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Comparison of Binary and Traditional Partial Least Squares Structural Equation Modeling: A Study on The Role of Multidimensional Poverty Dimension to Social Protection in Java Island

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Abstract

Introduction/Main Objectives: The traditional Partial Least Squares Structural Equation Modeling (PLS-SEM) method uses an ordinary least squares regression approach that assumes that indicators must have a continuous scale. When the indicators are categorical, the use of traditional PLS-SEM becomes less appropriate. **Background Problems:** Multidimensional poverty consists of dimensions that are measured by a binary scale. The use of binary PLS-SEM is better than traditional PLS-SEM in modeling the effect of dimensions on social protection on Java Island. **Novelty:** The use of binary PLS-SEM with factor scores from the item response theory model applied to the role of dimensions of multidimensional poverty to social protection has not been carried out yet. **Research Methods:** This study introduces binary PLS-SEM, which is modified from traditional PLS-SEM by changing the data input using a tetrachoric correlation matrix. **Finding/Results:** Empirical results show that the binary PLS-SEM measurement model is better than traditional PLS-SEM. Evaluation of the structural model shows that the path coefficients of binary PLS-SEM are better than traditional PLS-SEM. Both approaches have an overall model fit. The order of multidimensional poverty dimensions that affect social protection are education, living standard, and health.

1. Introduction

Partial least squares structural equation modeling (PLS–SEM) is one of the methods commonly used in estimating complex relationships between indicators and their latent variables [1]. PLS-SEM is formed from two models, namely the measurement model and the structural model [2]. The measurement model is used to describe how well the observed indicators are able to be a measuring tool for the latent variables while the structural model is used to see the relationship between the latent variables [3]. Latent variables can be measured in a reflective and formative way. The reflective method assumes that the indicator is caused by the latent variable while the formative method assumes that the latent variable is formed by its indicators [4].

PLS–SEM uses an iterative algorithm in finding a linear combination of indicators to form factor scores as latent variables and based on these factor scores the parameters of the model are estimated [5]. The algorithm in PLS-SEM also uses the ordinary least squares regression approach so that the data type of the indicator is required to have a continuous scale [6]. In other words, the use of PLS-SEM if the indicator data is categorical is less appropriate [7]. Forcing indicators with a category type to be treated as continuous can produce biased estimates [6]. Currently, there is a PLS-SEM approach that can be used to overcome the problem of ordinal scale category data, namely ordinal PLS (OrdPLS) [6], [8], [9], [10]. This OrdPLS approach is still based on the traditional PLS-SEM algorithm with the main modification being in the input data. With ordinal scale data, the input data used is a polychoric correlation matrix [6]. With slight modifications to the input data, this approach can also be used for indicators with binary scale data, namely using a tetrachoric correlation matrix.

PLS-SEM requires the use of factor scores as a proxy for each latent variable in the structural model [11]. Factor scores in traditional PLS-SEM are obtained from the sum of the multiplication of weights and indicators. This process cannot be done simply when the indicators are categorical [12]. In the OrdPLS method, factor scores are obtained using the mean, median and mode approaches [8]. This approach does not consider opportunities so that another approach is needed that is still related in terms of obtaining factor scores when the data is categorical. One approach that can be used is the item response theory (IRT) model which was originally developed for categorical data, especially binary data [13].

One application that uses binary data is multidimensional poverty measurement. Multidimensional poverty is another approach to poverty measurement that has been used so far, namely the monetary approach. If the monetary approach uses the concept of the ability to meet basic needs for food and non-food from an economic perspective, while multidimensional poverty arises when people do not have resources so that they do not have adequate education, or have poor health conditions, or feel insecure, or low self-confidence, or a sense of helplessness, or the absence of the right to freedom of speech [14].

The measurement of poverty using the World Bank's monetary approach is still the most commonly used measure of poverty worldwide [15]. However, since 2010, the United Nation Development Program (UNDP) and the Oxford Poverty and Human Development Initiative (OPHI) have agreed on a new poverty measurement initiative through the Multidimensional Poverty Index (MPI) based on the multidimensional measure of Alkire-Foster [16]. The MPI approach to poverty measurement uses ten indicators divided into 3 dimensions, namely health (2 indicators), education (2 indicators), and standard of living (6 indicators). Indonesia is one of the countries that still uses a monetary approach in measuring its poverty and has not officially used multidimensional poverty. However, there have been many articles that present the MPI in Indonesia. Some fairly recent articles related to measuring the MPI in Indonesia include [12] [15] [17]. All of these articles use the Alkire-Foster (AF) method approach in calculating multidimensional poverty and utilize national socio-economic survey (Susenas) data. Although using the same data and methods, the indicators used are not exactly the same. For example, the standard of living dimension in [18] was replaced by the expenditure dimension in [15]. The use of these different indicators shows that measuring multidimensional poverty in Indonesia is still under development [12].

This paper attempts to utilize OrdPLS from [8] which uses a polychoric matrix as input data so that it can also be used for a tetrachoric matrix for binary data. In addition, the use of the ability parameters from the IRT model as factor scores for the values of the latent variables is also utilized. Furthermore, a comparison of traditional PLS-SEM with binary PLS-SEM is carried out. As an application for this binary PLS-PM, household data from the 2021 Java Island National Socio-Economic Survey (Susenas) is used. This data has been processed in such a way that it becomes indicators involving dimensions that form multidimensional poverty based on the multidimensional measure of Alkire-Foster [16]. By using the writing of [17], the role of which multidimensional poverty dimensions have a greater influence on social protection will be determined.

2. Material and Methods

2.1. Partial Least Squares Structural Equation Modeling

PLS-SEM with latent variables are formed from two models, namely measurement models and structural models [2]. The measurement model describes how well the observed indicators function as measurement instruments for latent variables [3] while the structural model describes the relationship paths between latent variables. The structural model of PLS-SEM is represented by a linear relationship (Rademaker, 2020)

$$\boldsymbol{l}_{endo} = \mathbf{B}\,\boldsymbol{l}_{endo} + \boldsymbol{\Gamma}\,\boldsymbol{l}_{exo} + \boldsymbol{\zeta} \tag{1}$$

Meanwhile, the linear relationship between the measurement model and the reflective type is stated by [19]

$$\mathbf{x} = \boldsymbol{\Lambda}_x \boldsymbol{l}_{exo} + \boldsymbol{\varepsilon}_x \tag{2}$$

$$\mathbf{y} = \boldsymbol{\Lambda}_y \boldsymbol{l}_{endo} + \boldsymbol{\varepsilon}_y \tag{3}$$

Note that the structural relationship in (1) can be rewritten in matrix notation as follows [9]

$$\boldsymbol{\eta} = \begin{bmatrix} \eta_{exo} \\ \eta_{endo} \end{bmatrix} = \begin{bmatrix} l_{exo} \\ l_{endo} \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{O} \\ \boldsymbol{\Gamma} & \mathbf{B} \end{bmatrix} \begin{bmatrix} l_{exo} \\ l_{endo} \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \boldsymbol{\zeta} \end{bmatrix} = \mathbf{D}\boldsymbol{\eta} + \mathbf{v} \tag{4}$$

where $\boldsymbol{\eta}_{exo}$ and $\boldsymbol{\eta}_{endo}$ are vector of n exogenous and m endogenous latent random variables which defining vector $\boldsymbol{\eta} = [\eta_1, \dots, \eta_n, \eta_{n+1}, \dots, \eta_{n+m}]^T$, $\boldsymbol{\zeta}$ a is the vector of m error components. $\boldsymbol{\Gamma}$ dan $\mathbf{B}$ are $(m \times n)$ and $(m \times m)$ matrices containing the structural parameters. $(\mathbf{I} - \mathbf{B})$ is nonsingular. $\mathbf{0}$ of size $(n \times 1)$ is vector zero, $\boldsymbol{\zeta}$ $(m \times 1)$ is vector of error component assumed to have zero expected value, $E(\boldsymbol{\zeta}) = \mathbf{0}$, and is uncorrelated with $\boldsymbol{\eta}_{exo}$. $\boldsymbol{v}$ of size $(n + m \times 1)$ is the error vector.

The reflective measurement model can be written in as

$$\boldsymbol{\xi} = \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Lambda}_x & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Lambda}_y \end{bmatrix} \begin{bmatrix} l_{exo} \\ l_{endo} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_x \\ \boldsymbol{\varepsilon}_y \end{bmatrix} = \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{5}$$

where the random variable vector $\mathbf{y}$ of size $(p \times 1)$ and $\mathbf{x}$ of size $(q \times 1)$ are the observed variables, $\boldsymbol{\Lambda}_y$ of size $(p \times m)$ and $\boldsymbol{\Lambda}_x$ of size $(q \times n)$ are coefficient matrices indicating the relationship of $\mathbf{y}$ to $\boldsymbol{l}_{endo}$ and $\mathbf{x}$ to l_{exo}, respectively, and $\boldsymbol{\varepsilon}_y$ of size $(p \times 1)$ and $\boldsymbol{\varepsilon}_x$ of size $(q \times 1)$ are the measurement errors in $\mathbf{y}$ and $\mathbf{x}$, respectively. This measurement model describes the relationship between each latent variable η_j in $\boldsymbol{\eta}$ and a block K_j of manifest indicators, ξ_{jk}; $k = 1,2, \dots, K_j$, elements of the random variable vector ξ of size $(q + p \times 1)$.

Once the model is available, the next step is to estimate the parameters. PLS-SEM parameter estimation uses an algorithm consisting of three sequential stages. In the first stage, the latent variable scores are estimated iteratively for each observation in the sample. In the second stage, the scores obtained from stage 1 are used to calculate the parameters of the measurement model (called outer coefficients and outer loadings). Similarly, in the third stage the structural parameters (also called path coefficients) are finally estimated. The first stage is what makes PLS-PM a novel method while the second and third stages are about performing a series of traditional ordinary least squares (OLS) regressions. For this task, the algorithm needs to determine the construct scores that are used as inputs for the partial regression models (single and multiple) in the path model. After the algorithm calculates the construct scores, they are used to estimate each partial regression model in the path model. As a result, estimates are obtained for all the relationships in the measurement model such as the indicator weights or loadings and the structural model, namely the path coefficients.

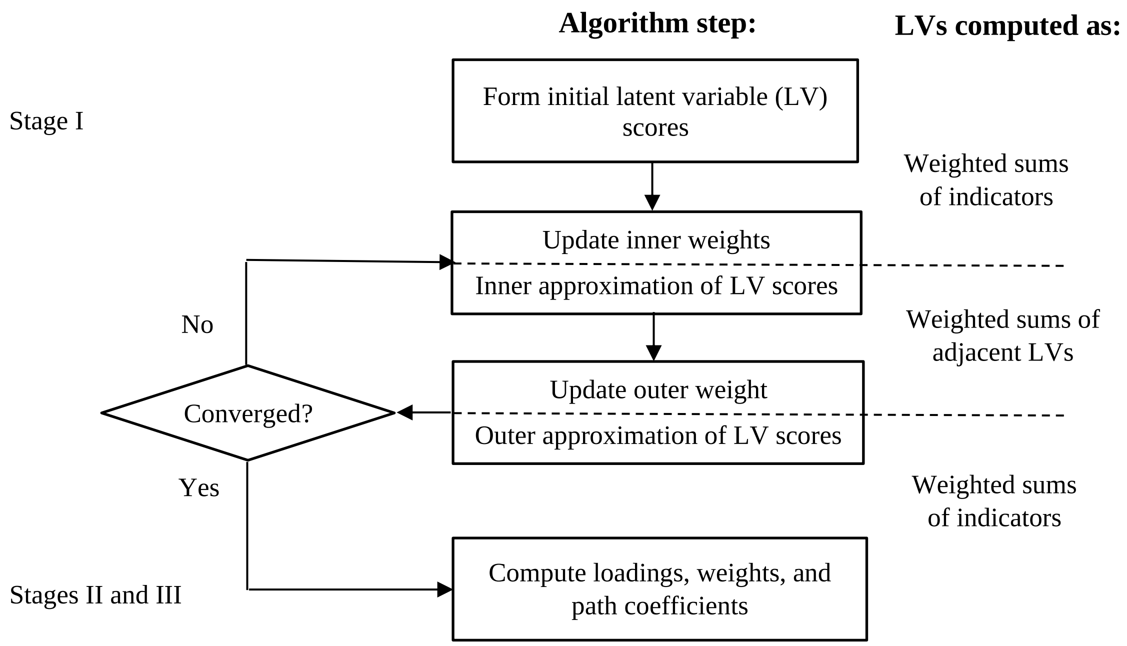

Figure 1. Algorithm steps of PLS-SEM (adapted from [20])

The estimation procedure in PLS-SEM involving a series of iterative stages and steps has the consequence that the path coefficient estimates obtained at the end of the procedure cannot be expressed as an explicit function of the indicator data. Therefore, it is impossible to obtain the exact sampling distribution of the estimator in question. Therefore, the only feasible way to perform inferences such as calculating p-values and confidence intervals for the PLS-PM model is through bootstrapping [21].

2.2. Binary Partial Least Squares Structural Equation Modeling

PLS-SEM measurement model describes the relationship between each latent variable η_j in $\boldsymbol{\eta}$ and one construct K_j of manifest indicators, Y_{jk}; $k = 1, \dots, K_j$, elements of the random variable vector $\boldsymbol{Y}$ of size $(p \times 1)$. Suppose there is a measurement model of the reflective type as follows

$$\mathbf{Y} = \Lambda\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{6}$$

If the indicators are binary, then it is assumed that for the set of binary variables $\boldsymbol{Y}$ there are K-dimensional unobserved continuous indicators $\boldsymbol{Y}^*$ represented on an interval scale by a multinormal distribution function [22] [23]. Each observed binary indicator Y_{jk} can assume an existing category that is related to the corresponding continuous indicator Y_{jk}^* through a nonlinear monotone function. From this function, a tetrachoric correlation matrix is obtained which will be used in the PLS-SEM algorithm.

With the presence of indicators with a binary scale, models (1) and (2) need to be modified where the observed variable Y in (2) is replaced with the underlying unobserved continuous indicator Y^*.

$$\mathbf{Y} \leftarrow \mathbf{Y}^* = \Lambda\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{7}$$

The dependency relationship between Y and Y^* is not explicitly written because for subject $s = 1,2, \dots, N$ the actual score of y_{ks}^* for each indicator y_k^* cannot be identified, it is only assumed that the value belongs to the interval determined by the threshold value of the nonlinear function owned as a description of the observed category y_{ks}. The PLS algorithm with binary data (binary PLS) and traditional PLS are not much different apart from changes in the input data and the calculation process that adjusts due to the use of tetrachoric matrices as input data. The occurrence of categorical data being treated as continuous often occurs in applications that cause the resulting Pearson correlation estimate to be biased [24].

Handling of binary category indicators in PLS-SEM based on OrdPLS (ordinal PLS) from [8] uses the same algorithm as in traditional PLS only making modifications to the input data where binary PLS-SEM enters the tetrachoric correlation matrix as input to its algorithm [12]. In the context of binary categories, it can be assumed that the relationship between two dichotomous variables representing continuous variables that are categorized is the tetrachoric correlation coefficient. Tetrachoric correlation is obtained by hypothesizing the existence of a continuous latent variable underlying the true and false dichotomy imposed in scoring a dichotomous item so that it can classify variables into a frequency distribution [25]. The tetrachoric correlation algorithm used is the method from [26].

Compute $\boldsymbol{\Sigma}_{XX}$ (in the case of binary data is a tetrachoric correlation matrix)

Determine the initial weights $\mathbf{W} = \left[\mathbf{w}_1, \ldots, \mathbf{w}_j, \ldots, \mathbf{w}_{n+m}\right]$

Iterative phase

Set $\mathbf{W}_{TEMP} = \mathbf{W}$

Compute:

$$\boldsymbol{\Sigma}_{\hat{Y}\hat{Y}} = \mathbf{W}^T \boldsymbol{\Sigma}_{XX} \mathbf{W}$$

$$_S\mathbf{W} = \mathbf{W}\left\{\left[\mathbf{W}^T \boldsymbol{\Sigma}_{XX} \mathbf{W}\right] * \mathbf{I}\right\}^{-1/2} = \mathbf{W}\left[\boldsymbol{\Sigma}_{\hat{Y}\hat{Y}} * \mathbf{I}\right]^{-1/2}$$

$$\boldsymbol{\Sigma}_{\hat{Y}\hat{Y}} = \mathbf{P}_{\hat{Y}\hat{Y}} = {}_S\mathbf{W}^T \boldsymbol{\Sigma}_{XX}\, {}_S\mathbf{W}$$

$$\boldsymbol{\Upsilon} = \left(\mathbf{T} + \mathbf{T}^T\right) * sign\left(\boldsymbol{\Sigma}_{\hat{Y}\hat{Y}}\right)$$

$$\boldsymbol{\Sigma}_{XZ} = \boldsymbol{\Sigma}_{XX}\, {}_S\mathbf{W}\boldsymbol{\Upsilon}$$

$$\boldsymbol{\Sigma}_{X\hat{Y}} = \boldsymbol{\Sigma}_{XX}\, {}_S\mathbf{W}$$

$$\mathbf{C} = \boldsymbol{\chi}_{\mathbf{w}} * \boldsymbol{\Sigma}_{XZ}$$

$$\pm = sign\left\{\mathbf{1}_{p+q}^T\left[sign\left(\boldsymbol{\chi}\mathbf{w}\boldsymbol{\Sigma}_{X\hat{Y}}\right)\right]\right\}$$

Update weight $\mathbf{W} = \mathbf{C}\left[diag\left(1_{p+q}^T \mathbf{C}\right)\right]^{-1} diag\left(\pm\right)$

Obtain $_S\mathbf{W}$

Check if $\left\|\mathbf{W} - \mathbf{W}_{TEMP}\right\| < \varepsilon$

Figure 2. PLS algorithm using matrix as input data (adapted from [8])

Suppose there is a 2×2 contingency table with frequencies given by $a, b, c,$ and d. Any continuous random variable Y can be transformed into a standard normal variable Z_Y by the formula $Z_y = \Phi^{-1}[\Phi_Y(Y)]$ where Φ_Y is the cumulative density function (cdf) of Y, Φ is the cdf of the standard normal distribution, and N is the total frequency. The variable Z_Y is called the standard normal deviate (SND) corresponding to Y. Let z_1 and z_2 be the standard normal deviations corresponding to the marginal probabilities $(a+c)/N$ and $(a+b)/N$, respectively, that is

$$\Phi(z_1) = (a+c)/N, \quad z_1 = \Phi^{-1}\{(a+c)/N\}$$

$$\Phi(z_2) = (a+b)/N, \quad z_2 = \Phi^{-1}\{(a+b)/N\}$$

then the tetrachoric correlation ρ_{tet} is a correlation coefficient that satisfies

$$\frac{a}{N} = \int_{-\infty}^{z_2}\int_{-\infty}^{z_1} \Phi\left(y_1, y_2; \rho_{tet}\right) dy_1 dy_2$$

where $\Phi(y_1, y_2; \rho_{tet})$ is the bivariate normal probability density function (pdf) with mean zero and variance one.

$$\Phi\left(y_1, y_2; \rho\right) = \frac{1}{2\pi\left(1-\rho^2\right)^{1/2}} \exp\left[-\frac{1}{2\left(1-\rho^2\right)}\left(y_1^2 - 2\rho y_1 y_2 + y_2^2\right)\right]$$

The probability of the four quadrants formed by performing a dichotomy of variables with the line $y_1 = z_1$ and $y_2 = z_2$ is the same as a/N, b/N, c/N and d/N. This correlation value will be formed into a matrix form called the tetrachoric correlation matrix which will later be used as input data in the PLS-SEM algorithm.

2.3. Score Factor of Item Response Theory Model

In item response theory (IRT) model, factor scores are known as ability parameters (θ). [27] states that there are three popular methods for estimating ability in IRT model, namely Maximum likelihood (ML), Bayesian Maximum a Posteriori (MAP), and Bayesian Expectation a Posteriori (EAP). These methods use a single function called the likelihood function (LF). The ML method has problems when the answer pattern is all true or all false. While the use of MAP has problems with asymmetric LF and iterative arithmetic operations. So that, the ability parameter estimation used in this paper is the EAP approach with the Markov Chain Monte Carlo (MCMC) algorithm because it is generally more robust for complex models [28] [29] [30].

The IRT model used in this study is a two-parameter logistic (2PL) model. The 2PL model use the parameters of the difficulty level of the question b and the discriminatory power a. Parameter a shows the slope and item characteristic curve (ICC) at point b on a certain ability scale. The discriminatory power a functions to determine whether or not a question item can distinguish a group in the aspect being measured, according to the differences in the group. The value of a ranges from -∞ to ∞, but the value of a can be categorized as good if it is in the range of 0 to 2 [31]. The formula for the 2PL model is as follows [32]

$$p\left(y_j = 1 \mid \theta, a_j, b_j\right) = \frac{e^{a_j\left(\theta - b_j\right)}}{1 + e^{a_j\left(\theta - b_j\right)}} \tag{8}$$

In addition, the estimated factor scores with the EAP approach with R quadrature points are [33]

$$\hat{\theta}_i = \frac{\sum_{r=1}^{R} Y_r L\left(Y_r\right) A\left(Y_r\right)}{\sum_{r=1}^{R} L\left(Y_r\right) A\left(Y_r\right)} \tag{9}$$

where Y_r is a node or quadrature point, $L(Y_r)$ is the likelihood function when Y_r is approximating quadrature, $A(Y_r)$ is the quadrature weight corresponding to Y_r which reflects the height of the function g(θ|υ) around Y_r, g(θ|υ) is the continuous population distribution of individuals and υ represents a vector containing the location and scale parameters of the population which have values 0 and 1 respectively [34].

2.4. Multidimensional Poverty

The building of multidimensional poverty in this paper is using M_0 of the method proposed by [35] which is also known as the adjustment headcount ratio. Suppose $x_{ij} \in \mathbb{R}_+$ is the achievement of each individual $i = 1, \dots, n$ on each indicator $j = 1, \dots, d$, and suppose z_j is the deprivation cutoff of the indicator j. Individual deprivation i on the indicator j is defined as $g_{ij}^0 = 1$ when $x_{ij} < z_j$ and $g_{ij}^0 = 0$ otherwise. Then, the deprivation of each individual is weighted by the indicator weight w_j such that $\sum_{j=1}^{d} w_j = 1$. Furthermore, a deprivation score is calculated for each individual, which is then defined as the weighted sum of deprivations $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$. With this score, poor individuals are identified using the second cutoff or poverty cutoff symbolized by , which represents the minimum proportion of deprivation that an individual must experience in order to be identified as a poor individual. In other words, an individual is poor if $c_i \geq k$.

The deprivation of those not identified as poor is then ignored or technically they are censored. Formally, censored deprivation is defined as $g_{ij}^0(k) = g_{ij}^0$ if $c_i \geq k$ and $g_{ij}^0(k) = 0$ otherwise. Analogously, the censored deprivation score is defined as

$c_i = \sum_{j=1}^{d} w_j g_{ij}^0\,(k)$.

Once multidimensionally poor individuals are identified, the measure M_0 combines two fundamental sub-indices, namely the proportion of multidimensionally poor individuals (also called poverty incidence) and the poverty intensity, which is the weighted average of deprivation among poor individuals. Formally, the proportion of poor individuals is given by $H = q/N$, where q is the number of individuals identified as poor. The poverty intensity is given by $A = \sum_{i=1}^{n} c_i(k)/q$. The MPI as M_0 is the product of these two sub-indices

$$MPI = M_0 = H \times A = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{d} w_j g_{ij}^{0}(k) \tag{10}$$

By adjusting the incidence of multidimensional poverty based on its intensity, M_0 satisfies dimensional monotonicity [35]. That is, if poor individuals become deprived on additional indicators, then M_0 will increase.

Because of its additive structure, the M_0 measure allows for two types of decompositions that are useful for policy information. First, M_0 can be decomposed into population subgroups. This is because the overall M_0 is the population-weighted sum of the subgroup poverty rates. Then, the percentage contribution of the subgroup to overall poverty can be calculated from the subgroup M_0 weighted by its population contribution compared to the overall M_0. Second, after identification, M_0 can be divided by indicators. The overall M_0 can be expressed as the weighted sum of the proportion of the total population that has been identified as poor and deprived in each indicator (weights refer to the relative weight of each indicator). This proportion is the so-called censored headcount ratio. The percentage contribution of an indicator to overall poverty is calculated as the censored headcount ratio multiplied by its relative weight, divided by the overall M_0 measure.

2.5. Social Protection

Social protection is one of the concepts that has developed in relation to solving multidimensional poverty problems. According to [36], social protection is aimed at addressing the root causes of poverty and is not limited to actions that only solve poverty problems at the symptom level. More broadly, social protection is based on the view that the causes of poverty are related to various social risks faced by the poor and their vulnerability to the impacts of emerging social risks. The emphasis on risk and vulnerability, which are the main causes of poverty, indicates that social protection should have a forward-looking vision and focus on the importance of developing holistic strategies and policies to reduce risks and vulnerabilities for poor groups before they actually occur. Because the concept of social protection is aimed at addressing poverty and vulnerability, the concept of social protection includes two dimensions of social security, namely basic social security for all (horizontal dimension) and the gradual implementation of social security with higher standards (vertical dimension). These two dimensions have been mandated in the ILO Convention Number 102 of 1952 concerning Minimum Standards for Social Security. Therefore, the concept of social protection is not only related to social assistance and social security. Even according to[37], social protection traditionally has a broader concept than social security, social insurance, and social safety nets. Furthermore, [38] stated that social protection is a collection of public efforts to face and overcome vulnerability, risk and poverty that has exceeded the limit. This means that the focus of social protection is on preventing poverty and providing assistance to the poorest people.

Furthermore, the concept of social protection has developed. For example, [39] stated that the concept of social protection traditionally focuses more on short-term protection programs, such as protection mechanisms for people from the impact of shocks caused by natural disasters, unemployment, and death. In contrast, [40] views that social protection has broader components, including protection, prevention, and promotion components to reduce the vulnerability of each individual in the future. Meanwhile, [41] view social protection as having a transformative role, where social protection is aimed at improving status and opening up more livelihood opportunities for marginalized groups in society.

Basically, the framework of social protection refers to the fundamental principle of social justice and the fulfillment of specific universal rights for every person. Everyone should receive social security and an adequate standard of living in obtaining health and welfare services for themselves and their families. [42] states that social protection aimed at overcoming poverty, underdevelopment, and inequality must be complemented by other strategies, such as strengthening labor institutions and social institutions and promoting a pro-worker microeconomic environment. These elements have been included by several countries in their social protection systems. Furthermore, [42] emphasizes that countries with lower middle incomes should create social protection programs that are in line with efforts to reduce poverty, inequality and other social transformations. Furthermore, [36] suggests that social protection should also be aimed at overcoming the root causes of poverty and not limited to actions to resolve symptoms of poverty. This means that social protection must be "forward looking" to avoid various persistent risks that may be faced by poor and vulnerable communities, so that social protection is a way out of the poverty trap.

2.6. Data

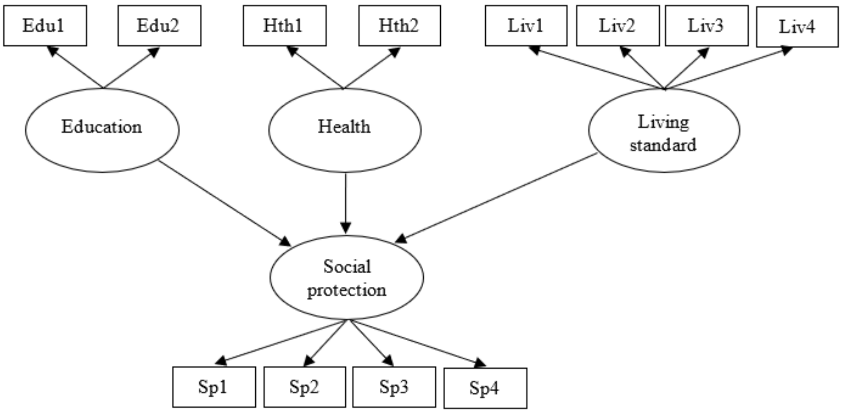

Figure 3. The conceptual framework of the research

The data used in this research is cross-sectional data taken from the 2021 Susenas of Java Island with the unit of analysis being 105200 households. Table 1 shows details of the latent variables and indicators used. Of these latent variables, the dimensions of health, education and living standards are the dimensions that form multidimensional poverty. Figure 3 shows the indicators and latent variables as well as the relationships related to the model studied.

Table 1. Dimensions, indicators, and observed variables

Dimensions	Indicators	Observed Variables
Education	Years of Schooling (EDU1)	- There are household members who do not graduate from junior high school
	School attendance (EDU2)	- There are household members of school age (7-15 years) who do not attend school
Health	Vaccination (HTH1)	- There are births that are not assisted by medical personnel
	Health Insurance (HTH2)	- Households are not covered by health insurance
Living standards	Durability (LIV1)	- Households with non-durable houses
	Sanitation (LIV2)	- Households with inadequate sanitation
	Electricity (LIV3)	- Households with non-Electric Lighting Sources
	Cooking fuel (LIV2)	- Households with biomass/solid cooking fuel
Social protection	Non-cash food assistance (SP1)	- There are household members who receive non-cash food assistance
	Routine assistance (SP2)	- Households receive assistance/social assistance/ subsidies from the local government in the form of routine assistance
	Family hope program (SP3)	- Households receive assistance from the Family Hope Program
	Smart Indonesian program (SP4)	- There are household members who receive assistance from the Smart Indonesia Program

As an empirical study of PLS-SEM, we applied social protection model from [17]. This model is used to show how work affects multidimensional poverty and how education (edu), health (health) and standard of living which are dimensions of multidimensional poverty, affect social protection (SP). All measures are scored for each item on a binary scale. Figure 3 shows the research model used.

3. Results and Discussions

3.1. *Evaluation of Measurement Model*

The PLS-SEM reflective measurement model was evaluated using reliability and validity measures. Reliability was measured at the indicator level and the latent variable level (internal consistency reliability). Validity assessment focused on convergent validity measured using the average variance extracted (AVE). In addition, the heterotrait-monotrait correlation ratio (HTMT) can also be used to assess the discriminant validity of the construct measured reflectively compared to other construct measures in the same model. Table 2 displays the reliability of the indicator using the loading value. The recommended loading value is above 0.708 because it indicates that the latent variable explains more than 50 percent of the indicator's variance, thus providing acceptable indicator reliability [43]. According to [44], indicators with very low loading (below 0.40) should always be removed from the measurement model. Indicator loading between 0.40 and 0.708 can be considered to be included in the model. Table 2 also shows that in traditional PLS-SEM there are still 5 indicators that are very low (below 0.04) while in binary PLS-SEM only one indicator that is below 0.40. However, because this article aims to compare the method, these indicators are maintained. So that it can be said that the binary PLS-SEM latent variable is better at explaining the variance of each indicator.

The internal consistency reliability and convergent validity is shown in Table 3. There are theree measures to assess internal consistency reliability, namely Cronbach alpha, composite reliability (ρC), and reliability coefficient (rho-A). The recommended value for internal consistency reliability is greater than 0.7 but a value greater than 0.6 is often considered acceptable [45]. Table 3 shows that all measures from binary PLS-SEM for each latent variable is greater than traditional PLS-SEM. So that it can be said that reliability of binary PLS-SEM is better than traditional PLS-SEM.

Table 2. Loading value by dimension and indicator

Dimension	Indicators	Traditional PLS	Binary PLS
Education	Edu1	0.99	0.94
	Edu2	0.18	0.54
Health	Hth1	0.02	0.32
	Hth2	0.99	0.99
Living Standard	Liv1	0.20	0.69
	Liv1	0.71	0.72
	Liv1	0.12	0.72
	Liv1	0.82	0.78
Social protection	Sp1	0.84	0.90
	Sp2	0.31	0.48
	Sp3	0.83	0.93
	Sp4	0.53	0.69

Table 3. Validity and reliability value by dimensions

Dimension	Traditional PLS				Binary PLS			
	Cronbach's α	ρC	ρA	AVE	Cronbach's α	ρC	ρA	AVE
Education	0.08	0.58	0.29	0.51	0.76	0.73	0.58	0.59
Health	0.10	0.51	1.66	0.50	0.83	0.66	1.60	0.55
Living Standard	0.23	0.55	0.37	0.31	0.82	0.82	0.72	0.53
Social protection	0.56	0.74	0.71	0.44	0.85	0.89	0.89	0.64

The next step is to assess the convergent validity of each latent variable. Convergent validity is the extent to which the construct converges to explain the variance of its indicators. The measure used to evaluate the convergent validity of a construct is the AVE for all indicators in each construct. AVE is defined as the overall average value of the squared loadings of the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators). An AVE of less than 0.5 is considered inadequate, because more variance is due to error variance than indicator variance [44]. Therefore, AVE is equivalent to the communality of a construct. The minimum acceptable AVE is 0.50 where an AVE of 0.50 or higher indicates that the construct explains 50 percent or more of the variance of the indicators that make up the construct [44]. In traditional PLS-SEM, there are two latent variables that have an AVE value of less than 0.5 or invalid, namely living standard and social protection. While the education and health variables are valid. In addition, in the binary PLS-SEM, all latent variables are valid because they have an AVE value greater than 0.5.

The next measure is to assess discriminant validity. This measure indicates the extent to which a latent variable captures the variance of related indicators relative to indicators related to other latent variables in the measurement model. The higher the correlation between a latent variable and its indicators compared to its correlation with other indicators in the model, the clearer the latent variable is. Measures to measure discriminant validity include the heterotrait-monotrait ratio correlation (HTMT) from [46]. HTMT is the ratio of the correlation between traits to the correlation within traits. The HTMT is the average of all indicator correlations across constructs measuring different constructs (i.e., heterotrait-heteromethods correlations) relative to the (geometric) average of the average of indicator correlations measuring the same construct (i.e., monotrait-heteromethods correlations [44].

Table 4. HTMT value by relationships

Relationships	Traditional PLS	Binary PLS
Education – health	0.89	0.54
Education – living standard	0.65	0.49
Education – social protection	0.68	0.50
Health – living standard	0.52	0.31
Health – social protection	0.33	0.21
Living standar – social protection	0.34	0.35

The heterotrait-monotrait ratio (HTMT) of correlations is the average of the heterotrait-heteromethod correlations (i.e., indicator correlations across constructs measuring different phenomena), relative to the average of the monotrait-heteromethod correlations (i.e., indicator correlations within the same construct). [46] proposed a cutoff value of 0.90 for structural models with conceptually very similar constructs. An HTMT value above 0.90 indicates no discriminant validity. However, when the constructs are conceptually more dissimilar, a lower, more conservative cutoff value such as 0.85 is suggested [46] [47]. From Table 4 it can be seen that in both traditional PLS-SEM and binary PLS-SEM the HTMT value for each relationship is less than the recommended 0.85 except for the education-health relationship in traditional PLS-SEM which is 0.89. It can be concluded that binary PLS-SEM is better when viewed from the HTMT value.

3.2. Evaluation of Structural Model

Assessment of model structural can be seen from the significance of the path coefficient and the relevance of the path coefficient are evaluated. The path coefficient is significant at the 5% level if the zero value is not included in the 95% confidence interval. In general, the percentile method should be used to construct the confidence interval [48]. The path coefficient is usually between −1 and +1, with coefficients approaching −1 indicating a strong negative relationship and those approaching +1 indicating a strong positive relationship. Table 5 shows the results of the path coefficients for each dimension of multidimensional poverty. It appears that for each dimension, binary PLS-SEM has a larger path coefficient than traditional PLS-SEM. In other words, the dimensions of multidimensional poverty with the binary PLS-SEM approach show a stronger relationship than traditional PLS-SEM. Meanwhile, if we look at the magnitude, it can be seen that both binary and traditional PLS-SEM have the same order with the Education dimension being the strongest in relation to social protection, followed by the dimensions of standard of living and health.

In the binary PLS-SEM approach, the Education dimension has a path coefficient value of 0.315. This shows that when Education increases by one standard deviation unit, social protection will increase by 0.315. Meanwhile, the dimensions of standard of living and health each have path coefficients of 0.289 and -0.285. Of course, attention is paid to the health dimension because it has a negative path coefficient sign. The reason that can be given is whether there is indeed no longer any deprivation in the health dimension or whether there is an error in the data.

Table 5. Estimates of the parameter

Dimension	Traditional PLS				Binary PLS			
	Coefficient	Standard deviation	Perc. 2.5%	Perc. 97.5%	Coefficient	Standard deviation	Perc. 2.5%	Perc. 97.5%
Education	0.185	0.003	0.179	0.191	0.315	0.020	0.315	0.315
Health	-0.140	0.003	-0.146	-0.135	-0.285	0.018	-0.285	-0.285
Living Standard	0.175	0.003	0.169	0.182	0.289	0.024	0.289	0.289

Table 6. Explanatory power of the model and model fit

Dimension	Traditional PLS	Binary PLS
R-square (R^2)	0.08	0.08
Standardized root mean squares residual (SRMR)	0.07	0.07

The next step in evaluation of structural model involves examining the coefficient of determination (R^2) of the endogenous constructs. R^2 represents the variance explained in each endogenous construct and is a measure of the explanatory power of the model [49], also referred to as in-sample predictive power [50]. R^2 ranges from 0 to 1, with higher values indicating greater explanatory power. As a general rule of thumb, R^2 values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak, respectively, in many social science disciplines [51]. However, acceptable R^2 values are based on the research context, and in some disciplines, R^2 values as low as 0.10 are considered satisfactory [52]. Table 6 shows that the R^2 values in traditional and binary PLS-SEM are not much different but the path coefficient values of binary PLS-SEM are bigger than those of traditional PLS-SEM. Meanwhile, because the SRMR value is belom the recommendation threshold which is 0.08 than that model from the two approaches are fit.

4. Conclusions

In general, from the indicator reliability measures and internal consistency reliability used, namely loading, Cronbach's alpha, composite reliability, and rho-A, the binary PLS-SEM approach shows better performance than traditional PLS-SEM. Likewise, for the validity measures measured using AVE and HTMT, the binary PLS-SEM approach shows better performance. From these results, it can be concluded that if the indicator is a category, then the recommended approach to use is binary PLS-SEM because it produces better measurement model performance.

In the assessment of the structural model, the binary PLS-SEM path coefficient shows a greater value than traditional PLS-SEM. This means that binary PLS-SEM has better performance. Judging from the dimensions of multidimensional poverty, the Education dimension has the largest role in social protection. Followed by the dimensions of standard of living and health. Meanwhile, from the R2 value and SRMR value, the two approaches produce performance that is not much different.

From the applied side, if there are no obstacles in providing social protection, then the three dimensions of multidimensional poverty can be used as a basis for policy. Meanwhile, if there are obstacles such as funds, it is suggested that the education dimension be made the main priority in terms of social protection.

In terms of statistical methods, there are several limitations in this paper. One of them is that the indicators used are only in binary scale. If the indicator is continuous, then the population correlation matrix used is Pearson. Meanwhile, if the indicator is ordinal, then the one used is polychoric correlation.

The next research that can be proposed is to consider using a combination of categorical and continuous indicators as input data. In addition, it can also consider using a high-order model for its dimensions.

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The Ethical approval statement should be provided including the consent. If not appropriate, authors should state: “Not required.”

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