OPHI MPI Methodological Note 63

The global Multidimensional Poverty Index (MPI) 2025: Changes over time results for 88 countries

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Attribution

2021–24. The global MPI harmonised level estimates and their changes over time published in the most recent four rounds (2021–24) were produced by Professor Sabina Alkire, Dr Usha Kanagaratnam and Dr Nicolai Suppa for over 80 countries using over 200 harmonised surveys Since 2021, a new and well-conceived production process was implemented by Dr Kanagaratnam and Dr Suppa to enable transparent, reproducible and user-friendly access to the data, which had not been possible in earlier rounds. The details of the data repository are documented in their jointly published open-access paper in *Scientific Data* (Suppa and Kanagaratnam, 2025).

Following the attribution presented in the Methodological Note 60 published in 2024, all earlier published work continued to be acknowledged.

The following attribution is based on Alkire, Kanagaratnam and Suppa (2024) as presented in the OPHI MPI Methodological Note 60, Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

2011. The changes over time estimates using global MPI specifications was first published by Alkire et al. (2011), comparing changes in MPI for 10 countries and 158 subnational regions using DHS data across two periods of time.

2013. Alkire and Roche (2013) published harmonised levels and changes estimates for 22 countries using comparable DHS data across two periods. The methodological specifications were discussed in Alkire et al. (2013). In addition, a country-specific analysis on the change in multidimensional poverty in India between 1998–99 and 2005–06 was published by Alkire and Seth (2015).

2014. Alkire and Vaz (2014) documented changes over time results for 34 countries and 338 subnational regions. The methodological specifications were highlighted in Alkire et al. (2014). The harmonised estimates were based on comparable DHS datasets across two time points, except for two countries (Ethiopia and Peru), where the comparison included three time points. Alkire, Roche, et al. (2017) presented the changes estimates for 34 countries and their subnational regions.

2016–17. Alkire et al. (2016) extended the harmonised estimates to 50 countries (16 new countries, in addition to 34 previously harmonised countries). This round included comparisons using Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) data and, for three countries (Nigeria, Senegal and Zimbabwe), the analysis was extended from two to three time points. This was followed by a publication that focused on changes in multidimensional poverty among countries in sub-Saharan Africa (Alkire, Jindra, et al., 2017).

2018. A country-specific analysis on the change in multidimensional poverty in India between 2005–06 and 2015–16 was published by Alkire, Oldiges, et al. (2021).

2019. The 2019 global MPI covered harmonised intertemporal estimations using two data points for 10 countries (Alkire, Kovesdi, Mitchell and others, 2019).

2020. The 2020 global MPI covered harmonised intertemporal estimations using two data points for 80 countries (Alkire, Kovesdi, et al., 2020).

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1. Overview

This methodological note outlines the methodology and policies applied to harmonise 244 survey datasets, which form the basis for generating the harmonised level estimates and their changes over time in multidimensional poverty for **88 countries** and **882 subnational regions**. Forty of the 88 countries have data for one period spanning two points in time, while poverty trends in 35 countries are based on three points in time. Nine countries (Benin, Bolivia, Eswatini, Kyrgyzstan, Nigeria, the Philippines, Senegal, Tanzania and Thailand) have results spanning four points in time. One country (Ghana) provides trends across five time periods, while Mexico, Peru and Nepal have the longest coverage, with trends for six time periods.

We also estimate how multidimensional poverty has changed by four major age categories (0–9 years, 10–17 years, 18–59 years, and 60 years and over) and by two age categories covering children aged 0–17 years and adults 18 years and older in all countries. Our results also show poverty trends by rural and urban areas. Indicator standardisation is detailed in Alkire et al. (2025a), while indicator harmonisation is detailed in Alkire et al. (2025b) and in earlier publications by Alkire, Kanagaratnam and Suppa (2024, 2023, 2022, 2021).

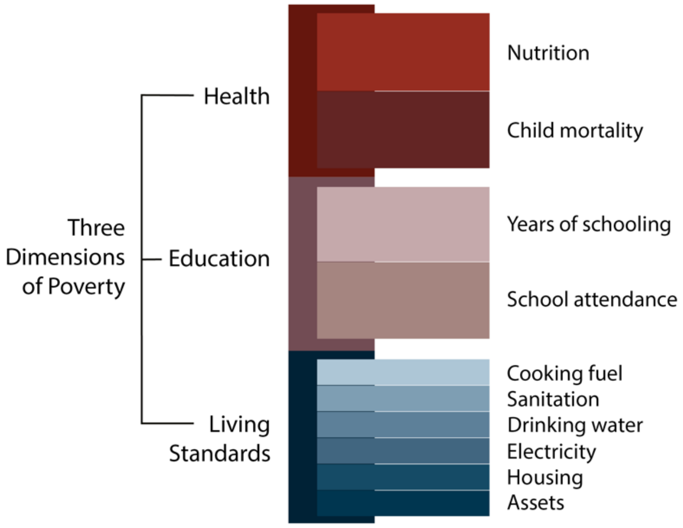
The global MPI harmonised level estimates and their changes over time remain an ongoing area of innovation. The number of harmonised countries, datasets and survey periods will increase as we continue to harmonise earlier surveys, alongside upcoming surveys. As the survey time points grow longer, we may review the methodology and policies that underlie the harmonisation principles. This is because some of the policies for harmonisation may be more relevant for surveys with two time points, but less relevant with a greater number of survey time points.

This note focuses on the harmonisation methodology and principles of the 2025 round and is structured as follows. Section 2 presents the global MPI structure and indicator definitions, while Section 3 outlines the global MPI and its partial indices that we estimate and publish. Section 4 summarises the changes over time methodology and Section 5 elaborates on the toolbox designed to estimate the global MPI. Section 6 summaries the harmonised surveys. Section 7 outlines the principles and decisions that underlie our harmonisation work. Section 8 summarises the country-specific decisions applied to the datasets harmonised in this round. We conclude with key highlights of the work implemented in this round.

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.

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



Source: OPHI 2018.

The first major revision of the global MPI was undertaken in 2018, adjusting the definitions of five of the ten indicators (Alkire and Jahan, 2018). Alkire, Kanagaratnam, et al. (2022) provide a comprehensive analysis of the consequences of the 2018 revision. The normative and empirical decisions that underlie the revision of the global MPI, and adjustments related to the child mortality, nutrition, years of schooling and housing indicators, are discussed in Alkire and Kanagaratnam (2021). The revision of the assets indicator is detailed in Vollmer and Alkire (2022).

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).

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 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.

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.

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 deprivation score, or the average percentage of poor people in the population. We then compute the intensity of poverty (A), representing the average percentage of weighted deprivations experienced by poor people. We then compute the adjusted poverty headcount ratio (M_0) or MPI by combining H and A in a multiplicative form (MPI = H x A).

Both the incidence and the intensity of these deprivations are highly relevant pieces of information for poverty measurement. The incidence of poverty is intuitive and understandable by anyone. Yet, the proportion of poor people as a headline figure does little to shed light on the poorest of poor people. For example, the trends of multidimensional poverty for India between 2005–06 and 2015–16 indicate that the poorest states within India had slower progress by incidence of poverty. However, by MPI value, the poorest states showed the fastest reduction, because the intensity of deprivations experienced by the poorest people in these states reduced much faster compared to those who are less poor (Alkire, Oldiges, et al., 2021). By combining the two pieces of information – the change in intensity of deprivations and the change in proportion of poor people – the MPI captures the progress observed among those in poverty. The MPI puts a spotlight on the poorest of poor people, affirming that they are not left behind in poverty reduction efforts.

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 one-third 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 those in **severe** poverty, meaning those deprived in 50% or more of the weighted indicators.

The Alkire-Foster method has a property that makes the global MPI even more useful – dimensional breakdown. This property 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. The weighted sum of censored headcount ratios of all MPI indicators is equal to the MPI value.

4. Changes over time methodology

Trends are estimated using indicators in the global MPI that are harmonised across time periods. Harmonisation is necessary to ensure that any differences observed are due to changes in the conditions of poverty in the country rather than changes in the questionnaire. We estimate the harmonised levels of the MPI and its partial indices using the harmonised indicators. This is important: in poverty analysis, the headline of interest is often the overall change in poverty. People want to know whether poverty has reduced, increased or remained unchanged over time. Therefore, a prominent component of poverty comparisons is the absolute pace of change across periods or points in time.

4.1 Absolute rate of change

The absolute rate of change is the simple difference in poverty levels between two periods. We denote the initial period by t^0, the subsequent period by t^1, and the corresponding achievement matrices for these two periods by X_{t^0} and X_{t^1}, respectively. Note that the parameters of the poverty measure – deprivation cutoffs z, weights w_j and poverty cutoff k – used in each period remain unchanged. The absolute rate of change (Δ) is the difference in the MPIs between two periods and is computed as (and similarly for H and A, which are not presented):

$$\Delta MPI = MPI(X_{t^1}) - MPI(X_{t^0})$$

The significance of the difference is determined by t-tests and is reported at 90% (*), 95% (**) and 99% (***) confidence levels in the global MPI 2025 release Table 6.

The absolute rate of change is indifferent to the initial level. For example, a 10-percentage point reduction could mean that the headcount ratio decreased from 80% to 70% or from 15% to 5%. To look at the proportion of the change with respect to the initial level we use a relative measure.

4.2 Relative rate of change

The relative rate of change is the difference in poverty as a percentage of the initial poverty level. Interpreting the analysis of absolute and relative changes together provides a clear sense of overall progress. The relative rate of change (δ) is computed for the MPI (and similarly for H and A, which are not presented) as:

$$\delta MPI = \frac{MPI(X_{t^1}) - MPI(X_{t^0})}{MPI(X_{t^0})} \times 100$$

4.3 Annualised change

However, the absolute and relative changes are not comparable for different countries when the reference periods (the duration between survey years) are of different length. To compare the rates of poverty reduction across countries that have different reference periods, annualised changes are used. The annualised absolute rate of change $(\underline{\Delta})$ is computed for the MPI as:

$$\underline{\Delta} MPI = \frac{MPI(X_{t^1}) - MPI(X_{t^0})}{t^1 - t^0}.$$

The annualised relative rate of change $(\underline{\delta})$ is computed for the MPI as:

$$\delta MPI = \left[\left(\frac{MPI(X_{t^1})}{MPI(X_{t^0})}\right)^{\frac{1}{t^1 - t^0}} - 1\right] \times 100$$

We use the same formula to compute, and report annualised changes in the other partial indices, namely H, A and censored headcount ratios.

For surveys that are fielded between two or more years, the analysis takes the average of the years for calculating annualised change. For instance, in the case of India, we compute changes in poverty using harmonised data from three survey datasets: Demographic and Health Surveys (DHS) 2005–06, 2015–16 and the most recent survey, 2019–21. The annualised change between 2005–06 and 2015–16 is then 2015.5 – 2005.5 = 10 years, while the annualised change between 2015–16 and 2019–21 is 2020 – 2015.5 = 4.5 years.

As a measure of robustness, we also computed annualised change using two alternative approaches in the case of India (Table 2). We assess the implications of two alternative year policies on the change in the headcount ratio, as this is the most sensitive result. The first alternative approach is counting the mean of the month and year of the interviews to produce the annualised change,

Table 2. Comparing alternative approaches to estimating annualised change for India

		t0 initial year		t1 final year				Duration between t0 and t1	Multidimensional headcount ratio (HT)		
		Survey	Year						t0	t1	Absolute annualised change
Current approach: for surveys fielded between survey years, the analysis takes the average of the years to compute annualised changes	India	DHS	2005–06	DHS	2015–16	2005.5	2015.5	10.0	55.07	27.68	-2.74
	India	DHS	2015–16	DHS	2019–21	2015.5	2020	4.5	27.68	16.39	-2.51
Mean approach: the average of the interview months and years used to compute the annualised changes	India	DHS	2005–06	DHS	2015–16	Mar 06	Dec 15	9.7	55.07	27.68	-2.83
	India	DHS	2015–16	DHS	2019–21	Dec 15	May 20	4.3	27.68	16.39	-2.60
Median approach: the median of the interview months and years used to compute the annualised changes	India	DHS	2005–06	DHS	2015–16	Mar 06	Dec 15	9.8	55.07	27.68	-2.81
	India	DHS	2015–16	DHS	2019–21	Dec 15	Feb 20	4.1	27.68	16.39	-2.76

Note: DHS surveys contain only the year and month of interview; the date of interview is not available.

while the second alternative approach is counting the median instead of the mean. The results for the current approach of the changes over time methodology, which takes the average across the survey years, indicate that we are going with a lower bound of possible absolute annual reduction.

4.4 Changes in deprivations among poor people

Changes in the MPI can be broken down by indicators. Analyses of changes in the MPI consider both changes in the raw or uncensored headcount ratios and in the censored headcount ratios. The changes in censored headcount ratios depict changes in deprivations among poor people.

4.5 Disaggregation by subgroups over time

Decomposable and subgroup-consistent poverty measures (Foster, Greer and Thorbecke, 1984; Foster and Shorrocks, 1991) fulfil the property that the change in overall (national) poverty is consistent with the changes in subgroup poverty. Suppose, MPIs at time t^0 and t^1 can be expressed as

$$MPI(X_{t^0}) = \sum_{\ell=1}^{m} v^{\ell} MPI(\mathrm{X}_{t^0}^{\ell})$$

$$MPI(X_{t^1}) = \sum_{\ell=1}^{m} v^{\ell} MPI(\mathrm{X}_{t^1}^{\ell})$$

Where, $MPI(\mathrm{X}_{t^i}^{\ell})$ denotes adjusted headcount ratio at time t^i and $v^{\ell} = n^{\ell}/\, n$ the populations share of subgroup ℓ. This enable us to meaningfully analyse how different subgroups contribute to overall poverty and how poverty changes across population subgroups to ascertain if poorest sub-group reduced poverty faster than less poor sub-groups and to understand the dimensional composition of the reduction across subgroups (Alkire et al., 2015). The contribution of population subgroups to overall reduction of poverty between two time points t^0 and t^1 is given as

$$\Delta MPI = \sum_{\ell=1}^{m} \left(v^{\ell}{}_{t^1} MPI(\mathrm{X}_{t^1}^{\ell})\right) - \left(v^{\ell}{}_{t^0} MPI(\mathrm{X}_{t^0}^{\ell})\right)$$

Where, ΔMPI represents total change in the MPI, which further can be decomposed by subgroup to show how each subgroup contributes to overall change in poverty levels between two time periods. For example, assuming the entire society is divided into three population subgroups (e.g. subnational regions): region 1, region 2 and region 3. Poverty in region 1 remains unchanged while poverty in region 2 and region 3 decreases. Overall poverty, that reflects subgroup poverty, must decrease.

In the harmonised global MPI, we have estimated changes in the MPI and its partial indices by age groups, rural and urban areas and subnational regions. Our analyses of poverty changes by population subgroups allows us to identify if the poorest subgroups reduced poverty faster than less poor subgroups and to see the indicator composition of reduction across subgroups. Note that the population shares for each period must always be analysed alongside subgroup trends to consider demographic shifts such as migration or population growth, as these can significantly influence the interpretation of results.

5. Tool to estimate the global MPI

The global MPI harmonised level estimates and their changes over time 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), and the censored and uncensored headcount ratios for each time period. It supports the estimation of change between time periods for each of the measures. The level and change estimates for harmonised datasets can be computed at the national level, by subnational regions, age cohorts and rural and urban areas, and could include other subgroup disaggregations. `mpitb` also simplifies estimations and analyses in cross-country settings. Suppa and Kanagaratnam (2023) present selected aspects related to the estimation procedures of the global MPI.

The package is available at the Statistical Software Components (SSC) Archive and on gitlab. The MPI toolbox is distributed free of charge under an MIT licence. The package is installed by issuing 'ssc install `mpitb` in Stata. To access its comprehensive help files, issue 'help `mpitb` after the installation. `mpitb` requires Stata 16 or higher.

6. Harmonised survey time periods and datasets

The global MPI trends over time have been released annually since 2021. The number of harmonised countries, datasets and survey periods will increase as we continue to harmonise earlier surveys, alongside with upcoming surveys.

6.1 Survey time periods

For this 2025 round, the analysis of changes in multidimensional poverty draws on **244 survey micro datasets** from 88 countries.[1] Forty of these countries have two points in time, and 35

[1] Twenty-six countries – Angola, Argentina, Barbados, Bhutan, Botswana, Brazil, Costa Rica, Cuba, El Salvador, Fiji, Georgia, Guatemala, Kiribati, Libya, Maldives, Myanmar, Papua New Guinea, Paraguay, Saint Lucia, Samoa, Seychelles, South Africa, Sri Lanka, Tonga, Tuvalu and Uzbekistan – have surveys for one period and so are part of the countries covered in our current release (Alkire et al. (2025a); see results in the [global MPI 2025 release Data Table 1](). However, these countries are not part of the harmonisation and changes over time analysis because we

countries have trends for three points in time. Changes in multidimensional poverty in nine countries (Benin, Bolivia, Eswatini, Kyrgyzstan, Nigeria, the Philippines, Senegal, Tanzania and Thailand) cover four points in time, one country (Ghana) covers five points in time, and Mexico, Peru and Nepal have trends for six points in time.

Table 3 provides an overview of coverage by country and subnational region for each release since 2021.

Table 3. Harmonised survey details for each publication round, 2021–25

Publication year	Country coverage	Countries with subnational regions	Country coverage in terms of survey time points	Survey micro datasets
2025	88	79 (882 regions)	48 (three or more points in time) 40 (two points in time)	244
2024	86	78 (863 regions)	46 (three or more points in time) 40 (two points in time)	233
2023	84	77 (814 regions)	39 (three or more points in time) 45 (two points in time)	211
2022	84	76 (810 regions)	36 (three or more points in time) 48 (two points in time)	205
2021	84	77 (793 regions)	28 (three points in time) 56 (two points in time)	196

Collectively, for this 2025 round, we standardised and harmonised 244 survey datasets [(40*2) + (35*3) + (9*4) + (1*5) + (3*6)] to produce harmonised MPI estimates for 88 countries at the national level; and by age groups and rural and urban areas.

In addition, we produced harmonised MPI estimates for 882 subnational regions in 79 of the 88 countries, using 217 of the 244 harmonised survey datasets.

6.2 Survey datasets

In 29 countries, we harmonised DHS datasets across all time points, while in 22 countries we used only Multiple Indicator Cluster Surveys (MICS) datasets. For four countries (China, Ecuador, Jamaica and Mexico), the harmonisation work is exclusively based on national datasets, while for Morocco we have used the Pan Arab Project for Family Health (PAPFAM) survey across two time points. For Bolivia and Peru, the harmonised datasets include a combination of DHS surveys and

have yet to identify relevant comparable surveys from an earlier time period. We continue to explore survey options for these countries, with the aim of including them in the Global MPI Harmonised Level Estimates and their Changes over Time database.

national surveys. We have used a mix of DHS and MICS across time points for 30 countries: Afghanistan, Azerbaijan, Bangladesh, Benin, Cameroon, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of Congo, Dominican Republic, Eswatini, Gambia, Ghana, Guinea, Guyana, Honduras, Madagascar, Malawi, Mali, Mauritania, Moldova, Nepal, Nigeria, São Tomé and Príncipe, Sierra Leone, Togo, Ukraine, Yemen and Zimbabwe. The decision to use mixed data sources between time points was possible because MICS and DHS have comparable sample designs and survey questionnaires (Khan and Hancioglu, 2019).

It is not unusual for survey providers to change the sampling design of long-running surveys over time. Such cases present an issue where the older and newer surveys have incomparable sample designs. For example, the sample design for the Jamaica Survey of Living Conditions (JSLC) 2018 was revised by the survey providers and therefore direct comparisons with previous survey rounds, JSLC 2010 and 2014, are not recommended (PIOJ and STATIN, 2021, p.139). However, we continue to include JSLC 2010 and 2014 as part of our harmonised estimates, with JSLC 2018 restricted to the non-harmonised recent estimates that are presented in global MPI 2025 release Data Table 1 (Alkire et al., 2025a). A similar limitation is evident in the Niger ENAFEME 2021 survey which, despite adopting a survey design reportedly similar to DHS, did not provide strata variables in the dataset, thereby preventing harmonisation with earlier Niger surveys (DHS 2006 and DHS 2012). In practical terms, while it is not possible to use the recent survey data to construct consistent poverty trends in Niger and Jamaica, we continue to report changes in MPI estimates in earlier periods for each country.

7. Harmonisation principles and decisions

It is common for indicator definitions to vary across survey years, as survey providers may have changed how questions are asked, from whom these are collected or the response categories. Another reason may be that we are using different survey sources with comparable sampling designs to capture changes over time in a country, and as such indicator definitions may require adjustment across these survey sources (e.g. comparing DHS and MICS). Harmonisation seeks to make two or more MPI estimations comparable by aligning the indicator definitions as closely as possible. The next section describes the indicator-specific decisions required in the harmonisation process.[2]

[2] Indicator-specific decisions are also summarised in Suppa and Kanagaratnam (2023).

7.1 Indicator-specific harmonisation decisions

7.1.1 Nutrition

In recent surveys there are often two variables – children's age in days and age in months – which can be used to compute nutrition statistics for children under five years of age, while many earlier surveys, notably DHS, do not include the age-in-days variable. We continue to use children's age in days for surveys that have this information, given its accuracy for nutrition statistics. For surveys that lack data on 'age in days', we use the 'age in months' variable when calculating the nutrition statistics for children. We do not harmonise this information between surveys.

Most MICS surveys used in this analysis collect anthropometric measurements only for children under five years of age. In comparisons where in one year is a DHS survey and the other year a MICS survey, the nutrition indicator is harmonised to include anthropometric information only for children under five years of age.

Following this principle, adult nutrition is excluded from the harmonised nutrition indicator for 30 of the 88 countries, involving 47 of the datasets.[3]

For surveys of which we used information from children and adults to construct the nutrition indicator, if the reference populations were changed, the harmonised estimates follow the year with the more limited eligibility conditions.[4] This restricted condition principle also applies when one year includes nutrition information from men and the other year does not; in that case, men's nutritional information would be excluded from the harmonised indicator.

If one year the surveys did not collect the information needed to construct the nutrition indicator and the other year did, the nutrition indicator is dropped from the year that includes the information, and the indicators within the dimensions reweighted to maintain equal weights across dimensions and match the survey with the restricted data. In our sample of 88 countries, nine

[3] These countries and datasets are: Armenia DHS 2015–16, Azerbaijan DHS 2006, Bangladesh DHS 2014 and 2022, Burkina Faso DHS 2010, Benin DHS 2017–18, Cameroon DHS 2011 and 2018, Comoros DHS 2012, Congo Republic DHS 2005, Democratic Republic of Congo DHS 2007 and 2013–14, Eswatini DHS 2006–07, Ethiopia DHS 2011 and 2016, Gambia DHS 2013 and 2019–20, Guinea DHS 2018, Ghana DHS 2008, 2014 and 2022, Guyana DHS 2009, Honduras DHS 2005–06 and 2011–12, Kyrgyzstan DHS 2012, Madagascar DHS 2008–09 and 2021, Mali DHS 2006 and 2018, Moldova Republic DHS 2005, Mauritania DHS 2019–21, Malawi DHS 2010 and 2015–16, Nepal DHS 2006, 2011, 2016 and 2022, Senegal DHS 2010–11, São Tomé and Príncipe DHS 2008–09, Sierra Leone DHS 2019 and 2013, Togo DHS 2013–14, Vanuatu MICS 2023, Zambia DHS 2007 and 2013–14, and Zimbabwe DHS 2010–11 and 2015.

[4] For example, in the Peru ENDES 2018, 2019, 2021, 2022 and 2023 surveys, eligible females for height and weight measurements included all females aged 12–49 years, whereas in Peru DHS 2012, eligible females included all females aged 15–49 years. Therefore, in Peru, only females aged 15–49 years are considered eligible for the nutrition measurement for all survey years.

countries dropped the nutrition indicator from one year to match the year that did not collect anthropometric measurements.[5]

7.1.2 Child mortality

The child mortality indicator was constructed using birth history information – whether the mother gave birth in the five years preceding the survey and how old the child was when they died. A few surveys do not include a birth history questionnaire and thus do not have information on the age and date of death of the child. When one year includes birth history information and the other does not, the restricted condition principle is followed, and information on age and year of death are removed from the survey that has these. The child mortality indicator then takes the deprivation cutoff from the 2010 global MPI specifications, which considers whether any child has died in the household.[6]

However, the issue of missing birth history information is usually limited to a single survey, largely the first survey period. It may not be reasonable to continue to exclude birth history information from more recent datasets as we continue to increase the survey period coverage of a given country. In this case, we may review the restricted condition principle. A sensitivity analysis can be conducted by comparing estimates between two specifications. The first specification applies the restricted condition principle across the datasets if at least one survey has missing birth history information. The second specification retains the birth history information in all datasets that have this information, despite its unavailability in a single survey year. If there are significant differences in the levels of the MPI and H estimates between both specifications, then a decision may be made to exclude the single dataset with missing birth history information from the analysis of poverty trends of the given country.

Birth history information was consistently not collected across all the survey datasets of four countries. For these countries, we applied the 2010 global MPI specifications, which considers whether any child has died in the household.[7]

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[5] These countries are Afghanistan, Colombia, Dominican Republic, Indonesia, Nigeria, the Philippines, Trinidad and Tobago, Ukraine and Vietnam.

[6] Birth history information is excluded from the harmonised child mortality indicator for 10 of the 88 countries, involving 14 of the datasets. These include Belize MICS 2015–16, Central African Republic MICS 2019, Chad DHS 2014–15 and MICS 2019, Ecuador ENSANUT 2018, Morocco PAPFAM 2017–18, Mongolia MICS 2013 and 2018, Turkmenistan MICS 2019 and 2015–16, Togo MICS 2017 and DHS 2013–14, Trinidad and Tobago MICS 2022 and Vanuatu MICS 2023.

[7] These datasets are Kazakhstan MICS 2010–11 and 2015, Montenegro MICS 2013 and 2018, Serbia MICS 2019, 2014 and 2010, Thailand MICS 2022, 2019, 2015–16 and 2012, and Vanuatu MICS 2023 and 2007.

In addition, attention was also paid to which individuals provide information on child mortality to ensure the applicable populations match between survey years. For instance, in the Bolivia 2023 dataset, women who are eligible to provide child mortality information are all women aged 12 to 49 years, while in Bolivia 2016 dataset the same information is provided by women aged 14-49 years, and in the 2008 and 2003 datasets, eligible women were aged 15–49 years. Therefore, only child mortality information from women aged 15–49 years is included in the indicator for all four years, following the restricted condition principle. However, child mortality information from eligible men was not excluded even when not present in the other year, as it is only used to identify zero child mortality at the household level in the absence of information from eligible women.

If the surveys did not collect the information needed to construct the child mortality indicator in one year and did in the other year, the indicator was dropped from the year that includes the information and the indicators within the dimensions reweighted to maintain equal weights across dimensions and to match the survey with the restricted data. This occurred in two countries (North Macedonia and Suriname) in our sample of 88 countries.

7.1.3 Years of schooling

For the years of schooling indicator, DHS data contain a variable that states the total number of years of education for the individual, but MICS data do not provide an equivalent variable. Instead, when using MICS data, the total number of years of schooling is computed by combining the education level and highest-grade variables, taking into consideration the country's national education system, as described in the survey report. In cases where this information is not included in the survey report, we refer to the UNESCO Institute for Statistics (UIS) data browser. Where there is a mismatch between the survey report and the national guidance, we investigate this issue with the respective national statistical offices or survey providers. For the DHS and MICS comparisons, the DHS variable was treated as equivalent to the MICS composite variable (e.g. six years of schooling in the DHS variable corresponds to the first six years of education in MICS).

All adults are eligible for the years of schooling indicator, while the youngest eligible people are specified using country-specific age cutoffs that correspond to the age at which they are expected to complete class six (Alkire, Kanagaratnam and Suppa, 2020). For example, in India, children start school at six years old, so we would expect a 12-year-old child to have completed six years of schooling. Hence the minimum age of eligibility for the years of schooling indicator for India is 12 years old. In Indonesia, children start school at seven years old and so would complete six years of schooling by the time they are 13. Hence the minimum eligibility for the years of schooling indicator in Indonesia is 13 years old.

7.1.4 School attendance

Eligibility for the school attendance indicator is computed using the age range based on the national entry age to compulsory schooling. The official national entry age to compulsory schooling is selected using the survey report where possible, or UNESCO Institute for Statistics data if this is not available in the survey report. Where there is a mismatch between the report and UNESCO guidance, we consult the national statistical offices or survey providers.

For most countries included in the changes over time analysis, the official entry age for primary schooling is six years, although this differs for a few countries. For example, the official entry age is seven years old in Indonesia and five years old in Pakistan. When the official entry age changes between surveys, often due to education policy changes, we retain the exact official entry age in each survey and do not harmonise across the years, in order to fully capture the range of eligible children.

Additionally, we construct school age eligibility using information on age at the beginning of school year, if surveys have this information. Most MICS datasets have the 'schage' variable which represents this information. For surveys that lack information on age at the beginning of school year, we use information on age that was collected from the household roaster to construct the school age eligibility. We do not harmonise school age eligibility across survey years in order to reduce the bias we usually observe with the general age variable from the household roaster, compared to the more accurate variable on age at the beginning of school year.

7.1.5 Electricity

The electricity indicator does not have any indicator-specific harmonisation decisions, beyond the general principles of only using information that is available in datasets from both survey years.

7.1.6 Sanitation

For the sanitation indicator, two conditions are used – whether other households share the toilet facility and whether the toilet facility is considered an improved or unimproved facility – to define a household's access to improved sanitation. If there is no information on whether the facility is shared in one year, but the other years do have that information, the principle of restricted condition may be considered. In the future, if data on sharing a facility are not collected in recent surveys because almost 100% of the households in the country use private toilet facilities, as indicated by the survey provider, then we may consider that all households do not share toilet facilities.

If survey report classifications of types of toilet facilities as improved or unimproved differ between the two years, we consider the more recent data's definition of improved facilities for both years. If a first-year survey specifies a category for sanitation facilities that the second year does not, we would leave the category labelled as is in the first year.

7.1.7 Drinking water

For the drinking water indicator, there are two conditions to consider in defining a household's access to basic drinking water. First, whether the main drinking water source is considered an improved or unimproved source. Second, how long it takes the respondent to fetch water from the main drinking water source of the household.

In cases where different main drinking water sources are considered improved between the two years, we follow the standard in the more recent survey. For example, in surveys released since 2020, bottled water and water delivered via truck are considered to be improved sources of drinking water.

If one year does not have information on how long it takes to fetch water but the other year does, this information may be dropped to accord with the year that has the more limited information.[8] Alternatively, we may also review the restricted condition principle to consider variables that may inform whether access to drinking water is within or outside of dwellings.

7.1.8 Cooking fuel

If in one year, there is no information on type of fuel used for cooking, but the other year does have that information, that information may be dropped to accord with the year that has the more limited information.[9] In the future, if data on cooking fuel are not collected in recent surveys because almost 100% of the households in the country use clean fuel, as indicated by survey provider, then we may consider all households as not deprived in cooking fuel.

7.1.9 Housing

For the housing indicator, the household is considered as deprived if they live in inadequate housing, where the floor is of natural materials, or the roof or walls are of natural or rudimentary materials. Following the principle of differing classifications reverting to the more recent standard, when the first year considers a housing material as natural or rudimentary and the more recent year does not, both years are coded to consider that material as an improved housing material.

[8] We currently adopt the restricted condition principle, where information on time taken to collect water is excluded from the harmonised drinking water indicator for four countries involving six datasets: Bangladesh 2019 and 2014, Jordan 2023, Republic of Moldova MICS 2012 and the State of Palestine MICS 2019–20 and 2014.

[9] We removed the cooking fuel indicator in five countries: Afghanistan, Bangladesh, Egypt, Eswatini and Turkmenistan.

When information on one or two of the three housing components (floor, roof or walls) is missing in one year, the information from the year where it exists is removed to match the missing year.[10] However, the issue of missing components is usually limited to a single survey, largely the first survey period. It may not be reasonable to continue to exclude housing components from more recent datasets as we continue to increase the survey period coverage of a given country.

In this case, we may review the restricted condition principle. A sensitivity analysis can be conducted by comparing estimates between two specifications. The first specification excludes information on missing housing components across all survey datasets of a given country if it has a missing component in at least one survey period. The second specification retains the components in all datasets that have the information, despite its unavailability in a single survey year. If there are significant differences in the levels of the MPI and H estimates between both specifications, then a decision may be made to exclude the single dataset with a missing housing component from the analysis of the country's poverty trends.

7.1.10 Assets

The assets indicator considers whether a household owns a radio, television, telephone, computer, animal cart, bicycle, motorbike, refrigerator or car/truck. When in one year there is no information on certain assets, those assets are dropped from the indicator in the later years to accord with the more limited information available. The most common missing asset item is a computer, followed by an animal cart. In 31 countries, across 43 datasets, we excluded computer from the harmonised assets indicator because this information was not available in at least one of the surveys.[11]

However, the principle of restricted condition in the case of asset-related items should be reviewed as the survey period coverage of each country increases, with sensitivity analysis applied to ascertain whether there is value in excluding asset items from a series of survey years simply because the data were not collected in an earlier survey. The sensitivity analysis may show that there are no

10 This restricted condition principle was applied on the harmonised housing indicator for seven countries involving 12 datasets: Democratic Republic of Congo DHS 2013–14 and 2017–18, Mali MICS 2015 and DHS 2018, Mozambique DHS 2022 and 2011, Niger DHS 2012, the State of Palestine MICS 2014 and 2019–20, São Tomé and Príncipe MICS 2014 and 2019 and Yemen DHS 2013.

11 These datasets are Afghanistan MICS 2022–23, Azerbaijan DHS 2006, Bosnia and Herzegovina MICS 2011–12, Burkina Faso DHS 2010, Cambodia DHS 2021–22, Central African Republic MICS 2010 and 2019, Chad MICS 2019, Comoros MICS 2022, Colombia DHS 2015–16, Eswatini MICS 2021–22, Democratic Republic of Congo DHS 2013–14 and 2017–18, Republic of Congo DHS 2005, Ethiopia DHS 2016 and 2019, Gabon DHS 2012, Gambia DHS 2013, MICS 2018 and DHS 2019–20, Guinea MICS 2016 and DHS 2018, Indonesia DHS 2017, Kenya DHS 2022, Madagascar MICS 2018 and 2021, Malawi DHS 2015–15 and MICS 2019–20, Mozambique DHS 2022–23, Namibia DHS 2013, Niger DHS 2012, Suriname MICS 2006 and 2018, Tanzania DHS 2022 and 2015–16, Timor-Leste DHS 2016, Togo DHS 2013–14 and MICS 2017, Uganda DHS 2016, Zambia DHS 2013–14 and 2018, Yemen MICS 2022–23 and Vanuatu MICS 2023.

significant differences in estimates, either by excluding or retaining items in the aggregated asset indicator, if these items are consistently available in newer surveys but missing in one or two of the older surveys.

Our definition of telephone ownership includes information on whether a household owns a landline or mobile telephone. In earlier surveys, as with Mozambique DHS 2003, the questionnaire did not include a question on whether the household owned a mobile telephone (as they were not as common as they are today).

In these cases, for the second year, as in the case of Mozambique DHS 2011, we kept the telephone information from both the landline and mobile phone questions (as opposed to excluding the information on whether the household owns a mobile phone), as we believe that the changes in phone ownership are best reflected with the inclusion of all available information on telephone devices as individuals may own a mobile phone instead of, rather than in addition to, a landline.

7.1.11 Principles for subnational disaggregation of harmonised trends

The principles for subnational disaggregation using harmonised datasets build on the principles discussed in Alkire et al. (2025b) for standardised datasets. The decision whether a country qualifies for a harmonised subnational disaggregation was determined by three criteria: (1) the sample was representative at the subnational level across harmonised surveys; (2) the subnational unit definitions are comparable across harmonised surveys; and (3) the sample size after the treatment of missing data was reasonably high across harmonised surveys.

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. Two countries – Armenia and Bosnia and Herzegovina – have surveys in one or both years that did not satisfy this principle according to their survey reports, and are therefore excluded from subnational analysis. The remaining 86 countries met this principle.

The second criterion requires subnational units to be comparable across harmonised surveys. In four countries – Côte d'Ivoire, Morocco, Nepal and Sudan – subnational regions have changed boundaries or been split into new regions over the years. We exclude subnational disaggregations for these countries where changes in the subnational unit definitions between time periods are incomparable. In the future, we may renew this policy to recognise that some periods may permit comparable subnational disaggregation whereas other periods do not.

Besides these cases, a number of countries had regional changes between the time points that did not violate the principle of comparability, and we were therefore able to harmonise and obtain subnational estimates for these countries. To ensure comparable estimates are derived across time periods, where possible, regions were aggregated to recreate the regions presented in the survey with the more limited regional classification. For instance, with India DHS 2019–21 and DHS 2015–16, we aggregated the regions of Andhra Pradesh and Telangana to recreate the Andhra Pradesh region; and aggregated the regions of Punjab and Chandigarh to recreate Punjab, as presented in DHS 2005–06. Similarly, we aggregated the regions of Jammu and Kashmir and Ladakh in the most recent survey to recreate the Jammu and Kashmir region that is present in DHS 2015–16 and 2005–06.

In a few exceptional cases, a different number of regions were surveyed across years due to accessibility, physical security, or cost issues. For example, India DHS 2015–16 and 2019–21 surveyed additional regions (union territories) that are not available in the earlier DHS 2005–06 survey. This presented a problem for the estimation of trends over time as we aimed to preserve the national estimates while ensuring that subnational estimates are comparable between the two times. Our approach was to estimate national poverty using all available regions in both years (even if some were not present earlier) in order to preserve the weighting scheme for obtaining the national estimates. Subnational estimates utilise the individual regional weights and, in cases where additional regions were surveyed in one year compared to those in the other, our analysis omits the extra regions in its estimation of the regional results, but the weights and sample are retained for national analyses.

The third 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 specify the third criterion in three ways.

First, the national sample size for all surveys must be at least 85% of the original sample after missing data is treated. This is because a lower sample size may affect accurate comparability across subnational estimations. We identified four datasets representing three countries that did not meet this cutoff. In the Montenegro MICS 2018 dataset, we retained 80% of the weighted sample for estimation after dropping observations that had missing data in any of the 10 global MPI indicators. Similarly, in the Vanuatu MICS 2007 dataset, we retained 82% of the weighted sample for estimation, while for Mexico ENSANUT 2012 we retained 86% of the weighted sample for estimation.

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 particular subnational region, which may distort the subnational comparisons. Our analyses indicate that the Central Region in Montenegro MICS 2018 dataset, Torba in Vanuatu 2007 and México City in Mexico ENSANUT 2012 recorded sample drops of 27%, 25% and 29%, respectively.

Third, a bias analysis test is carried out for each region whose sample size is lower than 75% and whose national sample size is lower than 85% of the original. We identify the major cause of the sample reduction (in these cases, child mortality for Montenegro and child nutrition for Vanuatu and Mexico), divide the entire sample into two groups based on this cause and check the headcount ratios of the other indicators across these two groups. Suppose there is a systematic and statistically significant difference (at a 1% significance level) between the headcount ratios across these two groups. In this case, that region does not satisfy 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 Central Region of Montenegro. Results indicate that the likelihood of being deprived in child mortality differs between those who are missing the nutrition indicator and those who are not. Those without a missing nutrition indicator are systematically more likely to be deprived in child mortality. This suggests that the sampling structure would need to be revised to assure representativity. In addition, some 55% of the population live in the Central Region. Following the bias observed in the Montenegro MICS 2018 dataset, and given that the region accounts for a high share of the population, we exclude the harmonised dataset for Montenegro from the subnational analysis and limit the estimates to the national level (Alkire, Kanagaratnam and Suppa, 2024). In the case of Vanuatu, bias test results show a higher likelihood of missing nutrition data among those with missing child mortality data; however, the differences are not statistically significant. The Torba region constitutes 11% of the Vanuatu population and has 19% of missing cases in child nutrition. Due to the combination of low retained sample and missing data, Vanuatu was excluded from the subnational harmonisation, and only national estimates were retained. In the analysis of the Mexico ENSANUT 2012 dataset, for all of the indicators except access to water and years of schooling the difference between missing and non-missing nutrition was not statistically significant, indicating the absence of systematic bias. The region of México City constitutes 5% of the Mexico population and has 30% missing cases in child nutrition. For access to water and years of schooling, missing in nutrition is associated with lower deprivation, indicating a small potential bias in the retained sample.

In this round of the global MPI, although subnational disaggregation is theoretically possible for 84 of the 88 countries, only 79 countries, with 882 regions, satisfy the principles for subnational disaggregation and are therefore used to estimate changes in poverty over time at the subnational level.

8. Country-specific considerations

This section details the country-specific harmonised decisions concerning indicator availability and data treatment for each country with the updated survey.

8.1 Azerbaijan

The most recent survey for Azerbaijan is MICS 2023. This survey is harmonised with an earlier survey, DHS 2006.

The 2006 DHS dataset includes anthropometric data for children under five years of age, females aged 15–49 years and men aged 15–59 years. However, for harmonisation purposes, we only utilised children's anthropometric information so as to align with the MICS dataset.

The earlier survey does not include information on whether the household owns a computer, and likewise, the harmonised assets indicator does not include this item despite the availability of this information in the recent survey. For future rounds, when new surveys are available for Azerbaijan, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer ownership from the harmonised assets indicator. If this analysis indicates that there is no significant change in MPI estimates, we may conclude there is no reason to exclude items from the aggregated asset indicator if these items are consistently available in newer surveys, even if these were not collected in one or two of the older surveys.

At the subnational level, we harmonised the regions by combining the administrative sub-regions of Ganja-Dashkasan and Gazakh-Tavuz into a single Ganja Gazakh region, and Central Aran, Mil-Mughan and Shrivan-Salyan into Aran region in the MICS 2023 dataset, consistent with administrative definitions and representativeness at this level. We dropped Nakhchivan from MICS 2023 as it was not sampled in DHS 2006. Therefore, we estimated the MPI and its partial indices for nine economic regions of the country, as the samples across the harmonised datasets are representative at this level (State Statistical Committee of the Republic of Azerbaijan and UNICEF, 2024; State Statistical Committee of the Republic of Azerbaijan and Macro International, 2008).

8.2 Bangladesh

The most recent survey for Bangladesh is DHS 2022. This survey is harmonised with two earlier surveys, MICS 2019 and DHS 2014.

The DHS 2022 datasets contain anthropometric information for children under five years of age, females aged 15–95 years and men aged 18–95 years. However, for harmonisation purposes, we only use the anthropometric information from children, to align with the MICS 2019 datasets.

For harmonisation purposes, we removed the cooking fuel information from MICS 2019 and DHS 2014 to align with the DHS 2022 dataset, which did not include questions on energy use in the household questionnaire. Therefore, the remaining five living standards indicators (sanitation, drinking water, electricity, housing and assets) are reweighted so that each contributes one-fifteenth to the total, which accounts for one-third of the dimension weight. The DHS 2022 and DHS 2014 surveys also do not include information on whether the household owns an animal cart, while this information was collected in MICS 2019. For harmonisation, the assets indicator does not include animal cart across all three surveys.

At the subnational level, we calculated the MPI and its partial indices for seven administrative divisions (Barishal, Chattogram, Dhaka, Khulna, Rajshahi, Rangpur and Sylhet). We harmonised the regions by combining the administrative divisions of Dhaka and Mymensingh into a single Dhaka administrative region for the MICS 2019 and DHS 2022 datasets, in alignment with the administrative structure, since the samples across all three harmonised datasets are representative at this level (NIPORT and ICF, 2024; Bangladesh Bureau of Statistics and UNICEF Bangladesh, 2019; NIPORT, Mitra and Associates and ICF International, 2016).

8.3 Bolivia

The most recent survey for Bolivia is EDSA 2023. This survey is harmonised with three earlier surveys, EDSA 2016, DHS 2008 and DHS 2003.

The EDSA 2023 dataset contains anthropometric information for children aged 0–72 months, females aged 6–59 years and males aged 6–59 years. For harmonisation, we only use anthropometric information from children aged 0–5 years and females aged 15–49 years, to align with DHS 2008 and DHS 2003.

In this survey, data on child mortality were collected from females aged 12–49. For harmonisation purposes, we use the data from females aged 15–49 to align with the earlier DHS surveys.

Neither the DHS nor the EDSA surveys provide data on whether the household owned an animal cart; therefore, the assets indicator in all four surveys excludes this item.

We present the harmonised MPI results and their partial indices by nine departments of the country – Chuquisaca, La Paz, Cochabamba, Oruro, Potosí, Tarija, Santa Cruz, Beni and Pando – as the samples across the harmonised datasets are representative at this level (Instituto Nacional de Estadística, 2025; 2016; Coa and Ochoa, 2009; Sardán et al., 2004).

8.4 Jordan

The most recent survey for Jordan is DHS 2023. This survey is harmonised with an earlier survey, DHS 2012.

The DHS 2023 dataset contains anthropometric information from children under five years of age and females aged 15–49 years. Harmonised estimates include anthropometric data from both children and females in the 15–49 age group.

The earlier survey lacks information on the time taken to collect water. For harmonisation purposes, the definition of the drinking water indicator in DHS 2023 is therefore limited to the source of drinking water.

The DHS 2023 survey did not include a direct question on access to electricity, as recent World Bank data report that 100% of the population in Jordan has access to electricity (World Bank, 2023). We therefore used the variable 'source of lighting' to determine access to electricity. The response to the question on source of lighting aligns with the Jordan DHS report, which assumes electricity as the primary source of lighting.

The initial survey does not include information on whether the household owns a motorbike, cycle or animal cart, and likewise, the harmonised assets indicator does not include these items despite the availability of this information in the later survey. For future rounds, when additional new surveys are available for Jordan, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer ownership from the harmonised assets indicator. If sensitivity analysis indicates that there is no significant change in the MPI estimates, then we may conclude that there is no reason to exclude items from the aggregated assets indicator, even if these items were not consistently available in older surveys, provided they are consistently available in newer surveys.

The earlier survey, DHS 2017–18, has been excluded from the harmonised estimates. This dataset lacked anthropometric data on children under five years of age or data on household ownership of a motorbike, cycle or animal cart. By excluding this survey from the harmonised datasets, we were able to retain anthropometric information of children under five years of age, as well as data on females aged 15–49 years, collected in DHS 2023 and DHS 2012.

The MPI estimates are harmonised across the disaggregated 12 governorates of the country, as the samples in all the harmonised datasets are representative at this level (Department of Statistics and ICF, 2024; Department of Statistics and ICF International, 2013).

8.5 Kyrgyzstan

The most recent survey for Kyrgyzstan is MICS 2023. This survey is harmonised with three earlier surveys, MICS 2018, MICS 2014 and DHS 2012.

All three MICS datasets have anthropometric information from children under five years of age, while DHS 2012 has anthropometric data for both children under five years of age and females aged 15–49 years. To facilitate harmonisation across MICS and DHS surveys, we only use the anthropometric information from children, to align with the MICS datasets.

MICS 2005–06 has been excluded from the harmonisation set because it lacks birth history data for the child mortality indicator and does not facilitate consistent subnational comparison over time, primarily due to the administrative merger of Osh and Osh City into a single region classified as Osh. To address this gap and ensure comparability across time, we have included DHS 2012 in the harmonisation set.

Kyrgyzstan is divided into nine regional levels – Batken, Bishkek C, Chui, Issyk-Kul, Jalal-Abad, Naryn, Osh, Osh City and Talas (NSC and UNICEF, 2024, 2019, 2016; NSC, Ministry of Health and ICF International, 2012). The MPI and all its partial estimates across all the harmonised datasets are representative at the regional levels.

8.6 Lao PDR

The most recent survey for Lao PDR is MICS 2023. This survey is harmonised with two earlier surveys, MICS 2017 and MICS 2011–12. No indicator-specific harmonisation was applied across all three datasets.

At the subnational level, Xaisomboun Special Region, which was originally sampled in Lao PDR MICS 2011–12 survey, was dissolved into two provinces, Vientiane and Xiangkhouang, in 2006. Xaisomboun was re-established as new province in December 2013. For harmonisation purposes, we have grouped Vientiane and Xiangkhouang into a single Xaisomboun province in the MICS 2017 and 2023 survey rounds. We estimated the MPI and its partial indices for 18 autonomous districts of the country since the survey sample across all three harmonised datasets is representative at this level (Lao Statistics Bureau and UNICEF, 2025; Ministry of Health and Lao Statistics Bureau, 2012).

8.7 Lesotho

The most recent survey for Lesotho is DHS 2023–24. This survey is harmonised with two earlier surveys, DHS 2014 and DHS 2009.

All three DHS datasets contain anthropometric information from children under five years of age, females aged 15–49 years and males aged 15–59 years. Harmonised estimates include anthropometric data from children and females aged 15–49 years and males aged 15–59 years. No other indicator-specific harmonisation decision was applied across all three datasets.

MICS 2018 has been excluded from the harmonisation set due to a lack of information on adult nutritional information and because it does not support regional-level comparisons over time. MICS 2018 only provides disaggregated data by four ecological regions, not by districts. Furthermore, it does not include information on cooking fuel. To address these gaps and ensure harmonisation over all 10 indicators, DHS surveys have been included in the harmonisation set.

We estimated the MPI and all its partial estimates for the 10 administrative regions of the country, as the survey sample across all three harmonised datasets are representative at this level (Ministry of Health and ICF, 2024; Ministry of Health and ICF International, 2016; Ministry of Health and Social Welfare and ICF Marco, 2009).

8.8 Mexico

The most recent survey for Mexico is the National Health and Nutrition Survey (ENSANUT) 2023. This survey is harmonised with five earlier ENSANUT surveys: 2022, 2021, 2020, 2016 and 2012. These are open-access, nationally representative surveys (Shamah-Levy et al., 2024, 2023, 2022, 2021, 2020; Gutiérrez et al., 2012).

The sample design differs between the four most recent surveys and the earlier two surveys, but the estimates defined on geographic regions (rural and urban localities) are comparable because the sampling is probabilistic and the survey questions are comparable (Shamah-Levy et al., 2021, p.28; 2022).

For harmonisation purposes, we only use the anthropometric data from children under five years of age to compute the nutrition indicator across all datasets. Anthropometric data were collected from individuals aged five years and older across the datasets but were not used in the MPI estimation because of a high non-response rate and potentially biased estimates, particularly in the 2020, 2021, 2022 and 2023 datasets. For example, in the 2021 dataset, if the nutrition indicator was constructed using a combination of children under five years of age and selected individuals who are five years and older, then the sample size after the treatment of missing data is quite low at the national level – only 64%.

The bias test compared whether those with and those without a missing value in the nutrition indicator experience other deprivations similarly. If this is the case, we may assume that the missing nutrition value is distributed randomly. However, if those with and those without a missing value in the nutrition indicator experience other deprivations significantly differently, then estimates are potentially biased. The bias analysis based on the 64% retained sample using the 2021 dataset indicates that the likelihood of being deprived in housing, sanitation and living in urban areas is not the same for those who have a missing value in the nutrition indicator and those who do not. In addition, a probit regression (dependent variable: 1=missing nutrition; 0=not missing nutrition) shows that there are observable exogenous variables that are significant predictors of the risk of having a missing value in the nutrition indicator.

Those who are most likely to have a missing nutrition value significantly increase if they are male, between 18–59 years of age, living in urban areas, residing in the central regions of the country, and are in a male-headed household. This suggests that the missing values of the nutrition indicator are not entirely distributed at random, and there is a high risk of bias in the national-level estimates. As such, we opted to construct the nutrition indicator using anthropometric data from only children under five years of age consistently across the Mexico datasets, which resulted in a much lower sample drop, and bias analysis indicates that the missing nutrition value is random.

All six surveys lack information on the time taken to collect water; hence, the definition of the drinking water indicator is limited to the source of drinking water.

All six surveys do not collect information on whether the household owns a bicycle or an animal cart, and so the assets indicator for Mexico does not include these two items.

We do not report estimates for Mexico's subnational regions due to the fact that it failed to satisfy the low retained sample principle of harmonisation. As such, Mexico was excluded from subnational estimations for the 2025 round of the global MPI.

8.9 Peru

The most recent survey for Peru is ENDES 2023. This survey is harmonised with the 2022, 2021, 2019, 2018 ENDES and 2012 DHS survey datasets. ENDES are national, open-access surveys.

Anthropometric measurements were collected from all children under five years of age across the surveys. In addition, anthropometric measurements were also collected from females aged 12–49 years in the ENDES surveys, while in the DHS survey, data collection covered females aged 15–49 years. The harmonised nutrition indicator only considers data from children under five years of age and from females aged 15–49 years.

Similarly, child mortality information was provided by females aged 12–49 years in the 2019 and 2018 ENDES surveys, while ENDES 2022, 2021 and the 2012 DHS covered females aged 15–49 years. The harmonised child mortality indicator across the surveys only considers data from females aged 15–49.

The survey sample for each of the survey periods is representative of the 24 administrative regions and the capital district of Callao. We estimated the MPI and its partial indices for all 25 regions of the country across the surveys (INEI, 2024, 2023, 2022, 2020, 2019, 2013).

8.10 Senegal

The most recent survey for Senegal is DHS 2023. This survey is comparable with three earlier DHS surveys: 2019, 2017 and 2010–11.

The DHS 2023 dataset collects data on anthropometrics for children under five years of age. We have harmonised nutrition indicators across all four DHS rounds for children under five years of age.

In the previous year's harmonisation exercise, DHS 2005 was included in the harmonisation set. However, this dataset did not record information about housing components (walls and roof) and did not list ownership of an animal cart as a household asset. Additionally, in DHS 2005, disaggregation of the MPI and partial indicators was possible down to the nine administrative regions, compared to 14 regions in DHS surveys conducted from 2010–11 onwards. To ensure consistency in the harmonisation, we have included DHS 2010–11 in place of DHS 2005.

We presented the harmonised MPI results and their partial indices for 14 administrative regions of the country across the four survey datasets, as the survey sample is representative at this level (ANSD and ICF, 2024, 2020, 2018; ANSD and ICF International, 2012).

8.11 Vanuatu

The most recent survey for Vanuatu is MICS 2023. This survey is harmonised with the earlier MICS survey fielded in 2007.

Both the 2023 and 2007 MICS surveys collected anthropometric measurements from children under five years of age and females aged 15–49 years (Vanuatu Bureau of Statistics, 2024; Ministry of Health, 2008). However, as MICS 2007 did not include anthropometric information for women in the survey report, we did not include this information in the harmonisation process. Consequently, for harmonisation purposes, we only include nutrition information from children under five years of age in the harmonised nutrition indicator across the two survey periods.

The earlier MICS survey does not include information on whether the household owns a fridge, computer or animal cart. The harmonised assets indicator therefore does not include these items, despite the availability of information on ownership of fridges and computers in the latest survey.

We do not report estimates for Vanuatu's subnational regions as it fails to comply with the principle of disaggregated analysis detailed in the previous section. As such, Vanuatu was excluded from subnational estimations for the 2025 round.

9. Concluding remarks

The global MPI 2025 includes harmonised levels and changes over time estimates for 88 countries. We estimated how multidimensional poverty changed by four major age categories – 0–9 years, 10–17 years, 18–59 years, and 60 years and over – in 88 countries using harmonised datasets. In addition, we also published the disaggregation by two major age groups: for children aged 0–17 years and adults 18 years and older. At the area level, we were able to produce changes in multidimensional poverty by rural or urban area for all countries. At the subnational level, we reported the changes in MPI estimates by 882 subnational regions in 79 countries.

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