OPHI MPI Methodological Note 65

The global Multidimensional Poverty Index (MPI) 2026: Disaggregation results and methodological note

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Attribution
The estimates of the global MPI and its partial indices are disaggregated by several different population groups. This includes by age groups (OPHI's Data Table 3), urban and rural areas (Data Table 4), subnational regions (Data Table 5) and gender of household head (Data Table 7). All tables based on disaggregated analysis are produced by the authors.

During her leadership of the global MPI team between 2018 and 2024, Dr Usha Kanagaratnam developed Stata scripts (do-files) for data cleaning and indicator construction, which were then applied to the underlying microdata of each country survey. Dr Kanagaratnam also led the construction of the variables required for disaggregation analysis. For the 2025 and 2026 updates, the authors utilised her cleaned microdata from 82 countries and modified the do-file for 26 new and revised surveys, including 13 countries for the 2026 release.

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1. Overview

This methodological note presents the methodology and technical decisions that underlie the published **disaggregation** results (age groups, urban and rural areas, subnational regions and gender of household head) of the global Multidimensional Poverty Index (MPI) 2026. The 2026 MPI disaggregation results are based on the most recent data from 108 countries, covering 6.3 billion people. We estimate the MPI and its associated statistics by four age categories (0–9 years, 10–17 years, 18–59 years, and 60 years and over) as well as two broad age categories covering children aged 0–17 years and adults 18 years and older, by urban and rural areas and by the gender of the household head. The MPI is also computed for 1,360 subnational regions across 100 countries to show disparities in poverty within countries. Subnational disaggregations are published when the survey used for the global MPI is representative at the subnational level, and the retained sample permits such disaggregation.

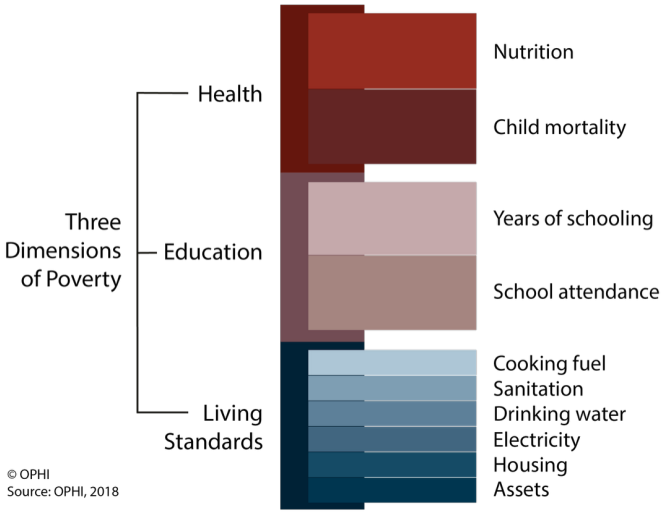
This note is structured as follows. Section 2 presents the global MPI structure and indicator definitions[1] and Section 3 outlines the global MPI and its partial indices that we estimate and publish. Section 4 details the disaggregation methodology, while Section 5 outlines the principles and decisions that underlie our disaggregation work. Section 6 summarises the country-specific decisions applied to the new or updated datasets in this round. Section 7 concludes.

2. The global MPI structure

The global MPI, published annually since 2010, captures acute multidimensional poverty in developing regions of the world (Alkire and Santos, 2014, 2010). This measure is based on the dual cutoff counting approach to poverty measurement developed by Alkire and Foster (2011). The global MPI is composed of three dimensions (health, education and living standards) and 10 indicators (Figure 1). Each dimension is equally weighted, and each indicator within a dimension is also equally weighted. The first major revision of the global MPI was undertaken in 2018, with adjustments in the definitions of five out of the ten indicators (see Alkire et al., 2022; Alkire and Kanagaratnam, 2021; Alkire and Jahan, 2018; Vollmer and Alkire, 2022).

[1] This methodological note builds on previous methodological notes by Alkire, Kanagaratnam and Suppa between 2018 and 2024, with the year, datasets, country-specific adjustments and country briefings updated where required. The text in this section draws on methodological notes published for each update of the global MPI (see previous updates by the authors in 2024, 2023, 2022, 2021, 2020 and 2019) and the book by Alkire et al. (2015).

Figure 1. Composition of the global MPI – dimensions and indicators



Source: OPHI (2018).

The global MPI begins by establishing a deprivation profile for each person, showing in which of the 10 indicators they are deprived. Each person is identified as deprived or non-deprived in each indicator based on a deprivation cutoff (Table 1). In the case of health and education, each household member may be identified as deprived or not deprived according to the information available for other household members. For example, if any household member for whom data exist is undernourished, each person in that household is considered deprived in nutrition. Taking this approach – which was required by the data – is intuitive and assumes shared positive (or negative) effects of achieving (or not achieving) certain outcomes. Next, looking across indicators, each person's deprivation score is constructed by adding up the weights of the indicators in which they are deprived. The indicators use a nested weight structure: equal weights across dimensions and an equal weight for each indicator within a dimension.

Table 1. The global MPI – dimensions, indicators, deprivation cutoffs and weights

Dimensions	Indicator	Deprived if ...	SDG area	Weight
Health	Nutrition	Any person under 70 years of age for whom there is nutritional information is **undernourished**.[1]	SDG 2	1/6
	Child mortality	A child **under 18** has **died** in the household in the five-year period preceding the survey.[2]	SDG 3	1/6
Education	Years of schooling	**No** eligible household member has completed **six years** of **schooling**.[3]	SDG 4	1/6
	School attendance	Any school-aged child is **not attending** school **up to** the age at which he/she would complete **class 8**.[4]	SDG 4	1/6
Living standards	Cooking fuel	A household cooks using **solid fuel**, such as dung, agricultural crop, shrubs, wood, charcoal or coal.[5]	SDG 7	1/18
	Sanitation	The household has **unimproved** or **no** sanitation **facility** or it is improved but **shared** with other households.[6]	SDG 6	1/18
	Drinking water	The household's source of **drinking water** is **not safe** or safe drinking water is a **30-minute** or **longer walk** from home, round trip.[7]	SDG 6	1/18
	Electricity	The household has **no electricity**.[8]	SDG 7	1/18
	Housing	The household has **inadequate** housing materials in **any** of the three components: **floor**, **roof** or **walls**.[9]	SDG 11	1/18
	Assets	The household does **not own more than one** of these **assets**: radio, TV, telephone, computer, animal cart, bicycle, motorbike or refrigerator, and does not own a car or truck.	SDG 1	1/18

Notes: The global MPI is related to the following SDGs: No Poverty (SDG 1), Zero Hunger (SDG 2), Health and Well-being (SDG 3), Quality Education (SDG 4), Clean Water and Sanitation (SDG 6), Affordable and Clean Energy (SDG 7) and Sustainable Cities and Communities (SDG 11).

[1] Children under five years of age (60 months and younger) are considered undernourished if their z-score of either height-for-age (stunting) or weight-for-age (underweight) is below minus two standard deviations from the median of the reference population. Children 5–19 years (61–228 months) are identified as deprived if their age-specific Body Mass Index (BMI) cutoff is below minus two standard deviations. Adults aged 20–70 years (229–840 months) are considered undernourished if their BMI is below 18.5 m/kg^2.

[2] The child mortality indicator of the global MPI is based on birth history data provided by mothers aged 15–49. In most surveys, men have also provided information on child mortality, but this lacks the date of birth and death of the child. Hence, the indicator is constructed solely from mothers' responses. However, if the data from the mother are missing, and if the male in the household reported no child mortality, then we identify no child mortality in the household.

[3] If all individuals in the household are in an age group where they should have formally completed six or more years of schooling, but none have this achievement, then the household is deprived. However, if any individuals aged 10 years and older reported six years or more of schooling, the household is not deprived.

[4] The data sources for the age that children start compulsory primary school are Demographic and Health Surveys (DHS) or Multiple Indicator Cluster Surveys (MICS) survey reports, and the UNESCO Institute for Statistics data browser (http://data.uis.unesco.org).

[5] If the survey report uses other definitions of solid fuel, we follow the survey report.

[6] A household is considered non-deprived in sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared. If the survey report uses other definitions of improved sanitation, we follow the survey report.

[7] A household is considered non-deprived in drinking water if the water source is any of the following types: piped water, public tap, borehole or pump, protected well, protected spring or rainwater. It must also be within a 30-minute walk, round trip. If the survey report uses other definitions of improved drinking water, we follow the survey report.

[8] A small number of countries do not collect data on electricity because of 100% coverage. In such cases, we identify all households in the country as non-deprived in electricity.

[9] A household is considered deprived if the floor is made of natural materials (mud/clay/earth, sand or dung) or if the dwelling has no roof or walls or if either the roof or walls are constructed using natural or rudimentary materials such as carton, plastic/polythene sheeting, bamboo with mud/stone with mud, loosely packed stones, uncovered adobe, raw/reused wood, plywood, cardboard, unburnt brick or canvas/tent. The definition of natural and rudimentary materials follows the classification used in country-specific DHS or MICS questionnaires.

3. The global MPI and its partial indices

In the global MPI, a person is identified as multidimensionally poor (MPI poor) if they are deprived in at least one-third of the weighted MPI indicators. After the poverty identification step, we aggregate across individuals to obtain the incidence of poverty, or headcount ratio (H), which represents the percentage of poor people in the population. We then compute the intensity of poverty (A), representing the average deprivation score, or the average percentage of weighted deprivations experienced by poor people. We then compute the adjusted poverty headcount ratio (M_0) or the MPI by combining H and A in a multiplicative form (MPI = H x A). A headcount ratio is also estimated using two other poverty cutoffs. The global MPI identifies individuals as **vulnerable** to poverty if they are not poor but are close to the poverty threshold; that is, if they are deprived in 20% to 33.32% of weighted indicators. The method also applies a higher poverty cutoff to identify individuals in **severe poverty**, meaning those deprived in 50% or more of the dimensions.

The Alkire-Foster method has a property that makes the global MPI even more useful – dimensional breakdown. This makes it possible to consistently compute the percentage of the population who are multidimensionally poor and simultaneously deprived in each indicator. This is known as the censored headcount ratio of an indicator. While MPI to be the product of H x A, the MPI can equivalently be computed as the weighted sum of the censored headcount ratios of all MPI indicators.

The censored headcount ratio shows the extent of deprivations among poor people but does not reflect the weights or relative values of the indicators. Two indicators may have the same censored headcount ratios but different contributions to overall poverty, as the contribution depends both on the censored headcount ratio and on the weight assigned to each indicator. As such, a complementary analysis to the censored headcount ratio is the actual and/or the percentage contribution of each indicator to overall multidimensional poverty.

4. Subgroup disaggregation or decomposability

A component of the Alkire-Foster method is the link between overall poverty and poverty in different subgroups of the population. Population subgroup decomposability specifies that overall (national-level) poverty is a population-share weighted sum of subgroup poverty levels. This

principle is useful for identifying and reporting the poverty of different population subgroups in a country, and for comparing them with other subgroups and with aggregate national poverty.

Using the same procedure as for national estimates, we disaggregate the country-level **MPI**, **H**, **A**, **vulnerable** to poverty and **severe poverty** by each population subgroup: age groups, urban and rural areas, subnational regions, and gender of household head. The population share for each subgroup is obtained by applying the sampling weight in the respective survey dataset to the final retained sample used for the computation of the reported statistics. We compute the **censored headcount ratios of each subgroup** to show the extent of deprivation among poor people in the subgroup. In addition, we compute the weighted **contribution of each indicator** to poverty for each subgroup.

The survey datasets used in the global MPI 2026 were collected in different years, ranging from 2013–14 to 2024–25. We rescale the sampling weights for each national survey so that they add up to the population of that country in the chosen common time period or reference year. In this round, we rescaled the weights to add up to the 2024 populations as reported in World Population Prospects 2024 (UNDESA, 2024). We compute population size for subgroups using a combination of the population share and the 2024 population to facilitate comparisons of the number of poor people in each subgroup. All disaggregated estimates are based on the global MPI specification outlined in Alkire, Mishra and Suppa (2026a).

5. Tool to estimate the global MPI

The global MPI estimates are produced using the Stata package 'mpitb', which is documented in Suppa (2023). `'mpitb'` facilitates the estimation of measures such as the MPI (adjusted headcount ratio), H (headcount ratio), A (intensity), the censored and uncensored headcount ratios, and percentage contribution of each indicator. `'mpitb'` supports estimations by population subgroups relevant to this methodological note, namely age groups, urban and rural areas, subnational regions and gender of household head. It is also possible to include any other subgroup disaggregations that are possible with the survey sample. `'mpitb'` supports the estimation of levels and change between time periods for each of the measures specified in Alkire, Mishra and Suppa (2026c) and across the national levels and subgroups. `'mpitb'` also simplifies estimations and analyses in cross-country settings.

6. Disaggregation principles and decisions

6.1 Disaggregation by age groups

We disaggregate the MPI and its partial indices by the following age groups: 0–9 years, 10–17 years, 18–59 years, and 60 years and over; and children aged 0–17 years and adults 18 years and older. We use information on age of household members from the household roster to construct the age groups. Age is a self-reported category across most surveys, except the survey for China, where age was constructed using birth month and year information. In cases where respondents have missing age information, we exclude them from the age-group computation, though they are included in the national MPI. The number of observations with missing age data is fewer than 100 across the 108 countries. This issue therefore does not affect the population-share weighted sum of age-group poverty levels when compared to overall poverty.

6.2 Disaggregation by urban and rural areas

We disaggregate the MPI and its partial indices by urban and rural areas in 105 countries; for one country (Argentina) we disaggregate by only urban area; and for Naeoro and Seychelles, we are unable to disaggregate by area due to limitations in the sample stratification. The definitions of urban and rural are taken directly from the surveys used to construct the MPI; these definitions may vary across countries. The stratification used in the sample design of the datasets defines the geographic units within which the sample was designed. This determines the possibility for disaggregation by urban and rural areas.

Across the 105 country surveys with urban–rural disaggregation, the sample was designed to be self-weighting within urban areas and rural areas. The area variable in the datasets defines the urban and rural areas, and we have used this variable for our disaggregation work. In addition, we refer to survey reports produced by data providers to ascertain the sample stratification. In cases where the sample design was stratified beyond urban–rural units, we make use of the additional information for disaggregation. In the Palestine MICS 2019–20 dataset, the sample was designed to be self-weighting within urban, rural and camp areas. The MPI estimation at the area level in this country is based on these three categories.

In cases where the sample design is stratified to certain areas, we restrict the disaggregation to the area that was sampled. The sample for Argentina MICS 2019–20 did not cover rural areas, due to the cost of surveying these areas, as well as the small rural population in the country (9% of the total population) (UNICEF and SIEMPRO, 2021). The MPI estimation at the area level in Argentina is therefore restricted to urban areas.

For Naeoro and Seychelles, the sample is self-weighting at the national level. This means any estimation based on this dataset is restricted to the national level. Following this, information on urban and rural areas is also not included in the Naeoro MICS 2023 and Seychelles QFLS 2019 datasets, as reported by the survey providers.

6.3 Disaggregation by subnational regions

In the 2026 round, we disaggregate the MPI and its partial indices by 1,360 subnational regions in 100 countries. The decision on whether national estimates could be disaggregated at the subnational level was based on two criteria established in our earlier work.[2] These criteria were (1) the sample was representative of subnational regions; and (2) the sample size after the treatment of missing data was reasonably high.[3]

Since 2018, our estimates have been reported along with standard error estimates and confidence intervals. Poverty measures should be accompanied by standard errors to evaluate their precision and properly rank regions of a country. In cases where the subnational estimates are zero, the standard errors establish whether these are true zeros.

The first criterion for disaggregation is that the survey report must establish that the sample is representative at the subnational level following the survey metadata on sample design. In 2026, 100 country surveys fulfilled this criterion. Four countries – Armenia, Naeoro, Seychelles and Tuvalu – have sample sizes that are representative at the national level but not at the subnational level. These countries were excluded at this stage.

The second criterion emphasises that the sample size after the treatment of missing data must be reasonably high at the national and subnational levels. For borderline cases, bias analyses are conducted to exclude those cases where the sample reduction leads to statistically significant bias. We apply bias tests across subnational regions in countries where a) the retained national sample size is lower than 85% of the original, or b) retained sample size is lower than 75% of the original in one or more subnational regions. This occurs in three steps.

First, the national sample size must be at least 85% of the original sample after dropping observations that had missing data in any of the 10 global MPI indicators. This is because a lower sample size may affect accurate comparability across subnational estimations. We identified four countries that did not meet this cutoff (Table 2). The sample drop across these countries ranges

[2] See Alkire and Santos (2014); Alkire et al. (2011).

[3] A key criterion for poverty trends is that regions must be harmonised for comparability over time. This is covered in Methodological Note 66 (Alkire, Mishra and Suppa, 2026b).

between 17% and 22%. Collectively, these four countries represent under 1% of the 6.3 billion people covered in the global MPI 2026.

Second, every subnational region in a country must have a retained sample size of at least 75% of the original sample. A smaller sample creates a problem of representativeness for that subnational region, which may distort the subnational comparisons. Our analyses indicate that five subnational regions across three countries fall short with respect to this sub-criterion (Table 3). The retained sample size across these five regions ranges from 56% to 75%.

Table 2. Global MPI countries with national sample size below 85% of the original sample after missing data is treated

Country	Survey	Year	Total sample size used to compute the MPI (weighted) (%)	Total sample drop (weighted) (%)
Georgia	MICS	2018	82	18
Maldives	DHS	2016–17	83	17
Montenegro	MICS	2018	80	20
South Africa	DHS	2016	78	22

Source: Alkire, Kanagaratnam and Suppa (2023).

Table 3. Subnational regions of three countries with sample size below 75% of the original sample after missing data is treated

Country	Survey	Year	Subnational region	Population share of region (%)	Total sample size used to compute the MPI (weighted) (%)	Total sample drop (weighted) (%)
Maldives	DHS	2016–17	Malé	41	75	25
Maldives	DHS	2016–17	Central Region	7	74	26
Montenegro	MICS	2018	Central Region	55	73	27
South Africa	DHS	2016	Gauteng	26	71	29
South Africa	DHS	2016	Western Cape	11	56	44

Source: Alkire, Kanagaratnam and Suppa (2024).

Third, a bias analysis test is carried out for each of the five regions whose retained sample size is lower than 75% of the original, and for countries where the retained national sample size is lower than 85% of the original. We identify the major cause of the sample reduction (in this case, nutrition for all three countries listed in Table 3), divide the entire sample into two groups based on this cause and check the headcount ratios of the other indicators across these two groups. If a systematic and statistically significant difference (at a significance level of 1%) is observed between the headcount ratios across these two groups, the region is considered to have failed the bias

analysis test. If a region with a large population share (more than 20%) within a country does not pass the test, we exclude the country from our subnational analysis.

Following this sub-criterion, we carried out the bias test for the five regions with a low retained sample. The results for the regions in Maldives, Montenegro and South Africa indicate that the likelihood of being deprived in child mortality (as well as in other indicators) is not the same for those who are missing the nutrition indicator compared to those who have this indicator. Those with a nutrition indicator are systematically more likely to be deprived in child mortality (or in other indicators). This suggests that the sampling structure would need to be revised to ensure representativity, as those who are dropped from the sample are likely to be people who are not poor.

Further, Malé and the Central Region collectively account for almost half of the population in the Maldives (Table 3). Across the three major regions of Montenegro, the Central Region is the most populous – 55% of the population lives in this region. The Gauteng and Western Cape regions are home to one-third of South Africa's population. Based on the observed biases, we exclude these countries from our subnational analysis.

In addition, we implemented bias tests on all regions of Georgia, as Georgia has a weighted sample loss of 18% at the national level, meaning it was borderline whether it could be disaggregated at the subnational level. Two of the 10 subnational regions within the country (Kakheti and Shida Kartli) had a retained sample of 77%. Both regions had the highest missing values for nutrition and child mortality. Those with nutrition indicators are systematically more likely to be deprived in child mortality, suggesting that non-poor people are being excluded. Given that the national sample loss exceeds 15% and two of its subnational regions, home to 45% of the population, yield biased estimates, we exclude Georgia from the subnational disaggregation.

Although subnational disaggregation is theoretically possible for 104 of the 108 countries, only 100 countries (with 1,360 regions) in this round of the global MPI meet the subnational disaggregation principles and are therefore used for subnational analysis.

6.4 Disaggregation by gender of household head

Of the 108 countries in the 2026 global MPI, disaggregated results by female-headed and male-headed households were produced for 107 countries – all except China. Information on the household members and their relationship to the head of household based on the household listing, was not available in the China CFPS 2014 dataset. Across all the surveys, household headship is a self-reported category. The selection of a household head by householders may be

based on a person's economic status (main provider), age hierarchy (older) or cultural preference (men). Despite variations in the definition of household head, there may be value in presenting a global account of multidimensional poverty by the gender of the household head, even though comparability is limited due to the mixed definitions of headship.

In our microdata work, we constructed the 'gender of household head' variable using information drawn from two variables in the datasets – sex and relationship to household head. In all datasets except one, sex is reported as a binary variable; hence, the gender of the household head is reported as binary. In a small number of cases, the category 'household head' is not assigned to any household members. In such cases, if information about the spouse (male or female) was available, we replace them as the household head. Fewer than 50 observations were replaced across the 108 surveys. Replacing the missing value therefore did not affect the final aggregate numbers.

7. Country-specific considerations for new or updated surveys

This section details the country-specific disaggregation decisions for each of the 13 new or updated countries included in the global MPI 2026.

7.1 Angola DHS 2023–24

The sample for this dataset was designed to provide statistically reliable estimates for urban and rural areas, as well as for each of the 18 provinces (Instituto Nacional de Estatística, Ministério da Saúde, Ministério do Planeamento and ICF, 2025). The MPI and its associated statistics are estimated by provinces since the survey sample is representative at this level. We publish MPI estimates for all 18 provinces, as well as for urban and rural areas.

7.2 Congo (Democratic Republic of the) DHS 2023–24

The sample design of the Congo (Democratic Republic of the) DHS dataset was designed to produce reliable estimates for both urban and rural areas, as well as for each of the 26 provinces (Institut National de la Statistique, École de Santé Publique de Kinshasa and ICF, 2024). As such, the global MPI subnational estimates cover 26 provinces since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

7.3 Egypt EFHS 2021

The EFHS dataset was designed to produce reliable estimates across 26 governorates of the country, as well as in urban and rural areas (Central Agency for Public Mobilisation and Statistics

2022). Reportedly, the Frontier Governorates do not include North Sinai Governorate as it was not included in the sampling. We publish the MPI estimates and associated statistics for all 26 governorates, as well as for urban and rural areas.

7.4 Kazakhstan MICS 2024

The Kazakhstan dataset was designed to produce statistically reliable estimates for urban and rural areas across 20 administrative regions (Bureau of National Statistics and UNICEF, 2025). Accordingly, urban–rural and subnational estimates were generated in line with the sampling design. We publish the MPI estimates and related statistical measures for all 20 administrative regions, covering both urban and rural areas, as detailed in the survey report.

7.5 Malawi DHS 2024

The Malawi DHS dataset sample design offers statistically reliable estimates across 32 domains – 28 districts and four cities – disaggregated by urban and rural areas (National Statistical Office, Utica International and ICF, 2025). An extra domain (domain 33), consisting of 24 clusters, was created for the Dzaleka refugee camp in Dowa district and was surveyed separately. Because data from the Dzaleka camp were not included in the 2024 Malawi DHS report, they are also excluded from this analysis (p.377). Both subnational and urban–rural estimates are calculated according to the methods specified in the survey report.

7.6 Mali DHS 2023–24

This sample was designed to produce statistically reliable estimates for urban and rural regions, as well as the nine subnational regions of Mali (INSTAT, CPS/SS-DS-PF and ICF, 2025). We calculate the MPI and related statistics for districts because the survey sample accurately represents these levels. Our estimates at the area level include both urban and rural areas.

7.7 Mexico ENSANUT 2024

The sample for the National Health and Nutrition Survey (ENSANUT) was structured to generate statistically representative estimates at both the national and regional levels, covering urban and rural regions each year, and after five years, to achieve state-level representativeness (Shamah-Levy et al., 2025). Our estimates at the area level encompass data from both urban and rural regions. Although the dataset includes a variable intended to identify 31 federal entities, ENSANUT 2024 did not collect data from Sinaloa (Shamah-Levy et al., 2025). Given discrepancies in geographic identifiers and following helpful consultation with ENSANUT staff, we restrict the subnational

analysis of Mexico to nine major regions, consistent with the sampling guidelines outlined in the survey report.

7.8 Nepal MICS 2024–25

The survey dataset was designed to produce statistically representative estimates at the national level and for urban and rural areas across seven provinces: Koshi, Madhesh, Bagmati, Gandaki, Lumbini, Karnali and Sudurpashchim (National Statistics Office, 2026). We report estimates for Nepal's seven major subnational regions and for urban and rural areas, in line with the survey's sampling specifications.

7.9 Nigeria DHS 2024

The survey sample was designed to yield representative estimates at the national level and for rural and urban areas. The survey report indicated that the estimates are also representative at six zones and 37 subnational units – 36 states and the Federal Capital Territory (Federal Ministry of Health and Social Welfare, National Population Commission and ICF, 2025). We present the MPI and related estimates for both urban and rural regions, covering all 37 subnational units available in the microdata.

7.10 Peru ENDES 2024

The sample for Peru ENDES was designed to provide representative estimates at the national level, for 24 administrative regions, and for the capital district of Callao (Instituto Nacional de Estadística e Informática, 2025). Our estimates at the area level encompass both urban and rural areas. We publish the MPI estimates and associated statistics for all 25 administrative regions, as well as urban and rural areas.

7.11 Tajikistan DHS 2023

The Tajikistan DHS 2023 sample was designed to provide representative estimates at the national level and across five administrative regions (Agency on Statistics under the President of the Republic of Tajikistan, Ministry of Health and Social Protection of Population and ICF, 2025). Our area-level estimates include both urban and rural locations. We provide the MPI estimates and related statistics for these five regions as well as for urban and rural areas.

7.12 Turkmenistan MICS 2024

The Turkmenistan MICS survey was designed to yield reliable estimates at the national level and for urban and rural areas, and across the seven regions in Turkmenistan (State Committee of

Statistics of Turkmenistan, 2026). As such, our subnational estimates cover seven subnational regions as well as urban and rural areas.

7.13 Zambia DHS 2024

The Zambia DHS (ZDHS) survey was designed to provide representative estimates for both urban and rural regions, as well as for each of the six provinces (Zambia Statistics Agency, Ministry of Health and ICF, 2024). Our subnational MPI and related estimates are calculated for all six provinces because the survey sample adequately represents each province. These area-level estimates encompass both urban and rural populations.

8. Concluding remarks

This methodological note outlines the principles underlying poverty estimation across different population subgroups, going beyond the national aggregate. The global MPI 2026 covers 108 countries, of which 13 countries have new or updated surveys. We compute estimates of the MPI and its partial indices by six major age groups, by urban and rural areas for 106 countries (excluding Seychelles and Naeoro due to lack of data on urban–rural areas), and by the gender of the household head for 107 countries (excluding China due to a lack of data on household head).

Our subgroup disaggregation also includes estimates of the MPI and its partial indices by 1,360 subnational regions across 100 countries (excluding four countries due to constraints in sample representation and four countries due to bias in regional estimates). All 13 countries with new or updated surveys were included in our subnational-level estimates. Collectively, these 13 countries account for 231 subnational regions that are home to 12.6% of the total global population who are poor (25.6 million poor people) – now with new or updated disaggregated estimates.

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