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MULTIDIMENSIONAL POVERTY MODELING IN CENTRAL JAVA, DI YOGYAKARTA, AND EAST JAVA PROVINCES

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ABSTRACT

Indonesia has a National Medium-Term Development Plan (RPJMN) for 2020-2024 to reduce the poverty rate to 6 to 7 percent. However, the poverty rate has only declined by less than one percent in the past year, indicating the need for optimization to achieve the goal. Despite being located in Java, the center of development and economy in Indonesia, the poverty rate in Central Java, DI Yogyakarta, and East Java still exceeds the national average. This study used SUSENAS 2023 March KOR data to address this challenge and examine the multidimensional indicators affecting poverty. The Alkire-Foster method was used to obtain the Multidimensional Poverty Index (MPI) number, which was then analyzed using the Structural Equation Model (SEM) with the Asymptotically Distribution-free (AD-f) method approach. SEM is used to observe latent variables that cannot be measured and the relationship between variables that form a multidimensional poverty index. AD-f method approach is used to overcome data non-normality in SEM processing. The study revealed that the percentage of multidimensional poverty in the three provinces is higher than monetary poverty due to the household unit of analysis used. The standard of living dimension was the most deprived in most households, followed by the health dimension. To tackle this issue, the study recommends optimizing access to the Internet, assets, preschool participation, and nutrition.

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1. INTRODUCTION

One of the top priorities among the 17 Sustainable Development Goals (SDGs) is "No Poverty" [1]. According to the BPS, poverty is the inability to satisfy basic needs for a reasonable quality of life [2]. The National Long-Term Development Plan (RPJPN) 2005-2025 takes a multidimensional approach to poverty, including poverty vulnerability, fundamental rights, and dignified living conditions [3]. Poverty has far-reaching consequences, such as homelessness, unemployment, violence, and humiliation [4]. Since 1990, The World Bank's poverty measurement has gone beyond income alone, incorporating health, education, access to essential services, and participation in decision-making processes [5]. It is crucial to address poverty in all dimensions to guarantee that individuals can access necessities and live dignified lives [5].

According to recent BPS data, the poverty rate in Indonesia reached a peak of 10.41 percent in 2021 but has since decreased to 9.36 percent as of March 2023 [6]. It indicates an improvement in Indonesia's economy. However, this figure is still far below the RPJMN 2020-2024 target, which sets the poverty rate at 6 to 7 percent by 2024 [7]. In addition, the decrease in poverty percentage from March 2022 to March 2023 is less than one percent. Achieving the 2020-2024 RPJMN targets will be easier with better poverty alleviation policies.

Based on data provided by BPS, the poverty rate in Central Java, DI Yogyakarta, and East Java decreased in March 2023. However, it should be noted that the poverty rate in these regions is still above 10%, higher than the national average. Despite being located on Java Island, considered the center of development and economic activity in Indonesia, poverty alleviation programs in these regions have yet to be entirely thriving. The decline in the poverty rate in these provinces was less than 1 percent.

BPS measures poverty in Indonesia by meeting basic needs, viewing poverty as an economic inability to fulfill these needs. BPS designates individuals as poor if their average per capita monthly expenditure falls below the predetermined poverty line. This study employs the calculation of the Multidimensional Poverty Index (MPI), following the United Nations Development Programme (UNDP) and the Oxford Poverty and Human Development Initiative (OPHI), using the Alkire-Foster method [8]. The Multidimensional Poverty Index (MPI) comprises three dimensions: health, education, and standard of living, each explained by specific indicators [9]. Subsequently, an analysis is conducted using Structural Equation Modeling (SEM) with an Asymptotically Distribution-free (AD-f) method approach. SEM is used to observe latent variables that cannot be measured and the relationship between variables that form a multidimensional poverty index. AD-f method approach is used to overcome data non-normality in SEM processing. PRAKARSA, in 2023, calculates the Multidimensional Poverty Index in Indonesia by considering five dimensions: health, education, housing, basic needs, and social protection and participation [10]. Alkire et al. calculated the Multidimensional Poverty Index in various developing countries by considering three dimensions: education, health, and living standards [4]. Pardede used the SEM method to analyze multidimensional poverty by considering health, education, and quality of life [11]. There are two main differences between this study and previous research. This study calculates the Multidimensional Poverty Index and then looks at the relationship between variables using the SEM method. In addition, this study uses indicators of health insurance, preschool participation, and the Internet to represent the dimensions of health, education, and living standards.

The analysis unit typically employed in multidimensional poverty analysis consists of individuals and households [11]. This study delves into the issue of multidimensional poverty in Central Java, DI Yogyakarta, and East Java, focusing on households as the unit of analysis. It aims to pinpoint the various indicators that impact poverty from a multidimensional perspective, thereby aiding in developing more effective and targeted government programs.

2. RESEARCH METHODS

2.1 Data Sources

The data used in this study is secondary data sourced from the National Socioeconomic Survey (SUSENAS) 2023 March KOR. SUSENAS is a survey conducted by BPS regularly twice a year. The sample data available in SUSENAS consists of 341,802 households spread throughout Indonesia, with the number of samples in Central Java, DI Yogyakarta, and East Java provinces amounting to 66,428 households. In this study, the unit of analysis used is the household.

2.2 Multidimensional Poverty Index (MPI)

The Multidimensional Poverty Index offers a comprehensive assessment of the range of deprivations that impoverished households experience, which is concurrently achieved by considering various indicators that gauge different aspects of life [12]. The Multidimensional Poverty Index (MPI) is calculated using the Alkire-Foster method with a household unit of analysis. The MPI is based on four dimensions: health, education, housing, and living standards. It is based on modified PRAKARSA research [10]. The MPI processing is conducted using RStudio software. Each dimension and indicator are calculated with equal weighting, ensuring that all dimensions carry the same weight and are further divided based on the number of indicators used This article has four dimensions, each assigned a weight of 1/4. Subsequently, the weight of each dimension is distributed among the number of indicators within that dimension. For example, the health dimension has three indicators, so the weight for each indicator is 1/4 divided by 3, which equals 1/12. More details can be found in Table 1.

Table 1. MPI forming dimensions, indicators, and deprived cutoff

Dimension (Latent variable)	Indicators (Manifest variable)		Deprived Cutoff	Indicators Weight	Dimension Weight	Total Weight (4)x(6)
(1)	(2)		(3)	(4)	(5)	(6)
Health	K1	Nutrition	There are toddlers aged 1 to 2 years in the household where one of the foods to meet balanced nutrition for toddlers needs to be fulfilled/unknown.	1/3	1/4	1/12
	K2	Morbidities	There are individuals in households who experience health complaints that interfere with daily activities.	1/3		1/12
	K3	Insurance	There are individuals in households who do not have health insurance	1/3		1/12
Education	P1	School Participation	There were residents aged 7 to 18 years in the household during the past week who have not/never attended school and are not currently attending school.	1/3	1/4	1/12
	P2	Years of Schooling	There are residents aged 18 to 30 years in households with education below junior high school or do not have an elementary school diploma.	1/3		1/12
	P3	Preschool Participation	If the child aged $\leq$ 10 years in the household has not/never attended preschool education.	1/3		1/12
Housing	PR1	Housing Feasibility	If the house uses roofing materials other than concrete, roof tile, wood/shingle, and zinc. Other than suitable walls include GRC board, woven bamboo/wire stucco, wood/boards, and logs. Floors other than worthy floors include marble/granite, ceramics, parquet/vinyl/carpet, tile/tile/terrazzo, wood/boards, and cement/red brick.	1/2	1/4	1/8
	PR2	Household Density	If the floor area of the house per person is less than 7.2 m^2	1/2		1/8
Standard of Living	SH1	Safe Drinking Water	If the household uses drinking water other than bottled water, refill, and plumbing and does not use drilled wells, protected wells, or protected springs	1/5	1/4	1/20
	SH2	Cooking Fuel	If other than households not cooking or using electricity and non-subsidized	1/5		1/20

Dimension (Latent variable)	Indicators (Manifest variable)	Deprived Cutoff	Indicators Weight	Dimension Weight	Total Weight (4)x(6)
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
		gas/LPG (5.5 kg and 12 kg, city gas, biogas) for cooking			
	SH3 Sanitation Eligibility	If the sanitation facility is not used by the household alone or in conjunction with other specific households, the toilet is not a gooseneck, and the landfill is not a septic tank or wastewater treatment system (SPAL).	1/5		1/20
	SH4 Internet	If no one in the household has used the internet in the past three months.	1/5		1/20
	SH5 Assets	If the household does not own at least more than one asset, i.e., 5.5 kg or more gas cylinder, refrigerator, air conditioner, water heater, landline telephone (PSTN), computer/laptop/tablet, gold/jewelry (at least 10 grams), motorcycle, boat, motorboat, car, flat screen television (at least 30 inches), and land.	1/5		1/20

Source: *PRAKARSA* ***[10]***, *OPHI* ***[13]***, *Leseman et al* ***[14]***, *Yang et al* ***[15]***, *Xiao et al* ***[16]***, *Khaleel et al* ***[17]***

In **[18]**, the MPI concept refers to the *i*-th household that falls into the multidimensionally poor category with a deprivation score more significant than the cutoff (k), equal to 1/3 of the total weighted indicators. Once we have determined the number of multidimensionally poor households (q) in the population, the MPI value can be obtained using the following method.

1. Calculate the headcount ratio (H). H is the proportion of poor households in the population. So,

$$H = \frac{q}{n} \tag{1}$$

where,
$q =$ The number of households categorized as multidimensionally poor
$n =$ Total population

2. The deprivation score of each household is calculated by taking a weighted sum of the number of deprivations as in the following formula.

$$c_i = w_1 I_1 + w_2 I_2 + \ldots + w_{13} I_{13} \tag{2}$$

where,
$w_i = i^{th}$ weight, $i = 1,2, \ldots ,13$
w_1=1/12, w_2=1/12, …, w_{13}=1/20 (according to 6th column Tabel 1)
column 4 = the number of indicators per total indicators in each dimension.
column 5 = the number of dimensions per total dimensions.
column 6 = column 4 x column 5
$I =$ indicator

3. Determining the poverty intensity value (A) where $\sum_{i=1}^{n} c_i$ is above the cutoff (k) of 1/3 **[18]**. This process is imperative in measuring poverty across various dimensions and can provide valuable insights into the extent of deprivation in a given area. So,

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q} \tag{3}$$

where,

$c_i(k) =$ Censored deprivation score of household i

q = The number of households categorized as multidimensionally poor

4. To calculate the Multidimensional Poverty Index (MPI), you can obtain its value by multiplying H and A as in the following formula.

$$MPI = H \times A \tag{4}$$

2.3 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a statistical methodology that uses a confirmatory approach to analyze structural theories related to various phenomena [19]. Whether with covariance or variance-based multivariate techniques that explain measurement and structural correspondence [20]. In the measurement model, constructs are defined by indicators collectively. In the structural model, constructs relate to each other by correlation and dependence [20]. SEM can combine variables with unobserved (latent constructs) and observed (manifest) measurements. Latent variables cannot be measured directly because they cannot be observed, while manifest variables are measured in the sample [21]. We used AMOS software to process SEM. SEM can represent knowledge or hypotheses related to the phenomenon under study. The model is based on existing or proposed theories that describe and explain the phenomenon being studied. Once a theory is developed, it can be tested with empirical data using SEM. This testing process is often called the confirmatory mode of SEM application [21]. In this study, we used four latent variables, namely education, health, housing, and living standards, measured by several indicators, as shown in Table 1. The SEM processing in this study uses AMOS 26 software, and to present the SEM model diagram attractively, diagrams.net software is employed.

When forming a model, it is crucial to consider the relationship between latent variables and indicators [11]. Parameters are the key elements in the SEM model [21]. Parameters are unknown aspects of a phenomenon estimated by fitting the model to the sample [21]. A path diagram can be created to explain SEM and facilitate understanding. In SEM, there are independent variables and dependent variables. A dependent variable is a variable that receives at least one path from another variable or is influenced by another variable. In contrast, an independent variable is a variable that generates a path and is not influenced by another variable or does not receive a path from another variable. In this article, the path diagram used is shown in Figure 1.

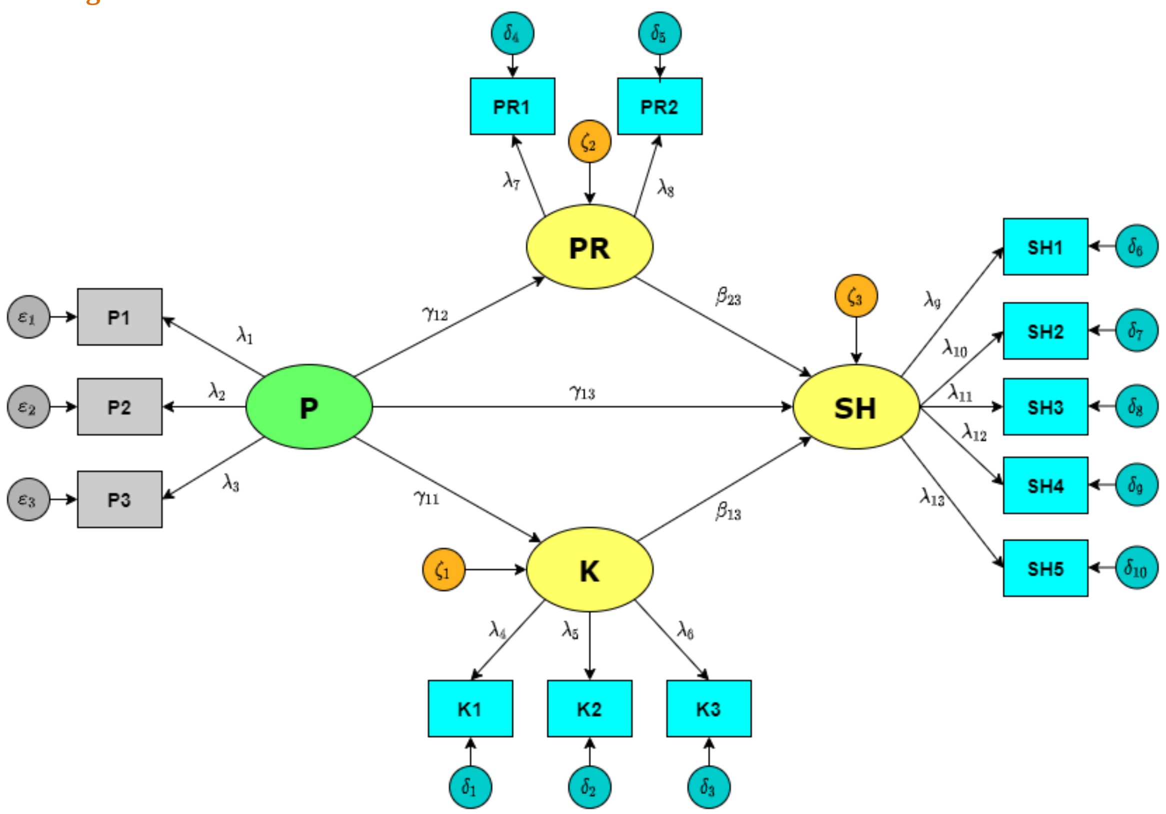

Figure 1. MPI path diagram

According to [22], there are two models in SEM: the structural and the measurement models. The models in this study can be written with the following formula.
Structural Model:

$$K = \gamma_{11}P + \zeta_1 \tag{5}$$

$$PR = \gamma_{12}P + \zeta_2 \tag{6}$$

$$SH = \gamma_{13}P + \beta_{13}K + \beta_{23}PR + \zeta_3 \tag{7}$$

where,
K = latent variable of Health
P = latent variable of Education
PR = latent variable of Housing
SH = latent variable of Standard of Living
$\gamma_{11}, \gamma_{12}, \gamma_{13}$ = coefficient of P
β_{13} = coefficient of K
β_{23} = coefficient of PR
ζ_i = error model, i=1,2,3

Measurement Model:

$$P1 = \lambda_1 P + \varepsilon_1 \tag{8}$$

$$P2 = \lambda_2 P + \varepsilon_2 \tag{9}$$

$$P3 = \lambda_3 P + \varepsilon_3 \tag{10}$$

$$K1 = \lambda_4 K + \delta_1 \tag{11}$$

$$K2 = \lambda_5 K + \delta_2 \tag{12}$$

$$K3 = \lambda_6 K + \delta_3 \tag{13}$$

$$PR1 = \lambda_7 PR + \delta_4 \tag{14}$$

$$PR2 = \lambda_8 PR + \delta_5 \tag{15}$$

$$SH1 = \lambda_9 SH + \delta_6 \tag{16}$$

$$SH2 = \lambda_{10} SH + \delta_7 \tag{17}$$

$$SH3 = \lambda_{11} SH + \delta_8 \tag{18}$$

$$SH4 = \lambda_{12} SH + \delta_9 \tag{19}$$

$$SH5 = \lambda_{13} SH + \delta_{10} \tag{20}$$

where,
$P1$ = indicator of Participation school in Education latent variable
$P2$ = indicator of Years Schooling in Education latent variable
$P3$ = indicator of Preschool Participation in Education latent variable
$K1$ = indicator of Nutrition in Health latent variable
$K2$ = indicator of morbidities in Health latent variable
$K3$ = indicator of insurance in Health latent variable
$PR1$ = indicator of Housing Feasibility in Housing latent variable
$PR2$ = indicator of Household density in Housing latent variable
$SH1$ = indicator of Safe drinking water in Standard of Living latent variable

$SH2$ = indicator of Cooking Fuel in Standard of Living latent variable
$SH3$ = indicator of Sanitation Eligibility in Standard of Living latent variable
$SH4$ = indicator of the Internet in Standard of Living latent variable
$SH5$ = indicator of Assets Fuel in Standard of Living latent variable
λ_i = coefficient of P, i=1,2,3
λ_i = coefficient of K, i=4,5,6
λ_i = coefficient of PR, i=7,8
λ_i = coefficient of SH, i=9,10,11,12,13
ε_i = measurement error of exogenous indicators, i=1,2,3
δ_i = measurement error of endogenous indicators, i=4,5,6,7,8,9,10,11,12,13

Equation (8) - **Equation (20)** can be written as follows

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} P + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix} \tag{21}$$

$$\begin{bmatrix} K_1 \\ K_2 \\ K_3 \end{bmatrix} = \begin{bmatrix} \lambda_4 \\ \lambda_5 \\ \lambda_6 \end{bmatrix} K + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{bmatrix} \tag{22}$$

$$\begin{bmatrix} PR_1 \\ PR_2 \end{bmatrix} = \begin{bmatrix} \lambda_7 \\ \lambda_8 \end{bmatrix} PR + \begin{bmatrix} \delta_4 \\ \delta_5 \end{bmatrix} \tag{23}$$

$$\begin{bmatrix} SH_1 \\ SH_2 \\ SH_3 \\ SH_4 \\ SH_5 \end{bmatrix} = \begin{bmatrix} \lambda_9 \\ \lambda_{10} \\ \lambda_{11} \\ \lambda_{12} \\ \lambda_{13} \end{bmatrix} SH + \begin{bmatrix} \delta_6 \\ \delta_7 \\ \delta_8 \\ \delta_9 \\ \delta_{10} \end{bmatrix} \tag{24}$$

$$\begin{gathered} \mathbf{\Sigma}_P = \mathbf{\Phi}_P \\ \begin{bmatrix} \sigma_{P_{11}} & \sigma_{P_{12}} & \sigma_{P_{13}} \\ \sigma_{P_{12}} & \sigma_{P_{22}} & \sigma_{P_{23}} \\ \sigma_{P_{13}} & \sigma_{P_{23}} & \sigma_{P_{33}} \end{bmatrix} = \begin{bmatrix} \phi_{P_{11}} & \phi_{P_{12}} & \phi_{P_{13}} \\ \phi_{P_{12}} & \phi_{P_{22}} & \phi_{P_{23}} \\ \phi_{P_{13}} & \phi_{P_{23}} & \phi_{P_{33}} \end{bmatrix} \end{gathered} \tag{25}$$

$$\begin{gathered} \mathbf{\Sigma}_K = \mathbf{\Psi}_K \\ \begin{bmatrix} \sigma_{K_{11}} & \sigma_{K_{12}} & \sigma_{K_{13}} \\ \sigma_{K_{12}} & \sigma_{K_{22}} & \sigma_{K_{23}} \\ \sigma_{K_{13}} & \sigma_{K_{23}} & \sigma_{K_{33}} \end{bmatrix} = \begin{bmatrix} \psi_{K_{11}} & \psi_{K_{12}} & \psi_{K_{13}} \\ \psi_{K_{12}} & \psi_{K_{22}} & \psi_{K_{23}} \\ \psi_{K_{13}} & \psi_{K_{23}} & \psi_{K_{33}} \end{bmatrix} \end{gathered} \tag{26}$$

$$\begin{gathered} \mathbf{\Sigma}_{PR} = \mathbf{\Psi}_{PR} \\ \begin{bmatrix} \sigma_{PR_{11}} & \sigma_{PR_{12}} \\ \sigma_{PR_{12}} & \sigma_{PR_{22}} \end{bmatrix} = \begin{bmatrix} \psi_{PR_{11}} & \psi_{PR_{12}} \\ \psi_{PR_{12}} & \psi_{PR_{22}} \end{bmatrix} \end{gathered} \tag{27}$$

$$\boldsymbol{\Sigma}_{SH} = \boldsymbol{\Psi}_{SH}$$
$$\begin{bmatrix} \sigma_{SH_{11}} & \sigma_{SH_{12}} & \sigma_{SH_{13}} & \sigma_{SH_{14}} & \sigma_{SH_{15}} \\ \sigma_{SH_{12}} & \sigma_{SH_{22}} & \sigma_{SH_{23}} & \sigma_{SH_{24}} & \sigma_{SH_{25}} \\ \sigma_{SH_{13}} & \sigma_{SH_{23}} & \sigma_{SH_{33}} & \sigma_{SH_{34}} & \sigma_{SH_{35}} \\ \sigma_{SH_{14}} & \sigma_{SH_{24}} & \sigma_{SH_{34}} & \sigma_{SH_{44}} & \sigma_{SH_{45}} \\ \sigma_{SH_{15}} & \sigma_{SH_{25}} & \sigma_{SH_{35}} & \sigma_{SH_{45}} & \sigma_{SH_{55}} \end{bmatrix} = \begin{bmatrix} \psi_{SH_{11}} & \psi_{SH_{12}} & \psi_{SH_{13}} & \psi_{SH_{14}} & \psi_{SH_{15}} \\ \psi_{SH_{12}} & \psi_{SH_{22}} & \psi_{SH_{23}} & \psi_{SH_{24}} & \psi_{SH_{25}} \\ \psi_{SH_{13}} & \psi_{SH_{23}} & \psi_{SH_{33}} & \psi_{SH_{34}} & \psi_{SH_{35}} \\ \psi_{SH_{14}} & \psi_{SH_{24}} & \psi_{SH_{34}} & \psi_{SH_{44}} & \psi_{SH_{45}} \\ \psi_{SH_{15}} & \psi_{SH_{25}} & \psi_{SH_{35}} & \psi_{SH_{45}} & \psi_{SH_{55}} \end{bmatrix} \tag{28}$$

where, $\boldsymbol{\Sigma}_P$, $\boldsymbol{\Sigma}_K$, $\boldsymbol{\Sigma}_{PR}$ and $\boldsymbol{\Sigma}_{SH}$ are sample covariance matrices from all indicators, respectively. And $\boldsymbol{\Phi}_P$, $\boldsymbol{\Psi}_K$, $\boldsymbol{\Psi}_{PR}$ and $\boldsymbol{\Psi}_{SH}$ are implied covariance matrices, respectively. All $\lambda's$ estimators can be obtained by iteratif processing. In this article, we use AMOS software to find all the estimators.

Then, **Equation (5)**- **Equation (7)** can be written as follows

$$\begin{aligned} SH &= \gamma_{13}P + \beta_{13}(\gamma_{11}P + \zeta_1) + \beta_{23}(\gamma_{12}P + \zeta_2) + \zeta_3 \\ &= (\gamma_{13} + \beta_{13}\gamma_{11} + \beta_{23}\gamma_{12})P + \beta_{13}\zeta_1 + \beta_{23}\zeta_2 + \zeta_3 \\ &= \beta_* P + \zeta_* \end{aligned} \tag{29}$$

$$\begin{gathered} \begin{bmatrix} K \\ PR \\ SH \end{bmatrix} = \begin{bmatrix} \gamma_{11} \\ \gamma_{12} \\ \beta_* \end{bmatrix} P + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_* \end{bmatrix} \\ \mathbf{y} = \boldsymbol{\gamma} P + \boldsymbol{\zeta} \end{gathered} \tag{30}$$

$$\hat{\boldsymbol{\gamma}} = \mathbf{R}^{-1}\mathbf{r}_{yP} \tag{31}$$

$$\sqrt{n}(\hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma}) \xrightarrow{D} N(\mathbf{0}, \boldsymbol{\Omega}) \text{ [23]} \tag{32}$$

where, $\mathbf{y}$ are all latent endogenous variables and P is latent exogenous variable. And $\boldsymbol{\gamma}$ is the coefficient of exogenous and endogenous variables, respectively. Then, $\boldsymbol{\zeta}$ is the error model. $\hat{\boldsymbol{\gamma}}$ is the estimator of $\boldsymbol{\gamma}$. $\mathbf{R}^{-1}$ is the invers of correlation matrix. $\mathbf{r}_{yP}$ is correlation vector of exogenous and endogenous variables. By **[23]** we have $\sqrt{n}(\hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma})$ convergence in distribution to Normal with mean $\mathbf{0}$ and covariance matrix $\boldsymbol{\Omega}$. .

This study employs the Asymptotically Distribution-free (AD-f) method, a technique used to handle data that is not generally distributed because it does not require a theory of data distribution **[23]**. This is because AD-f is not based on normality theory **[24]**. Structural Equation Modeling (SEM) typically assumes a normal data distribution, but this method does not rely on normal theory. It can be applied to ordinal, continuous, and dichotomous variables and is particularly effective for large data sets **[23][25]**. The AD-f method requires the sample size to be at least ten times the estimated parameters, as per Raykov & Marcoulides' statement, to ensure reliable results **[19]**. Furthermore, using the AD-f method may produce better goodness-of-fit values than the Maximum Likelihood method when dealing with non-normally distributed data **[26]**.

3. RESULTS AND DISCUSSION

3.1 Multidimensional Poverty Index

We use R software to process the SUSENAS data. After processing with R software, the values related to multidimensional poverty are presented in **Table 2**; weighting in SUSENAS is used to reduce bias from the survey sample and make the results more representative of the target population.

Table 2. Multidimensional poverty index

Region	MPI	H	A	Number of Poor Households
Indonesian	0.0669	0.1552	0.4310	11,337,203
Central Java	0.0403	0.1004	0.4014	1,006,064
DI Yogyakarta	0.0188	0.0477	0.3939	54,843
East Java	0.0380	0.0948	0.4012	1,085,852

***Data source**: SUSENAS 2023 March KOR (processed)*

Indonesia has a Multidimensional Poverty Index (MPI) of 0.0669, which means that those considered multidimensionally poor in the country experience 6.69 percent of the total deprivation that would be encountered if everyone were deprived on all indicators simultaneously. The headcount of 0.1552 indicates that 15.52 percent of households in Indonesia are experiencing multidimensional poverty. At the same time, the intensity of 0.4310 means that, on average, the multidimensionally poor in Indonesia are deprived in 43.10 percent of the weighted indicators. The number of poor households in Indonesia is 11.33 million.

The MPI of 0.0403 for Central Java Province means that the multidimensionally poor in the province experience 4.03 percent of the total deprivation that would be experienced if everyone were deprived on all indicators simultaneously. The headcount of 0.1004 indicates that 10.04 percent of households in Central Java Province are experiencing multidimensional poverty. At the same time, the intensity of 0.4014 means that, on average, the multidimensionally poor in the province are deprived in 40.14 percent of the weighted indicators. The number of poor households in Central Java Province is one million households.

The MPI of 0.0188 for DI Yogyakarta Province means that the multidimensionally poor people in the province experience 1.88 percent of the total deprivation that would be experienced if everyone was deprived on all indicators simultaneously. The headcount of 0.0477 indicates that 4.77 percent of households in Yogyakarta Province are experiencing multidimensional poverty. At the same time, the intensity of 0.3939 means that, on average, the multidimensionally poor in the province are deprived in 39.39 percent of the weighted indicators. The number of poor households in Yogyakarta Province is 54 thousand households.

The MPI of 0.0380 for East Java Province means that the multidimensionally poor in the province experience 3.80 percent of the total deprivation that would be experienced if everyone was deprived on all indicators simultaneously. The headcount of 0.0948 indicates that 9.48 percent of households in East Java Province are experiencing multidimensional poverty. At the same time, the intensity of 0.4012 means that, on average, the multidimensionally poor in the province are deprived in 40.12 percent of the weighted indicators. The number of poor households in East Java Province is 1.08 million households.

According to BPS, the percentage of the poor population in Indonesia in March 2023 is 9.36 percent, half of the number of multidimensional poor households in Indonesia. It indicates that multidimensional poverty better represents the phenomenon of poverty because it considers poverty from various areas such as health, education, housing, and the standard of living. Meanwhile, the percentage of the poor population in Central Java, DI Yogyakarta, and East Java is 10.77 percent, 11.04 percent, and 10.35 percent, respectively, higher than that of the population in multidimensional poverty. This occurs due to the difference in approaches, where BPS uses an individual approach. In contrast, this study uses a household approach.

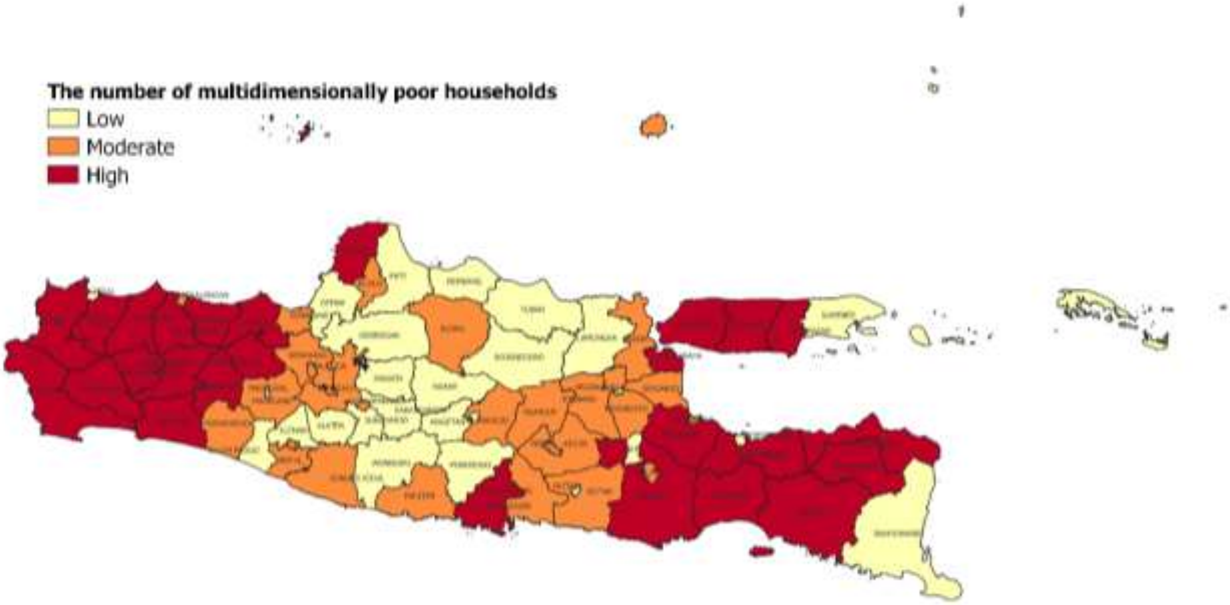

Figure 2. Thematic map of the distribution of multidimensional poor households

We use QGIS software and natural breaks as the cutoff of poor households Figure 2 shows that multidimensional poor households tend to be concentrated in border areas, specifically the western part of Central Java Province and the eastern part of East Java Province. Border areas experience high poverty due to the uneven distribution of development policies [27]. Meanwhile, in the Special Region of Yogyakarta (DI Yogyakarta), regencies/cities have few multidimensional poor households. This is partly because most areas in DI Yogyakarta are tourist destinations, contributing to a significant economic turnover [28].

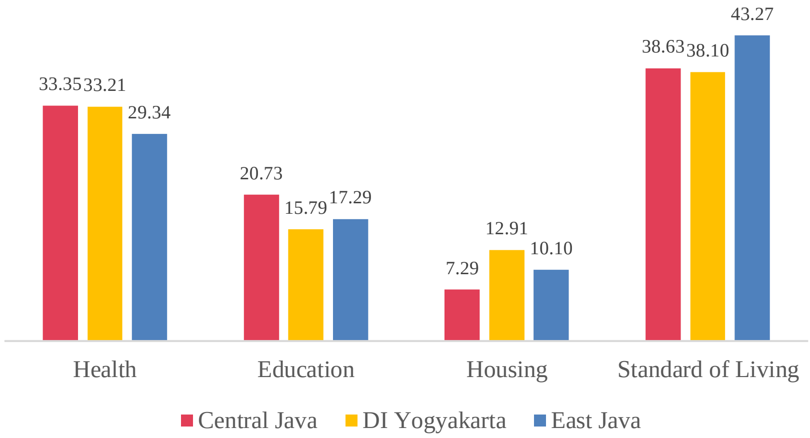

Figure 3. Percentage of deprived dimensions in multidimensional poor households

Figure 3 shows that most households examined in the three provinces are deprived of the dimensions of a standard of living and health. Regarding the standard of living, East Java Province has the highest deprivation rate, indicating that many households lack proper sanitation and internet usage. It suggests that many households in East Java Province still need more sanitation facilities and use the internet. On the other hand, in terms of health, East Java Province has the lowest deprivation rate, as the number of households deprived of nutrition and morbidity indicators is lower. This indicates that households in East Java Province tend to have better health knowledge and healthier lifestyles than the other two provinces.

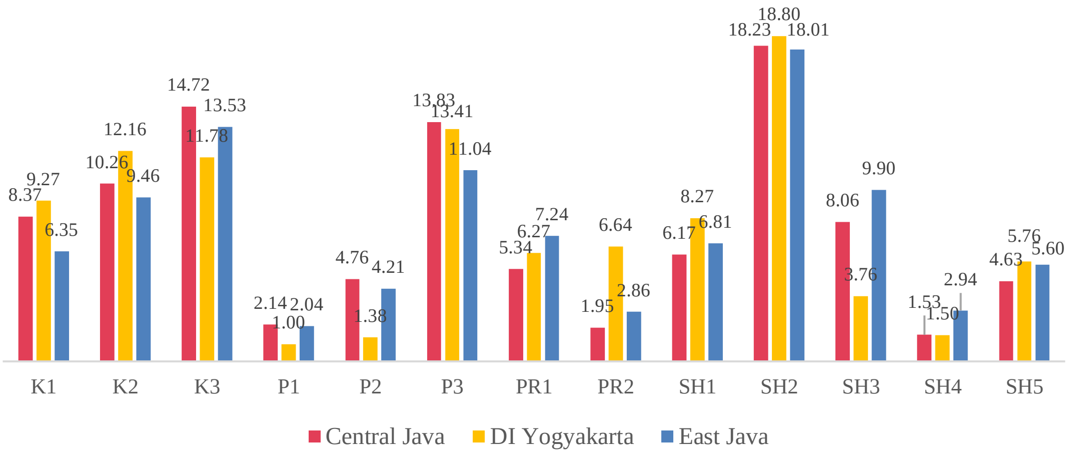

Figure 4. Percentage of deprivation indicator in multidimensional poor households

Figure 4 shows that most deprived dimensions in the standard of living are related to cooking fuel indicators. This is because, from SUSENAS 2023 March KOR results, more than 80 percent of Central Java, Yogyakarta, and East Java use 3 kg LPG gas, which impacts high deprivation. Furthermore, for the health dimension, the indicator contributing the most is health insurance. This signifies that many households need more awareness of the benefits and necessity of financial protection in health expenditures.

3.2 Structural Equation Modeling (SEM)

The estimation of the SEM model only uses SUSENAS KOR 2023 sample data for Central Java, Yogyakarta, and East Java provinces, totaling 66,428 households. The sample size for each province was 29,858 in Central Java, 4,026 in DI Yogyakarta, and 32,544 in East Java. After processing using AMOS software, the results revealed that the relationships among the variables composing the multidimensional poverty index were obtained, as shown in **Figure 5**.

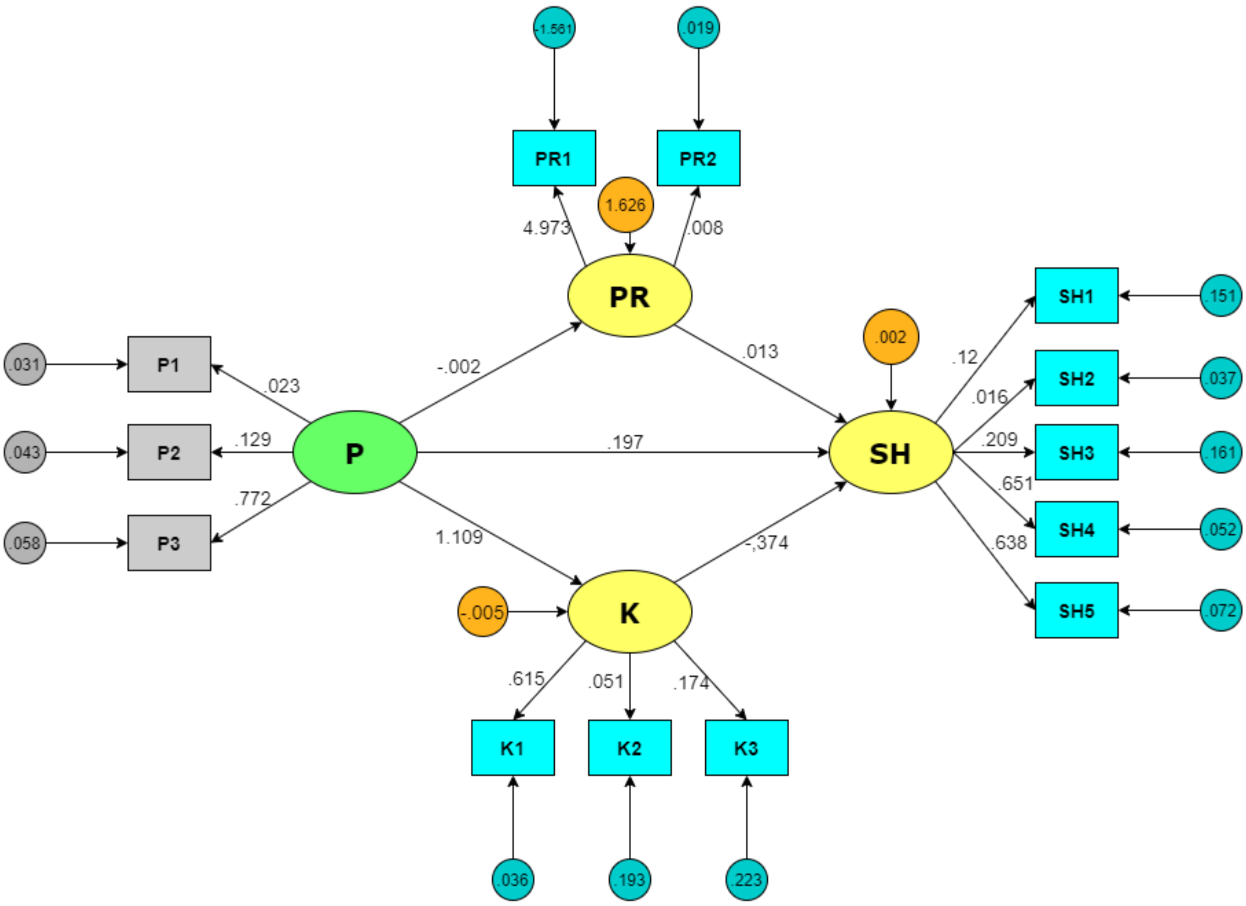

Figure 5. SEM AD-F output

Table 3. GFI dan AGFI

Model	GFI	AGFI
Default model	0.982	0.973
Saturated model	1.000	
Independence model	0.953	0.945

***Data source**: SUSENAS 2023 March KOR (processed)*

One can examine the values of the Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) to assess the model's suitability. Jöreskog and Sörbom stated that GFI and AGFI values range from zero to 1.00, and a value closer to 1.00 indicates a good fit for the model [19]. GFI is considered good if it is above 0.90 [20]. Like GFI, the expected value for AGFI is more than 0.90 [29]. Table 3 illustrates that GFI and AGFI values are above 0.90 and approaching 1.00, indicating that the obtained SEM model demonstrates a good fit.

Table 4. RMSEA

Model	RMSEA
Default model	0.042
Independence model	0.059

***Data source**: SUSENAS 2023 March KOR (processed)*

Browne and Cudeck argued that a Root Mean Square Error of Approximation (RMSEA) with a value less than 0.05 suggests a good fit with a reasonable error boundary of 0.08 [19]. Table 4 reveals that the RMSEA value of the model obtained indicates a good fit.

Table 5. Regression

Path			Unstandardized Estimate	S.E.	C.R.	P	Standardized Estimate
PR	<---	P	-0.601	0.326	-1.843	0.065	-0.002
K	<---	P	40.686	8.724	4.664	***	1.109
SH	<---	P	2.298	0.996	2.308	***	0.197
SH	<---	K	-0.119	0.023	-5.182	***	-0.374
SH	<---	PR	0	0.015	0.031	0.975	0.013
SH1	<---	SH	1				0.120
SH2	<---	SH	0.064	0.021	3.018	***	0.016
SH3	<---	SH	1.824	0.097	18.764	***	0.209
SH4	<---	SH	4.129	0.204	20.205	***	0.651
SH5	<---	SH	4.717	0.234	20.163	***	0.638
PR1	<---	PR	1				4.973
PR2	<---	PR	0.001	0.029	0.031	0.975	0.008
P1	<---	P	1				0.023
P2	<---	P	6.597	1.431	4.609	***	0.129
P3	<---	P	72.107	15.524	4.645	***	0.772
K1	<---	K	1				0.615
K2	<---	K	0.151	0.014	10.779	***	0.051
K3	<---	K	0.562	0.016	34.231	***	0.174

***Data source**: SUSENAS 2023 March KOR (processed)*

Table 5 illustrates the relationship between latent variables and indicators. A relationship between variables is considered significant if it has a Critical Ratio (C.R.) value > 1.96 or a P value < 0.05. Almost all relationships between variables in the model are found to be significant. Variables that are not significant are those related to latent housing. This occurs because latent housing variables are measured only by two indicators, resulting in a need for more information in the model. Variables unrelated to latent housing are significant and consistent with the initial research hypothesis.

The Standardized Estimate in **Table 5** indicates the magnitude of the influence of each latent variable and indicator relationship. Variables with standardized estimate regression values exceeding 0.5 are considered to have a strong relationship **[29]**. The Standard of Living latent variable is measured using five indicators, and those strongly related to the Standard of Living latent variable are the internet and assets. This is in line with **[30]**,**[31]**,**[32]**,**[33]**,**[34]**. It suggests that improving the quality of living standards can be emphasized in the areas of internet accessibility and asset ownership. Equalizing internet access throughout Indonesia could be given more attention, and stable internet connectivity is expected to improve, as even urban areas still face inadequate internet quality. Internet usage can reduce multidimensional poverty because Internet use can significantly increase household income and expenditures **[15]**,**[35]**. Asset ownership also reflects the standard of living because an increase in assets signifies increased prosperity for the household.

The education variable is measured by three indicators, with preschool participation being the indicator with the strongest relationship to the education latent variable, which is in line with **[36]**. Increasing preschool participation for children can be a strategy to alleviate poverty in education because education can help improve the quality of human resources, which will have an impact on the economy **[37]**,**[3]**,**[39]**,**[40]**,**[41]**. Early childhood education is crucial in breaking the cycle of poverty **[14]**.

Housing feasibility is the indicator with the strongest relationship to the Housing latent variable and is in line with **[42]**. Housing feasibility is also a requirement for issuing an IMB so that the building can be officially recognized by the state **[43]**. The feasibility of building houses is an important factor in determining housing quality **[34]**.

Three indicators measure the health variable, and the nutrition indicator has the strongest relationship to the health latent variable, which aligns with **[44]**,**[45]**. Increasingly nutritious food can improve health and reduce health disparities **[46]**. According to the available data, nutrition indicators for children aged 1 to 2 years significantly impact the health variable. This is in line with **[47]**,**[48]**. UNICEF states that nutritional deficiencies in children can limit physical and cognitive capacities and are closely related to poverty due to the lack of parental knowledge **[49]**. Socialization about balanced nutrition has proven to be optimal in increasing parents' knowledge for improving child development **[50]**.

4. CONCLUSIONS

Although the highest monetary poverty is found in the province of DI Yogyakarta, the multidimensional poverty index is the lowest. Most households in the three provinces are deprived of the standard of living dimension, where the cooking fuel indicator contributes the most to the multidimensional poverty rate. It is followed by the health dimension, dominated by the health insurance indicator, indicating that many households need more awareness of the benefits and necessity of financial protection in the context of health expenditures. Therefore, the government can focus more on cooking fuel, especially 3 kg LPG gas, where many illegal practices still increase market prices. The government can also raise awareness about the importance of health insurance, as many people still need health insurance, either from the government's BPJS or private providers. Based on the SEM results, internet and assets indicators are strongly related to the Standard of Living latent variable. Then, preschool participation is the indicator with the strongest relationship to the latent variable in Education. Housing feasibility is the indicator with the strongest relationship to the Housing latent variable. The nutrition indicator has the strongest relationship to the Health latent variable.

rom the path model, we obtain that Education significantly affects health and standard of living. Then, health significantly affects the standard of living. But Education doesn't significantly affect them. Likewise, Housing doesn't significantly affect the Standard of Living.

In this study, we used only three provinces: Central Java, DI Yogyakarta, and East Java. For future research, we suggest studying all the provinces in Indonesia.

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