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# Enhancing Poverty Alleviation Through Village-Level Multidimensional Poverty Measurement

**Siectio Dicko Pratama[1*], Devi Novanti[2]**

[1]Senior Statistician, BPS-Statistics of Lampung Utara, Indonesia
[2]Junior Statistician, BPS-Statistics of Lampung Utara, Indonesia

* Correspondence E-mail: siectio@hotmail.com

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## Abstract

Poverty in Indonesia remains a persistent challenge, particularly in rural areas, where national strategies often fail to address local complexities. This study aims to enhance poverty alleviation efforts by constructing a village-level Multidimensional Poverty Index (MPI) tailored to the specific context of Candimas Village. Indicators were selected through literature review and consultation with village officials, followed by descriptive, contingency, and logistic regression analysis. The results reveal that 14.13% of households are multidimensionally poor, with inadequate housing, health vulnerability, and joblessness as key contributing factors. However, only 6.53% of these families receive government assistance, while 32.18% of non-poor families do highlighting critical targeting gaps. Spatial disparities also suggest misallocation across neighborhood units. Regression analysis confirms the significant influence of BPJS PBI ownership, housing conditions, and unsafe drinking water on low-income levels. The study concludes that a locally-adapted MPI is more effective in identifying and prioritizing vulnerable households than conventional approaches. Its application can inform village-level resource allocation (e.g., BLT Desa) and support more equitable and data-driven poverty alleviation strategies.

## Introduction

Poverty is mostly defined as a condition where someone lacks the resources to meet their basic needs and to have a decent standard of living. However, the definition above is just a simplified explanation of poverty, where poverty is a series of complex phenomena that consists of many interlocked dimensions such as limited access to basic infrastructure, unemployment, low level of education, and health issues (Alkire et al., 2015a). In Indonesia, poverty has always been an underlying challenge, hence it becomes the government's priority to ends poverty in every possible form by the next 2030.

Indonesian Government believes that village has always been a crucial entity to promote poverty alleviation, village are expected to contribute to the achievement of development targets (Pradhan et al., 2000). Referring to The Indonesian Law Number 6 of 2014 regarding the Villages, the government of the villages has to be the organizer of statistical activities suggesting the changing role of the villages. The villages are no longer the object of development, but the subject of development. In addition, the village fund that has been distributed to the villages every year strengthen the resources of the village in the expectation of reducing poverty. However, poverty incidence in rural areas has been stagnant with the figure of 11 to 13 percent according to the BPS-Statistics Indonesia, (2024). Azmi et al. (2020) added with their findings that allocation of village funds cannot reduce the poverty in 23 regencies in Aceh.

The main challenge faced by the village government is the lack of tool to measure the welfare level of individuals in the village-level. The inexistence of the tool caused some overlapping programs since there are a lot of programs for the people in the village from many parties. For instance, a family who has received the food assistance program from the central government could receive another aid program from the villages. It happened because the village did not know which people should be given the aid as they do not have the reliable data. Furthermore, the capacity of human resources contributes to this issue as they do not have capabilities to construct the measure. Therefore, our study aims to complement it by providing the tool to measure poverty at the village level.

Previous work regarding the construction measure of poverty has been implemented in Indonesia, but there are still limited studies about the measure that quite comprehensive to capture poverty and practical for policy. Kartanegara et al., (2023) studied the multidimensional poverty in Sukamulya village using descriptive analysis. The study provided the four categories of poverty, but it was less practical for policy since it is still unknown the contributing factor of poverty. Another research from Rimajuwikah et al. (2021) construct the multidimensional poverty level at the village level using primary data, referencing to multidimensional poverty index of Alkire & Foster (2011). However, since they use the similar dimension, the measure only captures the multidimensional aspect of poverty that left the economic factor, making it less accurate to predict the poor people at the village level. Further research conducted by Wang & Wang (2016) was able to provide tools to identify, locate and describe the characteristic of the poor people in the village. Similar to the previous research, the economic factor was also left out since they focused on socio-economic classification. Since the monetary poverty approach is extremely difficult to apply at the village level, the poverty measure needs to cover the aspect as it is crucial. This study is considered to fulfil the gap.

In the rise of the multidimensional poverty index, the economic factor or income remains to be the critical aspect to define the poor. As Laderchi (1997) studied, even he found that income variable was insignificant in all of the models he developed, it could not prove that income did not matter. But, the role of income in determining a person's shortfalls depends on a plurality of personal, household and regional characteristics. Reflecting on the importance of the economic dimension, Mexico is one of the countries that has include income in the construction of multidimensional poverty index (CONEVAL, 2012). It is implemented in the consideration that the measure should involve all dimension the policy must address. Further, Battiston et al. (2013) combines the income approach with dimensions such as school attendance, education of household head, sanitation, water and shelter to calculate the multidimensional poverty for six Latin American Countries. The result provided a fuller understanding of the evolution of poverty in the selected countries and pointed out the education of household head and proper sanitation are the highest contributors of poverty. All those researches were still implemented in the national level and not even in Indonesia.

Another issue for constructing the poverty measurement at the village level is data availability. Since there is neither individual data at the village level nor any secondary data that is representative at the village level, it necessary to pick a village as a case study. The collaborative effort of BPS-Statistics of Lampung Utara Regency and The Village Officials of Candimas in Lampung Utara make it possible to provide the data. The effort aimed to organise statistical activities from scratch, starting from data collection to dissemination by considering the statistical business process that is available globally. The data collected is not only limited to the poverty, but to other important aspect considered important by both parties. Even so, the data is sufficient to fulfil the needs to construct the poverty measure. In addition, Lampung Utara regency is the regency with the most percentage of poor people in Lampung province while Candimas Village is the village categorized as developed village in Lampung Utara. Hence, both conditions make it a proper study location since the village has resources to construct the data in the regency that has the most of poor people.

In sum, our study aims to construct the poverty measure that capture multidimensional aspect of poverty, including the economy aspect, and provide the number of poor people as well as its contributing factor at the village level. The result is expected to give necessary properties for constructing poverty alleviation policy at the village level that cover the identification of the poor, their location and their main compounding factor. Accordingly, the result of this study is expected to trigger targeted poverty alleviation policies in Candimas Village. For that reason, three research questions needed to be addressed in this study. First, what are the dimensions and magnitude of poverty in Candimas Village. Subsequently, how the poverty measure could improve the targeting of poverty alleviation program in the Village. Lastly, what are the main factors of poverty that contribute to the low income of the people in Candimas Village.

The contribution of this paper lies in three aspects. First, it operationalizes multidimensional poverty analysis at the smallest administrative level using locally validated data. Second, it introduces a participatory weighting and validation process that increases community ownership of poverty data. Third, it provides empirical evidence that links measurement innovation with practical policy use, bridging the gap between statistics and governance. In doing so, the paper contributes to the growing literature on localized poverty measurement and extends its application to the domain of rural development policy.

# Methods

This study employs a mixed-methods strategy that blends quantitative and qualitative techniques to answer the research questions regarding the multifaceted facets of poverty in Candimas. Qualitative method is adopted on the selection of Multidmensional Poverty Index by involving the village officer and did some literature research to support the indicator's selection. Then, the analysis of the index is conducted through descriptive analysis and the contingency table to respond to the first and second research questions. Accordingly, the final question is responded by using the logistic regression. By implementing these processes, we expect to fully document the aspects and causes of poverty at the village level and offer practical advice for focused initiatives to reduce poverty.

The data used in this research is collected by the village officials as the result of the collaboration between BPS of Lampung Utara regency and Candimas Village. The survey was mainly designed to satisfy the needs of the data at the village and fulfil the needs to identify the welfare level of people in the Candimas village. As the purpose of the data collection is to improve the statistical business process at the village, all the questions constructed refer to the Decree of the Head of BPS-Statistics Indonesia Number 850 of 2023. The data was collected by 21 village officers and directly supervised by the village secretary and one of village section chief. It was also validated before it was further processed by a modest data entry program. However, since we focus on identifying the poor, the data used was only those who related to our research.

## *3.1.Descriptive Analysis of Multidimensional Poverty Measure*

Alkire & Foster (2011) known as the AF method is the method employed to construct the multidimensional poverty measure. Its robustness in terms of the choice on indicators, weighting and cut-off (Alkire & Santos, 2014) make it perfect fit for capturing the poverty at the village level since it is possible to choose indicators based on the data availability. Additionally, the MPI can be disaggregated to reveal the composition of poverty, aligning with the research questions of the study.

The first step to calculate the multidimensional poverty measure is to select the indicators, cut-off and weighting. The multidimensional poverty index is constructed under the capability theory of poverty. Then, the selection of the dimension and indicators need to refer to the people values. Alkire (2008) suggested that the selection of the dimension should be on the empirical basis of survey and behaviour analysis. Furthermore, it needs to pass the two-stage process from what is the ideal and what is feasible and include the important element.

Considering that, our selection procedure combined the existing literature regarding the dimension and indicator of MPI Indonesia and the input from the village officials. In Indonesia, PRAKARSA is the institution that has calculated MPI Indonesia for years. In its publications on MPI (Aidha et al., 2020; Budiantoro et al., 2016; Perkumpulan PRAKARSA, 2023), there were different dimension and indicators, indicating the changing perspective and input from expert and stakeholders regarding the multidimensional aspect of poverty as time flies. Since PRAKARSA has done the research several times, its choice of indicators and dimension should be more reliable to depict the multidimensional poverty in Indonesia. Therefore, indicators and dimension as used in Perkumpulan PRAKARSA (2023) are used as the first list indicators of MPI. Then, the interview with the village officials was done to complement how those indicators can capture the poor people at the village level.

The next step after defining indicators and dimensions is determining the deprivation, weighting and cutoff. Deprivation can be defined as the capabilities where the people lack of. This is crucial in terms of connection the capability poverty approach with its measurement. Hence, the deprivation is determined by the process of identify the dimensions and indicators, which is through the previous literature and the interview to incorporate the local condition. Then, the weighting and cut-off followed the common method that had been used by many countries and researchers in building MPI. It is also the suggestion from Alkire as the creator which is the equal weighting and the cut-off is one-third of the total deprivation score.

Since the cut-off is one-third, an individual is considered as poor if the total deprivation score is above 0.33. After defining the deprivation, each individual was classified as deprived by each indicator if the deprivation cannot be fulfilled. For instance, a person is deprived if he lived in a house where the floor is under 7.2 m2. Then, he will be coded 1 if he fits the criteria and vice versa, meaning that he gets one score of deprivation on the indicator. After assessing this for all indicators, each indicator is aggregated with the equal weighting to form a deprivation score. If the total of this score exceeds 0.33, then the individual is categorized as poor. This is how the poor is counted.

Then, the final procedure is to count the headcount ratio of the multidimensional poor people. The formula is similar to the common headcount ratio, which is dividing the number of poor people with the total people in the village. Afterwards, the percentage of poor people in Candimas village is earned. In the steps to calculate the MPI, there were still steps to calculate the intensity of poverty, which is computing the average share of weighted indicators, and the multidimensional poverty index. However, as our study aim to produce the tool to identify the number of poor people, those steps were not implemented. The index is usually helpful when it is compared by other indexes in different areas or time. Since we only calculate in the village, the index is not relevant. So, the calculation is only up to the headcount ratio that is used as an approach to count the poor family in the village.

Further analysis on the headcount ratio of the multidimensional poverty is conducted through descriptive statistical analysis and the contingency table. The descriptive statistical analysis is an analysis used to describe the meaning behind the produced figure. The analysis is meant to reveal the magnitude of poverty in Candimas Village. Then, we use the contingency table to compare the poor families as the result of the measure and the families who received the assistance from the government. This approach could shed light on how effective the distribution of government assistance in the multidimensional poverty perspective in Candimas village. As the analysis is implemented in the level of the smallest local environmental unit and the family level, the number of the families that has not received the assistance but classified as poor can be revealed. It can help improve the targeting at the village level.

### *3.2. Logistic Regression*

Turning to the method to identify the main factor affecting the low income of people, the binary logistic regression is employed. This method is used to associate the poverty indicator towards the level of income of the people obtained from the data collection. The income level dichotomous that is coded as 1 and 0, which represent either they have low income or not respectively. Specifically, people whose income under 1.5 million rupiahs is coded as 1 (low income), while those with income above 1.5 million rupiahs as 0 (non-low income). This classification is implemented to reduce the bias that commonly entailed the income data. Binary logistic regression is appropriate here because it follows a Bernoulli distribution, which is commonly used for dichotomous response variables (Agresti, 2013). The following is the logistic regression model used in this research.

$$\log Y_j = \alpha + \theta_i X_{ij} + \varepsilon_j$$

Keterangan

$Y_j$ : Dummy of the family income. Code 1 if the income is below 1.5 Million rupiahs and code 0 if the income is above 1.5 Million rupiahs.

$X_{ij}$ : Independent Variables that consisted of the indicators of multidimensional poverty. The code classification is similar to the determination of deprivation in each variable.

$\varepsilon_j$ : Error term for the j-th observation

$\theta_i$ : Odds Ratio for i-th variable

Several tests are necessary to ensure the model fulfil all the statistical requirement for the logistic regression and can depict a convincing result. Accordingly, the first test needed to conduct is the Likelihood Ratio test (LR Test) that is employed to assess the overall significance of the model. Referring to Hosmer et al. (2013), LR test follows a chi-square distribution, when the probability of the test reach 0.05 significance level, we reject the null hypothesis when the p-value reach 0.05 significance level, meaning that the explanatory variables have some effect in predicting the response variable. Subsequently, the Wald Test is important to identify the significance for individual regression slope coefficients. The Wald values are obtained by dividing the slope coefficients by their standard error. If the null hypothesis is rejected, each independent variables has a significant impact on the dependent variables. Finally, the Pseudoe-R2 value is also calculated since it is capable to provide information on the suitability of the logistic regression model. (Hemmert et al. (2018) suggest that if a Pseudo-R2 value between 0.2 and 0.4 indicates a good level of fit and a value above 0.4 means the level of fit is very good.

The odds ratio is a key component in the analysis, as it directly addresses the research questions by quantifying the strength and direction of the association between predictor variables and the likelihood of a particular outcome. Once the model meets the necessary statistical assumptions, the odds ratios offer meaningful interpretations of how specific poverty-related factors influence household income levels. In logistic regression, the odds ratio reflects the likelihood of an outcome occurring in one group relative to a reference group. Since we use the binary variable as independent variable, taking the size of the house as an example, the odds ratio of 2 would indicate that families living in small houses (lower than seven square meters) are twice as likely to have low income compared to those in larger houses.

## Result

### *3.1. Multidimensional Poor People in Candimas Villag*

The result of our interview suggested the inclusion of job as the replacement of indicators in participation dimensions from MPI constructed by Perkumpulan PRAKARSA (2023). Job was seen as important factor that could define the welfare status of people in the village. According to the village officials, people in the village who have no jobs tend to be the old people who live alone. They depend on their relatives that did not live in the same house. So, in terms of welfare, they have sufficient life and tend to be poor. Meanwhile, the use of internet does not suggest any welfare characteristic in the village. It is difficult to believe those who do not access the internet are poor. Therefore, the variable regarding the jobs was added while the internet was left out. The following table is the list of variables used to construct the multidimensional poverty measure in Candimas Village.

**Table 1**. List of Dimensions and Indicators used to Construct the Multidimensional Poverty Measure

| Dimension and Indicators | Poor if | Additional Notes | Weighting |
|---|---|---|---|
| **Health** | | | |
| **BPJS PBI** | No family members have BPJS PBI (Premium Assistance Recipients of National Health Insurance) | This is a proxy indicator to see whether the people poor in health perspective as also used by Septya et al. (2024). The indicator is modified to only BPJS PBI as this program meant to poor people (Hasibuan et al., 2024) | 1/5 |
| **Education** | | | |
| **School Participation** | No individuals in the family who have ever attended school or been continuing their schooling according to their age and the education they have received | | 1/10 |
| **School Years** | No individuals in the family aged 19-30 have their last education level below junior high school | | 1/10 |
| **Housing** | | | |
| **Housing Condition** | The housing condition where the family live is either roof, floor or wall are made of unproper material | The proper materials are<br>Roofs are concrete, tiles, zinc, or asbestos<br>Floors are granite, ceramic, carpet or tile | 1/10 |

| Dimension and Indicators | Poor if | Additional Notes | Weighting |
|---|---|---|---|
| | | Walls are walls, plastering bamboo, woods or boards | |
| **Overcrowdedness** | The floor size of house where the family is below 7.2 square meters | | 1/10 |
| **Basic Needs** | | | |
| **Drinking Water** | The source of drinking water in the family is not from bottled/refillable water, plumbing or well-drilling/pump | | 1/15 |
| **Sanitation** | The sanitation used by the family is plunge (cemplung/cubluk) | | 1/15 |
| **Cooking Fuel** | The cooking fuel is kerosene or firewood | | 1/15 |
| **Economy** | | | |
| **Jobs** | No one in the family has job | Included as suggested by the village officer that considered the characteristic of the people in the village. The use of this dimensions in MPI refer to (Suppa, 2018) | 1/5 |

Source: Adapted with some modification from Perkumpulan PRAKARSA (2023)

The number of families who are poor according to the multidimensional poverty measure is 14.13 percent. The proportion is even lower than the poverty rate in Lampung Utara regency, which is 16.92 percent in 2024. The indicators contributing to the classification of the poor family are health and jobs since it has high percentage and high weighting. Health indicator has proportion for about 39.55 percent, indicating that there are 39.55 percent families in Candimas are vulnerable in their health since BPJS PBI is meant to those who are vulnerable to health. In addition, there are 22.58 percent families that no family members do not works or unemployed. Accordingly, both variables become important as the contributing factor of poverty in Candimas village since if a family has BPJS PBI and no family members work, it means the family are categorized as poor.

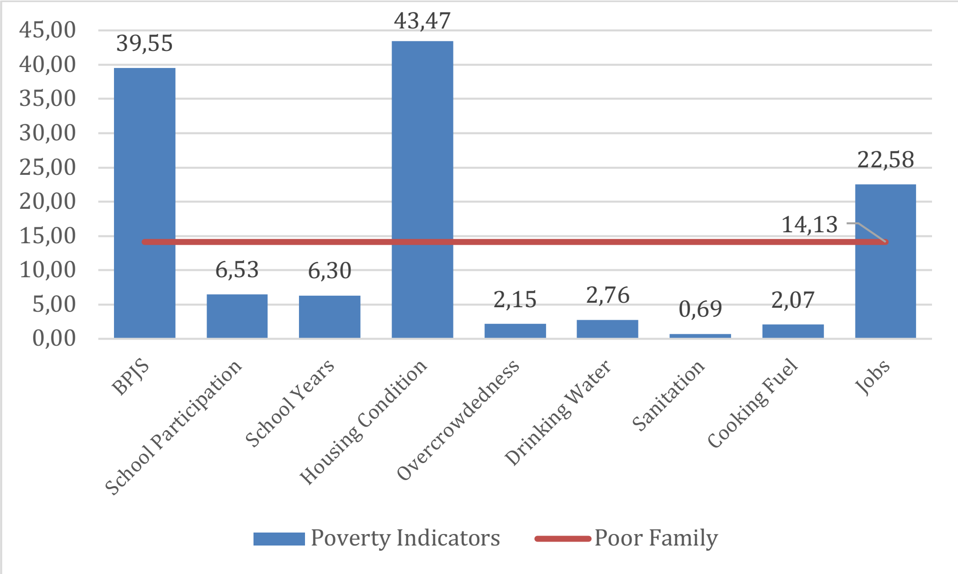


**Fig. 1**. Percentage of Poor Family and Its Compounding Indicators in Candimas Village

The housing condition may have the biggest proportion of other indicators, but the weighting is only about one tenth. It means the indicator is not strong enough to reflect the multidimensional poverty since if a family has no BJPS PBI and also poor housing condition, the score is only 0.3 which does not exceed the threshold. It is different if another variable is jobs since the weighting is higher, the total score would be 0.4. Figure 1 underline the characteristic of poverty in Candimas, which is mostly people who are vulnerable to health and jobs.

The dominance of both indicators aligns with the explanation of the village officers regarding the dominance of elderly in the village. In the interview regarding the poverty indicators, the village officers raise concern on them who live alone in their old age. The elderly who live usually have the health insurance and has no jobs, which are enough to be classified as poor. This classification invites discussion and debate on whether they deserved to be classified poor. However, it is better to consider Haughton & Khandker (2009) opinion on poverty measurement that there are no perfect measures. Every measure is constructed according to its own purposes. Hence, as it is required by the users who want to address those people, it should be fine as the elderly is also vulnerable. In addition, the elderly tend to have no fixed income makes them possess higher chance to experience poverty.

### *3.2. The Poor Family and The Government Assistance*

The result of the multidimensional poverty measure at Candimas village is 14,13 percent which seems reasonable. As can be seen in Figure 2, the poverty distribution reflects a similar perspective with the condition of poor people across the smallest local environment units (SLS) according to the village officers. RT 2 Dusun 2 and RT 2 Dusun 4 are the ones with the lowest percentage of poor people. It makes senses since people in both areas mostly work as civil servant which make it reasonable why the percentage is the lowest. On the other hand, the highest percentage of poor is in

Dusun 5 which located in the interior of the village and most of the people work in the agricultural sector.

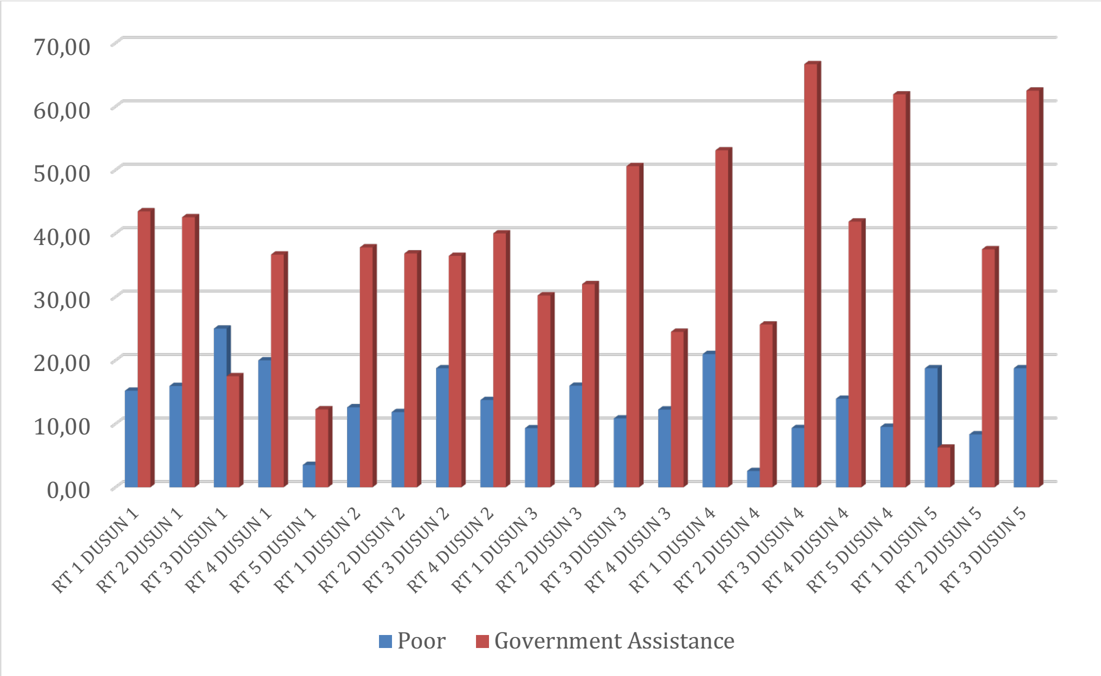


**Fig. 2.** Percentage of Poor Family and Percentage of Family who received Government Assistance by Local Environmental Units (SLS).

Figure 2 also describes the distribution of the poor family and the government assistance received in the family across SLS in Candimas. The biggest gap is occurred in RT 1 Dusun 5 while there are a lot of poor people but the government assistance is low. Meanwhile, there are much government assistance in RT 3 Dusun 4 while the poverty is low. Considering the data, the surplus in RT 3 Dusun 4, assuming it was distributed to the non-poor family, can be given to the family in RT 1 Dusun 5. However, since the village cannot manage the recipients of assistance from regional or national government, it is not possible to reallocate the government assistance. The solution is to cover those who are poor with the assistance from village funds.

Table 2 identify the coverage of poor family according to the multidimensional poverty measure whether they received the government assistance. The result show that there is only 2.07 percent of poor family who receive assistance while 12.06 percent who are not poor received the assistance. This proportion seems to indicate that the distribution of the government assistance is not pro poor. However, it can be caused by the different kind of indicator and requirement used by the central government to define the targeting. It is important to note that every government assistance has its own purposes such as health insurance was meant to the people who are vulnerable to health, the non-cash food subsidy was for reduce the food expense and increase the food security, and even the family hope program (PKH) aimed for the poor but still have some criteria needs to be fulfilled and targeted to the poorest people in the regency that is possible it is only a few in the village. Hence, there are lots of factor that cause the small percentage of the family who are poor and received the government assistance.

Table 2. Contingency Table of Poor Family and Family who Received Government Assistance

| Poor Family | Received Government Assistance | | Total |
|---|---|---|---|
| | No | Yes | |
| No | 49.23 | 36.64 | 85.87 |
| Yes | 12.06 | 2.07 | 14.13 |
| Total | 61.29 | 38.71 | 100 |

Nevertheless, the result from Table 2 can trigger a better targeting of conditional cash transfer assistance initiated by the village (BLT Desa). According to the regulation of the Ministry of Finance Number 108 of 2024, the village can give BLT Desa up to 15 percent of the total of the village funds received by the village. The value of the assistance is to be around three hundred thousand rupiah per month. If the people of Candimas village is about 1,300 people, there could be around 184 families that are poor and need to be assisted. Specifically, 157 families that are poor and did not receive any assistance from the government. Accordingly, the village would need around 47 million rupiah per month. In addition, if the village fund is about 1 billion rupiahs, then the assistance could be made for only three months per year to those families that are poor and do not receive any assistance. This scheme should represent evidence-based policy in alleviating poverty at the village level.

## *3.3. Analysis of Poverty Indicators Trends*

After revealing the magnitude of poverty and how it affects the targeting, the next analysis is about the trends of poverty indicators towards the income level of the families. As the approach to define poverty in this study is different from the official poverty measure, it is important to align it so the focus to alleviate poverty can be captured in the national level. Accordingly, the indicators of the multidimensional poverty employed in this study that has significantly affected the income level of families could contribute to identify the families that are multidimensionally and economically poor. This section discusses further the result of the logistic regression analysis that could reveal whether the poverty indicators have tendency for the families to have lower income based on the collected data in 2024.

The result of the equation for the logistic regression show a good sign as all the necessary requirement fulfilled. The proportion of the dependent variables should normally be evenly distributed. As presented in Table 3, the total observation of 1302 was divided nearly equal to both income level that become the binary outcome, allowing proportional allocation by the observation unit. In addition, the LR Test also show the significance level at 95 percent confidence level. Both results empowered the good result of the equation. Hence, the statistical assumption of the overall equation is statistically satisfied.

**Table 3**. The Distribution of the Level of Families' Income Data

| Income Level | Class Size | Class Distribution (Percent) |
|---|---|---|
| Low Income Families | 631 | 48.46 |
| Non Low-Income Families | 671 | 51.54 |

Turning to the partial relationship of the explanatory variables, the Wald test figured that there are only two variables that significantly affect the income level of the families at 95 percent confidence level as served in table 4. Those are the housing condition and the ownership of BPJS PBI. This finding conforms the previous finding as the indicators with high proportion in the family. Also, it helps focusing the intervention of the government to both of these indicators as indicators that experienced the most by the families and has significance impact on their income level. In addition, the drinking water indicator is also significant at 90 percent confidence level, underlining its importance on influencing the income level of the families.

**Table 4**. The Result of The Logistic Regression Analysis

| Explanatory Variables | B | Exp(B) (Odds Ratio) | S.E | P-value |
|---|---|---|---|---|
| School Participation | -.094 | .910 | .249 | .704 |
| School Years | .205 | 1.228 | .261 | .431 |
| Housing Condition* | 1.081 | 2.949 | .126 | .000 |
| Overcrowdedness | .487 | 1.627 | .454 | .284 |
| Drinking Water** | -.677 | .508 | .400 | .090 |
| Sanitation | .782 | 2.186 | .775 | .313 |
| Jobs | -.082 | .921 | .150 | .586 |
| Cooking Fuel | .495 | 1.640 | .458 | .280 |
| BPJS PBI* | -1.268 | .281 | .130 | .000 |
| Constant | -.046 | .955 | .108 | .669 |

In terms of odds ratio, the families living in an improper house condition increase the odds of having a low-income significantly, while those who owns a health insurance (BPJS PBI) drop the odds of being in a low-income household. Families living in an improper house have tendency around 2.95 times higher to have low-income level than those with proper houses. In contrast, a family with at least one family member owning a BPJS PBI tend to have the higher chance to be in non-low income families. Following Hosmer et al. (2013), the odds ratio that is below 1 can also be interpreted as the risk for families who does not own BPJS PBI to have low income is 3.56 times higher than those who have BPJS PBI. Similarly, the odds ratio of drinking water indicator is also below one, meaning that the families with safe drinking water have the odds of 1.96 times higher to have low income. Then, the ownership of BPJS PBI and safe access to drinking water contribute to the higher chance of the families to be classified as non-low income families.

The finding on BPJS PBI and drinking water indicators suggested the opposite direction of those indicators with the economy level of the families. Several assumptions could arise to support the reason of those findings, such as the mistargeting of BPJS PBI or the tendency of drinking water source that is similar to all families. It is possible the BPJS PBI is also owned by those who economically better so it cause the odds ratio to be high in non-low income families. For the drinking water indicator, the small proportion of families with unsafe drinking water, it could contribute to why the odds of those families is high to be as non low income families. According to our data collection, the families with drinking water source reach 86.54 percent, with 63.46 percent with well and 23.09 percent with pump. As most families use similar water source, it is reasonable the odds ratio is high towards non low income families. Hence, the one to note from this finding is to focus on housing condition indicator if the village want to focuses on alleviating poverty that is also captured by the official poverty measure that relied on economic aspect.

Another interesting finding is the jobs indicator that is not seemed to be in line with the income level of the families although it is economy-related indicator. The result of Wald test is not significant and even the value of the odds ratio only gives a slight chance. The odds ratio is 0.92, indicating that the unavailability of jobs in a family give the chance of 1.085 higher to be in a low-income family. The reason could be the phenomenon that the people in Candimas village are dominated by the elderly who have retired. Then, the unavailability of jobs does not indicate that they are poor since they have routine earning from the government or supported by their families.

## Discussion

The development of a multidimensional poverty measure at the village level has demonstrated tangible potential for improving program targeting and institutionalizing evidence-based policymaking. In Candimas Village, the MPI framework identified approximately 14 percent of households as poor, with 157 families falling outside existing government assistance. This information enables the local government to allocate village funds directly to unserved poor families, thereby transforming the poverty measure into an operational budgeting tool. Such practice reflects the intent of Indonesia's Village Law No. 6 of 2014, which envisions villages not as passive objects of development but as active subjects that plan, implement, and evaluate their own welfare programs.

The flexibility of the Alkire–Foster (AF) method further supports this transformation. Because the MPI can be decomposed by dimension, policymakers can adjust priorities according to local needs. For instance, once health deprivation has been addressed through insurance coverage, interventions can shift toward unaddressed dimensions such as housing or sanitation. This adaptability is consistent with the strength of the AF framework that lies in its capacity to guide targeted, context-specific actions rather than serve as a static index (Oxford Poverty and Human Development Initiative, 2015). Consequently, the Candimas MPI provides not only a diagnostic picture of poverty but also a dynamic mechanism for strategic planning and program alignment.

Still, the adequacy of certain indicators deserves reflection—particularly BPJS PBI ownership and employment status, which yielded unexpectedly high associations with poverty. Theoretically, health deprivation is more accurately captured by nutrition or morbidity data, while economic vulnerability is best represented by income or expenditure. However, given the human-resource and data-collection constraints at the village level, the use of health insurance and employment proxies remains a pragmatic compromise. Similar methodological trade-offs were noted by Santos & Villatoro (2020) in defending the MPI-LA: indicator selection must balance conceptual precision with policy relevance and data feasibility. Within Candimas, the chosen proxies are justified because they align with local administrative data and reflect deprivations recognized by village officers.

The convergence between statistical identification and community perception strengthens the credibility of the poverty measure. For example, Howe & McKay (2007) demonstrate that combining survey data with participatory poverty assessment in Rwanda reveals deeper insights into chronic poverty than either approach alone. It shows that empirical validity is strengthened when local perceptions align with quantitative findings. In this case, households classified as poor by the measure were also widely recognized by local leaders as genuinely disadvantaged. This alignment indicates that, despite indicator imperfections, the constructed measure maintains adequate construct validity and contextual resonance, key qualities for sustaining trust in data-driven governance.

The logistic regression analysis further illuminates how specific deprivations interact with monetary poverty. Among all dimensions, only housing condition showed a significant and consistent relationship with income, implying that improving housing quality could simultaneously reduce both monetary and multidimensional poverty. While the divergence between other indicators and income may appear problematic, it simply reflects that multidimensional poverty captures broader welfare deficits beyond consumption levels. From a policy perspective, this divergence is beneficial since it helps identify households that may be overlooked by income-based targeting yet remain vulnerable in other aspects of life.

More broadly, this study illustrates how small-scale statistical innovation can empower local governments to practice evidence-based policymaking. With limited resources but clear methodological guidance, the Candimas initiative demonstrates that villages can independently generate, analyze, and apply data for program refinement. Such bottom-up data systems complement national statistics by adding granularity and immediacy, echoing calls by (Alkire et al., 2015b) for local adaptation of multidimensional poverty frameworks. The success of this collaboration between BPS–Lampung Utara and Candimas Village shows that the institutionalization of evidence-based policy at the village level is both feasible and impactful when supported by political will and technical mentoring.

Nevertheless, scalability remains a challenge. Future research should develop a standardized yet adaptable indicator set that allows comparability across villages while respecting local context. Integrating nutrition-based and dynamic economic variables could refine the sensitivity of the index. Expanding such efforts across multiple rural communities would contribute to a more decentralized, data-driven approach to poverty alleviation, aligning with Indonesia's continuing agenda of village empowerment and inclusive development.

## Conclusion

This study has developed and applied a village-level multidimensional poverty measurement framework in Candimas Village to support more targeted and effective poverty alleviation strategies. By combining quantitative and qualitative methods, and integrating input from local stakeholders, this research responds to three central questions: the dimensions and magnitude of poverty at the village level, the relevance of this measurement in improving program targeting, and the key contributing factors influencing poverty and low income in the village.

The findings reveal that poor families in Candimas are about 14.13 percent according to the multidimensional poverty measure. This rate, although slightly lower than the regency average, reflects local realities more accurately due to the tailored indicators used. The inclusion of job availability, health access (measured through BPJS PBI ownership), and housing quality allowed for a more contextualized understanding of deprivation. The analysis revealed that poor health status and the absence of employment, particularly among elderly residents, were significant in classifying families as poor. Moreover, nearly half of the households live in inadequate housing, emphasizing structural poverty often masked by income-based metrics.

Furthermore, the implementation of the multidimensional poverty index highlights a critical gap between poverty incidence and government assistance distribution. It is enhanced by the fact that only 2.07% of families classified as multidimensionally poor received any form of aid, while 12.06% of non-poor families benefited from assistance programs from the government. In addition, Spatial mismatches were also apparent across Satuan Lingkungan Setempat (SLS), particularly in Dusun 5, where high levels of poverty coincided with limited aid coverage. These discrepancies underline the need for a data-informed targeting mechanism at the village level. The study suggests that the multidimensional poverty index developed in this study can be instrumental in guiding the allocation of village funds (BLT Desa) and in complementing national programs by filling local-level data gaps.

Finally, the logistic regression analysis identified three key indicators—BPJS PBI ownership, housing condition, and access to safe drinking water—as significant predictors of low-income status. However, only housing condition significantly aligns with the economic poverty. Families living in inadequate housing face nearly three times higher odds of being low-income, reinforcing its relevance for both monetary and multidimensional measures. Interestingly, job availability was not significantly correlated with income levels, largely due to the demographic structure of Candimas, where many unemployed residents are elderly individuals supported by pensions or family members. This insight calls for differentiated policy responses that recognize non-monetary forms of vulnerability, especially among the aging population.

In conclusion, this study contributes to the literature by offering a replicable, locally grounded framework for measuring and analysing poverty at the village level. It not only identifies who is poor but also reveals where they are and why, enabling targeted interventions that are responsive to actual conditions. The integration of economic and non-economic dimensions enhances the accuracy of poverty identification and strengthens the accountability of village-level policy implementation. Future research can expand this approach to other villages, enabling broader policy adoption and contributing to the national poverty reduction agenda, particularly in support of Indonesia's 2030 development goals.

Nevertheless, some improvements could be made for further research considering several limitations embodied in this study. Firstly, since the data were primarily collected for administrative purposes, some dimensions of poverty may be underrepresented such as the health dimension. If there is a heavy mistargeting on BPJS PBI, then the eligibility of it as poverty indicator mas be doubted. Moreover, the selection of indicators also relied heavily on qualitative justification and may carry subjective bias. Therefore, future research should be specifically design for multidimensional poverty measurement and incorporate a more standardized validation process, such as expert panels or consensus-building methods, to enhance indicator robustness and the accuracy of the analysis. In evaluating government assistance distribution, the study does not fully account for program-specific eligibility criteria, which may explain mismatches in targeting. A more nuanced assessment of these criteria would offer better policy alignment.

## Declarations

No ethical issues have arisen during the study and all procedures followed comply with the ethical standards.

## Authors contribution statement

The paper was inspired by the main author who responsible for most of the studies from designing the study and implement it. The second author contributed on the introduction and managing the data for the poverty measure calculation. In addition, she was also responsible for the field data collection and the intense communication with the village officers.


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## Data availability statement

Data is available upon request.

## Declaration of interests statement

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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