AGRARIS: Journal of Agribusiness and Rural Development Research

Vol. 11 No. 2 July – December 2025, Pages: 255-275

RESEARCH ARTICLE

Article history:
Submitted : December 27th, 2024
Revised : June 28th, 2025
Accepted : November 27th, 2025

Lukman Hakim[1,2*], Lala M. Kolopaking[1], Sofyan Sjaf[1], and Rilus A. Kinseng[1]

[1] Department of Communication and Community Development Sciences, Faculty of Human Ecology, IPB University, Bogor, Indonesia
[2] Rural Sociology Study Program, Faculty of Human Ecology, IPB University, Bogor, Indonesia

**) Correspondence email: lukmanhakim@apps.ipb.ac.id*

Understanding Poverty and Social Assistance Distribution: A Multidimensional Approach to Rural Poverty in Indonesia

DOI: https://doi.org/10.18196/agraris.v11i2.725

ABSTRACT

Poverty is a crucial issue to address in sustainable development, particularly in rural areas. Despite the government's attempts to intervene through social assistance programs for people experiencing poverty, poverty remains unabated. This study investigated rural poverty in Indonesia using three major analytical frameworks: the World Bank's poverty line, the BPS-Statistics Indonesia poverty line, and Indonesia's Law on Poverty Alleviation. Employing a quantitative approach with 289 respondents across three villages in West Java, the study integrated income-based and access-based indicators to construct six categories of poverty: (1) extreme poverty, (2) vulnerable to extreme poverty, (3) non-monetary poverty, (4) regional poverty, (5) vulnerable to regional poverty, and (6) non-poor. The findings revealed that 35.99% of social assistance distribution was misallocated, with 12.46% of poor people excluded and 23.53% of non-poor beneficiaries incorrectly included. By introducing a refined, empirically grounded classification system, this research enhanced multidimensional poverty measurement and advocated for systemic reforms in data collection to improve the accuracy and targeting of rural social assistance programs.

Keywords: Poverty categories; Rural poverty; Social assistance; Social protection

INTRODUCTION

Poverty remains a persistent and multifaceted challenge in global development, particularly in developing countries. In this context, the concept of social protection has emerged as an essential policy framework for poverty alleviation. According to Barrientos (2011), social protection encompasses various public policies and programs designed to safeguard individuals and households against risks, vulnerabilities, and poverty. In developing countries, social protection has a primary focus on reducing extreme poverty and empowering the most vulnerable populations. Social protection has three key roles: ensuring the fulfillment of basic needs, facilitating investment in productive assets to improve long-term welfare, and strengthening the participation of people experiencing poverty in economic development. However, challenges such as a weak governance system, corruption, and limited state capacity remain significant obstacles to its implementation (Banerjee, Hanna, Olken, & Lisker, 2024).

Both structural and cultural factors cause poverty in Indonesia. Structural drivers include economic inequality, limited access to resources, inadequate education, deficient basic services, and a bureaucracy often lacking transparency and accountability (Asian Development Bank, 2023; World Bank Group, 2021). At the cultural level, a fatalistic worldview, dependency norms, and entrenched social constructs that marginalize vulnerable groups, particularly women and youth, serve to perpetuate poverty (Handoyo, Hidayatina, & Purwanto, 2021; Sriwahyuni et al., 2025; Tetep, Suherman, Susanti, & Nisa, 2022). These structural and cultural dimensions are mutually reinforcing, generating a persistent cycle of poverty that is hard to overcome, especially in rural areas (Ambya, Nairobi, & Rizqiandri, 2019; Hanandita & Tampubolon, 2016; Sjaf, 2023).

Countries have adopted social assistance programs since the 1980s to address poverty. However, their effectiveness is still widely debated. Social protection, primarily through income support and cash transfers, plays a significant role in stabilizing household incomes during major crises such as the COVID-19 pandemic (Brik, 2024; Brollo, Ibarra, & Vale, 2024; Gasior, Jara, & Makovec, 2024; Roelen et al., 2024). In the early stages, social assistance can provide real benefits to ensure people's purchasing power (Agustanta, Dewi Anggalini, Septiningrum, & Dewanti, 2024; Unnikrishnan, 2022), but in the later stages, these programs often create dependency that hinders the economic independence of recipients (Gassmann, Martorano, & Waidler, 2022; Jara & Ludeña, 2024; Reyes, 2024). This challenge is widely felt by developing countries encountering structural poverty issues. Although social assistance provides economic benefits in the initial stages, the emergence of economic dependency indicates challenges to the long-term effectiveness of these social protection programs. The politicization of social protection programs exacerbates this further.

Politically, social protection programs are often employed as political instruments. According to Tekgüç (2018), social assistance serves not only as an instrument to overcome poverty but also as a means for political actors to raise their popularity and garner support from the electorate in general elections. Social protection programs, such as direct cash assistance, have different impacts on the level of political support for the government between recipients and non-recipients. The politicization of social assistance harms accurate distribution targets, exacerbating social inequality and contributing to political instability (Kosec & Mo, 2024). The deviation in the utilization of social assistance instruments from the government in addressing people's economic problems also impacts ecological degradation (Gupta et al., 2021).

Poverty is a significant development issue in Indonesia. The national poverty rate declined from 17.8% in 2006 to 9.4% in 2019. However, the COVID-19 pandemic has led to a temporary rise in poverty rates, particularly among women and young workers, although the government has responded by implementing social assistance programs (Adam & Negara, 2024). Several studies have demonstrated that Indonesia's social assistance programs remain ineffective. It has been depicted that social assistance spending has no discernible impact on poverty rates in several locations (Putri, Abral, & Amri, 2025). In the context of managing COVID-19, social assistance programs frequently encounter issues with disparate and overlapping budget allocations in each ministry, unintegrated recipient data, non-inclusive data collection, and an aid distribution system that fails to reach its targets (Kari, Satar, & Tedong, 2024; Ncube & Murray, 2024; Saddam & Saribulan, 2024). Unsynchronized budget allocations, unintegrated data recipients, improper distribution methods, and politicization of social assistance are among the general issues with the operation of social assistance programs (Gromadzki, Sałach, & Brzeziński, 2024; Hidayat, 2024). The top-down method of selecting aid recipients is frequently exclusive, which means it does not fully address the needs of people experiencing poverty. It implies that the accuracy of the data is critical to the effectiveness of social assistance programs. Ineffective policies, exclusive innovations, and program budgeting that could lead to corruption are all consequences of insufficient data (Gaduh, Hanna, & Olken, 2024; Pitaloka, Hendriyani, Eriyanto, & Haryatmoko, 2022; Saffanah, Hapsari, & Iskanda, 2024; Sjaf et al., 2022). As a result, social assistance programs, which frequently serve as instruments to alleviate poverty, do not, in actuality, significantly reduce poverty.

Since 2010, the Indonesian government has implemented various initiatives to alleviate poverty, one of which is the establishment of the National Team for Accelerating Poverty Reduction (TNP2K). This strategy involves reducing the financial burden on low-income groups through subsidies and social assistance, while also empowering them to enhance their economic productivity (Amin, 2021). In 2022, President Joko Widodo abolished the elimination of extreme poverty through Presidential Instruction No. 4 of 2022. These efforts include reducing the expenditure of the extreme poor, empowering communities, and building basic service infrastructure. However, the challenge of poverty is increasingly acute in rural areas, which are often the epicenter of extreme poverty. Village governments, through the Direction of the Ministry of Villages, Development of Disadvantaged Regions, and Transmigration (Kemendes PDTT), have implemented programs such as Village Cash for Work (PKTD), Village Fund Direct Cash Assistance (hereafter referred to as BLT in Indonesia), and strengthening Village-Owned Enterprises (BUMDes). However, the implementation of programs at the village level also faces various obstacles, including poor data collection, minimal community participation, and dependence on external assistance.

Poverty in rural Indonesia is not only about low income but also the inability to meet basic needs. There is a consensus among poverty researchers that poverty is multidimensional (Hick, 2016; Iglesias, Suter, Beycan, & Vani, 2017; Mideros M., 2012; Peichl & Pestel, 2013; Rao & Min, 2018). Poverty conditions are characterized by a lack of income, limited access to basic services, restricted social networks, and limited economic opportunities (Barrientos, 2011). Therefore, this study attempts to identify the level of poverty in rural areas based on three main measurement approaches: the World Bank (WB) Poverty Line, Statistics Indonesia Poverty Line, and the Poverty Line as defined in Indonesia's Law on Poverty Alleviation (Law No. 13/2011, hereafter UUFM), and integrate the three measurements. The WB and Statistics Indonesia poverty measurements emphasize income parameters, whereas the UUFM focuses on the accessibility of basic needs. By integrating monetary and non-monetary approaches, this study evaluated the relationship between income and fulfillment of basic needs. This multidimensional poverty measurement helps see the relationship between income and the fulfillment of basic needs (Alkire & Foster, 2011; D'Attoma & Matteucci, 2024; Evans, Nogales, & Robson, 2024; You, Kontoleon, & Wang, 2019). Additionally, this study examined the accessibility of social assistance programs and the effectiveness of their distribution in rural areas.

The urgency of this research lies in addressing the knowledge gap regarding the effectiveness of poverty alleviation policies, particularly in rural areas. Through multidimensional poverty measurement, this research aims to provide data-driven recommendations that enhance program implementation, support sustainable development, and significantly reduce poverty in Indonesia.

This study offers two main implications: theoretically, it advances the multidimensional measurement of poverty by introducing six empirically derived categories that integrate both monetary and non-monetary indicators, thus providing a more comprehensive understanding of rural poverty; and practically, it provides evidence-based recommendations to improve the accuracy of social assistance targeting through the strengthening of data systems that position villages as key subjects within a bottom-up framework and by formulating social assistance program interventions specifically designed to meet the needs of each poverty category in rural areas.

RESEARCH METHOD

This study was conducted through sequential stages: (1) site selection and justification, (2) sampling design and respondent criteria, (3) primary data collection, (4) poverty measurement using three established frameworks (WB, BPS, and UUFM), and (5) analysis using the Poverty Severity Index (PSI) and Poverty Gap Index (PGI). These stages were designed to ensure systematic methodology and procedural transparency throughout the research process.

The research was carried out in three villages in West Java Province, Indonesia: (1) Gelaranyar Village, Cianjur Regency; (2) Margahayu Village, Subang Regency; and (3) Pantai Bahagia Village, Bekasi Regency. These locations were purposively selected based on four criteria. First, West Java Province had one of the highest poverty rates in Indonesia, with 4,070,980 people living in poverty—3,010,360 in urban areas and 1,060,630 in rural areas (BPS-Statistics Indonesia, 2023b). Second, the province had the highest inequality rate nationally, with a Gini Index consistently above 0.4 from 2014 to 2022, peaking at 0.417 (BPS-Statistics Indonesia of Jawa Barat Province, 2022). Third, Cianjur and Subang regencies possessed poverty rates of 11.18% and 10.03%, respectively—both higher than the provincial average of 8.40%—while Bekasi regency depicted a contrasting case with a relatively low rate of 5.21% (BPS-Statistics Indonesia, 2023a). Fourth, the selected villages could represent distinct ecological typologies: a highland plantation (Gelaranyar), a rice field (Margahayu), and a coastal area (Pantai Bahagia).

Using a proportionate cluster random sampling technique, a total of 289 individuals aged 17 years and above were selected from different community units (RW), across the three villages. The sampling frame was based on secondary data drawn from the Precision Village Data (PVD), a village-level census-based data system developed in Indonesia, covering a total population of 9,054 eligible individuals for the period 2021–2022.

This study analyzed poverty using three measurement approaches: WB, BPS, and UUFM. It also calculated the Poverty Severity Index (PSI) and Poverty Gap Index (PGI). The WB framework defined poverty as a loss of welfare, determined through income or expenditure. Under this standard, individuals earning less than USD 2.15 per day or IDR 973,634 per capita per month (based on an exchange rate of IDR 15,095.10 /USD) were classified as poor.

The BPS framework defined poverty as the inability to meet minimum basic needs, as measured by monthly per capita expenditure (BPS-Statistics Indonesia, 2021). The poverty line varied by region; in this study, the thresholds were IDR 466,509 in Gelaranyar, IDR 674,924 in Pantai Bahagia, and IDR 434,161 in Margahayu (BPS-Statistics Indonesia, 2024). Individual income was estimated by aggregating each respondent's monthly expenditure, including food, non-food essentials, housing, utilities, education, debt repayments, savings, social costs (zakat, infaq, and sedekah), and transportation. These expenditure values were then compared against both WB and BPS poverty thresholds to determine classification.

According to UUFM, individuals were classified as poor if they were unemployed or unable to meet basic needs despite having income. Basic needs included food, clothing, housing, health, education, employment, and access to social assistance. This study assessed deprivation based on a range of indicators, including occupation, education level, source of drinking water, type of housing structure (floor, wall, and roof), toilet ownership, type of cooking fuel, completeness of daily meals, eating frequency, frequency of clothing purchases, electricity access, and house occupancy status.

All data were processed using Microsoft Excel for initial data handling and computation. Household expenditures were aggregated and converted into monthly per capita values to assess income-based poverty according to the WB and BPS thresholds. For the UUFM approach, poverty was measured using a weighted scoring system based on previously defined indicators of basic needs. Individuals whose scores were below the established adequacy threshold were classified as poor. Subsequently, these three frameworks were integrated to generate six intersecting categories of poverty. The final analysis examined mismatches in social assistance distribution by comparing classification outcomes with actual recipient data.

This study also measured PSI and PGI. PSI is proper for providing an overview of the distribution of expenditure among people experiencing poverty. The higher the PSI value, the greater the inequality of expenditure among people with low incomes. Furthermore, PGI is useful for providing an overview of the gap between the average expenditure of the poor and the poverty line. The higher the PGI value, the further the average expenditure of the poor is from the poverty line. The following is the calculation formula for PSI and PGI.

$$PSI=\frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^{\alpha} \tag{1}$$

α was 2; Z indicates the poverty line; y_i denotes the average monthly per capita expenditure of the population living below the poverty line ($i=1,2,3,\ldots,q$), $y_i < Z$; q signifies the number of people living below the poverty line; and n represents the number of people.

$$PGI= \frac{1}{n} \sum_{i=1}^{q} \left[\frac{z-y_i}{Z}\right] \quad (2)$$

z depicts the poverty line; y_i exhibits the average monthly per capita expenditure of the population living below the poverty line ($i=1,2,3,\ldots,q$), $y_i < Z$; q implies the number of people living below the poverty line; and n refers to the number of people.

RESULTS AND DISCUSSION

Applying the WB Poverty Measurement

In three study areas, nearly two-thirds of the sample were classified as poor based on the WB poverty measurement. The percentage of people living in poverty was 68.04% in Gelaranyar Village, 66.32% in Margahayu Village, and 68,04% in Pantai Bahagia Village. According to this, 68.04% of people in Gelaranyar Village and 66.32% of people in Margahayu Village made less than IDR 973,634 per month. Furthermore, 68,04% of the people in Pantai Bahagia Village made less than IDR 973,634 a month.

TABLE 1. NUMBER AND PERCENTAGE OF POOR POPULATION BASED ON WB POVERTY MEASUREMENT

Village	Poor		Non-poor		Total	
	Individual	Percentage (%)	Individual	Percentage (%)	Individual	Percentage (%)
Gelaranyar	66	68.04	31	31.96	97	100.00
RW 1	18	18.56	5	5.15	23	23.71
RW 2	4	4.13	16	16.50	20	20.62
RW 3	15	15.46	8	8.25	23	23.71
RW 4	15	15.46	1	1.03	16	16.49
RW 5	14	14.43	1	1.03	15	15.46
Margahayu	63	66.32	32	33.68	95	100.00
RW 1	13	13.68	0	0.00	13	13.68
RW 2	5	5.26	10	10.53	15	15.79
RW 3	7	7.37	1	1.05	8	8.42
RW 4	6	6.32	3	3.16	9	9.47
RW 5	11	11.58	0	0.00	11	11.58
RW 6	3	3.16	11	11.58	14	14.74
RW 7	9	9.47	1	1.05	10	10.53
RW 8	9	9.47	6	6.32	15	15.79
Pantai Bahagia	66	68.04	31	31.96	97	100.00
RW 1	17	17.53	8	8.25	25	25.77
RW 2	6	6.18	7	7.22	13	13.40
RW 3	12	12.37	4	4.12	16	16.49
RW 4	1	1.03	6	6.19	7	7.22
RW 5	10	10.31	2	2.06	12	12.37
RW 6	20	20.62	4	4.12	24	24.74
Total	**195**	**67.47**	**94**	**32.53**	**289**	**100.00**

Note: RW or called as Rukun Warga in Indonesian is the smallest neighborhood-level administrative unit in Indonesia

Moreover, an unequal distribution was observed in each village when examining the distribution at the RW level (Table 1). Nearly all RW in Gelaranyar Village contributed significantly to the poverty rate of over 14%. Areas with high poverty rates were RW1, RW3, RW4, and RW5. The only area with a low contribution to Gelaranyar Village's 4.12% poverty rate was RW2. The majority of RWs in Margahayu Village possessed poverty rates around 10%, except for RW1 (13.68%) and RW5 (11.58%), accounting for a larger portion of the village's poverty rate. Three RWs in Pantai Bahagia Village—RW1, RW3, RW5, and RW6—significantly raised the village's poverty rate. The poverty percentage in the area was more than 10%. In Pantai Bahagia Village, RW2 and RW4 had minimal effect on the poverty rate.

These data indicated that poverty in the three villages was concentrated in micro-administrative areas. These findings support the structural poverty theory of Hanandita & Tampubolon (2016), which posits that poor distribution is linked to the allocation of resources, infrastructure, and community institutions. The concentration of poverty in numerous RWs illustrated that village leadership, public service quality, and social networks affected welfare.

This finding exhibited that income-based measurements like the WB Poverty Line ignored spatial and institutional factors, unlike Sjaf (2023) and Widyastuti, Hartono, Sidig, & Rusmawati (2023), who emphasized multidimensional poverty based on access to services and social resilience. This study has expanded the understanding of aggregate poverty and revealed micro-level clustering patterns in RW areas, which have been rarely discussed.

Applying the Statistics Indonesia Poverty Measurement

According to Statistics Indonesia poverty measures conducted in three research areas, the most significant proportion of poverty was identified in Gelaranyar Village (36.08%), followed by Margahayu Village (31.58%) and Pantai Bahagia Village (24.74%). It signified that 36.08% of the people in Gelaranyar Village earned less than IDR 466,509 per month, while 31.58% of people in Margahayu Village earned less than IDR 434,161 per month. Additionally, 24.74% of people in Pantai Bahagia Village earned less than IDR 674,924 monthly.

RWs 1 and 4 in Gelaranyar Village emerged as the main contributors to the village's poverty rate. The poverty rate in these RWs exceeded 10%. Areas RW2, RW3, and RW5 had minimal contributions to Gelaranyar Village's poverty rate, standing at 1.03%, 2.06%, and 7.22%, respectively. In Margahayu Village, less than 10% of RWs lived in poverty, except for RW1, which accounted for the most considerable portion of Margahayu Village's poverty rate (11.58%). Additionally, five RWs in Pantai Bahagia Village—RW1, RW2, RW3, RW5, and RW6—significantly raised the village's poverty rate. The poverty rate in this region exceeded 4%. The only area not classified as having a poor population was RW4. According to BPS poverty measures, the number and percentage of persons living in poverty are distributed as follows (Table 2).

According to structural poverty theory, poverty develops from systematic disparity in resource availability between regions (Najitama, Maski, & Manzilati, 2020), and this study's findings disclosed that poverty was concentrated at the RW level. These findings suggested that income-based measures, such as the BPS version, remained relevant but did not fully capture the complexity of rural poverty. In contrast, D'Attoma & Matteucci (2024) and Sjaf (2023) emphasized non-monetary factors, including social resilience and access to basic services. These findings have contributed to a local approach to poverty identification, a novelty not previously observed in earlier studies.

TABLE 2. NUMBER AND PERCENTAGE OF THE POOR BASED ON THE BPS POVERTY MEASUREMENT

Village	Poor		Non-poor		Total	
	Individual	Percentage (%)	Individual	Percentage (%)	Individual	Percentage (%)
Gelaranyar	35	36.08	62	63.92	97	100.00
RW 1	15	15.46	8	8.25	23	23.71
RW 2	1	1.03	19	19.59	20	20.62
RW 3	2	2.06	21	21.65	23	23.71
RW 4	10	10.31	6	6.19	16	16.49
RW 5	7	7.22	8	8.25	15	15.46
Margahayu	30	31.58	65	68.42	95	100.00
RW 1	11	11.58	2	2.10	13	13.68
RW 2	1	1.05	14	14.74	15	15.79
RW 3	2	2.11	6	6.31	8	8.42
RW 4	1	1.05	8	8.42	9	9.47
RW 5	8	8.42	3	3.16	11	11.58
RW 6	0	0.00	14	14.74	14	14.74
RW 7	6	6.32	4	4.21	10	10.53
RW 8	1	1.05	14	14.74	15	15.79
Pantai Bahagia	24	24.73	73	75.27	97	100.00
RW 1	6	6.18	19	19.59	25	25.77
RW 2	4	4.12	9	9.28	13	13.40
RW 3	4	4.12	12	12.37	16	16.49
RW 4	0	0.00	7	7.22	7	7.22
RW 5	4	4.12	8	8.25	12	12.37
RW 6	6	6.19	18	18.56	24	24.74
Total	**89**	**30.80**	**200**	**69.20**	**289**	**100.00**

Poverty Severity Index (PSI) and Poverty Gap Index (PGI)

This study also calculated PSI and PGI using the WB poverty line, which was IDR 973,634 per capita per month, and the BPS poverty line, which was IDR 466,509 per capita per month in Gelaranyar Village, IDR 434,161 per capita per month in Margahayu Village, and IDR 674,924 per capita per month in Pantai Bahagia Village. Based on the BPS and WB poverty lines in the three villages, PSI and PGI were calculated as follows (Table 3).

Based on the calculations of PSI and PGI, Gelaranyar Village generated the highest PSI and PGI compared to the other two villages. High PSI indicated high income inequality among people experiencing poverty in Gelaranyar Village. In Gelaranyar Village, a high PGI signified the extreme severity of poverty. It implied that the gap between the average income and the WB and BPS poverty lines in Gelaranyar Village was significantly lower. Meanwhile, Margahayu Village was depicted as having a lower level of poverty severity compared to Gelaranyar Village, which fell into the medium category. However, Margahayu Village's PGI belonged to the high category.

TABLE 3. PSI AND PGI BASED ON THE WB AND BPS POVERTY LINES

Village	PSI		PGI	
	WB	BPS	WB	BPS
Gelaranyar	0.21	0.07	0.50	0.37
Margahayu	0.20	0.05	0.48	0.34
Pantai Bahagia	0.07	0.01	0.28	0.18
Low (< 0.1) Medium (0.1-0.2) high (>0.2)				

Meanwhile, Pantai Bahagia village had a relatively lower PSI and PGI compared to other villages. Pantai Bahagia Village's low PSI indicated a relatively even distribution of income among the poor population. However, the classification of Pantai Bahagia Village's PGI as high indicated that the average income of the poor remained significantly lower than the WB and BPS poverty lines.

TABLE 4. NUMBER AND PERCENTAGE OF POOR POPULATION BASED ON UUFM POVERTY MEASUREMENT

Village	Poor		Non-poor		Total	
	Individual	Percentage (%)	Individual	Percentage (%)	Individual	Percentage (%)
Gelaranyar	20	20.62	77	79.38	97	100.00
RW 1	0	0	23	23.71	23	23.71
RW 2	1	1.03	19	19.59	20	20.62
RW 3	19	19.59	4	4.12	23	23.71
RW 4	0	0	16	16.49	16	16.49
RW 5	0	0	15	15.46	15	15.46
Margahayu	0	0	95	100.00	95	100.00
RW 1	0	0	13	13.68	13	13.68
RW 2	0	0	15	15.79	15	15.79
RW 3	0	0	8	8.42	8	8.42
RW 4	0	0	9	9.47	9	9.47
RW 5	0	0	11	11.58	11	11.58
RW 6	0	0	14	14.74	14	14.74
RW 7	0	0	10	10.53	10	10.53
RW 8	0	0	15	15.79	15	15.79
Pantai Bahagia	5	5.15	92	94.85	97	100.00
RW 1	0	0	25	25.77	25	25.77
RW 2	1	1.03	12	12.37	13	13.40
RW 3	0	0	16	16.49	16	16.49
RW 4	0	0	7	7.22	7	7.22
RW 5	2	2.06	10	10.31	12	12.37
RW 6	2	2.06	22	22.68	24	24.74
Total	**25**	**8.65**	**264**	**91.35**	**289**	**100.00**

Applying the Indonesia's Law on Poverty Alleviation (UUFM) Measurement

UUFM was the third measure of poverty in this study. UUFM has placed a strong emphasis on non-income factors, including the availability of people's basic needs, such as food, clothing, housing, health, occupation, and education. According to the measurement results, 25 people from the three villages lived in poverty. The analysis unveiled that Margahayu Village had no poor people, while Pantai Bahagia Village possessed 5.15% and Gelaranyar Village had 20.6%. The UUFM poverty measurement revealed the following numbers and percentages of individuals living in poverty (Table 4).

According to the UUFM criteria, the majority of people in the three villages were able to fulfill their basic needs. They also had adequate access to clothing, food, shelter, health, occupation, and education. UUFM classified a small percentage of the population as poor in Gelaranyar Village and Pantai Bahagia Village. Low incomes could also contribute to their limited ability to fulfill basic needs. They were impoverished people lacking both financial resources and having low accessibility to fulfilling basic needs.

Intersection of poverty: World Bank (WB), Statistics Indonesia (BPS), and Indonesia's Law on Poverty Alleviation (UUFM)

The intersection between the poverty measurements of WB, BPS, and UUFM has become an intriguing observation. The WB poverty measurement successfully identified 195 people categorized as poor, accounting for 67.47% of the population in the three villages. The BPS poverty measurement identified 89 people categorized as poor, amounting to 30.79% of the population in the three villages. Finally, the UUFM poverty measurement acknowledged 25 individuals as poor, totaling 8.65% of the population in the three villages. The following represents the total number of poor people as determined by the WB, BPS, and UUFM (Table 5).

TABLE 5. NUMBER OF POOR PEOPLE ACCORDING TO WORLD BANK (WB), STATISTICS INDONESIA (BPS), AND INDONESIA'S LAW ON POVERTY ALLEVIATION (UUFM)

Village	Number of Poor (Individuals)		
	WB	BPS	UUFM
Gelaranyar	66	35	20
Margahayu	63	30	0
Pantai Bahagia	66	24	5
Total	**195**	**89**	**25**

As the previous subchapter indicated, it is intriguing to observe the connections between these three measures of poverty. Are all three measures valid for classifying populations as poor? A Venn diagram was utilized to illustrate the intersection of WB, BPS, and UUFM.

The Venn diagram revealed several patterns in the distribution of the number of poor people based on WB, BPS, and UUFM standards (Figure 1). WB identified a total of 93 individuals living in poverty. UUFM alone distinguished eight poor people. There were no individuals classified as poor solely based on BPS, without any overlap with either WB or UUFM. It implied that both WB and UUFM standards entirely covered the BPS poverty line. WB utilized a poverty line of IDR 973,634 per capita per month, which was higher than the poverty line set by the BPS. It explained why, according to BPS, people experiencing poverty were also included in the WB category. Most people experiencing poverty, according to the WB, were not considered poor by BPS or UUFM. It indicated that WB has focused more on global economic vulnerability and poverty, without considering access to basic services. Thus, these 93 individuals required attention because they may be on the verge of local poverty but have not received adequate social intervention.

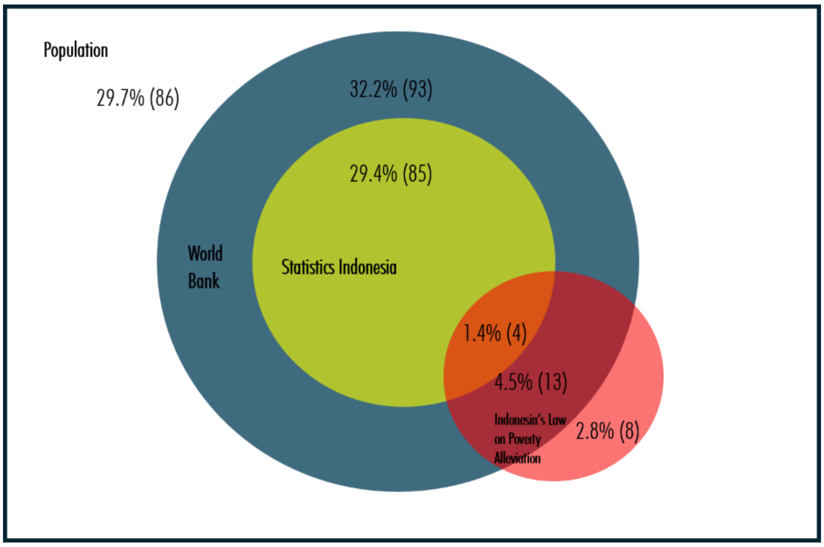

FIGURE 1. VENN DIAGRAM OF POVERTY ACCORDING TO WORLD BANK, STATISTICS INDONESIA, AND INDONESIA'S LAW ON POVERTY ALLEVIATION

BPS, which utilized the regional poverty line, failed to include individuals not covered by the WB. It indicated that the WB standard was more comprehensive in identifying impoverished individuals within the regional context. Even though their income exceeded the WB poverty line, individuals classified as poor by the UUFM and not covered by the WB or BPS (up to eight people) struggled to access necessities such as food, clothing, housing, healthcare, employment, and education. It highlights the significance of incorporating non-monetary dimensions into the analysis of rural poverty, as some individuals, despite not being economically impoverished, still faced multidimensional vulnerabilities. Therefore, programs prioritizing access to education, health, and basic needs were necessary for the eight individuals identified as poor by the UUFM. According to BPS and WB, there were 85 poor people; according to WB and UUFM, there were 13 poor people; and according to BPS and UUFM, there were no poor people. Finally, four poor people were identified according to WB, BPS, and UUFM. It demonstrated the distinct focuses of the WB, BPS, and UUFM approaches: First, WB highlights economically vulnerable individuals in a global context. Second, BPS stresses absolute regional poverty. Third, UUFM focuses on the dimensions of basic needs and access to services.

These findings have reinforced Alkire & Foster's (2011) multidimensional poverty model, which links low income to limited access to fundamental services, including education, health, and housing. According to WB, BPS, and UUFM, these metrics failed to capture the majority of impoverished people, highlighting the limitations of income metrics in assessing local vulnerability aspects. Those classified as poor by UUFM but not WB or BPS (eight people) expressed significant non-monetary poverty. Institutional determinants and availability to essential services have become crucial to rural poverty dynamics, as Najitama et al. (2020) discovered. D'Attoma & Matteucci (2024) emphasized the need to quantify poverty using income and non-income factors.

According to WB, BPS, and UUFM, the intersection of poverty formed six categories of poverty: extreme poverty, vulnerable to extreme poverty, non-monetary poverty, regional poverty, vulnerable to regional poverty, and non-poor (Table 6). (1) Extreme poverty refers to individuals who have incomes below the BPS and WB poverty lines, and have minimal accessibility to basic needs for food, housing, clothing, health, occupation and education; (2) Vulnerable to extreme poverty denotes individuals who have minimal fulfillment of basic needs for food, housing, clothing, health, occupation and education, have incomes above the BPS poverty line and are below the WB poverty line; (3) Non-monetary poverty exhibits individuals who have minimal fulfillment of basic needs for food, housing, clothing, health, occupation and education; (4) Regional poverty demonstrates individuals with incomes below the BPS and WB poverty lines but whose basic needs for food, housing, clothing, health, occupation and education are met; (5) Vulnerable to regional poverty indicates individuals who have incomes below the WB poverty line but above the BPS poverty line and whose basic needs for food, housing, clothing, health, occupation and education are met; (6) Non-poor depicts individuals with incomes above the BPS and WB poverty lines and whose basic needs for food, housing, clothing, health, occupation, and education are met.

TABLE 6. POVERTY CATEGORIZATION BASED ON THE INTERSECTION OF WORLD BANK, STATISTICS INDONESIA, AND INDONESIA'S LAW ON POVERTY ALLEVIATION STANDARDS

No.	Category	Income	Access to Basic Needs
1.	Extreme poverty	Below the poverty lines of WB and BPS	Low
2.	Vulnerable to extreme poverty	Above the BPS poverty line and below the WB poverty line	Low
3.	Non-monetary poverty	Above the WB poverty line	Low
4.	Regional poverty	Below the BPS poverty line and below the WB poverty line	Sufficient
5.	Vulnerable to regional poverty	Above the BPS poverty line and below the WB poverty line	Sufficient
6.	Non-poor	Above the WB poverty line	Sufficient

These data confirmed the significance of integrating income (WB, BPS) and non-income (UUFM) parameters to understand the complexity of poverty. UUFM has complemented the measurement deficiencies of WB and BPS by capturing dimensions of basic needs not quantified through income. Considering the fundamental differences between the approaches, this analysis could strengthen the argument for a more holistic poverty policy oriented toward the multidimensionality of basic needs, especially in rural areas.

These findings proved that poverty in rural Indonesia could not be fully captured by income-based measures alone. The distinct results across WB, BPS, and UUFM have reflected what Alkire and Foster (2011) defined as multidimensional poverty, where deprivation stems not only from low income but also from limited access to basic needs such as health, education, and shelter. It supports the structural poverty perspective, which views poverty as the result of systemic failures in data governance and resource distribution (Ambya et al., 2019; Hanandita & Tampubolon, 2016; Sjaf, 2023).

Distribution of Social Assistance

The main novelty of this study lies in its development of six categories of poverty, derived from the intersection of WB, BPS, and UUFM poverty measurements. This approach not only provided a more accurate identification of poverty but also challenged conventional classification models by integrating income and access-based metrics. Based on these categories, this study further examined the distribution of social assistance in rural areas to assess the accuracy and equity of current targeting practices.

This study investigated the implementation of social assistance programs in rural areas. Five categories, encompassing extreme poverty, vulnerable to extreme poverty, non-monetary poverty, regional poverty, and vulnerable to regional poverty, have been deemed eligible for social assistance, based on the intersection of poverty measurements by WB, BPS, and UUFM. Meanwhile, the entitlement to social assistance should not extend to non-poor individuals (Table 7).

In the extreme poverty category, out of 1.38% of individuals, 0.69% received the Family Hope Program (Indonesia's conditional cash transfer program or PKH in Indonesian); 0.35% attained two to three social assistance programs, and 0.35% did not obtain any social assistance at all. It indicated that the extreme poverty group had limited access to social assistance programs. In fact, this group was the one most in need of social assistance programs to improve and ease their standard of living. Second, of the 4.50% of individuals in the vulnerable to extreme poverty category, 2.08% received the Non-Cash Food Assistance (in Indonesia called as Bantuan Pangan Non-Tunai (BPNT)), 0.69% acquired two to three social assistance programs, 0.69% obtained rice food assistance, and 1.04% did not receive any social assistance.

Thirdly, of the 2.77% of the population living in non-monetary poverty, only a small portion received assistance, such as BPNT (0.69%) and rice food assistance (0.69%), while 1.04% did not receive any social assistance at all. Fourth, out of the 29.41% who fell under the regional poverty category, 4.48% received direct cash assistance from the Village Fund (Village Fund BLT), 9.69% obtained BPNT, 1.04% attained PKH, 8.65% acquired two to three social assistance programs, 0.35% accepted more than three social assistance programs, 1.38% received rice food assistance, and 3.46% had no social assistance whatsoever. Fifth, of the 32.18% vulnerable to regional poverty, 2.77% received Village Fund BLT, 4.15% attained BPNT, 0.69% acquired People's Business Credit (KUR), 1.38% obtained PKH, 12.11% had two to three social assistance programs, 0.35% got more than three social assistance programs, 4.15% received rice food assistance, and 6.23% acquired no social assistance at all. Meanwhile, out of the 29.76% of non-poor individuals, 4.84% obtained Village Fund BLT, 3.46% acquired BPNT, 0.35% attained KUR, 4.15% received PKH, 7.61% acknowledged two to three social assistance programs, 0.69% accepted more than three social assistance programs, 2.42% received rice food assistance, and 6.23% did not receive any social assistance.

TABLE 7. NUMBER AND PERCENTAGE OF INDIVIDUALS BASED ON POVERTY CATEGORIZATION AND ACCESS TO SOCIAL ASSISTANCE

Category	Direct cash assistance (Village Fund BLT)		Non-cash Food Assistance (BPNT)		People's Business Credit (KUR)		Family Hope Program (PKH)		2-3 Social Assistance Programs		> 3 Social Assistance Programs		Rice Food Assistance		Not received social assistance		Grand Total	
	Σ	%	Σ	%	Σ	%	Σ	%	Σ	%	Σ	%	Σ	%	Σ	%	Σ	%
Extreme poverty	0	0.00	0	0.00	0	0.00	2	0.69	1	0.35	0	0.00	0	0.00	1	0.35	4	1.38
Non-monetary poverty	1	0.35	2	0.69	0	0.00	0	0.00	0	0.00	0	0.00	2	0.69	3	1.04	8	2.77
Vulnerable to extreme poverty	0	0.00	6	2.08	0	0.00	0	0.00	2	0.69	0	0.00	2	0.69	3	1.04	13	4.50
Regional poverty	14	4.84	28	9.69	0	0.00	3	1.04	25	8.65	1	0.35	4	1.38	10	3.46	85	29.41
Vulnerable to regional poverty	8	2.77	12	4.15	2	0.69	4	1.38	35	12.11	1	0.35	12	4.15	19	6.57	93	32.18
Non-poor	14	4.84	10	3.46	1	0.35	12	4.15	22	7.61	2	0.69	7	2.42	18	6.23	86	29.76
Grand Total	**37**	**12.80**	**58**	**20.07**	**3**	**1.04**	**21**	**7.27**	**85**	**29.41**	**4**	**1.38**	**27**	**9.34**	**54**	**18.69**	**289**	**100.00**

The results of this study uncovered that 12.46% of the eligible community groups for social assistance did not receive any. On the other hand, 23.53% of the community groups that should not be entitled to social assistance actually received social assistance programs. In fact, 7.61% of the non-poor community groups attained two to three social assistance programs, and 0.69% acquired more than three social assistance programs. Thus, the level of inaccuracy in the distribution of social assistance was 35.99%. The main programs, such as Village Fund BLT, PKH, Rice Food Assistance, BPNT, and KUR, were primarily targeted at the extremely poverty, non-monetary poverty, regional poverty, and those vulnerable to extreme poverty. It suggested an issue with the distribution of social assistance.

On the other hand, the non-poor category still obtained a significant proportion of assistance, indicating the need for an evaluation of the distribution of social assistance. This discovery corroborates previous studies, which mentioned that the implementation of social assistance often fails and is ineffective due to inappropriate program targeting (Noerkaisar, 2021; Walker, Li, & Yang, 2022). These findings align with those of Pitaloka et al. (2022) and Sjaf (2023), who noted that data exclusion and centralized targeting systems often overlook local realities. However, unlike previous studies that focused on one-dimensional classifications, this study offers an empirically grounded, multidimensional categorization, enabling more accurate policy responses.

Theoretical and Practical Implications

Theoretically, this study has contributed to the literature on multidimensional poverty by proposing six categories of poverty, thereby offering a more comprehensive depiction of rural poverty. Unlike traditional unidimensional models that focus solely on income (Jadoon, Tanveer, Faiq Javed, & Sarwar, 2021), this approach incorporates both economic capacity and access to basic needs. While the dual cutoff method of Alkire & Foster (2011) identifies poverty based on complex deprivation aggregation and produces categories like poor, vulnerable non-poor, and non-poor (Ervin, Gayoso de Ervin, Molinas Vega, & Sacco, 2018), this study has introduced a simpler, context-driven classification based on intersecting WB, BPS, and UUFM criteria, resulting in six categories of poverty that are more distinct and policy-relevant for rural interventions.

This study introduced six poverty categories: extreme poverty, vulnerable to extreme poverty, non-monetary poverty, regional poverty, vulnerable to regional poverty, and non-poor. It has addressed criticisms of Indonesia's fragmented and overly technical poverty indices (Hanandita & Tampubolon, 2016) while responding to the global call for locally grounded measurements (D'Attoma & Matteucci, 2024). By building upon and enriching existing global typologies—such as monetary poverty (Jadoon, Tanveer, Faiq Javed, & Sarwar, 2021), human capital poverty (Burchi, Espinoza-Delgado, Montenegro, & Rippin, 2021; Mitra, Posarac, & Vick, 2013), social inclusion poverty (Sindzingre, 2013), living standards poverty, and disability-related poverty (Park & Nam, 2020)—this model could strengthen both the analytical relevance and practical applicability of multidimensional poverty frameworks in rural contexts.

Practically, this study reported that 35.99% of social assistance was misallocated—12.46% of people experiencing poverty received no aid, while 23.53% of the non-poor did. It has confirmed earlier findings that social assistance programs often fail due to inaccurate targeting (Noerkaisar, 2021; Walker et al., 2022). Three core issues underpin this failure: policymakers' inability to accurately identify people experiencing poverty; poverty measurement that overlooks non-monetary deprivations; and the lack of systemic reform to ensure inclusive and responsive social protection. Improving rural poverty alleviation requires a multidimensional data system that accurately captures income and basic needs, built on a bottom-up approach that empowers villages as data agents. This system should guide targeted social protection aligned with Sustainable Development Goals (SDGs) target 1.3 on inclusive coverage.

CONCLUSION

This study has confirmed that rural poverty in Indonesia could not be comprehensively understood solely through income-based measures. By intersecting three poverty frameworks—WB, BPS, and UUFM—this research identified six nuanced categories of poverty integrating both monetary and non-monetary dimensions. These categories have offered a more accurate representation of deprivation in rural areas and highlighted significant inconsistencies in the targeting of social assistance. With a 35.99% misalignment rate—where many eligible individuals were excluded, and many ineligible individuals benefited—this study underscored the limitations of current poverty targeting systems. The findings have reinforced the structural nature of poverty, shaped by institutional failures and data system deficiencies. As a practical response, this research proposed the implementation of a participatory, village-based data collection model and the development of differentiated social protection interventions customized to each poverty category. By offering a context-specific, multidimensional classification framework, this study has made both conceptual and operational contributions to the improvement of poverty alleviation strategies in Indonesia's rural areas. Future studies should validate this classification model in other regional contexts and examine its potential integration into national poverty reduction and social protection systems.

Acknowledgments: We would like to thank the Center for Educational Financial Services (PUSLAPDIK Indonesia), the Education Fund Management Institute (LPDP Indonesia), the Precision Village Data Laboratory, Faculty of Human Ecology, IPB University, and the Rural Sociology Study Program, Department of Communication Science and Community Development, Faculty of Human Ecology, IPB University. The authors would also like to thank the Center for Education Financial Services (PUSLAPDIK Indonesia) and the Indonesia Endowment Funds for Education (LPDP Indonesia) for providing a grant for this research.

Author contributions: LH: conceptualization, methodology, data collection, data analysis, writing original draft, writing review editing, and validation; LMK, SS, and RAK: conceptualization, methodology, validation; SS: conceptualization, methodology, supervision, and validation.

Conflict of interest: Authors declare no conflict of interest

REFERENCES

Adam, L., & Negara, S. D. (2024). Poverty Trends during the Jokowi Era: Achievements, Challenges and Prospects. In *Southeast Asian Affairs 2024* (pp. 109–126). ISEAS–Yusof Ishak Institute Singapore. https://doi.org/10.1355/9789815203516-008

Agustanta, N., Dewi Anggalini, T., Septiningrum, L., & Dewanti, P. (2024). Assessing the Effectiveness of Social Assistance Programs to Alleviating Poverty in Indonesia. *KnE Social Sciences*. https://doi.org/10.18502/kss.v9i7.15526

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, *95*(7–8), 476–487. https://doi.org/10.1016/j.jpubeco.2010.11.006

Ambya, Nairobi, & Rizqiandri, M. (2019). The Alleviation of Allocation Funding and Rural Poverty in Indonesia. *International Journal of Economics, Business, and Entrepreneurship*, *2*(2), 123–136. https://doi.org/10.23960/ijebe.v2i2.57

Amin, M. (2021). Strategi Penanggulangan Kemiskinan. Retrieved from Kompas website: https://www.kompas.id/baca/opini/2021/05/19/strategi-penanggulangan-kemiskinan-3/

Asian Development Bank. (2023). *Annual report 2023: Accelerating Climate Action for Sustainable Development*. Retrieved from https://www.developmentaid.org/api/frontend/cms/file/2022/08/adb-annual-report-2023.pdf

Banerjee, A., Hanna, R., Olken, B., & Lisker, D. S. (2024). *Social Protection in the Developing World* (No. 32382). Cambridge, United States. https://doi.org/10.3386/w32382

Barrientos, A. (2011). Social protection and poverty. *International Journal of Social Welfare*, 20(3), 240–249. https://doi.org/10.1111/j.1468-2397.2011.00783.x

BPS-Statistics Indonesia. (2021). *Village Potential Statistics of Indonesia*. Jakarta: BPS-Statistics Indonesia. Retrieved from https://www.bps.go.id/id/publication/2022/03/24/ceab4ec9f942b1a4fdf4cd08/statistik-potensi-desa-indonesia-2021.html

BPS-Statistics Indonesia. (2023a). Jumlah Penduduk Miskin (Ribu Jiwa) di Provinsi Jawa Barat, 2021-2023. Retrieved from BPS-Statistics Indonesia website: https://jabar.bps.go.id/id/statistics-table/2/ODMjMg==/jumlah-penduduk-miskin.html

BPS-Statistics Indonesia. (2023b). Profil Kemiskinan di Indonesia Maret 2023. Retrieved from BPS-Statistics Indonesia website: https://www.bps.go.id/id/pressrelease/2023/07/17/2016/profil-kemiskinan-di-indonesia-maret-2023.html

BPS-Statistics Indonesia. (2024). Garis Kemiskinan Menurut Kabupaten/Kota tahun 2022-2024. Retrieved from BPS-Statistics Indonesia website: https://www.bps.go.id/id/statistics-table/2/NjI0IzI=/garis-kemiskinan-menurut-kabupaten-kota.html

BPS-Statistics Indonesia of Jawa Barat Province. (2022). Rasio Gini Provinsi Jawa Barat. Retrieved from BPS-Statistics Jawa Barat Province website: https://jabar.bps.go.id/id/pressrelease/2023/01/16/1088/gini-ratio-september-2022-tercatat-sebesar-0-412-.html

Brik, A. Ben. (2024). Social protection and labor market policies during the COVID-19 pandemic in the MENA region. In *Public Policy in the Arab World* (pp. 193–215). Edward Elgar Publishing. https://doi.org/10.4337/9781035312696.00020

Brollo, F., Ibarra, G. L., & Vale, R. C. (2024). *Strengthening Income Stabilization through Soscial Protection in Emerging anda Developing Economies* (No. WP/24/52). Retrieved from https://www.elibrary.imf.org/downloadpdf/view/journals/001/2024/052/article-A000-en.pdf

Burchi, F., Espinoza-Delgado, J., Montenegro, C. E., & Rippin, N. (2021). An Individual-based Index of Multidimensional Poverty for Low- and Middle-Income Countries. *Journal of Human Development and Capabilities*, *22*(4), 682–705. https://doi.org/10.1080/19452829.2021.1964450

D'Attoma, I., & Matteucci, M. (2024). Multidimensional poverty: an analysis of definitions, measurement tools, applications and their evolution over time through a systematic review of the literature up to 2019. *Quality & Quantity*, *58*(4), 3171–3213. https://doi.org/10.1007/s11135-023-01792-8

Ervin, P. A., Gayoso de Ervin, L., Molinas Vega, J. R., & Sacco, F. G. (2018). Multidimensional Poverty in Paraguay: Trends from 2000 to 2015. *Social Indicators Research*, *140*, 1035–1076. https://doi.org/10.1007/s11205-017-1795-x

Evans, M., Nogales, R., & Robson, M. (2024). Monetary and Multidimensional Poverty: Correlation, Mismatches, and a Combined Approach. *The Journal of Development Studies*, *60*(1), 147–170. https://doi.org/10.1080/00220388.2023.2252140

Gaduh, A., Hanna, R., & Olken, B. A. (2024). The Marginal Disutility from Corruption in Social Programs: Evidence from Program Administrators and Beneficiaries. *American Economic Review: Insights*, *6*(1), 105–119. https://doi.org/10.1257/aeri.20230008

Gasior, K., Jara, H. X., & Makovec, M. (2024). Assessing the effectiveness of social protection measures in mitigating COVID-19-related income shocks in the European union. *Economic Analysis and Policy*, *83*, 583–605. https://doi.org/10.1016/j.eap.2024.07.004

Gassmann, F., Martorano, B., & Waidler, J. (2022). How Social Assistance Affects Subjective Wellbeing: Lessons from Kyrgyzstan. *The Journal of Development Studies*, *58*(4), 827–847. https://doi.org/10.1080/00220388.2021.1988079

Gromadzki, J., Sałach, K., & Brzeziński, M. (2024). When populists deliver on their promises: the electoral effects of a large cash transfer programme in Poland. *Economica*, *91*(361), 320–345. https://doi.org/10.1111/ecca.12505

Gupta, J., Bavinck, M., Ros-Tonen, M., Asubonteng, K., Bosch, H., van Ewijk, E., … Verrest, H. (2021). COVID-19, poverty and inclusive development. *World Development*, *145*, 105527. https://doi.org/10.1016/j.worlddev.2021.105527

Hanandita, W., & Tampubolon, G. (2016). Multidimensional Poverty in Indonesia: Trend Over the Last Decade (2003–2013). *Social Indicators Research*, *128*(2), 559–587. https://doi.org/10.1007/s11205-015-1044-0

Handoyo, F., Hidayatina, A., & Purwanto, P. (2021). The Effect of Rural Development on Poverty Gap, Poverty Severity and Local Economic Growth in Indonesia. *Jurnal Bina Praja*, *13*(3), 369–381. https://doi.org/10.21787/jbp.13.2021.369-381

Hick, R. (2016). The Coupling of Disadvantages: Material Poverty and Multiple Deprivation in Europe before and after the Great Recession. *European Journal of Social Security*, *18*(1), 2–29. https://doi.org/10.1177/138826271601800101

Hidayat, M. M. (2024). The 2024 General Elections in Indonesia: Issues of Political Dynasties, Electoral Fraud, and The Emergence of A National Protest Movements. *IAS Journal of Localities*, *2*(1), 33–51. https://doi.org/10.62033/iasjol.v2i1.51

Iglesias, K., Suter, C., Beycan, T., & Vani, B. P. (2017). Exploring Multidimensional Well-Being in Switzerland: Comparing Three Synthesizing Approaches. *Social Indicators Research*, *134*, 847–875. https://doi.org/10.1007/s11205-016-1452-9

Jadoon, A. K., Tanveer, A., Faiq Javed, M., & Sarwar, A. (2021). Minimum Wages and Poverty: A Cross-Country Analysis. *Asian Economic and Financial Review*, *11*(8), 632–643. https://doi.org/10.18488/journal.aefr.2021.118.632.643

Jara, H. X., & Ludeña, M. G. P. (2024). Rethinking social assistance amid the COVID-19 pandemic: Guaranteeing the right to income security in Ecuador. *Journal of International Development*, *36*(3), 1738–1764. https://doi.org/10.1002/jid.3878

Kari, F., Satar, N. M., & Tedong, P. A. (2024). Evaluation of Social Protection during the Covid-19 Pandemic among the Urban Poor in Permatang Pauh, Malaysia. In *In Post-Pandemic Economic and Social Development* (pp. 74–88). Routledge. Retrieved from https://www.taylorfrancis.com/chapters/edit/10.4324/9781003491736-6/evaluation-social-protection-covid-19-pandemic-among-urban-poor-permatang-pauh-malaysia-fatimah-kari-nurulhuda-mohd-satar-peter-aning-tedong

Kosec, K., & Mo, C. H. (2024). Does Relative Deprivation Condition the Effects of Social Protection Programs on Political Support? Experimental Evidence from Pakistan. *American Journal of Political Science*, *68*(2), 832–849. https://doi.org/10.1111/ajps.12767

Mideros M., A. (2012). Ecuador: Defining and measuring multidimensional poverty, 2006-2010. *CEPAL Review*, *2012*(108), 49–67. https://doi.org/10.18356/9ed3c0a9-en

Mitra, S., Posarac, A., & Vick, B. (2013). Disability and Poverty in Developing Countries: A Multidimensional Study. *World Development*, *41*, 1–18. https://doi.org/10.1016/j.worlddev.2012.05.024

Najitama, E., Maski, G., & Manzilati, A. (2020). Analysis of multidimensional poverty dynamics in Indonesia: The effect of demographic and institutional factors. *Journal of Innovation in Business and Economics*, *4*(02), 87–96. https://doi.org/10.22219/jibe.v4i02.15630

Ncube, T., & Murray, U. (2024). Reflections on government-led social assistance programmes under Zimbabwe's National Social Protection Policy Framework: A social contract lens. *International Social Security Review*, 77(3), 59–97. https://doi.org/10.1111/issr.12367

Noerkaisar, N. (2021). Efektivitas Penyaluran Bantuan Sosial Pemerintah untuk Mengatasi Dampak Covid-19 di Indonesia. *Jurnal Manajemen Perbendaharaan*, *2*(1), 83–104. https://doi.org/10.33105/jmp.v2i1.363

Park, E., & Nam, S. (2020). Multidimensional poverty status of householders with disabilities in South Korea. *International Journal of Social Welfare*, *29*(1), 41–50. https://doi.org/10.1111/ijsw.12401

Peichl, A., & Pestel, N. (2013). Multidimensional Well-Being at the Top: Evidence for Germany*. *Fiscal Studies*, *34*(3), 355–371. https://doi.org/10.1111/j.1475-5890.2013.12010.x

Pitaloka, R. D., Hendriyani, H., Eriyanto, E., & Haryatmoko, H. (2022). Communication practice in village data collection. *Jurnal Studi Komunikasi*, *6*(1), 179–198. Retrieved from https://scholar.ui.ac.id/en/publications/communication-practice-in-village-datacollection/

Putri, R. P., Abral, E., & Amri, M. (2025). The impact of social assistance and capital expenditure on poverty levels in Aceh Province. *Jurnal Teknik Industri Terintegrasi*, *8*(1), 550–558. https://doi.org/10.31004/jutin.v8i1.40258

Rao, N. D., & Min, J. (2018). Decent Living Standards: Material Prerequisites for Human Wellbeing. *Social Indicators Research*, *138*(1), 225–244. https://doi.org/10.1007/s11205-017-1650-0

Reyes, G. A. (2024). Assessment on Benefits of Conditional Cash Transfer Program as an Aid in Alleviating the Life of the Poorest of the Poor at Santa Maria Bulacan. *International Journal of Religion*, *5*(4), 330–339. https://doi.org/10.61707/stfdq544

Roelen, K., Ahmed, M. S., Chowdhury, K., Diwakar, V., Huq, L., Al Mamun, S., ... Sumanthiran, S. (2024). *Social Protection Experiences of and Attitudes Towards New Urban Poor After Covid-19 in Bangladesh* (No. 600). https://doi.org/10.19088/IDS.2024.006

Saddam, R., & Saribulan, N. (2024). Developing Social Protection Systems to End Poverty in Indonesia. In *Smart Technologies for Sustainable Development Goals: No Poverty* (p. 70). CRC Press. Retrieved from https://www.taylorfrancis.com/chapters/edit/10.1201/9781003519010-5/developing-social-protection-systems-end-poverty-indonesia-saddam-rassanjani-nur-saribulan

Saffanah, A. P., Hapsari, I. P., & Iskanda, H. (2024). Legal Review of Corruption Crimes in Covid 19 Social Assistance Funds. *Jurnal Ilmu Hukum, Humaniora Dan Politik*, *4*(2), 83–96. https://doi.org/10.38035/jihhp.v4i2.1860

Sindzingre, A. (2013). The Multidimensionality of Poverty: An Institutionalist Perspective. In *The Many Dimensions of Poverty* (pp. 52–74). London: Palgrave Macmillan UK. https://doi.org/10.1057/9780230592407_4

Sjaf, S. (2023). Covid 19, Inequality and Poverty in Rural Indonesia. *Sodality: Jurnal Sosiologi Pedesaan*, *11*(1), 97–110. https://doi.org/10.22500/11202346272

Sjaf, S., Sampean, Arsyad, A. A., Elson, L., Mahardika, A. R., Hakim, L., ... Rangkuti, M. R. (2022). Data Desa Presisi: A new method of rural data collection. *MethodsX*, *9*, 101868. https://doi.org/10.1016/j.mex.2022.101868

Sriwahyuni, E., Sjaf, S., Hakim, L., Sampean, Arsyad, A. A., Maulana, S. A. B., ... Iqbal, M. (2025). Population structure and village youth development planning. *International Journal of Adolescence and Youth*, *30*(1). https://doi.org/10.1080/02673843.2024.2448607

Tekgüç, H. (2018). Declining Poverty and Inequality in Turkey: The Effect of Social Assistance and Home Ownership. *South European Society and Politics*, *23*(4), 547–570. https://doi.org/10.1080/13608746.2018.1548120

Tetep, T., Suherman, A., Susanti, Y., & Nisa, A. (2022). Poverty and Socio-Economic Inequality from Socio-Cultural Perspective. *Proceedings of the 6th Global Conference on Business, Management, and Entrepreneurship*. Atlantis Press. https://doi.org/10.2991/aebmr.k.220701.008

Unnikrishnan, V. (2022). The Welfare Effects of Social Assistance Programs for Women in India. *The Journal of Development Studies*, *58*(6), 1211–1230. https://doi.org/10.1080/00220388.2022.2043277

Walker, R., Li, M., & Yang, L. (2022). Social Assistance: A Defence against Poverty. In C. Shei & T. Xue (Eds.), *Social Assistance: A Defence against Poverty*. Routledge. https://doi.org/10.4324/9780367565152-RECHS81-1

Widyastuti, A. T., Hartono, D., Sidig, D. S., & Rusmawati, E. (2023). Financial inclusion's impact on energy poverty: Evidence from Indonesia. *World Development Sustainability*, *3*, 100113. https://doi.org/10.1016/j.wds.2023.100113

World Bank Group. (2021). *Reversals of Fortune: Poverty and Shared Prosperity 2020*. Washington DC: World Bank Group. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/34496/9781464816024.pdf

You, J., Kontoleon, A., & Wang, S. (2019). Identifying a Sustained Pathway to Multidimensional Poverty Reduction: Evidence from Two Chinese Provinces. *The Journal of Development Studies*, *55*(1), 137–158. https://doi.org/10.1080/00220388.2017.1371295