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MULTIDIMENSIONAL POVERTY OF OLDER ADULTS IN JAVA ISLAND: A MULTILEVEL BINARY LOGISTIC REGRESSION ANALYSIS

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ABSTRACT

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Population aging is a global phenomenon, including in Indonesia, which poses socio-economic challenges. Many older adults still belong to the lowest 40% of household expenditure groups, indicating poor quality of life. Previous studies have generally used monetary measurements, while poverty in older adults is multidimensional, involving health, education, and living standards. This study addresses this gap by analyzing multidimensional poverty among older adults in Java in 2022 using multilevel binary logistic regression with a hierarchical data structure (individuals at level 1 and districts at level 2). The data sources include SUSENAS March 2022 and Province in Figures 2023. The results show that individual factors such as gender, marital status, type of occupation, functional impairment, savings ownership, and residential area, as well as regional factors like GRDP per capita and healthcare facilities ratio, significantly affect multidimensional poverty status among adults. The Intraclass Correlation Coefficient (ICC) is 0.383, confirming substantial variation at the district level, highlighting the importance of multilevel analysis. Furthermore, the model's goodness-of-fit test concluded that the model is appropriate for explaining the multidimensional poverty status among older adults in Java in 2022. The findings provide comprehensive insights into targeted policy interventions to improve older adults' welfare.

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1. INTRODUCTION

The aging population is a phenomenon that occurs globally, including in Indonesia. According to the 2020 Population Census, 9.93% (26.78 million) of Indonesia's population were older adults, projected to increase to 21.90% (72.03 million) by 2050 [1]. A country is considered to have entered the aging phase when the older adult population exceeds 10% of the total population [2] and Indonesia reached this stage in 2021. Java Island records the highest percentage of older adults at 11.62%, exceeding the national average. This demographic shift may contribute to a demographic burden (demographic tax) on economic growth [3]. Although the Indonesian government through Law No. 36 of 2009 has implemented various programs to improve older adults' welfare, many older adults still live in economic vulnerability. Based on BPS data, 41.32% of older adults are in the bottom 40% expenditure group [4]. Moreover, current poverty measurements mainly rely on monetary indicators, which may not adequately capture the broader deprivation experienced by older adults. To better understand this issue, it is important to consider poverty beyond just income indicators.

For older adults, poverty is not just about income limitations but also involves challenges related to health, housing, education, dignity, and social connections [5]. A multidimensional perspective on older adults' poverty can provide a more accurate understanding of their needs, enabling governments to design better policies and programs to improve their overall quality of life. Addressing this complexity requires a multidimensional measurement approach, such as the Alkire-Foster method, which has been adapted in Indonesia by PRAKARSA [6]. This approach sets the foundation for more comprehensive analyses in the context of older adults.

In line with the importance of using a multidimensional approach, several studies have examined poverty, especially among older adults. A study by Wang indicated that individual, household, and regional characteristics significantly affect the risk of older adults experiencing multidimensional poverty in China, including the risk of exiting and re-entering poverty [7]. Research by Zhou found that age, place of residence, education, pension/old-age security ownership, physical health, and mental health significantly influenced multidimensional poverty among older adults in China [8]. A study by Ainistikmalia highlighted that employment type, marital status, and literacy significantly impacted low economic status among older adult women [9]. Furthermore, research by Wirawan and Arka showed that variables such as education and GRDP per capita significantly affected the number of poor people in Bali Province [10]. Similarly, Savirra concluded that population size and the number of healthcare facilities significantly impacted poverty levels in Surakarta City [11]. These studies highlight the importance of considering both individual and regional characteristics in poverty analysis.

To effectively analyze both individual and contextual (regional) factors, it is necessary to use an appropriate statistical method. Multilevel regression analysis is used to study relationships between variables at different levels within a hierarchical data structure [12]. The approach using multiple linear regression can be applied to hierarchical data modeling by either aggregating or disaggregating variables. Variable aggregation refers to transforming lower-level variables to higher-level units, while disaggregation refers to transforming higher-level variables to lower-level units. However, several problems may arise from these approaches. When a lower-level variable is aggregated as if it were a higher-level variable, it leads to a reduction in the number of units, which may result in the loss of information at the lower level [12]. In contrast, when a higher-level variable is disaggregated to lower-level units, it causes the repetition of information across lower-level analysis units (creating dependency among observations), leading to statistical tests that tend to reject the null hypothesis. In other words, the model may yield significant results that are actually spurious [12]. Therefore, the use of multilevel regression, which explicitly considers hierarchical structures within a single model, helps to reduce errors in model specification.

Furthermore, the effect of explanatory variables in multilevel regression is determined by its regression coefficient [13]. If the coefficient is the same for all samples, the variable has a fixed effect. If the coefficient varies between subgroups, the variable has a random effect. Multilevel regression models include both fixed and random effects, which is why they are also called mixed models. Moreover, in many cases, the response variable follows a binomial distribution (binary data), which violates the assumption of normality [12]. To address this, the Generalized Linear Mixed Model (GLMM) framework is used, with parameter estimation following the Maximum Likelihood Estimation (MLE) approach.

When conducting multilevel analysis, two models are generally created: the null model and the conditional model [12]. The null model is a model without explanatory variables that is used to estimate the Intraclass Correlation Coefficient (ICC). Meanwhile, the conditional model includes explanatory variables at level one and higher levels. Random effects represent the variation that arises due to differences among level-2 units. The random effect test is conducted to determine the appropriate model choice between multilevel regression and single-level regression.

Although there have been many studies on poverty among older adults, most studies in Indonesia only focused on income or monetary aspects. Few studies examine poverty as a multidimensional issue that involves health, education, and living standards. In addition, most previous research does not consider the influence of regional or district-level factors together with individual characteristics. This leaves an important gap in understanding how regional aspects can affect the poverty of older adults. Therefore, this study is essential as it applies a multilevel analytical approach to comprehensively identify the determinants of multidimensional poverty among older adults in Java, providing more complete and useful insights for designing effective policies to reduce multidimensional poverty among older adults.

2. METHODS

Material and Data

This research covers the area of Java Island in 2022, consisting of 119 districts. The unit of analysis is older adults (aged 60 years and above) with 45,802 samples. This research uses secondary data from Susenas (Kor) March 2022 and Province in Figures 2023, with a two-level hierarchical data structure that includes both individual and regional levels. The analysis methods used descriptive and inferential analysis. Descriptive analysis is used to provide an overview of the multidimensional poverty status among older adults in Java. Meanwhile, inferential analysis is used to identify the explanatory variables that significantly affect the multidimensional poverty status of older adults in Java. Multilevel binary logistic regression with a random intercept is used with a significance level of 5 percent. The response variable is the multidimensional poverty status of older adults, determined using the Alkire-Foster method. Meanwhile, the explanatory variables include both individual and regional variables that are listed in

Table 1.

Table 1. Variables and Category

Notation	Variable Name	Category
Response Variable		
Poor	Multidimensional Poverty Status among Older adults	1 = Multidimensionally poor 0 = Multidimensionally not poor (*ref*)
Explanatory Variables		
Individual Level		
G	Gender	1 = Female 0 = Male (*ref*)
MS	Marital Status	1 = Unmarried 0 = Married (*ref*)
TO	Type of Occupation	1 = Unemployed 2 = Working in the agricultural sector 0 = Working in the non-agricultural sector (*ref*)
FI	Functional Impairment	1 = Yes 0 = No (*ref*)
SO	Savings Ownership	1 = No 0 = Yes (*ref*)
RA	Residential Area	1 = Rural 0 = Urban (*ref*)
Regional Level (District)		
GRDP	GRDP per Capita	Numeric
HEALTH	Healthcare Facilities Ratio	Numeric

Determining the Multidimensional Poverty Status of Older Adults

The response variable is the multidimensional poverty status of older adults. This status is categorized into two groups: multidimensionally poor and multidimensionally not poor. The multidimensional poverty status is determined by calculating a weighted deprivation score using the Alkire-Foster method, which is commonly used to calculate the Multidimensional Poverty Index (MPI). However, there is a step to determine the poverty status for each individual unit, making this method appropriate. The dimensions and indicators used to determine the multidimensional poverty status of older adults are presented in **Table 2**. Changing this poverty status into a binary (nominal) scale is important to make the results easier to understand and more useful for policy decisions. By classifying older adults simply as poor or not poor, it becomes clearer which groups need more help and targeted programs. Although some detailed information might be lost in this transformation, the main goal of this study is to clearly identify the most vulnerable groups rather than to provide detailed individual rankings. Using a binary outcome also allows us to apply multilevel binary logistic regression, which helps analyze both individual and regional factors together in a practical and meaningful way.

Table 2. Dimensions, Indicators, and Definitions of Deprivation

Dimension	Indicator	Definition of Being Deprived	Weight	Source
Health	Sanitation	Older adults without access to adequate sanitation facilities	1/9	OPHI and PRAKARSA
	Drinking water	Older adults without access to safe drinking water sources	1/9	OPHI and PRAKARSA
	Health Insurance	Older adults without health insurance coverage	1/9	Rastantra
Education	Latest Diploma	Older adults without at least a junior high school diploma	1/6	OPHI and PRAKARSA
	Literacy	Older adults who are illiterate	1/6	Sumargo and Simanjuntak
Living Standards	Cooking Fuel	Older adults do not use appropriate cooking fuels	1/9	OPHI and PRAKARSA
	Electricity	Older adults do not use electricity as a source of lighting	1/9	OPHI and PRAKARSA
	Housing	One of the three main parts of the house (roof, floor, or walls) is made of inadequate materials	1/9	OPHI and PRAKARSA

Source: OPHI [14]*, PRAKARSA* [6]*, Rastantra* [15]*, Sumargo and Simanjuntak* [16]

Multilevel Binary Logistic Regression Analysis

According to Hox et al. [12], the logistic regression equation formulated at level 1 is as follows:

$$Y_{ij} = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} X_{pij} + e_{ij} \tag{1}$$

Meanwhile, the multilevel binary logistic regression equation with a random intercept for level 2 is as follows:

$$\beta_{0j} = \beta_{00} + \sum_{q=1}^{Q} \beta_{0q} X_{qj} + u_{0j} \tag{2}$$

with the slope value for each group assumed to be constant, as expressed in the following equation:

$$\beta_{pj} = \beta_{p0} \text{ (For } p > 0) \tag{3}$$

next, equations (2) and (3) are substituted into equation (1), resulting in the following multilevel binary logistic regression equation:

$$ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_{00} + \sum_{p=1}^{P} \beta_{p0} X_{pij} + \sum_{q=1}^{Q} \beta_{0q} X_{qj} + u_{0j} + e_{ij} \tag{4}$$

In this study, multilevel binary logistic regression is used to identify individual and regional factors that affected the multidimensional poverty status of older adults in Java. The empirical model for the multilevel binary logistic regression with a random intercept is as follows:

$$\begin{aligned} ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = {} & \beta_{00} + u_{0j} + e_{ij} + \beta_{10} G_{ij} + \beta_{20} MS_{ij} \\ & + d_1 \beta_{30} TO\_unemployed_{ij} + d_2 \beta_{30} TO\_agricultural_{ij} \\ & + \beta_{40} FI_{ij} + \beta_{50} SO_{ij} + \beta_{60} RA_{ij} + \beta_{01} GRDP_j \\ & + \beta_{02} HEALTH_j \end{aligned} \tag{5}$$

with,

π_{ij} : the probability of success (being in multidimensional poverty) for older adults i in district j,

$1 - \pi_{ij}$: the probability of failure (not being in multidimensional poverty) for older adults i in district j,
i : the index for older adults (individual) samples (i = 1, 2, ..., 45802),
j : the index for regional (district) samples (j = 1, 2, ..., 119),
β_{00} : the intercept (baseline odds),
$\beta_{10}, \ldots, \beta_{60}$: fixed effects for explanatory variables at individual level (level 1),
β_{01}, β_{02} : fixed effects for explanatory variables at regional level (level 2),
u_{0j} : the random effect for district j (capturing the unobserved heterogeneity at level 2) which affects the likelihood of poverty for older adults in that district,
e_{ij} : the residual or error term at the individual unit at level 1 within group at level 2,
G_{ij} : gender variable for older adults i in district j,
MS_{ij} : marital status variable for older adults i in district j,
$TO\_unemployed_{ij}$: type of occupation (unemployed) variable for older adults i in district j,
$TO\_agricultural_{ij}$: type of occupation (working in the agricultural sector) variable for older adults i in district j,
FI_{ij} : functional impairment variable for older adults i in district j,
SO_{ij} : savings ownership variable for older adults i in district j.
RA_{ij} : residential area classification variable for older adults i in district j,
$GRDP_j$: Gross Regional Domestic Product (GRDP) per capita variable for district j,
$HEALTH_j$: healthcare facilities ratio variable for district j.

The steps of inferential analysis using multilevel binary logistic regression are as follows:

1. Random effect test

The random effect test is used to determine whether a multilevel regression model is better than a regular regression model. This test compares the -2 log-likelihood values of the model without random effects and the model with random effects that indicate how well the model fits the observed data [12]. The hypotheses are H_0: $\sigma^2_{uo} = 0$ (random effect is not significant) and H_1: $\sigma^2_{uo} \neq 0$ (random effect is significant), with the test statistics as follows:

$$LR = -2\ ln\left(\frac{L_0}{L_1}\right) = -2[ln(L_0) - ln(L_1)] \sim \chi^2_{(r)} \quad (6)$$

with L_0 represents the likelihood of the model without random effects, L_1 represents the likelihood of the model with random effects, and r is the difference in the number of parameters between level 1 and level 2. Reject H_0 if $LR > \chi^2_{(\alpha;r)}$ or p-value $< \alpha$. If H_0 is rejected, it means there is a significant random effect, and the multilevel binary logistic regression model provides a better fit to the observed data than the regular regression model.

2. Intraclass Correlation Coefficient (ICC)

The Intraclass Correlation Coefficient (ICC) is used to measure the variation in the response variable that can be explained by differences in characteristics between groups [12]. The ICC represents the proportion of variance at the group level compared to the total variance. To calculate the ICC, an intercept-only model is used (model without explanatory variables). This model decomposes the variance into two independent components variance at the lowest level ($\hat{\sigma}^2_e$) and variance at the highest level ($\hat{\sigma}^2_{u0}$).

$$\rho = \frac{\hat{\sigma}^2_{u0}}{\hat{\sigma}^2_{u0} + \hat{\sigma}^2_e} \quad (7)$$

The value of ICC ranges from 0 to 1. A higher ICC value means that variation at level 1 is more homogeneous, while variation at level 2 is more heterogeneous. Additionally, a larger ICC indicates that the variation in the response variable that can be explained by differences in characteristics at level 2 is greater, suggesting that the multilevel regression model is more appropriate.

3. Simultaneous parameter test

The simultaneous parameter test is used to determine the effect of entire explanatory variables with the response variable [17]. This test compares the log likelihood values of the null model and the conditional model, with the degrees of freedom corresponding to the difference in parameters between the two models. The hypotheses are H_0: $\beta_{10} = \beta_{20} = \cdots = \beta_{\text{p0}} = \beta_{01} = \cdots = \beta_{0\text{q}} = 0$ (there is no explanatory variables that affect the response variable) and H_1: at least one $\beta_{pq} \neq 0$ (at least one explanatory variable has an effect on the response variable), with the test statistics as follows:

$$G = -2\, ln \left(\frac{L_1}{L_2}\right) = -2[ln(L_1) - ln(L_2)] \sim \chi^2_{(r)} \tag{8}$$

with L_1 represents the likelihood of the null model (model without explanatory variables), L_2 represents the likelihood of the conditional model (model with explanatory variables), and r is the difference in the number of parameters between level 1 and level 2. Reject H_0 if $G > \chi^2_{(\alpha;r)}$ or p-value < α. If H_0 is rejected, it can be concluded that at least one explanatory variable has a significant effect on the response variable.

4. Partial parameter test

Partial parameter testing is used to determine which explanatory variables have a significant effect on the response variable at each level [17]. The hypotheses for level 1 are H_0: $\beta_{p0} = 0$ and H_1: $\beta_{p0} \neq 0$. Meanwhile, the hypotheses for level 2 are H_0: $\beta_{0q} = 0$ and H_1: $\beta_{0q} \neq 0$, with the test statistics as follows:

Level 1:

$$Z_{p0} = \frac{\hat{\beta}_{p0}}{se(\hat{\beta}_{p0})} \sim N(0,1) \tag{9}$$

Level 2:

$$Z_{0q} = \frac{\hat{\beta}_{0q}}{se(\hat{\beta}_{0q})} \sim N(0,1) \tag{10}$$

Reject H_0 if $|Z| > Z_{(\alpha/2)}$ or p-value < α. If H_0 is rejected, it can be concluded that the explanatory variable partially has a significant effect on the response variable.

5. Goodness-of-fit test

Model fit testing is performed to evaluate how well the model represents the data, specifically to determine whether the model is suitable for explaining the response variable [17]. The hypotheses are H_0: The model fits the data and H_1: The model does not fit the data, with the test statistics as follows:

$$\hat{C} = \Sigma_{k=1}^{g} \frac{(O_{1k} - n'_k \bar{\pi}_k)^2}{n'_k \bar{\pi}_k (1 - \bar{\pi}_k)} \tag{11}$$

with $\hat{C}$ is the Hosmer-Lemeshow test statistic, O_k is the observed number of outcomes in group k, n_k is the number of subjects in group k, $\bar{\pi}_k$ is the estimated mean probability for group k, and g is the number of groups formed. Reject H_0 if $\hat{C} > \chi^2_{(\alpha;g-2)}$ or if the p-value $< \alpha$. If H_0 is rejected, it indicates that the model does not fit the response variable.

6. Interpretation of odds ratio

The interpretation of parameters in the multilevel binary logistic regression model using the odds ratio (Equation), which shows how much each explanatory variable at each level affects the response variable.

Level 1:

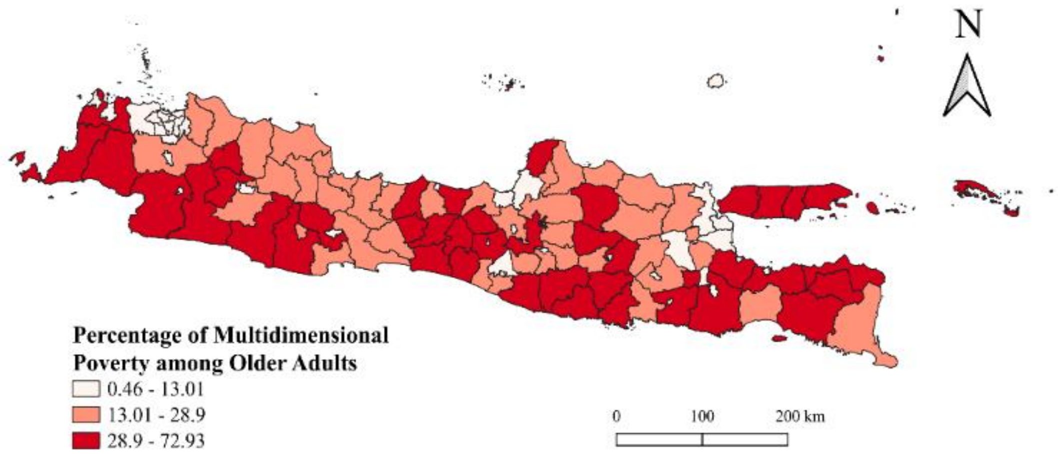
$$OR = \exp\left(\hat{\beta}_{p0}\right); p = 1, \ldots, \mathrm{P} \quad (12)$$

Level 2:

$$OR = \exp\left(\hat{\beta}_{0q}\right); q = 1, \ldots, \mathrm{Q} \quad (13)$$

3. RESULTS

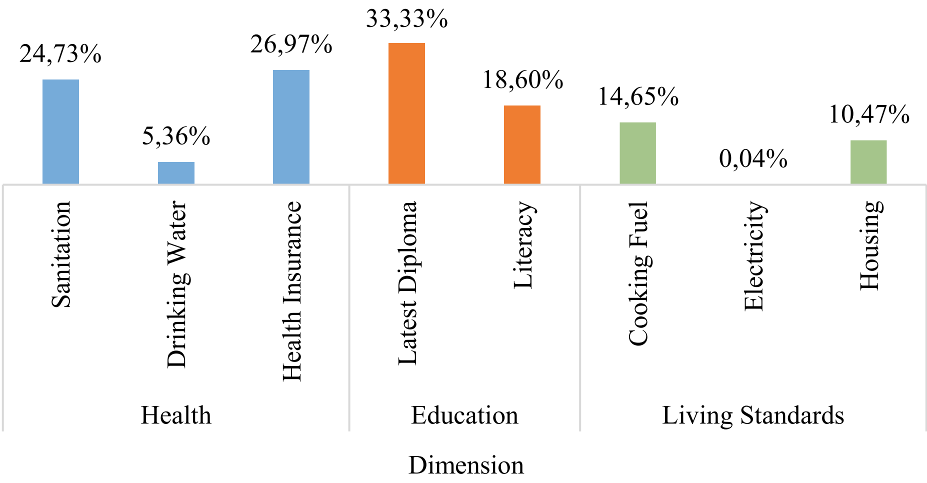
The multidimensional poverty status among older adults is determined using the Alkire-Foster method, with the unit of analysis being older adults. It is calculated based on health, education, and living standards dimensions. According to SUSENAS data, it is found that 16.99 percent of older adults in Java in 2022 are considered multidimensionally poor, while 83.01 percent are multidimensionally not poor. **Figure 1** shows that the percentage of multidimensional poverty among older adults is varying between districts.



Source: SUSENAS March 2022, processed

Figure 1. The distribution of multidimensional poverty among older adults in Java in 2022

The highest percentage of multidimensional poverty among older adults is found in Pandeglang Regency at 72.93 percent, while the lowest percentage is in South Jakarta City at 0.46 percent. Additionally, DKI Jakarta is the only province where the percentage of multidimensional poverty among older adults in each of its districts is categorized as low. The differences in percentage across districts indicate that there are regional factors influencing the multidimensional poverty among older adults in Java in 2022.



Source: SUSENAS March 2022, processed

Figure 2. The percentage of older adults based on the indicators of multidimensional poverty in Java in 2022

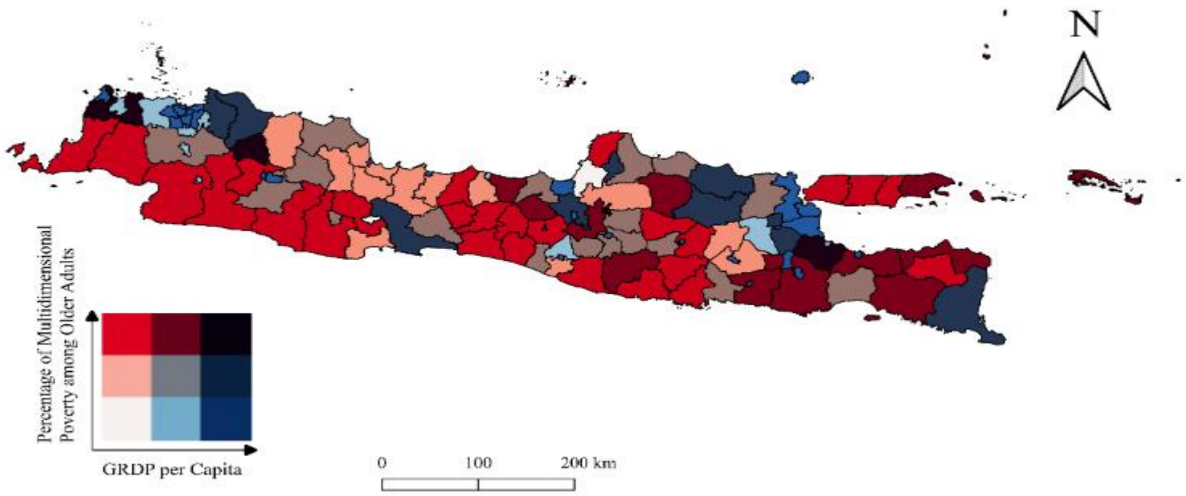
Furthermore, the percentage of older adults experiencing multidimensional poverty can be identified based on each of the contributing dimensions and indicators (**Figure 2**). In the health dimension, the indicators for health insurance and sanitation have high percentages at 26.97 percent and 24.73 percent. This means that many older adults in Java still lack health insurance and access to adequate sanitation. Meanwhile, the indicator for drinking water has the lowest percentage at 5.36 percent. This means that only a small proportion of older adults in Java do not have access to safe drinking water sources. In the education dimension, the indicators for latest diploma and literacy have high percentages at 33.33 percent and 18.60 percent. This indicates that many older adults in Java do not have at least a junior high school diploma (did not participate in a minimum of 9 years of formal education) and cannot read or write. In the living standards dimension, the indicators for cooking fuel and housing have high percentages at 14.65 percent and 10.47 percent. This indicates that many older adults in Java still lack access to cooking fuel and live in inadequate housing conditions. On the other hand, the indicator for lighting source has the lowest percentage, at 0.04 percent. This means that only a small number of older adults in Java have inadequate lighting (other than electricity).

Table 3. The Percentage of Multidimensional Poverty Among Older Adults Based on Individual Variables

Variable	Category	Multidimensionally poor (%)	Multidimensionally not poor (%)
Gender	Female	17.94	82.06
	Male (*ref*)	15.95	84.05
Marital Status	Unmarried	17.01	82.99
	Married (*ref*)	16.97	83.03
Type of Occupation	Unemployed	13.73	86.27
	Working in the agricultural sector	27.63	72.37
	Working in the non-agricultural sector (*ref*)	10.51	89.49
Functional Impairment	Yes	19.54	80.46
	No (*ref*)	15.64	84.36
Savings Ownership	No.	20.00	80.00
	Yes (*ref*)	8.94	91.06
Residential Area	Rural	30.81	69.19
	Urban (*ref*)	8.94	91.06

Source: SUSENAS March 2022, processed

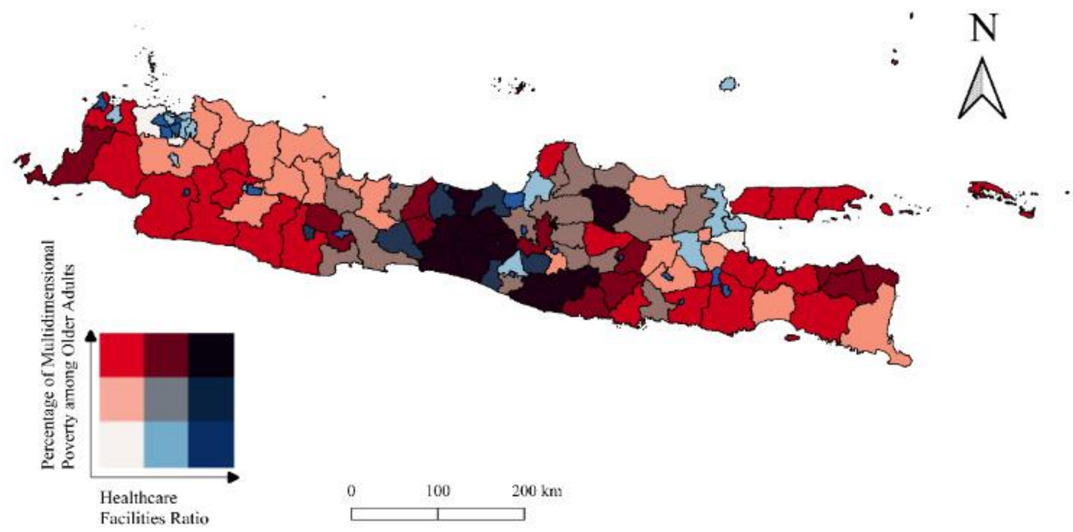
All predictor variables in this study are transformed into nominal (categorical) scales to reflect their actual group-based characteristics and to avoid assuming a linear relationship among categories. This approach allows for more precise identification of specific subgroups (e.g., gender, marital status, type of occupation), which is crucial for targeted policy recommendations. Using categorical predictors also aligns with common practices in social and demographic research, where group-based effects are often of primary interest. According to **Table 3**, older adults experiencing multidimensional poverty in Java are mainly women (17.94%), unmarried (never married, divorced, or widowed) (17.01%), working in the agricultural sector (27.63%), having functional impairment (19.54%), without savings (20.00%), and living in rural areas (30.81%). Furthermore, this research also provides an overview of the multidimensional poverty status of older adults based on regional variables, namely GRDP per capita and healthcare facilities ratio. **Figure 3** shows that districts with low GRDP per capita generally have moderate to high percentages of multidimensional poverty among older adults (indicated by red and pink colors). Meanwhile, districts with moderate to high GRDP per capita generally have low percentages of multidimensional poverty among older adults (indicated by dark blue and blue colors).



Source: SUSENAS March 2022, processed

Figure 3. The distribution of multidimensional poverty among older adults and GRDP per capita in Java in 2022

Figure 4 shows that districts with a low ratio of healthcare facilities generally have moderate to high percentages of multidimensional poverty among older adults (indicated by red and pink colors). Meanwhile, districts with a moderate to high ratio of healthcare facilities generally have low percentages of multidimensional poverty among older adults (indicated by dark blue and blue colors).



Source: SUSENAS March 2022, processed

Figure 4. The distribution of multidimensional poverty among older adults and the healthcare facilities ratio in Java in 2022

To identify the variables affecting the multidimensional poverty status among older adults in Java, an inferential analysis was conducted using multilevel binary logistic regression. First, a random effect test was performed using the likelihood ratio test. The test result showed a statistic of 6341.797 with a p-value of 0.000. Since the test statistic is higher than $\chi^2_{(0,05;1)} = 3{,}841$ and p-value < 0.05, the null hypothesis was rejected. This means there is a significant random effect, indicating that multilevel binary logistic regression is more suitable for modeling the multidimensional poverty status among older adults in Java compared to single-level binary logistic regression. Next, the Intraclass Correlation Coefficient (ICC) was calculated and found to be 0.383. This indicates that 38.3 percent of the variation in the multidimensional poverty status among older adults in Java is influenced by differences in characteristics between districts.

A simultaneous parameter test was performed. The test statistics obtained were 1876.720 with p-value of 0.000. Since the test statistic exceeds $\chi^2_{(0,05;9)} = 16{,}919$ and p-value < 0.05, the null hypothesis was rejected. Thus, it was concluded that at least one explanatory variable significantly affects the multidimensional poverty status among older adults in Java. Furthermore, partial parameter tests were performed to identify which explanatory variables at both the individual and regional levels significantly influence the multidimensional poverty status among older adults in Java, as shown in **Table 4**.

Based on these partial test results shown in **Table 4**, variables with $|Z|$ values greater than $Z_{(0.05/2)} = 1{,}96$ and p-value < 0.05 were identified, indicating that these variables significantly influence the multidimensional poverty status among older adults in Java in 2022. At the individual level, the significant variables are gender, marital status, type of occupation (working in the agricultural sector), functional impairment, savings ownership, and residential area. At the regional level (districts), the significant variables are GRDP per capita and healthcare facilities ratio.

Table 4. The Results of Multilevel Binary Logistic Regression Model Parameter Estimation

Variable	Category	Coefficient	Standard Error	*Z-value*	*p-value*	*Odds Ratio*
Intercept		-2.378	0.173	-13.772	0.000*	-
Individual Level						
Gender	Female	0.263	0.030	8.633	0.000*	1.301
	Male (*ref*)					
Marital Status	Unmarried	0.071	0.031	2.339	0.019*	1.074
	Married (*ref*)					
Type of Occupation	Unemployed	-0.064	-0.042	-1.515	0.130	0.938
	Working in the agricultural sector	0.457	0.041	11.095	0.000*	1.579
	Working in the non-agricultural (*ref*)					
Functional Impairment	Yes	0.317	0.029	11.043	0.000*	1.373
	No (*ref*)					
Savings Ownership	No.	0.562	0.035	16.263	0.000*	1.754
	Yes (*ref*)					
Residential Area	Rural	0.900	0.032	28.210	0.000*	2.460
	Urban (*ref*)					
Regional Level (District)						
GRDP per Capita		-0.052	0.010	-5.080	0.000*	0.949
Healthcare Facilities Ratio		-1.105	0.335	-3.298	0.001*	0.331

Source: SUSENAS March 2022, processed

Therefore, the multilevel binary logistic regression equation with a random intercept is formulated as follows:

$$ln\left(\frac{\hat{\pi}_{ij}}{1-\hat{\pi}_{ij}}\right) = -2.378 + u_{0j} + 0.263G_{ij} + 0.071MS_{ij} - 0.064TO\_unemployed_{ij} + 0.457TO\_agricultural_{ij} + 0.317FI_{ij} + 0.562SO_{ij} + 0.900RA_{ij} - 0.052GRDP - 1.105HEALTH_j \tag{14}$$

In addition, a multilevel binary logistic regression model with a random intercept produces a random effect denoted as u_{0j}, which captures the variability between groups (districts). By adding the fixed intercept estimate (-2.378) to the random effect for each district, different intercept values are obtained for each district. These differences indicate that the likelihood of older adults experiencing multidimensional poverty is influenced by regional variations. For example, the difference in intercept values will be illustrated from the districts with the highest and lowest percentages of multidimensional poverty of older adults in Java in 2022, namely Pandeglang Regency and South Jakarta City.

Pandeglang Regency:

$$ln\left(\frac{\hat{\pi}_{ij}}{1-\hat{\pi}_{ij}}\right) = -2.378 + 1{,}488 + 0.263G_{ij} + 0.071MS_{ij} - 0.064TO\_unemployed_{ij} + 0.457TO\_agricultural_{ij} + 0.317FI_{ij} + 0.562SO_{ij} + 0.900RA_{ij} - 0.052GRDP - 1.105HEALTH_j \tag{15}$$

South Jakarta City:

$$ln\left(\frac{\hat{\pi}_{ij}}{1-\hat{\pi}_{ij}}\right) = -2.378 - 0.701 + 0.263G_{ij} + 0.071MS_{ij} - 0.064TO\_unemployed_{ij} + 0.457TO\_agricultural_{ij} + 0.317FI_{ij} + 0.562SO_{ij} + 0.900RA_{ij} - 0.052GRDP - 1.105HEALTH_j \quad (16)$$

Furthermore, the model's goodness of fit was assessed using the Hosmer-Lemeshow test. The test statistic ($\hat{C}$) was 18.565 and p-value 0.137. Since the test statistic is smaller than $\chi^2_{(0,05;13)} = 22.362$ and p-value > 0.05, the null hypothesis could not be rejected. Therefore, it can be concluded that the model is appropriate for explaining the multidimensional poverty status among older adults in Java in 2022.

4. DISCUSSIONS

According to **Table 4**. The odds ratio for the gender variable is 1.301, which indicates that older adult women are 1.301 times more likely to experience multidimensional poverty compared to older adult men, assuming all other variables remain constant. This finding aligns with a study by Wang [7], which states that older adult women are more likely to experience multidimensional poverty than older adult men. This is because women are often more disadvantaged in accessing social resources such as financial assistance, education, and social relationships. Additionally, a study by Admasu [18] also indicates that women are more likely to experience multidimensional poverty compared to men.

The odds ratio for the marital status variable is 1.074, which indicates that older adults who are unmarried (single, divorced, or widowed) or do not have a partner are 1.074 times more likely to experience multidimensional poverty compared to older adults who are married or have a partner, assuming all other variables remain constant. This finding aligns with a study by Wang [7], which states that older adults with a partner are less likely to experience multidimensional poverty compared to those without a partner. This is because older adults without a partner tend to bear more financial and emotional pressure, increasing their risk of experiencing multidimensional poverty.

The odds ratio for the type of occupation working in the agricultural sector variable is 1.579, indicating that older adults working in the agricultural sector are 1.579 times more likely to experience multidimensional poverty compared to older adults working in the non-agricultural sectors, assuming all other variables are held constant. This finding is consistent with the research by Amalia [19], which suggests that agricultural households are more likely to experience multidimensional poverty than non-agricultural households. This is because the agricultural sector is highly unstable economically (dependent on weather and seasons) compared to the non-agricultural sector. Furthermore, non-agricultural sectors offer additional benefits for older adults, such as health insurance and retirement funds.

The odds ratio for the functional impairment variable is 1.373, which means that older adults with functional impairment are 1.373 times more likely to experience multidimensional poverty compared to older adults without functional impairment, assuming all other variables remain constant. This result is consistent with the study by Zhou [8], which found that older adults with functional impairment are more likely to experience multidimensional poverty than older adults without functional impairment. The better the health condition, the lower the likelihood of experiencing poverty.

The odds ratio for the savings ownership variable is 1.754, indicating that older adults without savings are 1.754 times more likely to experience multidimensional poverty compared to older adults with savings, assuming all other variables remain constant. This finding aligns with the study by Tran [20], which highlighted that individuals without savings are more prone to multidimensional poverty than individuals with savings. Savings provide financial security and act as an emergency fund. Additionally, having savings reflects effective financial management, enabling individuals to allocate their resources wisely and reduce the risk of multidimensional poverty.

The odds ratio for the residential area variable is 2.460, indicating that older adults living in rural areas are 2.460 times more likely to experience multidimensional poverty compared to older adults living in urban areas, assuming all other variables remain constant. This finding aligns with research by Wang [7], which highlights that older adults living in rural areas tend to face a higher likelihood of multidimensional poverty than their urban counterparts. Older adults' well-being depends significantly on physical and mental health, and urban communities generally offer better access to high-quality medical services and facilities, which are more effective in reducing multidimensional poverty.

The odds ratio for the GRDP per capita variable is 0.949, indicating that an increase of 10 million rupiahs in GRDP per capita in a district reduces the likelihood of older adults experiencing multidimensional poverty by 0.949 times, assuming all other variables remain constant. This finding aligns with research by Balasubramanian [21], which states that an increase in GRDP can alleviate multidimensional poverty. Higher GRDP is associated with improved income levels among districts, enabling older adults to afford necessary resources to support their lives, particularly in terms of healthcare and standard of living.

The odds ratio for the healthcare facility ratio variable is 0.331, indicating that for every one-unit increase in the number of healthcare facilities ratio per 10,000 people in a district, the likelihood of older adults experiencing multidimensional poverty decreases by 0.331 times, assuming all other variables remain constant. This finding aligns with Mustafa [22], who noted that limited access to healthcare facilities contributes to an increase in multidimensional poverty, particularly in the health dimension. Furthermore, an increased number ratio of healthcare facilities positively impacts the quality of life for older adults, helping them to maintain better health and live more productively.

5. CONCLUSION

Based on the findings of the study on multidimensional poverty among older adults in Java in 2022, it was revealed that only a small proportion of older adults were experiencing multidimensional poverty. In the health dimension, many older adults are deprived of sanitation and health insurance indicators. In the education dimension, many older adults are deprived of the latest diploma indicator. In the living standards dimension, many older adults are deprived of cooking fuel and housing indicators.

Furthermore, based on the multilevel binary logistic regression model, we obtained that at the individual and regional level, all the variables significantly affected the multidimensional poverty status among older adults except the type of occupation (unemployed) variable. Older adults experiencing multidimensional poverty are mainly women, unmarried (never married, divorced, or widowed), working in the agricultural sector, having functional impairment, without savings, and living in rural areas. Additionally, older adults are more likely to experience multidimensional poverty if they live in districts with low GRDP per capita and healthcare facilities ratio.

Therefore, the government is encouraged to reduce multidimensional poverty among older adults in Java with various policies based on the research findings, such as providing proper sanitation facilities as well as health insurance coverage for older adults, the distribution of cooking fuel, such as LPG or electricity, and livable housing through home renovation programs. Additionally, the government should enhance economic activities in leading economic sectors to increase GRDP per capita and build more healthcare facilities.

Finally, future research could use data collected over several years to see how multidimensional poverty changes over time among older adults. It is also recommended to include more detailed district-level factors (such as social support and community programs) to understand the local situation better. In addition, comparing different provinces in Indonesia can give more useful insights for local policymaking.

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