (SEM)
Structural Equation Modeling (SEM) is a statistical technique that can analyze patterns of linear relationships simultaneously between latent variables and indicator variables. Latent variables are variables that cannot be measured directly but can be represented or measured by one or more indicator variables [10]. SEM includes statistical techniques used to build and test statistical models that are usually in the form of causal models. SEM becomes a fairly powerful analytical technique because it considers interaction modeling, nonlinearity, correlated independent variables, measurement...
errors, correlated error terms, multiple latent independent variables in multiple where each is measured by many indicators, and one or two variables depending on latency which is also each measured by several indicators. SEM is based on analysis of covariance so that it gives a more accurate covariance matrix than linear regression analysis.

Data analysis techniques using SEM are used to explain the relationship between variables as a whole that exist in research. The fundamental reasons for using SEM in this research is [11]:

a. SEM can estimate relationships between variables that are multiple relationships. This relationship is formed in the structural model (the relationship between the dependent and independent variables).

b. SEM can describe the pattern of relationships between latent variables and indicator variables.

In general, SEM consists of two main parts, namely the structural model and the measurement model [12]. The structural model illustrates the pattern of relationships between endogenous (dependent) latent variables and exogenous (independent) latent variables, as in the following equation:

\[ \eta = B\eta + \Gamma\xi + \zeta \]  

(1)

Where, \( B \) is the structural coefficient matrix for the relationship between endogenous latent variables \( \eta \) size \( m \times m \) with diagonally zero elements \((|I - B| \neq 0)\), \( \Gamma \) is the structural coefficient matrix for the relationship between exogenous latent variables \( \xi \) and endogenous latent variables \( \eta \) size \( m \times n \), \( \zeta \) is an error vector size \( m \times 1 \) with \( E(\zeta) = 0 \) and \( \text{Cov}(\zeta) = \Psi \) (i.e., a diagonal matrix of residual variance for \( \eta \) sized \( m \times m \)), assuming the error term \( \zeta \) does not correlate with all other error terms and latent variable \( \xi \) [12]. While the measurement model draws a pattern of relationships between latent variables and their indicators, as in the following equation:

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

(2)

\[ x = \Lambda_x\xi + \delta \]  

(3)

Where \( y \) is an endogenous latent variable vector size \( p \times 1 \), \( x \) is an exogenous latent variable vector \( x \) size \( q \times 1 \), \( \Lambda_y \) is a loading factor matrix for \( y \) size \( p \times m \), \( \Lambda_x \) is a loading factor matrix for \( x \) size \( q \times n \), \( \eta \) is an endogenous latent variable vector measuring size \( m \times 1 \), \( \xi \) is an exogenous latent variable vector measuring size \( n \times 1 \), \( \epsilon \) is a measurement error vector at \( y \) scale \( p \times 1 \), and \( \delta \) is a measurement error vector at \( x \) size \( q \times 1 \). It is assumed that \( \epsilon \) and \( \delta \) are not correlated with each other [12].

2.5. Structural Equation Modelling-Partial Least Square (SEM-PLS)

Partial Least Square (PLS) is a method that was first introduced by Herman O.A. The world. PLS is an alternative technique in SEM analysis where the data used are generally not distributed multivariate. In SEM with PLS, the value of the latent variable is estimated according to the linear combination of the indicator variables associated with the latent variable and is treated to replace the indicator variable [13]. The advantages of SEM with PLS when compared to SEM-based covariance, SEM with PLS can handle two conditions where:

a. Factor Indeterminacy

Factor indeterminacy is a condition in which the resulting factor score has a different value when calculated from a single factor model. Especially for formative indicators, do not require the existence of a common factor so that it will always obtain a combined latent variable in the form of unity.

b. Inadmissible Solution

Unacceptable solution conditions will not occur in SEM with PLS, because SEM with PLS is based on variance and not covariance so that the singularity matrix problem will never happen. Besides, PLS works on a structural model that is recursive, so that is a problem unidentified, under-identified, or over-identified will never happen.

According to Monecke and Leisch [14], SEM with PLS consists of three components, namely structural models (inner models), measurement models (outer models), and weight relations. This
weight relation section is a unique feature of SEM with PLS and is not present in covariant-based SEM. SEM models with PLS are described as follows:

**Figure 1. SEM with PLS Model**

In Figure 1, the outer model for exogenous latent variables consists of 2 latent variables, namely X1 and X2. The latent variable X1 has 2 indicator variables, namely the I1X1 indicator and the I2X1 indicator. And the latent variable X2 also has 2 indicator variables namely I1X2 indicator and I2X2 indicator. While the outer model for endogenous latent variables consists of 1 latent variable namely Y, which consists of 2 indicator variables, I1Y indicator, and I2Y indicator. Then the inner model draws the relationship between latent variables X1, X2 and Y.

The use of SEM models has an underlying assumption that is multivariate normal distribution data and large sample sizes. The use of small sample size can produce parameter estimates that are not good even not convergent. So that one alternative to SEM that does not require multivariate normally distributed data is the Partial Least Square (PLS) approach. PLS is a powerful analysis method because it does not require the assumption of normality and can use a relatively small sample size [14]. In SEM with PLS only allowed recursive models (cause-effect) and did not allow non-recursive models (reciprocity) as in SEM which is covariant-based and SEM with PLS allows very complex models with many latent variables and indicators [14].

In the path analysis for SEM-PLS, there are three models, namely the inner model, outer model, and weight relation. The inner model shows the relationship between latent variables, the outer model shows the relationship between the latent variable and its indicator variables, and the weight relation shows the estimated value of the latent variable.

### 2.5.1. Structural Model (Inner Model)

Structural models or inner models describe the relationship model between latent variables that are formed based on the substance of the theory. PLS is designed for a recursive model, so there is a relationship between latent variables called the causal chain system with the following form of an equation:

\[
\eta_j = \Sigma \beta_{ji} \eta_i + \Sigma \gamma_{jb} \xi_b + \zeta_j
\]  

(4)

Where \(i, ..., b\) represents the range index along \(i\) and \(b\), \(j\) represents the number of endogenous latent variables, \(\beta_{ji}\) represents the path coefficient that connects the endogenous latent variable (\(\eta\)) with
endogenous ($\eta$), $\gamma_{fb}$ represents the path coefficient linking the endogenous latent variable ($\eta$) exogenous ($\xi$) and $\zeta$ represent the level of measurement error (inner residual variable) [14].

2.5.2. Measurement Model (Outer Model)
The measurement model or outer model generally describes the relationship between latent variables and indicators. In the outer model, there are two types of models, namely reflexive and formative indicator models. Reflexive models occur when indicator variables are influenced by latent variables. The equation for the reflexive indicator model is the same as the measurement model in covariance-based SEM. While the formative model assumes that the indicator variables affect latent variables. The direction of causality flows from the indicator variable to the latent variable. The equation for the developmental model is as follows:
\[
\xi = \Pi_x \xi + \delta_{\xi}
\]
\[
\eta = \Pi_y \eta + \epsilon_{\eta}
\]
Where, $\Pi_x$ and $\Pi_y$ represents the multiple regression coefficients of the latent variable to the indicator, $\delta_{\xi}$, and $\epsilon_{\eta}$ represent the level of measurement error (residual error) [14].

2.5.3. Weight Relation
According to Abdillah and Jogiayanto HM [15], the weight relation score shows the relationship of variance values between indicators with their latent variables so that it is assumed to have a mean equal to zero with a variance similar to one to eliminate constants in causality. The equation for weight relation is as follows:
\[
\xi_b = \sum_{k=1}^{K} w_{kb} x_{kb} 
\]
\[
\eta_i = \sum_{i=1}^{I} w_{ki} y_{ki}
\]
Where $w_{kb}$ and $w_{ki}$ declare the weights $k$ used to estimate latent variables $\xi_b$ and $\eta_i$.

In the use of PLS, there are several evaluations of structural models (inner models) and measurement models (outer models). In evaluating the measurement model, convergent validity testing is performed, reliability testing uses Composite Reliability (CR) and Average Variance Extracted (AVE) measures. Whereas in the evaluation of structural models the R-squared ($R^2$) test and the path coefficient estimation test are performed.

2.5.3.1 Convergent Validity
Convergent validity in SEM-PLS is used as an evaluation for the measurement model (outer model). Convergent validity is a type of validity that is related to the principle that measuring a variable must have a high correlation so that it is used to measure the magnitude of the relationship between latent variables and indicator variables in the reflexive measurement model. According to Hair [16], a correlation can be said to meet Convergent validity if it has a standardized loading factor $\lambda \geq 0.5$.

2.5.3.2 Reliability Test
Reliability test in SEM-PLS model is used as one of the evaluations for the measurement model (outer model). To measure the reliability of this research model, Composite Reliability (CR) and Average Variance Extracted (AVE) are used. Latent variables can be said to have excellent reliability if the value of composite reliability (CR) is more significant than 0.7 [16]. CR can be determined using the following formulation:
\[
CR = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + \sum_{i=1}^{n} e_i}
\]
where, $\lambda_i$ is the standardized loading factor and $e_i$ is the error value from $i$-th measurement with $e_i = 1 - \lambda_i^2$. Furthermore, latent variables can be said to have excellent reliability if the value of the Average Variance Extracted (AVE) is more significant than 0.5 [16]. AVE can be determined using the following formulation:
\[
AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} e_i}
\]
where, $\lambda_i$ is the standardized loading factor and $e_i$ is the error value from $i$-th measurement with $e_i = 1 - \lambda_i^2$.

2.5.3.3 R-Square ($R^2$) Test

R-squared ($R^2$) is a test conducted to measure the level of Goodness of Fit of a structural model. The value of R-squared ($R^2$) is used to measure how much influence the particular independent latent variable has on the latent dependent variable. According to Chin [17] $R^2$ Results of 0.67 indicate that the model is well categorized. Results $R^2$ Between 0.33 and 0.67 show that the model is classified as moderate. While the Results $R^2$ of 0.33 indicates that the model is categorized as weak.

2.5.3.4 Significance Test

Significance test aims to determine the effect of independent variables on the dependent variable. Significance test in the SEM model with PLS, what is meant by the independent variable is the exogenous latent variable and what is meant by the dependent variable is the endogenous latent variable. Estimated values for path relationships in the structural model are used to determine the significance of the relationships between latent variables. Significant value can be obtained by the bootstrapping procedure developed by Geisser & Stone. The formulation of the hypothesis in the significance test is as follows:

$H_0$: The independent variable does not significantly influence the dependent variable

$H_1$: The independent variable significantly influences the dependent variable.

The test statistics used are:

$$T_{statistik} = \frac{b_j}{s(b_j)} $$

(11)

Where $b_j$ represents the estimated value for $\beta_j$, $s(b_j)$ states the standard error for $b_j$. The test criteria are the significance level ($\alpha$). $H_0$ is rejected if $T$-statistic $> T$-table (df, $\alpha$) or p-value $< \alpha$ [18].

2.6. Bootstrap

Bootstrap is a nonparametric estimation method that can estimate the parameters of a distribution, the variance of a median sample, and can estimate errors [18]. In the bootstrap method, sampling is performed by returning the sample data. Determination of the value of the number of replications (B) is very varied because the size of the value of B can provide different results at each stage in the analysis. A large B value will usually be very good for determining confidence intervals.

2.7. Experimental Design

The analysis used in this study uses the SEM-PLS method with the help of SmartPLS 3.2.8 software. The following is a research method flowchart:
The initial stage begins by collecting data from the Badan Pusat Statistik (BPS) in the Provinces of Indonesia in 2015-2017, which consists of 34 Provinces totaling 102 samples. The raw data obtained will be prepared in advance in the SmartPLS 3.2.8 software. To conduct Structural Equation Modeling (SEM) analysis using PLS, it starts from designing structural models and measurement models based on the concepts and theories developed. Next, create a path diagram that explains the pattern of relationships between latent variables and indicator variables. Estimating SEM-PLS parameters through the bootstrapping stage with 500 sample cases, namely evaluating the measurement model (outer model) and evaluating the structural model (inner model). If the evaluation results are significant, then proceed to the interpretation phase of the hypothesis test. From tests conducted on the inner model, a structural model will be obtained for poverty cases in Indonesia.

3. Result and Discussion
3.1 Measurement Model Evaluation (Outer Model)
In this case, evaluation or analysis of the measurement model will be carried out, namely, the relationship between latent variables and their indicators. The purpose of this measurement model analysis is to determine the validity and reliability of indicators of a latent variable.

3.1.1. Convergent Validity
The convergent validity test is used to test whether the indicator variables used are really significant in terms of reflecting latent variables. Convergent validity test consists of validity and reliability tests. The good convergent validity is indicated by the high standardized loading factor (\( \lambda \)) value. Hair [16] suggests a value of \( \lambda \geq 0.5 \), meaning that a good convergent validity has been achieved. The results of convergent validity testing in Indonesia can be seen in the outer model loadings, as shown below.
Table 2. Indicator of Health Latent Variables

| Indicator of Health Latent Variables | Loading Factor | Evidence |
|-------------------------------------|----------------|----------|
| X1                                  | 0.746          | Valid    |
| X2                                  | 0.698          | Valid    |
| X3                                  | 0.792          | Valid    |
| X4                                  | 0.632          | Valid    |

Table 2 shows that for the population variable that treats in a modern way (X1), Women who are currently using birth control devices (X2), women whose birth process is assisted by Trained Health Workers (X3), and households that use a Source of Drinking Water in Packaging (X4) can be used to measure latent health variables because the loading factor value is > 0.5.

Table 3. Indicator of Poverty Latent Variables

| Indicator of Poverty Latent Variables | Loading Factor | Evidence |
|--------------------------------------|----------------|----------|
| Y1                                   | 0.973          | Valid    |
| Y2                                   | 0.998          | Valid    |
| Y3                                   | 0.977          | Valid    |

Table 3 shows that all indicator variables on the latent variable of poverty are valid because of the loading factor value > 0.5. This means that all indicators can be used to measure the latent variable of Poverty.

Table 4. Indicator of Education Latent Variables

| Indicator of Education Latent Variables | Loading Factor | Evidence |
|----------------------------------------|----------------|----------|
| Y4                                     | 0.953          | Valid    |
| Y5                                     | 0.850          | Valid    |
| Y6                                     | 0.181          | Not Valid|

Table 4 shows that for young age variables (15-24 years) who are not in school, work / attend training (Y6) is invalid because of the loading factor value < 0.5. As for the literacy number indicator (Y4) and the average length of school (Y5) can be used to measure the latent variable of Education.

Table 5. Indicator of Economic Latent Variables

| Indicator of Economic Latent Variables | Loading Factor | Evidence |
|---------------------------------------|----------------|----------|
| Y7                                     | 0.880          | Valid    |
| Y8                                     | 0.933          | Valid    |
Table 5. shows that all variables in the Economic latent variable are valid because the loading factor value > 0.5. This means that all indicators can be used to measure latent economic variables.

3.1.2. Convergence validity after the indicator is removed
Retest after invalid indicators are removed in the provinces of Indonesia, the path diagram is as follows:

![Figure 4. Poverty Line SEM-PLS Diagram in Indonesia after selection of invalid indicators](image)

The feasibility of a model can be shown that the indicator used is valid. This can be seen from the t-statistics value on the results of loading factor measurement models.

Following are the results of retesting after invalid indicators (Y6) are removed from the latent variables of education can be seen in Table 6 below.

| Latent Variable | Indicator | Loading factor | Standard Deviation | T-statistic |
|-----------------|-----------|----------------|--------------------|-------------|
| Health          | X1        | 0.738          | 0.107              | 6.919       |
|                 | X2        | 0.691          | 0.137              | 5.047       |
|                 | X3        | 0.796          | 0.040              | 19.760      |
|                 | X4        | 0.640          | 0.079              | 8.094       |
| Poverty         | Y1        | 0.973          | 0.005              | 179.426     |
|                 | Y2        | 0.998          | 0.001              | 738.353     |
|                 | Y3        | 0.977          | 0.004              | 243.279     |
| Education       | Y4        | 0.936          | 0.022              | 43.437      |
|                 | Y5        | 0.882          | 0.030              | 29.390      |
| Economic        | Y7        | 0.881          | 0.015              | 57.917      |
|                 | Y8        | 0.932          | 0.008              | 121.99      |

Based on Table 6 shows that the estimated loading factor value for each latent variable > 0.5 is significant, this is indicated by the t-statistic value > t-table 1.98 (2-tailed) at the level of significance (α) = 0.05. This means that all variables are statistically significant and valid in measuring all latent variables.

3.1.3 Reliability Test
The reliability test is used to determine the consistency of measuring indicators of a latent variable. To measure the reliability of this research model, Composite Reliability (CR) and Average Variance Extracted (AVE) are used. The results of reliability testing in Indonesia are as follows:
Table 7. Reliability Test Results

| Latent Variable | CR   | AVE  | Evidence |
|-----------------|------|------|----------|
| Health          | 0.810| 0.517| Reliable |
| Poverty         | 0.988| 0.966| Reliable |
| Education       | 0.905| 0.827| Reliable |
| Economy         | 0.903| 0.822| Reliable |

Table 7 shows the reliability test values using the CR and AVE values of each latent variable. Based on the CR value on each latent variable shows good results because of > 0.7, while for the value of AVE shows good results because it has a value > 0.5. So that the latent variables of health, poverty, education, and the economy are said to have excellent reliability.

3.2 Structural Model Evaluation (Inner Model)

Structural models or inner models describe the relationship between latent variables. In Partial Least Square, the path parameter coefficient is obtained through the weight of the inner model as seen from the t-statistic value through the bootstrapping stage with 500 sample cases. The hypothesis raised in this study are:

\[ H_1: \text{Health affects Education} \]
\[ H_2: \text{Health affects Economy} \]
\[ H_3: \text{Health affects Poverty} \]
\[ H_4: \text{Education affects Economy} \]
\[ H_5: \text{Education affect Poverty} \]
\[ H_6: \text{Economy affects Poverty} \]

The results of the path parameter coefficients in Indonesia from the structural model can be shown in the following Table 8

Table 8. Path Parameter Coefficients

| Variable       | Path Parameter Coefficients | Sample Mean | Standard Deviation | T-statistic |
|----------------|----------------------------|-------------|--------------------|-------------|
| Health \(\rightarrow\) Education | 0.603 | 0.596 | 0.094 | 6.390 |
| Health \(\rightarrow\) Economy    | -0.757 | -0.765 | 0.035 | 21.796 |
| Health \(\rightarrow\) Poverty     | -0.548 | -0.541 | 0.125 | 4.386 |
| Education \(\rightarrow\) Economy | -0.111 | -0.111 | 0.053 | 2.100 |
| Education \(\rightarrow\) Poverty  | -0.085 | -0.072 | 0.131 | 0.648 |
| Economy \(\rightarrow\) Poverty    | 0.128 | 0.135 | 0.115 | 1.113 |

Based on the results obtained, three structural equations are known:

\[ \text{Poverty} = -0.548 \text{Health} - 0.085 \text{Education} + 0.128 \text{Economy} \quad (12) \]
\[ \text{Education} = 0.603 \text{Health} \quad (13) \]
\[ \text{Economics} = -0.757 \text{Health} - 0.111 \text{Education} \quad (14) \]

The poverty model can be seen that health has a negative influence of -0.548 units and is significant, with a T-statistic value of 4.386 (> 1.98) on latent variables of poverty. Education also has a negative effect of -0.085 units but it is not significant with a T-statistic value of 0.648 (<1.98), while the Economic variable has a positive effect of 0.128 units and is not significant with a T-statistic value of 1.113 (<1.98) on the poverty model at 95% confidence interval or t-statistically. For the Education model, it is known that the Health latent variable has a positive influence of 0.603 and is significant, with a T-statistic value of 6.390 (> 1.98) on the latent educational variable. And for the Economic model it can be seen that the latent variables of health and education have a negative and significant correlation to the latent economic variable at 95% confidence intervals, as well as t-statistically with the estimated health variable path coefficient of -0.757 while the education variable path coefficient of -0.111.
The evaluation test value of the structural equation model in SEM-PLS can be known from the value of goodness of fit or R-square ($R^2$). The results of this research data processing using SmartPLS gives the value of $R^2$ like table 9 below:

| Latent Variable | $R^2$  |
|-----------------|--------|
| Economy         | 0.751  |
| Education       | 0.583  |
| Poverty         | 0.645  |

The results of the R-Square are for the Economic model of 0.751, for the Education model of 0.583 and for the Poverty model of 0.645, so the model obtained is feasible because the R-Square value > 0.5.

The R-square value ($R^2$) for the Economy is 0.751 which means that the model can explain the variation of the Economy in the case of poverty in Indonesia's Provinces by 75.1%, Education by 0.583 or 58.3% and the poverty model by 0.645 or 64.5%.

4. Conclusion
In this study, Structural Equation Modeling (SEM) Partial Least Square is used to determine the relationship between the factors that influence poverty in Indonesian Provinces. The results show that there is a significant negative effect from the health dimension on poverty, a negative influence exerted from the education dimension on poverty and a positive influence given from the economic dimension on poverty in Indonesia but it is not significant.

The structural model for poverty cases in Indonesia in 2015-2017 is as follows:

\[ \text{Poverty} = -0.548 \text{ Health} - 0.085 \text{ Education} + 0.128 \text{ Economy}. \]

For the relationship of the model obtained it can be concluded that if poverty in Indonesia increases, the health of poor households and education in Indonesia will decrease by 0.548 and 0.085 units respectively, whereas if poverty in Indonesia increases, the economy of poor families will increase of 0.128 assuming looking at the indicators that make up the latent economic variable. Thus, health is the variable that has the most dominant influence on poverty in Indonesia.

For further research, modeling the SEM-PLS structural equation can be done with the addition of poverty indicators and new variables to clarify the relationship between latent variables and indicator variables to obtain more significant results and better models.

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