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Household Characteristics and Settlement-Environment-Based Multidimensional Poverty in Gorontalo Province, Indonesia: A Multilevel Logistic Regression Analysis

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Abstract: Poverty assessment in Indonesian regions still relies mainly on a monetary line. Deprivations in settlement services, including household waste disposal, largely unobserved. Studies of the household determinants of multidimensional poverty seldom check whether reported associations survive once explanatory variables that overlap with index components are considered. This study examines whether household characteristics are associated with the probability of settlement-environment-based multidimensional poverty in Gorontalo Province. Data on 3,567 households came from the March 2025 National Socioeconomic Survey. Poverty status was identified with the Alkire-Foster method using ten indicators and a one-third cut-off, and its correlates were estimated with a two-level random-intercept logistic regression that accounts for the clustering of sampled households. The headcount ratio was 10.54 percent, and education contributed the largest share of the index. Household characteristics were jointly significant: the expenditure quintile showed a steep and stable gradient, and a higher dependency ratio raised the odds of poverty. A dimension-exclusion robustness test revealed that the apparent effects of the head's education and household size were largely artefacts of the schooling indicator. The novelty lies in a household waste indicator and a test separating substantive determinants from measurement artefacts.

Keywords: Multidimensional Poverty, Household Characteristics, Settlement Environment, Multilevel Logistic Regression, Gorontalo

INTRODUCTION

The 2030 Agenda for Sustainable Development Goals, treats poverty as a condition that goes well beyond low income. Goal 1 asks countries to reduce poverty "in all its dimensions", while Goals 6, 7 and 11 link human welfare to safe water, sanitation, clean energy and the management of settlement waste (United Nations, 2015). The Alkire-Foster counting method gives this idea an operational form. It records whether a household is deprived in each of

several indicators, identifies as poor those whose weighted deprivations exceed a cross-dimensional cut-off, and produces an index that can be broken down by region, group and indicator (Alkire & Foster, 2011). The global Multidimensional Poverty Index built on this method now covers more than eighty countries (Suppa & Kanagaratnam, 2025), and recent work shows that progress on it can stall quickly when shocks hit health and schooling (Alkire et al., 2021; Alkire et al., 2023).

In Indonesia, poverty targeting still leans on the monetary line calculated by Statistics Indonesia from the cost of basic needs. In March 2025, 13.24 percent of the population of Gorontalo Province lived below this line, well above the national average (BPS Provinsi Gorontalo, 2025). A monetary line captures purchasing power well, but it does not tell planners which households lack safe sanitation, clean cooking fuel or schooling. Indonesian evidence consistently shows that monetary and multidimensional poverty identify only partly overlapping groups of households (Artha & Dartanto, 2018), and that multidimensional poverty fell far more slowly than monetary poverty during the post-pandemic recovery (Harianto, 2026).

The settlement environment is where these non-monetary deprivations become most visible. The standard living standard dimension already contains water, sanitation, housing and cooking fuel, and energy deprivation alone affects a sizeable share of Indonesian households (Rizal et al., 2024). Household waste, however, is absent from both the global index and the national multidimensional poverty studies, even though open burning and dumping remain common. Household burning in Semarang was found to be roughly twice the official estimate (Ramadan et al., 2022), improper disposal in Medan is shaped by service fees and education (Hutagalung et al., 2026), and households in Gorontalo City still burn their waste or throw it into rivers and vacant land (Maryati et al., 2025). Whether this practice belongs in a poverty index, and whether it separates poor from non-poor households, has not been tested for Gorontalo.

Studies of the determinants of multidimensional poverty point to a familiar set of household characteristics. Low schooling of the household head, a high dependency ratio, informal or agricultural work and low income or expenditure are repeatedly associated with a higher risk of being poor in Ethiopia (Eshetu et al., 2022), India (Shah & Debnath, 2022; Septa et al., 2024), Nigeria (Abubakar, 2022) and Pakistan (Saleem et al., 2023). Indonesian studies report similar patterns and add gender and household composition: female-headed households tend to be more vulnerable (Soseco et al., 2022; Ekaputri et al., 2025), dependency ratios raise the risk of extreme poverty in Southwest Papua (Aminah et al., 2025), and education and employment separate chronic from transient poverty (Sugiharti et al., 2023). The evidence on household size and on the sex of the head, however, is far from uniform.

Two gaps remain. The first, and the main concern of this article, is conceptual. Several explanatory variables commonly used in determinant studies, such as the education of the household head, are measured in the same domain as the indicators that make up the index. If the head of the household has finished middle school, the entire family clears the education deprivation threshold by default. Naturally, bigger families have a much higher chance of hitting this minimum requirement just by virtue of having more members. A strong coefficient may therefore reflect the construction of the index rather than a behavioural relationship, yet few studies test for this. The second gap is methodological. Survey households are sampled in clusters and share local conditions, and models that ignore this dependence tend to understate standard errors (Austin & Merlo, 2017); multilevel applications to Indonesian survey data report substantial clustering (Putra & Istiana, 2025; Pujiwati et al., 2025).

This article addresses one research question: are household characteristics significantly associated with the probability that a household experiences settlement-environment-based multidimensional poverty in Gorontalo Province? The analysis stays at the household level. It adds household waste management as a separate living standard indicator, estimates the

household associations with a random-intercept model that treats the clustering of sampled households as a statistical control, and applies a dimension-exclusion robustness test to distinguish determinants that hold regardless of index composition from those produced by measurement overlap.

METHODS

Design, Data and Sample

This quantitative, cross-sectional study used household microdata from the March 2025 National Socioeconomic Survey (Susenas), which samples ten households per census block. The analytical sample comprised 3,567 households in 357 census blocks across all six districts of Gorontalo Province; 1,448 households (40.6 percent) lived in urban areas. For the random intercept, households were grouped into the 303 villages/subdistricts from the enumeration documents. Cluster size ranged from 9 to 40 households (median 10). No village-level variables enter the analysis.

Measurement of Multidimensional Poverty

The dependent variable was built exclusively from household-level Susenas items. Following Alkire and Foster (2011), ten indicators were grouped into three equally weighted dimensions (Table 1). Nutrition was measured as energy adequacy, with the threshold set at 70 percent of the national recommended dietary allowance (Kementerian Kesehatan Republik Indonesia, 2019). The living standard dimension adapts the global index by adding household waste management as a separate indicator. Each household received a weighted deprivation score c_i , and a household was identified as multidimensionally poor when $c_i \geq 1/3$. The headcount ratio (H), the average intensity among the poor (A) and the adjusted headcount ratio ($M_0 = H \times A$) were computed with survey weights, and the index was decomposed by indicator using censored headcount ratios.

Table 1. Dimensions, indicators, weights and deprivation cut-offs of the settlement-environment-based Multidimensional Poverty Index (MPI-L)

Dimension	Indicator	Weight	A household is deprived if
Health (1/3)	Nutrition (energy adequacy)	1/6	Daily per capita energy intake is below 70 percent of the recommended dietary allowance (Susenas consumption module)
	Health care access	1/6	A member had a serious health complaint but did not use modern health care because of cost or distance
Education (1/3)	Years of schooling	1/6	No member aged 15 or older has completed junior secondary school
	School attendance	1/6	Any child aged 7–18 is not attending school before completing senior secondary school
Living standards (1/3)	Drinking water	1/18	Unprotected source, or source less than 10 m from a septic tank
	Sanitation	1/18	No own or shared gooseneck toilet connected to a septic tank or treatment plant
	Roof and walls	1/18	Low-quality or non-permanent roof or wall materials
	Floor and space	1/18	Earth or bamboo floor, or less than 7.2 m ² of floor area per person
	Cooking fuel	1/18	Firewood, charcoal, kerosene, straw or coal
	Waste management	1/18	Waste is burned, buried in the yard, or dumped into rivers, drains or vacant land

Source: adapted from Alkire and Foster (2011) and Kementerian Kesehatan Republik Indonesia (2019); Susenas March 2025 questionnaire

Household Characteristics

Seven household characteristics served as explanatory variables: sex of the household head (female = 1), age of the head (in ten-year units, centred), education of the head (no certificate as reference; primary school; junior secondary school or higher), employment status of the head (working = 1), household size, the dependency ratio (members aged under 15 or over 64 divided by members aged 15 to 64), and the quintile of monthly per capita expenditure (quintile 1 as reference). Variance inflation factors were all below 3.4, and no separation was detected.

Statistical Analysis

The probability that household i in cluster j is poor, π_{ij} , was modelled with a two-level random-intercept logistic regression: $\text{logit}(\pi_{ij}) = \gamma_{00} + \sum \gamma_{p0} X_{pij} + u_{0j}$, with $u_{0j} \sim N(0, \tau_{00})$. The random intercept only accounts for the non-independence of households sampled in the same area; slopes were fixed because clusters were small. An empty model (Model 0) was estimated first to check whether this specification was needed, using the intraclass correlation coefficient, $ICC = \tau_{00}/(\tau_{00} + \pi^2/3)$ (Merlo et al., 2006), and a likelihood ratio test of $\tau_{00} = 0$ with the p-value halved because the null lies on the boundary of the parameter space (Self & Liang, 1987). Model 1 added the household characteristics; their joint contribution was tested with a likelihood ratio test of Model 1 against Model 0, and each coefficient with a Wald test at the 5 percent level. Estimation used maximum likelihood with 15-point adaptive Gauss-Hermite quadrature (Rabe-Hesketh & Skrondal, 2012), and both models converged. Index measures were weighted; the models were unweighted because their purpose was relational.

Two explanatory variables share a measurement domain with the dependent variable. Expenditure quintiles and the energy adequacy indicator both derive from the Susenas consumption module, and the education of the head directly enters the years-of-schooling indicator. To test this overlap, the dependent variable was rebuilt without the education dimension and without the health dimension (weights renormalised, cut-off kept at one-third), and Model 1 was re-estimated.

RESULTS AND DISCUSSION

1. Profile of Settlement-Environment-Based Multidimensional Poverty

Using the one-third cut-off, 422 of the 3,567 sampled households were identified as multidimensionally poor. After weighting, the headcount ratio for Gorontalo Province was 10.54 percent and the average intensity among the poor was 42.70 percent, giving an adjusted headcount ratio of 0.0450. In other words, about one in ten households experienced deprivations covering more than a third of the weighted indicators, and those households were, on average, deprived in 42.7 percent of them. Table 2 shows how each indicator contributed to this result.

Table 2. Prevalence, censored headcount and contribution of each indicator to the MPI-L, Gorontalo Province, 2025

Indicator	Weight	Prevalence (%)	Censored headcount (%)	Contribution (%)
Nutrition (energy adequacy)	0.167	5.97	2.68	9.94
Health care access	0.167	18.29	6.36	23.54
Years of schooling	0.167	20.67	7.30	27.03
School attendance	0.167	7.18	3.44	12.73
Drinking water	0.056	9.34	2.34	2.89
Sanitation	0.056	17.87	4.42	5.45
Roof and walls	0.056	0.92	0.46	0.56
Floor and space	0.056	7.88	3.26	4.02
Cooking fuel	0.056	1.99	0.96	1.18
Waste management	0.056	89.65	10.25	12.66
Contribution by dimension: health 33.48; education 39.76; living standards 26.76				
Headcount ratio (H) = 10.54%; intensity (A) = 42.70%; $M_0 = H \times A = 0.0450$				

Source: Susenas March 2025, processed (weighted estimates)

Waste management stands out. Almost nine in ten households (89.65 percent) were deprived, mainly because they burned their waste (76.47 percent of all households) or dumped it (13.18 percent). Schooling (20.67 percent), access to health care (18.29 percent) and sanitation (17.87 percent) followed at around one-fifth of households. Only 5.97 percent of households consumed less than 70 percent of the recommended energy intake. Deprivation in cooking fuel (1.99 percent) and in roof and wall quality (0.92 percent) was rare, reflecting the near-universal use of subsidised liquefied petroleum gas and the improvement of housing materials in the province.

The contribution figures tell a different story from the prevalence figures. The education dimension contributed 39.76 percent of the index, followed by health (33.48 percent) and living standards (26.76 percent). Because the three dimensions carry equal weights, these differences reflect actual deprivation patterns rather than weighting choices. Years of schooling alone contributed 27.03 percent. Waste management, despite being the most prevalent deprivation, contributed only 12.66 percent. Its censored headcount ratio (10.25 percent) almost equals the headcount ratio itself, which means that roughly 97 percent of poor households were also deprived in waste management; but so were most non-poor households. Unsafe waste disposal in Gorontalo is therefore a near universal practice rather than a marker of poverty, which extends the city-level observations of Maryati et al. (2025) to the whole province and is consistent with the scale of household burning documented elsewhere in Indonesia (Ramadan et al., 2022).

Poverty was markedly higher in rural areas (14.41 percent) than in urban areas (6.31 percent), and the adjusted headcount ratio in rural areas (0.0606) was more than double that in urban areas (0.0280). Across districts, the headcount ratio ranged from 16.04 percent in North Gorontalo to 4.05 percent in Gorontalo City. The 10.54 percent figure is close to, but conceptually distinct from, the monetary poverty rate of 13.24 percent (BPS Provinsi Gorontalo, 2025); the two measures use different units and concepts and, as earlier Indonesian studies show, identify partly different households (Artha & Dartanto, 2018; Harianto, 2026).

2. Characteristics of Sampled Households

The average household had 3.60 members (range 1 to 12) and a dependency ratio of 0.53. Household heads were on average 47.6 years old; 14.55 percent were women and 91.62 percent were working. More than half of the heads had low schooling: 28.29 percent held no certificate and 28.60 percent had completed only primary school, while 43.12 percent had completed junior secondary school or higher. The expenditure quintiles were reasonably balanced, from 17.80 percent of households in quintile 2 to 24.81 percent in quintile 5.

3. Household Characteristics and the Odds of Multidimensional Poverty

The empty model was estimated first as a specification check (Model 0 in Table 3). The clustering of sampled households was not negligible (ICC = 20.77 percent; $\chi^2 = 78.84$, $df = 1$, $p < 0.001$), so a single-level logit would have understated the standard errors of the household coefficients. The random intercept is therefore retained in Model 1 as a statistical control, and the discussion below concentrates on the household characteristics.

Table 3. Two-level logistic regression of multidimensional poverty on household characteristics (odds ratios and 95% confidence intervals)

Variable	Model 0	Model 1
Intercept	0.101 (0.085–0.121)***	0.727 (0.430–1.229)
Female household head		0.746 (0.508–1.097)
Age of head (per 10 years)		0.933 (0.846–1.030)
Head completed primary school		0.722 (0.560–0.931)*
Head completed junior secondary or higher		0.127 (0.087–0.185)***
Head working		0.872 (0.545–1.393)
Household size		0.830 (0.756–0.911)***
Dependency ratio		1.371 (1.131–1.663)**
Expenditure quintile 2		0.342 (0.246–0.476)***
Expenditure quintile 3		0.287 (0.200–0.414)***
Expenditure quintile 4		0.170 (0.112–0.256)***
Expenditure quintile 5		0.157 (0.101–0.245)***
<i>Random part</i>		
Between-village variance (τ_{00})	0.862	0.445
ICC (%)	20.77	11.92
<i>Model fit</i>		
Log-likelihood	–1,257.32	–1,073.62
AIC	2,518.64	2,173.24
BIC	2,531.00	2,253.58
LR test	$\chi^2 = 78.84$ (df 1) ^a	$\chi^2 = 367.39$ (df 11) ^b
Households / villages	3,567 / 303	3,567 / 303

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Reference categories: male head, head with no certificate, head not working, expenditure quintile 1. ^a Model 0 vs single-level logit (boundary-corrected $p < 0.001$). ^b Model 1 vs Model 0 ($p < 0.001$).

Source: Susenas March 2025, processed

Adding the household characteristics substantially improved the model. The likelihood ratio test of Model 1 against Model 0 was $\chi^2 = 367.39$ with 11 degrees of freedom ($p < 0.001$), and AIC fell from 2,518.64 to 2,173.24. The null hypothesis that all household coefficients are zero is therefore rejected: household characteristics are jointly and significantly associated with the probability of settlement-environment-based multidimensional poverty. Eight of the eleven coefficients were significant at the 5 percent level.

Economic capacity produced the clearest pattern. Compared with households in the lowest expenditure quintile, the odds of poverty were 0.342 times as high in quintile 2, 0.287 in quintile 3, 0.170 in quintile 4 and 0.157 in quintile 5, all significant at $p < 0.001$. The gradient is monotonic, and its steepest step occurs between the first and second quintiles, which suggests that the move out of the poorest fifth matters most for non-monetary deprivation. Using quintiles rather than a linear expenditure term allowed this non-linear shape to appear.

The dependency ratio was positively associated with poverty (OR = 1.371; 95% CI 1.131–1.663): each additional unit of the ratio raised the odds by about 37 percent. This makes sense from a household economics perspective: having more dependents simply drains the resources left for education, medical care, and decent housing. We see similar patterns playing out in other regions, from Southwest Papua and rural India to Pakistan (Aminah et al., 2025; Shah & Debnath, 2022; Saleem et al., 2023).

The education of the household head showed the largest coefficient. Households headed by someone who had completed junior secondary school or higher had 0.127 times the odds of poverty of those headed by someone with no certificate (95% CI 0.087–0.185), an 87 percent reduction; completion of primary school alone reduced the odds by 28 percent (OR = 0.722). Household size, by contrast, was negatively associated with poverty (OR = 0.830; 95% CI 0.756–0.911), implying that each additional member lowered the odds by 17 percent. This direction runs against most of the literature (Soseco et al., 2022; Eshetu et al., 2022). Both results call for caution, and the robustness test below explains why.

Three characteristics were not significant once the others were controlled: the sex of the head (OR = 0.746; 95% CI 0.508–1.097), the age of the head (OR = 0.933 per ten years; 95% CI 0.846–1.030) and the employment status of the head (OR = 0.872; 95% CI 0.545–1.393). The non-significance of female headship differs from the national findings of Ekaputri et al. (2025) but agrees with Soseco et al. (2022), who found that household composition predicted vulnerability better than the sex of the head. With 91.6 percent of heads working, employment status offers little contrast; the type and quality of work, which this study did not measure, is likely to matter more than whether the head works at all.

The non-significant coefficients are also informative. Age of the head is often linked to life-cycle poverty, but it showed no independent association once the expenditure quintile and the dependency ratio were in the model. The data do not allow a formal test of mediation, but this pattern is consistent with the view that life-cycle differences operate mainly through household resources and the number of dependants rather than through the age of the head itself.

4. Robustness to the Composition of the Index

Table 4 reports Model 1 re-estimated after removing, in turn, the education and the health dimension from the dependent variable. The results split into two groups.

Table 4. Robustness of Model 1 to the composition of the dependent variable (odds ratios)

Variable	Full MPI-L	Without education dimension	Without health dimension
Female household head	0.746	1.010	0.868
Age of head	0.933	0.924	0.994
Head completed primary school	0.722*	0.787	0.647***
Head completed junior secondary or higher	0.127***	0.818	0.040***
Head working	0.872	0.923	1.485*
Household size	0.830***	1.117**	0.562***
Dependency ratio	1.371**	1.138	1.971***
Expenditure quintile 2	0.342***	0.598***	0.509***
Expenditure quintile 3	0.287***	0.467***	0.400***
Expenditure quintile 4	0.170***	0.417***	0.269***
Expenditure quintile 5	0.157***	0.315***	0.293***
Headcount ratio (%)	10.54	22.16	25.41

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Remaining indicator weights were renormalised to sum to one; the poverty cut-off was kept at one-third.

Source: Susenas March 2025, processed

The expenditure gradient survived every specification. When the health dimension, which contains the energy adequacy indicator drawn from the same consumption module, was removed, all four quintiles remained significant at $p < 0.001$ and kept their ordered pattern; the odds ratio for the top quintile moved only from 0.157 to 0.293. The suspicion that the expenditure effect arises from a shared data source is therefore not supported. The dependency

ratio also remained positive and significant without the health dimension ($OR = 1.971$), although it lost significance when education was removed.

The education of the head did not survive. When the education dimension was excluded, the odds ratio for junior secondary schooling or higher rose from 0.127 to 0.818 ($p = 0.115$) and that for primary schooling to 0.787 ($p = 0.056$); neither remained significant. When the health dimension was removed instead, the relative weight of education in the index increased and the odds ratio fell sharply to 0.040. Both movements point to the same explanation: most of the strength of this coefficient comes from the construction of the years-of-schooling indicator, in which the head is one of the members whose schooling determines the household's deprivation. The coefficient cannot be read as the size of the effect of the head's education on poverty.

The household size coefficient reversed direction. It was 0.830 in the full index but 1.117 ($p < 0.01$) when education was excluded. The negative association in the full index is therefore a mechanical artefact: a household is non-deprived in schooling if at least one member aged 15 or over has completed junior secondary school, and the more members a household has, the more likely that at least one of them meets the threshold. Once this indicator is removed, larger households face higher odds of poverty, which agrees with most of the literature. Many poverty studies overlook a crucial structural bias: whenever an indicator requires "at least one member" to meet a certain standard, the results naturally skew in favor of larger households.

5. Discussion and Policy Implications

Three points emerge. First, economic capacity is the most robust household determinant of settlement-environment-based multidimensional poverty in Gorontalo. It holds across specifications and aligns with evidence from other developing regions that income or expenditure remains a key predictor even when poverty is measured without money (Septa et al., 2024; Abubakar, 2022). This does not make the multidimensional index redundant; the two measures still identify partly different households, but it does mean that livelihood and income support programmes are likely to reduce non-monetary deprivation as well.

The pattern across quintiles also carries a message for targeting. The largest drop in the odds occurs between the first and second quintiles, and the gap between the fourth and fifth quintiles is small (0.170 against 0.157). Non-monetary deprivation in Gorontalo is therefore concentrated in the poorest fifth of households rather than spread evenly along the expenditure distribution. This is in line with the Indonesian evidence that a large share of poverty is chronic and tied to persistent disadvantages in education, employment and location (Sugiharti et al., 2023), and with Vietnamese findings that diversified income sources protect households from multidimensional as well as income poverty (Tran et al., 2022). For the dependency ratio, the practical implication is that households with many children or elderly members relative to working-age adults deserve attention even when their per capita expenditure is not the lowest.

Second, the results should not be read as saying that education is unimportant. The decomposition shows that education is the largest source of deprivation, contributing almost 40 percent of the index. What this study cannot establish is the size of the head's education effect, because the measurement design does not separate the two. Policy discussions that cite large education odds ratios from similar models should take this into account. Pushing for nine years of basic education is obviously still critical. However, in the context of this study, that urgency stems from how the poverty index is broken down, rather than just taking the regression numbers at face value..

Third, the construction of household-based indicators deserves attention in index design. The schooling indicator, defined by whether at least one member aged 15 or over has completed junior secondary school, is standard in the global index and useful for describing deprivation, but it makes both the head's education and household size look more protective than they are. Where an index is used to study determinants, analysts could use an adult-share version of the

indicator or exclude the head from its construction. For waste management, the near-universal prevalence of burning means that programmes aimed only at poor households will miss most of the problem; behaviour change and reliable collection services need to reach all households, as studies in Medan also suggest (Hutagalung et al., 2026).

The novelty of this study lies in two contributions. This research brings two fresh perspectives to the table. By using Susenas data, we mapped out household waste management as its own distinct measure of environmental poverty. What we found is that since unsafe dumping is so common across the board, it isn't actually a great metric for separating the poor from the non-poor. Beyond that, we developed a straightforward robustness test—by dropping specific dimensions—that can easily be adapted for any other Alkire-Foster poverty model. This test proved that while household spending genuinely drives poverty levels, the supposed impacts of family size and the head's education level were mostly just side effects of how the index was built.

CONCLUSIONS AND RECOMMENDATIONS

Conclusion

Household characteristics are significantly associated with the probability of settlement-environment-based multidimensional poverty in Gorontalo Province. About one in ten households is multidimensionally poor, and deprivation in education contributes the largest share of the index. The expenditure quintile is the most robust determinant, and a higher dependency ratio raises the odds of poverty, whereas the sex, age and employment status of the head are not significant. The large coefficients for the education of the head and the negative coefficient for household size are largely produced by the construction of the schooling indicator, as the dimension-exclusion test shows. For poverty measurement in general, the study demonstrates that determinant models built on the Alkire-Foster index should routinely check for overlap between explanatory variables and index components before interpreting effect sizes.

Limitations

This study has several limitations. First, the cross-sectional design supports only associational, not causal, interpretations. Second, the models were estimated without survey weights, so the coefficients describe relationships in the sample rather than population parameters. Third, the waste management indicator has low discriminating power in a setting where unsafe disposal is nearly universal. Fourth, the employment variable records only whether the head works, not the type, sector or formality of the work. Finally, the expenditure quintile and the energy adequacy indicator come from the same survey module, and although the robustness test shows that the expenditure gradient does not depend on this overlap, a fully independent income measure was not available.

Recommendations

Future studies that wish to estimate the effect of education should construct a schooling indicator that excludes the household head, or use an education measure from a separate data source. Researchers could also test alternative weighting schemes for the waste indicator, add the sector and formality of the head's work, and apply the dimension-exclusion test to other provinces and survey rounds. For local governments, these findings point toward a more targeted approach. Financial aid should ideally go hand-in-hand with efforts to ensure basic education is completed, especially for families supporting many non-working members. When it comes to sanitation, waste management programs need to look beyond just low-income areas and instead focus on improving reliable trash collection and shifting community habits across the entire province.

Author Contributions

Abdurrahman Assel conceptualised the study, prepared the data, performed the analysis and drafted the manuscript. Mahludin H. Baruwadi, Sri Endang Saleh, Ani M Hasan and Margaretha Solang supervised the research, contributed to the conceptual framework and interpretation of the results, and revised the manuscript. All authors have read and approved the final version of the article.

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