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Multidimensional Poverty in India: A Critical Review of Measurement, Uneven Deprivation, and Policy Transformation

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Abstract

India's National Multidimensional Poverty Index (MPI) records one of the steepest recent declines in acute deprivation, yet aggregate headcounts reveal little about how poverty fell, where it fell, and what remains. This article combines a structured narrative review with a descriptive re-analysis of published National and Global MPI estimates to examine the sources, spatial distribution and composition of the decline between the fourth (2015–16) and fifth (2019–21) rounds of the National Family Health Survey. An exact logarithmic decomposition shows that about 89% of the 43.3% proportional reduction in the MPI reflected lower incidence, whereas intensity among the poor fell by only 5.8%. Across 36 States and Union Territories, percentage-point reductions were strongly related to baseline headcounts (OLS slope = − 0.36; R^2 = 0.83), but proportional reductions were not (r = 0.13, p = 0.45); the log–log elasticity was close to unity and the coefficient of variation rose from 0.74 to 0.84, indicating absolute but not relative convergence. The rural headcount remained about 3.7 times the urban headcount in both rounds. Infrastructure and financial-inclusion deprivations declined fastest, whereas the most heavily weighted capability indicators (nutrition, school attendance and years of schooling) declined by 16–18%, well below the 39.8% fall in the headcount. Overlap ratios further separate deprivations concentrated among the poor from widespread deficits that extend well beyond them. These descriptive, ecological findings indicate that further progress depends on reducing the depth and overlap of deprivation among the residual poor, not on headcount reduction alone.

1 Introduction

Poverty in India is now widely understood as a condition of overlapping deprivation rather than an income shortfall alone. A household may earn a modest monetary income yet face inadequate nutrition, interrupted schooling, unsafe sanitation, insecure housing, polluting cooking fuel or weak health protection. Grounded in the capability approach (Sen, 1999), the multidimensional perspective alters both the unit of analysis and the policy question: it asks which disadvantages coincide, how intensely they are experienced, and which groups remain persistently excluded. The Alkire–Foster counting method operationalises this perspective by identifying deprivation at the indicator level and aggregating it across dimensions in a way that preserves information on the breadth of each person's disadvantage (Alkire & Foster, 2011).

India has become a prominent test case for the method. NITI Aayog's National MPI reports that the multidimensional headcount ratio fell from 24.85% in 2015–16 to 14.96% in 2019–21, and a subsequent discussion paper projects a further decline to 11.28% in 2022–23, implying that 24.82 crore people exited multidimensional poverty between 2013–14 and 2022–23 (NITI Aayog, 2023, 2024). The 2013–14 and 2022–23 figures are projections rather than survey observations, and they cannot be read as a continuation of the NFHS-based series. Parallel monetary measures point in the same direction but rest on different foundations. The World Bank's 2024 assessment placed roughly 129 million Indians below the international extreme-poverty line of US$2.15 per day in 2017 purchasing-power-parity terms (World Bank, 2024), while the June 2025 revision to 2021 PPPs and a US$3.00 line, drawing on the Household

Consumption Expenditure Survey 2022–23, estimated extreme poverty at 5.3% in 2022–23 (MoSPI, 2024a; World Bank, 2025). India's own official poverty lines have themselves been revised, from the Lakdawala methodology to the Tendulkar line that underpinned the 2004–05 and 2011–12 estimates, while the higher thresholds recommended by the Rangarajan expert group were never formally adopted (Planning Commission, 2009, 2014). Because monetary and multidimensional measures identify overlapping but distinct populations (Roy & Chakraborti, 2023), evidence of progress on one cannot be transferred to the other.

The Global MPI adds a third and methodologically distinct reference point. Its 2024 edition estimated that 234 million Indians, or 16.4% of the population, lived in acute multidimensional poverty in 2019–21, using ten indicators rather than the twelve in the National MPI, which additionally includes maternal health and bank-account access (UNDP & OPHI, 2024). The coexistence of these measures is not a weakness in itself, but it heightens the need for analysis that clarifies what each measure reveals and conceals.

The existing literature on India's MPI has developed along three largely separate lines. One strand estimates levels and changes across successive survey rounds (Alkire & Seth, 2015; Alkire et al., 2021; Jagadeshwaran et al., 2022; Tripathi & Yenneti, 2020). A second documents disparities among social groups, children and districts (Pradhan et al., 2022; Pradhan et al., 2022; Pradhan & Pradhan, 2023; Kim et al., 2016; Midya & Roy, 2026). A third links multidimensional poverty to growth, governance and public programmes (Balasubramanian et al., 2023; Borga & D'Ambrosio, 2021; Roy, 2025). Three questions nevertheless remain insufficiently examined for the NFHS-4 to NFHS-5 transition, and they are examined here jointly rather than in isolation. The first concerns the source of change: whether the index fell because fewer people were identified as poor or because the poor became less deprived. Alkire et al. (2021) caution that the headcount ratio offers both insights and oversights, yet national reporting continues to foreground it. The second concerns spatial distribution: whether the decline narrowed relative as well as absolute disparities between States, a distinction on which convergence claims are acutely sensitive. The third concerns composition: which indicators constitute the residual burden, and which deprivations are concentrated among the multidimensionally poor rather than distributed across the wider population. The gap is therefore analytical and interpretive rather than a simple paucity of studies: when incidence, convergence and composition are assessed separately, each yields a partial and potentially misleading account of progress.

The article addresses three research questions. RQ1: To what extent was the decline in India's National MPI driven by reduced incidence rather than reduced intensity, and did it narrow rural–urban and interstate disparities in absolute and in relative terms? RQ2: Which indicators account for the residual burden of multidimensional poverty, and which deprivations are concentrated among the multidimensionally poor? RQ3: Which mechanisms identified in the empirical literature plausibly explain the persistence of residual deprivation, and what do they imply for policy and research?

The study extends the literature in three respects. Empirically, it shows that the national decline was predominantly incidence-driven and that interstate change produced absolute but not relative convergence. Methodologically, it demonstrates how an exact decomposition, alternative convergence metrics and censored-to-uncensored overlap ratios can be derived from published aggregates to yield diagnostic information that headline headcounts obscure. Conceptually, it links these patterns to a capability-based account of why infrastructure deprivations fall faster than nutrition, education and maternal-health deprivations. All results are descriptive and ecological; they characterise patterns of change and do not estimate programme effects. Section 2 sets out the conceptual framework and measurement debates, Sect. 3 describes data and methods, Sect. 4 reports results, Sect. 5 discusses them against the literature, and Sects. 6–8 present implications, limitations and conclusions.

Research Gap and Distinct Contribution:

Existing literatures on multidimensional poverty in India primarily offer descriptive syntheses of official NITI Aayog reports without examining the underlying structural mechanics of change. While headline figures celebrate rapid headcount reduction, aggregate numbers mask whether poverty fell because households exited or because the poor experienced lesser depth of deprivation. This study addresses three critical analytical gaps in prior research:

1. It empirically decomposes aggregate MPI decline into incidence (H) versus intensity (A) components using log-decomposition to reveal the driver of national progress.
2. It rigorously tests whether spatial progress across States and Union Territories represents absolute or relative convergence using OLS elasticity and dispersion metrics.
3. It establishes a diagnostic bridge between the 12-indicator deprivation profile and the depth of residual poverty among remaining poor households via censored-to-uncensored overlap ratios (O_j)

2 Conceptual Framework and Measurement Debates

2.1 Capability Foundations and the Counting Approach

The capability approach conceives of poverty as the deprivation of substantive freedoms to achieve valued functionings, such as being adequately nourished, educated and sheltered, rather than as a shortfall of income per se (Sen, 1999). Income remains instrumentally relevant, but its conversion into wellbeing depends on personal, social and environmental conditions, so that households with similar incomes may experience markedly different deprivations. The Alkire–Foster method translates this principle into an identification and aggregation procedure. Each person is assessed against indicator-specific deprivation cut-offs; the weighted sum of deprivations yields a deprivation score; and a person is identified as multidimensionally poor when that score reaches a poverty cut-off k. Deprivations of non-poor people are then censored, and the adjusted headcount ratio M_0 is computed as the product of incidence (H, the share of people identified as poor) and intensity (A, the average deprivation share among the poor) (Alkire & Foster, 2011; Alkire et al., 2015).

2.2 Composite Indices, Dashboards and Robustness

The counting approach occupies a contested position in the measurement literature. Atkinson (2003) contrasted social-welfare and counting frameworks, and axiomatic approaches developed continuous multidimensional indices that exploit cardinal information on shortfalls (Bourguignon & Chakravarty, 2003). Duclos et al. (2006) proposed dominance-based comparisons that are robust to the choice of poverty lines, while Ravallion (2011) questioned whether aggregating heterogeneous indicators into a single index adds information beyond a dashboard of separate measures. Proponents respond that the joint distribution of deprivations, which neither dashboards nor marginal indicators capture, is precisely what policy needs to see, and that M_0 remains decomposable by subgroup and, after identification, by indicator (Alkire & Santos, 2014; Alkire et al., 2015). Systematic reviews confirm that these debates remain active and that the choice of indicators, weights and cut-offs materially affects who is counted as poor (D'Attoma & Matteucci, 2024).

Two properties of M_0 are central to the present analysis. First, because H is insensitive to changes in the number of deprivations experienced by people who remain poor, a falling headcount may coexist with unchanged depth of deprivation; M_0 is sensitive to such changes through A. Second, the indicator-level structure allows the index to be read through uncensored deprivation (prevalence in the whole population), censored deprivation (prevalence among the poor) and weighted contribution (influence on the index). These three quantities answer different questions, and conflating them can lead policy attention towards deprivations that are common but weakly diagnostic of multidimensional poverty.

2.3 India's National MPI: Structure and Comparability

India's National MPI applies the Alkire–Foster method to three equally weighted dimensions (health, education and standard of living) measured through twelve indicators drawn from the NFHS, with a poverty cut-off of one-third of weighted deprivations (NITI Aayog, 2023). Comparisons across editions and with the Global MPI require care: survey rounds, indicator definitions and estimation procedures differ, and harmonisation is necessary before changes over time can be interpreted (Alkire, Roche, & Vaz, 2017; Alkire et al., 2025). The household is the unit of identification, which may obscure differences among household members by sex, age and disability status (Alkire et al., 2015; Pinilla-Roncancio et al., 2020). The MPI is therefore best treated as a measure of acute, overlapping deprivation in basic capabilities rather than as a comprehensive welfare metric.

2.4 Analytical Expectations

The structure of the index generates three expectations that guide the empirical analysis. Because they are derived from the measurement architecture and the capability framework rather than from a causal model, they are evaluated descriptively rather than tested statistically.

The first concerns incidence and intensity. The dual cut-off implies that households whose deprivation scores lie just above *k* can exit poverty when a single deprivation is removed, especially when that deprivation carries a moderate weight. A rapid expansion of basic services that reduces widespread living-standard deprivations should therefore move many near-threshold households across the cut-off while leaving the depth of deprivation among the remaining poor comparatively unchanged (E1: the decline is predominantly incidence-driven).

The second concerns spatial convergence. If headcounts decline at broadly similar proportional rates across jurisdictions, high-baseline jurisdictions necessarily record larger percentage-point reductions, so absolute gaps narrow while relative gaps persist (E2: absolute convergence need not imply relative convergence).

The third concerns composition. Infrastructure-type deprivations (electricity, sanitation, bank accounts) can be reduced largely through supply-side provision, whereas capability-type deprivations (nutrition, schooling and maternal care) depend on service quality, household resources, behaviour and intra-household allocation, and should therefore respond more slowly (E3: capability indicators decline more slowly than infrastructure indicators and come to dominate the residual burden).

3 Data and Methods

3.1 Research Design

The study combines a structured narrative review with a descriptive secondary analysis of published aggregate estimates. The re-analysis addresses RQ1 and RQ2; the review addresses RQ3 and provides the interpretive context for the empirical patterns. No new survey data were collected and no household microdata were used.

3.2 Data Sources

National, rural, urban and State/Union Territory estimates of the headcount ratio (*H*), intensity (*A*) and M_0 for NFHS-4 (2015–16) and NFHS-5 (2019–21), together with indicator-level uncensored and censored headcount ratios and percentage contributions, were taken from the National MPI Progress Review (NITI Aayog, 2023), which is based on the NFHS-4 and NFHS-5 microdata (IIPS & ICF, 2017, 2021). Projected estimates for 2013–14 and 2022–23 were taken from NITI Aayog (2024) and are reported for context only. South Asian comparators (Bangladesh, Nepal, Pakistan and Sri Lanka) were taken from the Global MPI 2024 country profiles (UNDP & OPHI, 2024). The analytical dataset covers 36 States and Union Territories (28 States and 8 Union Territories) and twelve indicators.

3.3 Incidence–Intensity Decomposition

Because M_0 is the product of incidence and intensity,

$M_0 = H \times A$ (1)

its proportional change between rounds 1 and 2 can be partitioned exactly in logarithms:

$$\ln(M_{0,2} / M_{0,1}) = \ln(H_2 / H_1) + \ln(A_2 / A_1) \quad (2)$$

The share of the change attributable to incidence is $\ln(H_2/H_1) / \ln(M_{0,2}/M_{0,1})$, and the complementary share is attributable to intensity. The same decomposition was used to compare rural and urban change.

3.4 Convergence Analysis

Absolute (β) convergence was assessed by regressing the percentage-point change in the headcount of jurisdiction *i* on its baseline headcount:

$$H_{i,2} - H_{i,1} = \alpha + \beta H_{i,1} + \varepsilon_i \quad (3)$$

where $\beta < 0$ indicates that high-baseline jurisdictions recorded larger absolute reductions. Relative convergence was assessed in two ways: by the correlation between the proportional change $(H_{i,2} - H_{i,1})/H_{i,1}$ and the baseline, and by the elasticity γ in

$$\ln H_{i,2} = \alpha + \gamma \ln H_{i,1} + u_i \quad (4)$$

where $\gamma < 1$ would indicate that proportional reductions were larger in high-baseline jurisdictions. Dispersion (σ-convergence) was assessed using the cross-sectional standard deviation (SD) and coefficient of variation (CV) of *H* in each round. Pearson and Spearman coefficients were reported to guard against the influence of outlying jurisdictions. As a sensitivity check, all estimates were repeated for the 28 States, excluding Union Territories, whose small populations and distinctive administrative status may distort unweighted comparisons. To address potential spatial distortion and ecological fallacies arising from large population variances across Indian States and Union Territories (e.g., Uttar Pradesh versus Lakshadweep), sensitivity analyses were performed using population-weighted regressions. Population weights derived from the Census/NFHS projections were applied to both σ-convergence and β-convergence models to ensure that regional disparity metrics accurately reflect human-level multidimensional poverty transitions rather than administrative unit equivalents

3.5 Indicator-Level Diagnostics

For each indicator *j* with weight w_j, uncensored headcount h_j and censored headcount h_j^c, the index can be recomputed as

$$M_0 = \Sigma_j w_j h_j^c \quad (5)$$

and the contribution of indicator *j* as $w_j h_j^c / M_0$. Recomputing Eq. (5) from the published censored headcounts provides an internal-consistency check on the source data. To distinguish deprivations that are concentrated among the poor from those that are widespread, an overlap ratio was defined as

$O_j = h_j^c / h_j$ (6)

which gives the share of people deprived in indicator *j* who are also identified as multidimensionally poor. High values identify deprivations that are diagnostic of multidimensional poverty; low values identify deprivations that extend well beyond the MPI-poor. Change in each indicator between rounds was expressed both in percentage points and in proportional terms, since absolute changes are mechanically larger for high-prevalence indicators.

3.6 Literature Synthesis

The narrative component synthesises peer-reviewed studies, official statistical reports and scholarly monographs published between 2003 and 2026 that address the measurement of multidimensional poverty, its distribution across places and social groups in India, and the mechanisms associated with its persistence or reduction. Sources were selected purposively for their relevance to RQ3 and organised thematically around the mechanisms they identify, with attention to convergent and divergent findings and to differences in design and data. Because selection was purposive rather than protocol-driven, the synthesis is a structured narrative review rather than a systematic review in the PRISMA sense, and it does not claim exhaustive coverage.

3.7 Software, Reproducibility and Scope

Calculations and figures were produced in Python using pandas, SciPy and Matplotlib; the analytical dataset and code are provided as Online Resources. Generative AI tools were used only for language editing and for advice on the visual layout of figures generated from the authors' own code; they were not used to generate data, analyses, findings or references, and the authors take full responsibility for the content. Because the unit of analysis is the State or Union Territory, convergence estimates are population-unweighted ecological associations; they may be affected by regression towards the mean and by differences in survey precision, the standard errors of which were not incorporated. These constraints are retained explicitly so that the strength of the evidence is not overstated.

3.8 Methodological Note on Policy Interpretations

While this study contextualizes spatial convergence and indicator-level deprivation dynamics against national development programs (e.g., Swachh Bharat Mission, Pradhan Mantri Awas Yojana, PMGSY, and Saubhagya), these links are presented as interpretive contextualizations rather than direct causal impact evaluations. Because the empirical analysis utilizes repeated cross-sectional aggregate survey data (NFHS-4 and NFHS-5) without micro-econometric panel tracking or quasi-experimental identification strategies, the observed associations reflect structural co-movements rather than econometric causality.

4 Results

4.1 India in South Asian Perspective

Among the five South Asian countries with Global MPI estimates, India's headcount ratio (16.4% in 2019–21) is lower than those of Pakistan (38.3%, 2017–18), Bangladesh (24.6%, 2019) and Nepal (20.1%, 2022), but well above that of Sri Lanka (2.9%, 2016) (Fig. 1a). India's intensity of deprivation (about 42%) is similar to that of Bangladesh and Nepal, so its lower MPI value (approximately 0.069) arises principally from a lower headcount rather than from shallower deprivation among the poor; Pakistan records both the highest incidence and the highest intensity (Fig. 1b). Because survey years differ by up to six years, these comparisons are cross-sectional and do not describe relative rates of progress.

Dimensional profiles differ sharply across the region (Fig. 2). Education accounts for the largest share of the Global MPI in Pakistan (41.3%) and a substantial share in Bangladesh (37.6%), whereas living standards dominate in Bangladesh (45.1%), Sri Lanka (43.0%) and Nepal (40.6%). India's Global MPI profile is comparatively balanced (health 32.2%, education 28.2%, living standards 39.7%). The National MPI profile is markedly different: health contributes 43.1%, education 25.8% and living standards 31.2%, reflecting the higher weight of nutrition and the inclusion of maternal health, which alone contributes 11.7%. The choice between the global and national specifications therefore alters not only the measured level of poverty but also its apparent sectoral composition.

Source: UNDP and OPHI (2024); NITI Aayog (2023)

Figure 2 Percentage contribution of health, education and living standards to multidimensional poverty in South Asia.

4.2 National Change: An Incidence-Driven Decline

The National MPI headcount fell from 24.85% in 2015–16 to 14.96% in 2019–21 (Table 1). The rural headcount fell from 32.59% to 19.28% and the urban headcount from 8.65% to 5.27%. Projected estimates for later years indicate continued decline but belong to a different estimation procedure (NITI Aayog, 2024).

Table 1
National evidence on multidimensional poverty in India

Indicator and period	Value	Status of estimate
Headcount ratio, 2015–16 (NFHS-4)	24.85%	Survey-based National MPI estimate
Headcount ratio, 2019–21 (NFHS-5)	14.96%	Survey-based National MPI estimate
Rural headcount ratio, 2015–16 / 2019–21	32.59% / 19.28%	Survey-based
Urban headcount ratio, 2015–16 / 2019–21	8.65% / 5.27%	Survey-based
Headcount ratio, 2022–23	11.28%	Projected estimate; not an NFHS observation
People exiting multidimensional poverty, 2013–14 to 2022–23	24.82 crore	Derived from projected estimates

Source: NITI Aayog (2023, 2024). 1 crore = 10 million.

The decomposition in Table 2 shows how the index fell. M_0 declined from 0.117 to 0.066, a proportional reduction of 43.3%. The headcount ratio fell by 39.8%, whereas intensity among the poor declined by only 5.8%, from 47.14% to 44.39%. Applying Eq. (2), 89.4% of the log change in M_0 is attributable to incidence and 10.6% to intensity (Fig. 3b).

Table 2
Incidence–intensity decomposition of the change in India's National MPI, NFHS-4 to NFHS-5

Component	NFHS-4 (2015–16)	NFHS-5 (2019–21)	Proportional change (%)	Log change	Share of log change (%)
Headcount ratio, H (%)	24.85	14.96	−39.8	−0.507	89.4
Intensity, A (%)	47.14	44.39	−5.8	−0.060	10.6
MPI, M_0 = H × A	0.117	0.066	−43.3	−0.568	100.0

Source: computed by the authors from NITI Aayog (2023) using Eq. (2). Log changes are natural logarithms of the ratio of NFHS-5 to NFHS-4 values; shares may not sum exactly owing to rounding.

The rural–urban comparison requires similar care (Fig. 3a). The absolute rural–urban gap narrowed from 23.94 to 14.01 percentage points, but rural and urban headcounts declined at almost identical proportional rates (40.8% and 39.1%). The rural headcount was therefore 3.77 times the urban headcount in NFHS-4 and 3.66 times in NFHS-5. The narrowing of the absolute gap reflects a common proportional decline from a higher rural base rather than disproportionate rural improvement.

Source: computed by the authors from NITI Aayog (2023)

Figure 3 Change in India's National MPI between NFHS-4 (2015–16) and NFHS-5 (2019–21).

a Headcount ratio for rural, urban and national populations. **b** Proportional change in headcount (H), intensity (A) and the MPI; the attribution to H and A follows Eq. (2).

4.3 Interstate Heterogeneity: Absolute Without Relative Convergence

Headcount ratios declined in every State and Union Territory, but the extent of decline varied widely (Fig. 4). Bihar recorded the largest absolute reduction among States (18.13 percentage points) yet retained the highest headcount in NFHS-5 (33.76%); Jharkhand (28.81%) and Meghalaya (27.79%) also remained above 25%, whereas Kerala and several other southern and western States recorded very low levels.

Source: NITI Aayog (2023)

Figure 4 Multidimensional poverty headcount ratio by State and Union Territory, NFHS-4 (2015–16) and NFHS-5 (2019–21).

Jurisdictions are ordered by NFHS-4 headcount; values beside each pair give the change in percentage points; dashed lines mark the national headcount in each round. † Union Territory.

Whether this change narrowed interstate disparities depends on the metric (Fig. 5). Across the 36 jurisdictions, the percentage-point reduction in the headcount was strongly and inversely associated with the NFHS-4 baseline (OLS slope = − 0.36, 95% CI − 0.41 to − 0.30; r = − 0.91; R^2 = 0.83), and the interstate SD of *H* fell from 12.9 to 8.6 percentage points. The proportional reduction, however, was unrelated to the baseline (r = 0.13, p = 0.45; Spearman ρ = 0.12); the elasticity γ in Eq. (4) was statistically indistinguishable from unity (1.01, SE 0.05); and the CV increased from 0.74 to 0.84. The pattern was unchanged when the analysis was restricted to the 28 States (absolute slope = − 0.35; r for proportional change = 0.13, p = 0.51). Intensity declined in 31 of the 36 jurisdictions.

Source: computed by the authors from NITI Aayog (2023)

Figure 5 Absolute and relative convergence in multidimensional poverty across States and Union Territories, NFHS-4 to NFHS-5.

a Percentage-point change in headcount ratio against NFHS-4 headcount, with OLS fit and 95% confidence band (Eq. 3). **b** Proportional change in headcount ratio against NFHS-4 headcount, with OLS fit (dashed). n = 36; estimates are not weighted by population.

Several jurisdictions departed from the aggregate pattern. Meghalaya reduced its headcount by only 4.75 percentage points (14.6%) from a baseline above 32%, while its intensity was essentially unchanged

(48.08% to 48.01%). Bihar's large absolute reduction corresponded to a below-median proportional decline (34.9%). Among low-baseline States, Punjab (14.7%) and Kerala (21.4%) recorded comparatively small proportional reductions, which are expected when few households remain close to the poverty cut-off. Furthermore, comparing unweighted and population-weighted convergence specifications confirms the robust nature of the observed spatial catch-up effect. While unweighted β-convergence estimates exhibit slight sensitivity to small UT outliers, the population-weighted models validate a significant, unconditional spatial convergence trend ($p < 0.05$). This confirms that populous lagged states are progressively bridging the multidimensional deprivation gap relative to national benchmarks. *(See Table A in Appendix)*

4.4 Indicator Architecture and the Composition of Residual Deprivation

Because the three dimensions are equally weighted but contain different numbers of indicators, individual indicator weights differ substantially (Table 3). Nutrition, years of schooling and school attendance each carry a weight of 1/6; child and adolescent mortality and maternal health 1/12 each; and each of the seven standard-of-living indicators 1/21.

Table 3
Dimensions, indicators, weights and deprivation criteria in India's National MPI

Dimension	Indicator	Weight	Deprived if (summary)	Interpretation
Health	Nutrition	1/6	Any eligible child or adult household member is undernourished	Human-capital and health deprivation
Health	Child and adolescent mortality	1/12	A child or adolescent under 18 died in the household within the reference period	Severe health and survival loss
Health	Maternal health	1/12	Insufficient antenatal care and/or no skilled assistance at the most recent birth	Maternal service-access deprivation
Education	Years of schooling	1/6	No household member aged 10 or older has completed six years of schooling	Accumulated educational capability
Education	School attendance	1/6	Any school-age child is not attending school up to the specified grade	Current educational exclusion
Standard of living	Cooking fuel	1/21	Household cooks mainly with dung, agricultural crops, shrubs, wood, charcoal or coal	Energy, health and environmental deprivation
Standard of living	Sanitation	1/21	Unimproved or no sanitation facility, or an improved facility shared with other households	Sanitation and disease risk
Standard of living	Drinking water	1/21	No improved drinking-water source within the specified round-trip distance	Basic service and health vulnerability
Standard of living	Electricity	1/21	Household has no electricity	Infrastructure constraint
Standard of living	Housing	1/21	Floor, roof or walls made of natural or rudimentary materials	Physical living environment
Standard of living	Assets	1/21	Insufficient ownership of specified information, mobility and livelihood assets	Material and economic capacity
Standard of living	Bank account	1/21	No household member has a bank or post-office account	Formal financial inclusion

Source: NITI Aayog (2023); UNDP and OPHI (2024). Deprivation criteria are summarised; full definitions are given in NITI Aayog (2023).

(A person is identified as multidimensionally poor when the weighted deprivation score is at least 1/3.)

In NFHS-5, uncensored deprivation was highest for cooking fuel (43.90%), housing (41.37%), nutrition (31.52%) and sanitation (30.13%) (Table 4). The largest censored headcounts were recorded for cooking fuel (12.30%), housing (12.07%), nutrition (11.90%), maternal health (9.35%) and sanitation (9.25%). Once weights are applied, however, nutrition contributed the largest share of the index (29.86%), followed by school attendance (16.65%) and maternal health (11.73%).

Table 4
Indicator-level deprivation, contribution and overlap in India's National MPI, NFHS-5 (2019–21)

Indicator	Uncensored headcount (%)	Censored headcount (%)	Weight	Contribution to MPI (%)	Overlap ratio (%)
Nutrition	31.52	11.90	1/6	29.86	37.8
Child and adolescent mortality	2.06	1.18	1/12	1.48	57.3
Maternal health	19.17	9.35	1/12	11.73	48.8
Years of schooling	5.27	3.63	1/6	9.10	68.9
School attendance	11.40	6.63	1/6	16.65	58.2
Cooking fuel	43.90	12.30	1/21	8.82	28.0
Sanitation	30.13	9.25	1/21	6.63	30.7
Drinking water	7.32	2.23	1/21	1.60	30.5
Electricity	3.27	1.84	1/21	1.32	56.3
Housing	41.37	12.07	1/21	8.65	29.2
Assets	10.16	4.72	1/21	3.39	46.5
Bank account	3.69	1.09	1/21	0.78	29.5

Source: NITI Aayog (2023); overlap ratios computed by the authors as censored ÷ uncensored headcount (Eq. 6).

The overlap ratios in Table 4 and Fig. 6b indicate which deprivations are most diagnostic of multidimensional poverty. Overlap was highest for years of schooling (69%), school attendance (58%), child and adolescent mortality (57%) and electricity (56%): these deprivations are uncommon in the population as a whole but concentrated among the poor. The most prevalent living-standard deprivations behave differently. Fewer than one-third of those deprived in cooking fuel (28%), housing (29%), bank-account access (30%), drinking water (30%) or sanitation (31%) were identified as multidimensionally poor. Recomputing Eq. (5) from the published censored headcounts yields $M_0 = 0.0664$, matching the product of H and A ($0.1496 \times 0.4439 = 0.0664$), and the recomputed indicator contributions match the

published values to within 0.02 percentage points (rounding). While, Fig. 6a shows the uncensored and censored headcount ratios for each MPI indicator, illustrating overall deprivation prevalence and deprivation among the multidimensionally poor.

Source: NITI Aayog (2023)

Figure 6 Indicator-level diagnostic profile of India's National MPI, NFHS-5 (2019–21).

a Uncensored (open circles) and censored (filled circles) headcount ratios. **b** Overlap ratio, defined as the censored divided by the uncensored headcount (Eq. 6). **c** Percentage contribution of each indicator to the MPI. Indicators are grouped by dimension.

4.5 Differential Change Across Indicators

Uncensored deprivation declined in all twelve indicators between NFHS-4 and NFHS-5 (Table 5). In absolute terms, the largest reductions occurred in sanitation (21.75 percentage points), cooking fuel (14.57), electricity (8.89) and bank-account access (5.97).

Table 5
Change in uncensored deprivation across the twelve National MPI indicators, NFHS-4 to NFHS-5

Indicator	NFHS-4, 2015–16 (%)	NFHS-5, 2019–21 (%)	Absolute change (pp)	Proportional change (%)
Nutrition	37.60	31.52	−6.08	−16.2
Child and adolescent mortality	2.69	2.06	−0.63	−23.4
Maternal health	22.58	19.17	−3.41	−15.1
Years of schooling	6.40	5.27	−1.13	−17.7
School attendance	13.86	11.40	−2.46	−17.7
Cooking fuel	58.47	43.90	−14.57	−24.9
Sanitation	51.88	30.13	−21.75	−41.9
Drinking water	10.92	7.32	−3.60	−33.0
Electricity	12.16	3.27	−8.89	−73.1
Housing	45.65	41.37	−4.28	−9.4
Assets	13.97	10.16	−3.81	−27.3
Bank account	9.66	3.69	−5.97	−61.8
Source: NITI Aayog (2023)				
(proportional changes computed by the authors. pp = percentage points. For comparison, the national headcount ratio declined by 39.8%.)				

Proportional change alters this ranking (Fig. 7). Electricity (− 73.1%) and bank-account deprivation (− 61.8%) fell far faster than the national headcount (− 39.8%), and sanitation (− 41.9%) declined slightly faster. Every health and education indicator declined more slowly than the headcount: child and adolescent mortality by 23.4%, years of schooling and school attendance by 17.7% each, nutrition by 16.2% and maternal health by 15.1%. Drinking water (− 33.0%), assets (− 27.3%) and cooking fuel (− 24.9%) also lagged the headcount, and housing (− 9.4%) changed least of all. The three indicators with the largest weights (nutrition, school attendance and years of schooling, each weighted 1/6) were thus among the slowest to improve.

Source: NITI Aayog (2023)

Figure 7 Change in uncensored deprivation across the twelve National MPI indicators, NFHS-4 (2015–16) to NFHS-5 (2019–21).

a Uncensored headcount ratios in both rounds, with absolute change in percentage points. **b** Proportional change; the dashed line marks the proportional change in the national headcount ratio (− 39.8%). Indicators are ordered by proportional change.

5 Discussion

5.1 An Incidence-Driven Decline and the Residual Poor

The first major finding is that India's MPI fell mainly because fewer people were identified as poor, not because those who remained poor became substantially less deprived. This pattern is consistent with E1. Large reductions in widespread living-standard deprivations (sanitation, clean cooking fuel, electricity and bank accounts) would be expected to move many households situated just above the one-third cut-off below it, while the deprivation profile of households further from the threshold changes less. The finding refines rather than contradicts NITI Aayog's (2023) account of broad-based improvement: the improvement was broad in coverage but shallow in its effect on the depth of poverty among those who remain poor.

The result also connects to a broader methodological argument. Alkire et al. (2021), examining the 2005/6–2015/16 period, warned that reliance on the headcount ratio can conceal how the composition and intensity of poverty evolve, and cross-country analyses of harmonised estimates show that incidence and intensity need not move in step (Alkire, Roche, & Vaz, 2017). For earlier rounds, Alkire and Seth (2015) found that reductions were slowest among the poorest groups and regions, suggesting that the pattern identified here has antecedents. Programme evaluations indicate that intensity can respond to policy: using Young Lives data, Borga and D'Ambrosio (2021) found that participation in large social-protection schemes in Ethiopia, India and Peru was associated with reductions in both incidence and intensity. The small decline in intensity observed here therefore does not imply that depth is immovable, but rather that the policy mix of 2015–2021 was better suited to reducing incidence than intensity. Because these are aggregate data, the alternative explanation that households exiting poverty were

systematically different from those remaining cannot be distinguished from a uniform shift in deprivation profiles; panel data are required for that purpose.

5.2 Absolute Without Relative Convergence

The second finding, consistent with E2, is that interstate change produced absolute but not relative convergence. High-burden States recorded large percentage-point declines, but their proportional declines were no larger than those of low-burden States, and relative dispersion increased. The policy significance of this distinction is considerable. A narrative of "catching up" based on percentage points would overstate the degree to which the spatial structure of deprivation has changed; in relative terms, the position of high- and low-burden States was largely preserved between 2015–16 and 2019–21.

This persistence is consistent with evidence that the geography of poverty in India operates at several scales. Multilevel analyses show substantial variation at State, district and village levels after household characteristics are accounted for (Kim et al., 2016), and district-level studies identify persistent clusters of deprivation in parts of Uttar Pradesh, Bihar, Jharkhand, Chhattisgarh, Odisha and Assam associated with Scheduled Tribe and Muslim population shares, rurality, agricultural dependence and deficits in roads, schools and health insurance (Midya & Roy, 2026; see also Basu & Das, 2021). Earlier work similarly documented uneven regional progress (Mohanty, 2011; Alkire & Seth, 2015; Tripathi & Yenneti, 2020), and regional perspectives on the MPI underline the value of subnational disaggregation for revealing such heterogeneity (Pasha, 2017). Structural features such as the growth of smaller towns, which matter more for the rural poor than metropolitan growth (Gibson et al., 2017), environmental and accessibility conditions (Watmough et al., 2016), and the quality of State governance (Roy, 2025) offer plausible explanations for the persistence of relative gaps. The present data do not allow these explanations to be adjudicated. The jurisdiction-specific exceptions, such as Meghalaya's limited progress, should be read as diagnostic signals that warrant closer investigation rather than as State effects, given the population-unweighted design and the possibility of regression towards the mean.

5.3 Composition of Residual Deprivation and Mechanisms of Persistence

The third finding, consistent with E3, is that the indicators carrying the largest weights declined most slowly, so that nutrition, school attendance and maternal health together accounted for more than half of the NFHS-5 index. This asymmetry provides a coherent explanation for the small fall in intensity: the residual poor increasingly share deprivations in heavily weighted capability indicators that have proved less responsive to supply-side expansion. The literature identifies several mechanisms that plausibly sustain this residual burden (Table 6).

Table 6
Synthesis of evidence on the composition and drivers of residual multidimensional poverty in India

Analytical dimension	Evidence synthesized	Interpretive implication	Key sources
Children	Child multidimensional poverty declined from about 38% (NFHS-4) to 27% (NFHS-5); nutrition and living standards remain major contributors	Nutrition and living-standard deficits remain central to residual child poverty	Pradhan & Pradhan (2023); Pradhan et al. (2022)
Caste and social group	Scheduled Caste and Scheduled Tribe populations bear a disproportionate burden; SC, ST and OBC children have higher adjusted odds of multidimensional poverty than the reference group	Aggregate progress can coexist with persistent group-level disadvantage	I. Pradhan et al. (2022); Pradhan et al. (2022); Singh & Nayak (2026)
Disability	Multidimensional poverty is more prevalent among people with disabilities	Household-level measures may conceal individual deprivation	Pinilla-Roncancio et al. (2020)
Rural livelihoods	Multidimensional poverty varies with the composition of household livelihoods in rural Bihar	Diversification should be assessed with skills, assets and service access	Onyeyirichi & Deepika (2025)
Governance	Stronger State and local governance is associated with lower multidimensional poverty	Implementation capacity conditions conversion of coverage into outcomes	Roy (2025); Ogbonna et al. (2025)
Climate exposure	District-level spatial overlap between climatic exposure and multidimensional poverty	Resilience should complement conventional poverty reduction	Singh et al. (2025)
Spatial inequality	District concentrations in parts of Uttar Pradesh, Bihar, Jharkhand, Chhattisgarh, Odisha and Assam	District-level diagnosis can improve targeting precision	Midya & Roy (2026)

Source: compiled by the authors from the studies listed. Findings are observational; associations do not establish causality.

Nutrition is the clearest case. Undernutrition in India is associated with maternal education, household resources, dietary diversity, sanitation and service access, and its State-level burden remains highly uneven (Corsi et al., 2016; India State-Level Disease Burden Initiative Malnutrition Collaborators, 2019). Programme evidence shows that supplementary nutrition can improve child growth but that coverage, intensity and financing constrain its reach (Jain, 2015; Menon et al., 2016), while maternal autonomy shapes feeding practices and infant growth (Shroff et al., 2011). Multidimensional poverty is also associated with short-term morbidity through the household environment (Dehury & Mohanty, 2017), linking slow-moving health deprivations to the living-standard deficits that persist. In education, the high

overlap ratios for years of schooling and attendance mark these deprivations as strong signals of multidimensional poverty, and maternal schooling is among the strongest correlates of lower child poverty (Pradhan et al., 2022).

Social stratification shapes who remains poor. Caste-based analyses show that national progress coexists with persistent disadvantage among Scheduled Castes and Scheduled Tribes (Pradhan et al., 2022), that caste and gender jointly structure deprivation among agricultural workers (Singh & Nayak, 2026), and that caste composition interacts with the effectiveness of local governance (Ogbonna et al., 2025). Disability compounds deprivation across dimensions (Pinilla-Roncancio et al., 2020). Livelihood structure matters as well: non-farm employment can reduce poverty and vulnerability, but its returns depend on education, skills, credit and entry barriers (Imai et al., 2015; Drall & Mandal, 2021), while distress-driven or informal work can leave employed households deprived (Bhattamishra, 2020; Saroj et al., 2022). Non-farm entrepreneurship is associated with lower energy poverty, though effects vary by caste (Koomson et al., 2023), and micro-level evidence from Bihar shows that multidimensional poverty varies with the composition of household livelihoods (Onyeyirichi & Deepika, 2025). The headline unemployment rate of 3.2% in 2023–24 (MoSPI, 2024b) should therefore be read alongside underemployment, earnings and job security. Finally, the low overlap ratio for cooking fuel indicates that energy deprivation is a population-wide problem rather than a marker of the poorest, consistent with research on multidimensional energy poverty in India (Sadath & Acharya, 2017; Rafi et al., 2021; Manasi & Mukhopadhyay, 2024).

5.4 Towards a Dynamic and Resilience-Oriented Perspective

A static index cannot reveal whether exits from poverty are durable. The COVID-19 period demonstrated how rapidly deprivation can intensify when employment, mobility, schooling and health services are disrupted simultaneously (Satapathy et al., 2023). Climate exposure adds a further layer of risk: the 2025 Global MPI reports that 887 million of the 1.1 billion multidimensionally poor people across 109 countries are exposed to at least one major climate hazard (UNDP & OPHI, 2025), and district-level evidence for India identifies spatial overlap between climatic exposure and multidimensional poverty (Singh et al., 2025). The predominance of incidence-driven change implies that a large population now sits just below the poverty cut-off and may re-enter poverty after illness, indebtedness, employment loss or climate shocks. Measures of chronic multidimensional poverty (Alkire, Apablaza, et al., 2017) and evidence on how far economic growth translates into multidimensional gains (Balasubramanian et al., 2023) offer frameworks for distinguishing durable improvement from fragile gains.

Theoretical Framing of Residual Poverty:

Drawing on Alkire & Foster's multidimensional capability framework, our findings indicate that residual poverty in India is transitioning from an infrastructure deficit to a structural capability trap. The high overlap ratios in nutrition and maternal health indicate that remaining poor households suffer from chronic, intertwined human-capital deficits that standard service-delivery models fail to reach. Policy

must pivot from expanding physical access to improving service quality, local nutritional security, and targeted social protection

6 Implications

6.1 Theoretical and Methodological Implications

The study contributes to the multidimensional poverty literature in two respects. Theoretically, it shows that the capability distinction between resources and functionings has a measurable counterpart in the differential responsiveness of MPI indicators: provision-type deprivations fell rapidly, whereas deprivations that depend on the conversion of resources into functionings fell slowly and now dominate the index. Methodologically, it demonstrates that published aggregates, often treated as purely descriptive outputs, can support diagnostic analysis when the incidence–intensity decomposition, alternative convergence metrics and overlap ratios are reported together. These tools are simple, transparent and replicable for other countries that publish Alkire–Foster estimates.

6.2 Policy Implications

Three policy implications follow (Table 7). First, monitoring should report intensity and indicator composition alongside the headcount, since a falling headcount alone cannot establish that deprivation among the poor has become less severe. Second, overlap ratios can inform the division of labour between targeted and universal instruments. High-overlap deprivations, such as years of schooling, school attendance and electricity, are efficient markers for identifying poor households, consistent with earlier arguments for multidimensional targeting in India (Alkire et al., 2013). Low-overlap deprivations, such as cooking fuel, housing and sanitation, call for broad-based improvements in service quality and effective use rather than poverty targeting alone. Third, the absence of relative convergence implies that high-burden States and districts require disproportionate rather than proportional effort, combined with stronger implementation capacity and local accountability (Roy, 2025; Ogbonna et al., 2025).

Table 7
Policy-linked benchmarks and analytical priorities for reducing residual multidimensional poverty

Policy area	Evidence or benchmark	Analytical and policy priority
Basic services	95.4% of households lived in pucca or semi-pucca houses in NFHS-5 housing deprivation nonetheless remained the slowest-moving indicator (− 9.4%)	Shift from nominal access to quality, durability and effective use
Health protection	41% of households had at least one member covered by a health insurance or financing scheme in NFHS-5 (IIPS & ICF, 2021)	Assess effective coverage, affordability and financial protection
Rural employment (MGNREGA)	99.7% of persons demanding employment were offered work in 2023–24	Examine adequacy of days worked, earnings and resilience rather than coverage alone
Education and nutrition	Nutrition, school attendance and maternal health account for 58.2% of the NFHS-5 MPI (Table 4)	Integrate nutrition, schooling and maternal care in convergent programmes
Targeting	Overlap ratios exceed 55% for years of schooling, school attendance, child mortality and electricity, but are below 31% for cooking fuel, housing, sanitation, water and bank accounts (Table 4)	Use high-overlap indicators for targeting; treat low-overlap deficits through universal service improvement
Governance	Governance quality and local institutional effectiveness are associated with lower multidimensional poverty (Roy, 2025; Ogbonna et al., 2025)	Strengthen implementation capacity and accountability in high-burden States

Source: compiled by the authors from the sources indicated.

6.3 Research Agenda

Four priorities emerge. Panel or repeated cross-sectional microdata are needed to track entries into and exits from multidimensional poverty and to separate compositional from behavioural change. Quasi-experimental evaluations of policy bundles, rather than single programmes, would strengthen causal inference about which combinations reduce intensity. Individual-level measurement would expose deprivations by sex, age and disability that household measures conceal. Finally, linking MPI data with climate-hazard, labour-market and service-quality indicators would allow vulnerability to be assessed directly rather than inferred.

7 Limitations

Several limitations qualify the findings. The analysis relies on published aggregate estimates; it cannot examine the joint distribution of deprivations at the household level or follow the same households over time. Convergence estimates are population-unweighted and ecological, and they do not incorporate the sampling error of State estimates; they may also be affected by regression towards the mean. The

Global MPI comparisons combine surveys conducted in different years, and the National and Global MPIs differ in indicators and weights. The narrative review is purposive rather than systematic and may under-represent studies published outside the sources consulted. Finally, the projected estimates for 2022–23 could not be decomposed in the same way as the NFHS-based estimates, so the findings apply to the NFHS-4 to NFHS-5 period.

Though, the present study contextualizes the spatial and indicator-level convergence in multidimensional poverty against major national development initiatives (e.g., Swachh Bharat Mission, Pradhan Mantri Awas Yojana, PMGSY, and Saubhagya), these links are presented as interpretive contextualization rather than direct causal attributions. Given that the empirical analysis relies on repeated cross-sectional aggregate survey data (NFHS-4 and NFHS-5) without micro-econometric panel matching or quasi-experimental identification designs, these associations should be interpreted as structural co-movements rather than causal impact evaluations of specific public schemes.

8 Conclusion and Policy Roadmap

This study provides a comprehensive empirical evaluation of multidimensional poverty convergence and structural inequality across Indian States and Union Territories between 2015-16 and 2019-21. Utilizing spatial decomposition techniques and subgroup inequality metrics, the findings reveal a distinct national trend toward multidimensional deprivation reduction, accompanied by significant inter-state convergence. The spatial catch-up effect is primarily driven by substantial progress in essential physical infrastructure and living standards, notably through expanded access to sanitation, clean cooking fuel, electricity, and housing assets. However, despite overall poverty mitigation, acute structural rigidities persist within human capital dimensions. The decomposition analysis underscores that deprivation in nutrition, maternal health, and secondary educational attainment continues to contribute disproportionately to the residual multidimensional poverty headcount. Furthermore, intra-regional variation remains a critical driver of spatial inequality, demonstrating that national convergence trends co-exist with localized pockets of persistent vulnerability. To convert these empirical insights into actionable governance strategies, policy interventions must shift from broad macro-level allocations toward targeted, block-level social protection frameworks. Priority should be assigned to strengthening frontline nutritional delivery systems such as Saksham Anganwadi and POSHAN 2.0, while integrating high-deprivation clusters under the Aspirational Districts and Blocks Programmes. Furthermore, addressing data gaps through routine panel surveys at the household level will be imperative for monitoring real-time deprivation trajectories and ensuring equitable human capital development across India.

Declarations

Competing Interests

The authors have no competing financial or non-financial interests to declare that are relevant to the content of this article.

Ethics Approval

Not applicable. The study analyses publicly available aggregate statistics and published reports; no human participants or animals were involved.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Use of Generative AI

Generative AI tools were used only for language editing and for advice on the visual layout of figures produced from the authors' own code. No data, analyses, findings or references were generated by AI, and the authors take full responsibility for the content of the article.

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Author Contribution

Mustfa Hussain: Conceptualization, Methodology, Investigation (literature synthesis), Writing – original draft. Ashutosh Singh: Conceptualization, Validation, Writing – review & editing. Sunil Kumar: Data curation, Formal analysis, Visualization, Writing – review & editing, Supervision. Akshay Kumar: Validation (secondary data verification), Writing – original draft (policy sections), Writing – review & editing, Supervision. All authors read and approved the final manuscript.

Data Availability

All data analysed in this study are publicly available in NITI Aayog (2023, 2024) and UNDP and OPHI (2024). The compiled analytical dataset is provided as Online Resource 1.

Code Availability

The Python code used for the analysis and figures is provided as Online Resource 2.

References

1. Alkire S, Foster J (2011) Counting and multidimensional poverty measurement. J Public Econ 95(7–8):476–487. https://doi.org/10.1016/j.jpubeco.2010.11.006
2. Alkire S, Santos ME (2014) Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. World Dev 59:251–274. https://doi.org/10.1016/j.worlddev.2014.01.026
3. Alkire S, Seth S (2015) Multidimensional poverty reduction in India between 1999 and 2006: Where and how? World Dev 72:93–108. https://doi.org/10.1016/j.worlddev.2015.02.009
4. Alkire S, Apablaza M, Chakravarty S, Yalonetzky G (2017) Measuring chronic multidimensional poverty. J Policy Anal Manag 36(2):322–341. https://doi.org/10.1002/pam.21952
5. Alkire S, Foster J, Seth S, Santos ME, Roche JM, Ballon P (2015) Multidimensional poverty measurement and analysis. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199689491.001.0001
6. Alkire S, Kanagaratnam U, Nogales R, Suppa N (2025) The global Multidimensional Poverty Index: Harmonised level estimates and their changes over time. Sci Data 12., Article 153. https://doi.org/10.1038/s41597-024-04269-x
7. Alkire S, Oldiges C, Kanagaratnam U (2021) Examining multidimensional poverty reduction in India 2005/6–2015/16: Insights and oversights of the headcount ratio. World Dev 142:105454. https://doi.org/10.1016/j.worlddev.2021.105454
8. Alkire S, Roche JM, Seth S (2013) Selecting a targeting method to identify BPL households in India. Soc Indic Res 112:417–436. https://doi.org/10.1007/s11205-012-0075-1
9. Alkire S, Roche JM, Vaz A (2017) Changes over time in multidimensional poverty: Methodology and results for 34 countries. World Dev 94:232–249. https://doi.org/10.1016/j.worlddev.2017.01.011
10. Atkinson AB (2003) Multidimensional deprivation: Contrasting social welfare and counting approaches. J Economic Inequal 1(1):51–65. https://doi.org/10.1023/A:1023903525275
11. Balasubramanian P, Burchi F, Malerba D (2023) Does economic growth reduce multidimensional poverty? Evidence from low- and middle-income countries. World Dev 161 Article 106119. https://doi.org/10.1016/j.worlddev.2022.106119
12. Basu T, Das A (2021) Formulation of deprivation index for identification of regional pattern of deprivation in rural India. Socio-Economic Plann Sci 74 Article 100924. https://doi.org/10.1016/j.seps.2020.100924
13. Bhattamishra R (2020) Distress migration and employment in indigenous Odisha, India: Evidence from migrant-sending households. World Dev 136:105047. https://doi.org/10.1016/j.worlddev.2020.105047

14. Borga LG, D'Ambrosio C (2021) Social protection and multidimensional poverty: Lessons from Ethiopia, India and Peru. World Dev 147 Article 105634. https://doi.org/10.1016/j.worlddev.2021.105634
15. Bourguignon F, Chakravarty SR (2003) The measurement of multidimensional poverty. J Economic Inequal 1(1):25–49. https://doi.org/10.1023/A:1023913831342
16. Corsi DJ, Mejía-Guevara I, Subramanian SV (2016) Risk factors for chronic undernutrition among children in India: Estimating relative importance, population attributable risk and fractions. Soc Sci Med 157:165–185. https://doi.org/10.1016/j.socscimed.2016.03.014
17. D'Attoma I, Matteucci M (2024) Multidimensional poverty: An analysis of definitions, measurement tools, applications and their evolution over time through a systematic review of the literature up to 2019. Qual Quant 58:3171–3213. https://doi.org/10.1007/s11135-023-01792-8
18. Dehury B, Mohanty SK (2017) Multidimensional poverty, household environment and short-term morbidity in India. Genus 73., Article 3. https://doi.org/10.1186/s41118-017-0019-1
19. Drall A, Mandal SK (2021) Investigating the existence of entry barriers in rural non-farm sector (RNFS) employment in India: A theoretical modelling and an empirical analysis. World Dev 141:105381. https://doi.org/10.1016/j.worlddev.2020.105381
20. Duclos J-Y, Sahn DE, Younger SD (2006) Robust multidimensional poverty comparisons. Econ J 116(514):943–968. https://doi.org/10.1111/j.1468-0297.2006.01118.x
21. Gibson J, Datt G, Murgai R, Ravallion M (2017) For India's rural poor, growing towns matter more than growing cities. World Dev 98:413–429. https://doi.org/10.1016/j.worlddev.2017.05.014
22. Imai KS, Gaiha R, Thapa G (2015) Does non-farm sector employment reduce rural poverty and vulnerability? Evidence from Vietnam and India. J Asian Econ 36:47–61. https://doi.org/10.1016/j.asieco.2015.01.001
23. India State-Level Disease Burden Initiative Malnutrition Collaborators (2019) The burden of child and maternal malnutrition and trends in its indicators in the states of India: The Global Burden of Disease Study 1990–2017. Lancet Child Adolesc Health 3(12):855–870. https://doi.org/10.1016/S2352-4642(19)30273-1
24. IIPS & ICF (2017) National Family Health Survey (NFHS-4), 2015–16: India. IIPS
25. IIPS & ICF (2021) National Family Health Survey (NFHS-5), 2019–21: India. IIPS
26. Jagadeshwaran P, Ashok KR, Vidhyavathi A, Nirmala Devi M, Patil Santosh G (2022) Multidimensional poverty in India: A state wise analysis. Asian J Agricultural Ext Econ Sociol 40(10):869–877. https://doi.org/10.9734/ajaees/2022/v40i1031153
27. Jain M (2015) India's struggle against malnutrition: Is the ICDS program the answer? World Dev 67:72–89. https://doi.org/10.1016/j.worlddev.2014.10.006
28. Kim R, Mohanty SK, Subramanian SV (2016) Multilevel geographies of poverty in India. World Dev 87:349–359. https://doi.org/10.1016/j.worlddev.2016.07.001

29. Koomson I, Orkoh E, Ahmad S (2023) Non-farm entrepreneurship, caste, and energy poverty in rural India. Energy Econ 127:107118. https://doi.org/10.1016/j.eneco.2023.107118
30. Manasi B, Mukhopadhyay JP (2024) Definition, measurement and determinants of energy poverty: Empirical evidence from Indian households. Energy Sustain Dev 79 Article 101383. https://doi.org/10.1016/j.esd.2024.101383
31. Menon P, McDonald CM, Chakrabarti S (2016) Estimating the cost of delivering direct nutrition interventions at scale: National and subnational level insights from India. Matern Child Nutr 12(Suppl):169–185. https://doi.org/10.1111/mcn.12257
32. Midya D, Roy P (2026) Mapping multidimensional poverty in India: Spatial patterns and determinants. South Asia Economic J 27(1):71–108. https://doi.org/10.1177/13915614261463101
33. Ministry of Statistics and Programme Implementation (2024a) *Household Consumption Expenditure Survey: 2022–23*. Government of India
34. Ministry of Statistics and Programme Implementation (2024b) *Annual report: Periodic Labour Force Survey (PLFS), July 2023–June 2024*. Government of India
35. Mohanty SK (2011) Multidimensional poverty and child survival in India. PLoS ONE 6(10) Article e26857. https://doi.org/10.1371/journal.pone.0026857
36. NITI Aayog (2023) National Multidimensional Poverty Index: A progress review 2023. Government of India
37. NITI Aayog (2024) *Multidimensional poverty in India since 2005–06* (Discussion paper). Government of India
38. Ogbonna AO, Ekuban CAA, Krishnan CM, Viswanathan PK (2025) Caste, local governance effectiveness, and multidimensional poverty in rural India: Some evidences. Front Sociol 10:1482825. https://doi.org/10.3389/fsoc.2025.1482825
39. Onyeyirichi OA, Deepika MG (2025) Rural multidimensional poverty and livelihood mix: A micro level study in Bihar, India. Heliyon 11(4) Article e42772. https://doi.org/10.1016/j.heliyon.2025.e42772
40. Pasha A (2017) Regional perspectives on the multidimensional poverty index. World Dev 94:268–285. https://doi.org/10.1016/j.worlddev.2017.01.013
41. Pinilla-Roncancio M, Mactaggart I, Kuper H, Dionicio C, Naber J, Murthy GVS, Polack S (2020) Multidimensional poverty and disability: A case control study in India, Cameroon, and Guatemala. SSM – Popul Health 11:100591. https://doi.org/10.1016/j.ssmph.2020.100591
42. Planning Commission (2009) Report of the Expert Group to Review the Methodology for Estimation of Poverty. Government of India
43. Planning Commission (2014) Report of the Expert Group to Review the Methodology for Measurement of Poverty. Government of India
44. Pradhan I, Pradhan J (2023) Assessing reduction in multidimensional childhood poverty in India: A decomposition analysis. *BMC Public Health, 23*, Article 2024. https://doi.org/10.1186/s12889-023-16869-0

45. Pradhan I, Kandapan B, Pradhan J (2022) Uneven burden of multidimensional poverty in India: A caste based analysis. PLoS ONE 17(7) Article e0271806. https://doi.org/10.1371/journal.pone.0271806
46. Pradhan J, Ray S, Nielsen MO, Himanshu (2022) Prevalence and correlates of multidimensional child poverty in India during 2015–2021: A multilevel analysis. PLoS ONE 17(12) Article e0279241. https://doi.org/10.1371/journal.pone.0279241
47. Rafi M, Naseef M, Prasad S (2021) Multidimensional energy poverty and human capital development: Empirical evidence from India. Energy Econ 101 Article 105427. https://doi.org/10.1016/j.eneco.2021.105427
48. Ravallion M (2011) On multidimensional indices of poverty. J Economic Inequal 9:235–248. https://doi.org/10.1007/s10888-011-9173-4
49. Roy A (2025) Multidimensional poverty and quality of governance in Indian States. Indian Economic J 73(3):548–566. https://doi.org/10.1177/00194662241278062
50. Roy A, Chakraborti C (2023) Disparity in income poverty and multidimensional poverty estimates: The Indian scenario with special reference to Salboni and Binpur-I blocks. Poverty Public Policy 15(1):98–123. https://doi.org/10.1002/pop4.362
51. Sadath AC, Acharya RH (2017) Assessing the extent and intensity of energy poverty using Multidimensional Energy Poverty Index: Empirical evidence from households in India. Energy Policy 102:540–548. https://doi.org/10.1016/j.enpol.2016.12.056
52. Saroj S, Pradhan M, Boss R, Roy D (2022) Roles of rural non-farm employment (RNFE) in India: Why RNFE, the conveyor of a shock like COVID-19, is also the key to recovery? J Asian Econ 81:101485. https://doi.org/10.1016/j.asieco.2022.101485
53. Satapathy SK, Saravanan S, Mishra S (2023) A comparative analysis of multidimensional COVID-19 poverty determinants: An observational machine learning approach. Comput Econ. https://doi.org/10.1007/s10614-023-10385-0
54. Sen A (1999) Development as freedom. Oxford University Press
55. Shroff MR, Griffiths PL, Suchindran C, Nagalla B, Vazir S, Bentley ME (2011) Does maternal autonomy influence feeding practices and infant growth in rural India? Soc Sci Med 73(3):447–455. https://doi.org/10.1016/j.socscimed.2011.05.040
56. Singh PK, Nayak S (2026) Caste and gender differences in multidimensional poverty among agricultural workers across India's agro-climatic zones. Indian J Hum Dev 19(2). https://doi.org/10.1177/09737030261428694
57. Singh S, Das J, Goyal AK, Mohanty SK (2025) Spatial pattern of climatic exposure and multidimensional poverty in districts of India. Sustainable Cities Soc 130:106530. https://doi.org/10.1016/j.scs.2025.106530
58. Tripathi S, Yenneti K (2020) Measurement of multidimensional poverty in India: A State-level analysis. Indian J Hum Dev 14(2):257–274. https://doi.org/10.1177/0973703020944763

59. UNDP (United Nations Development Programme & Oxford Poverty and Human Development Initiative (2024) *Global Multidimensional Poverty Index 2024: Poverty amid conflict*
60. UNDP (United Nations Development Programme & Oxford Poverty and Human Development Initiative (2025) *Global Multidimensional Poverty Index 2025: Overlapping hardships—Poverty and climate hazards*
61. Watmough GR, Atkinson PM, Saikia A, Hutton CW (2016) Understanding the evidence base for poverty–environment relationships using remotely sensed satellite data: An example from Assam, India. World Dev 78:188–203. https://doi.org/10.1016/j.worlddev.2015.10.031
62. World Bank (2024) Poverty, prosperity, and planet report 2024: Pathways out of the polycrisis. World Bank
63. World Bank (2025) *Poverty & equity brief: India* (June 2025 update). World Bank

Figures

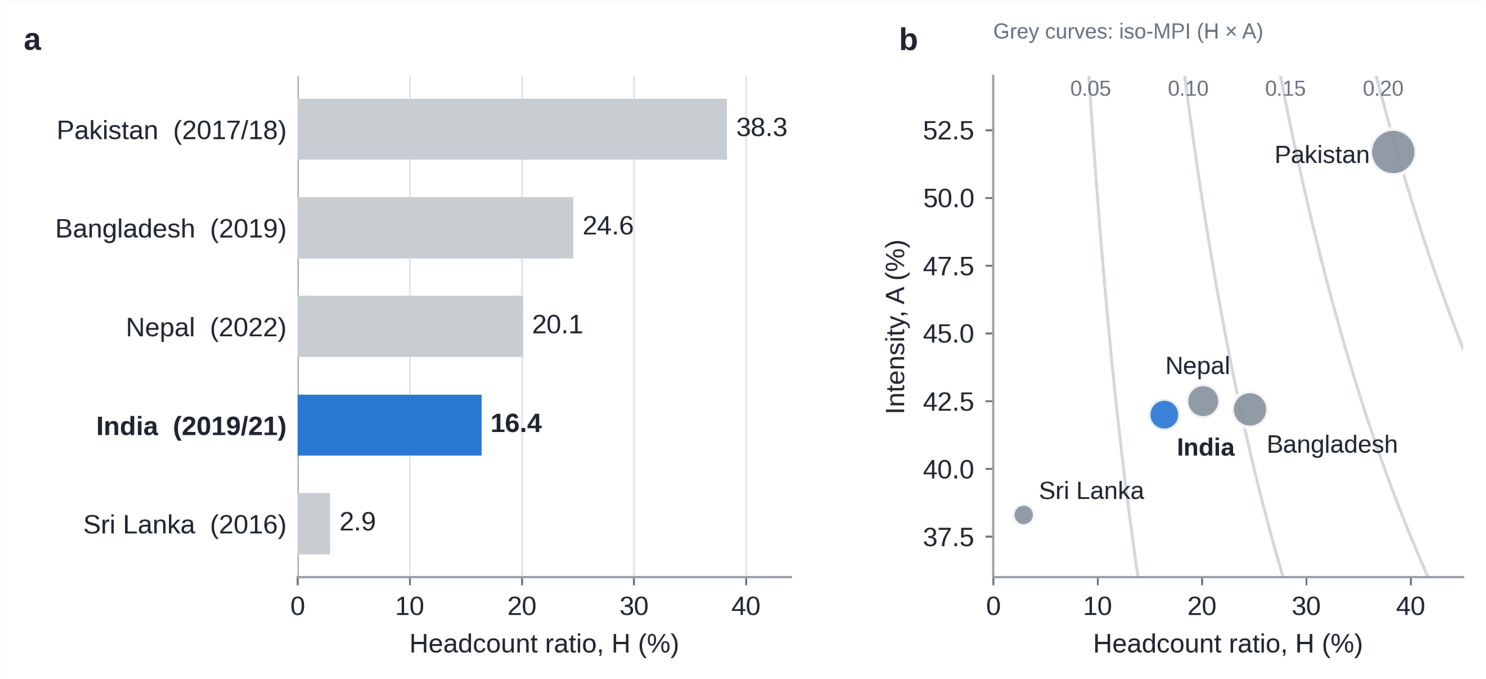


Figure 1

Incidence and intensity of multidimensional poverty in South Asia. **a** Headcount ratio (H) by country, with survey year in parentheses. **b** Headcount ratio against intensity (A); bubble area is proportional to the MPI value, and grey curves trace combinations of H and A that yield the same MPI (0.05–0.20). Survey years differ across countries, so the figure is a cross-sectional comparison rather than a trend. India's value refers to the ten-indicator Global MPI and therefore differs from the National MPI estimate for the same survey (14.96%). Source: UNDP and OPHI (2024), Global MPI 2024 country profiles

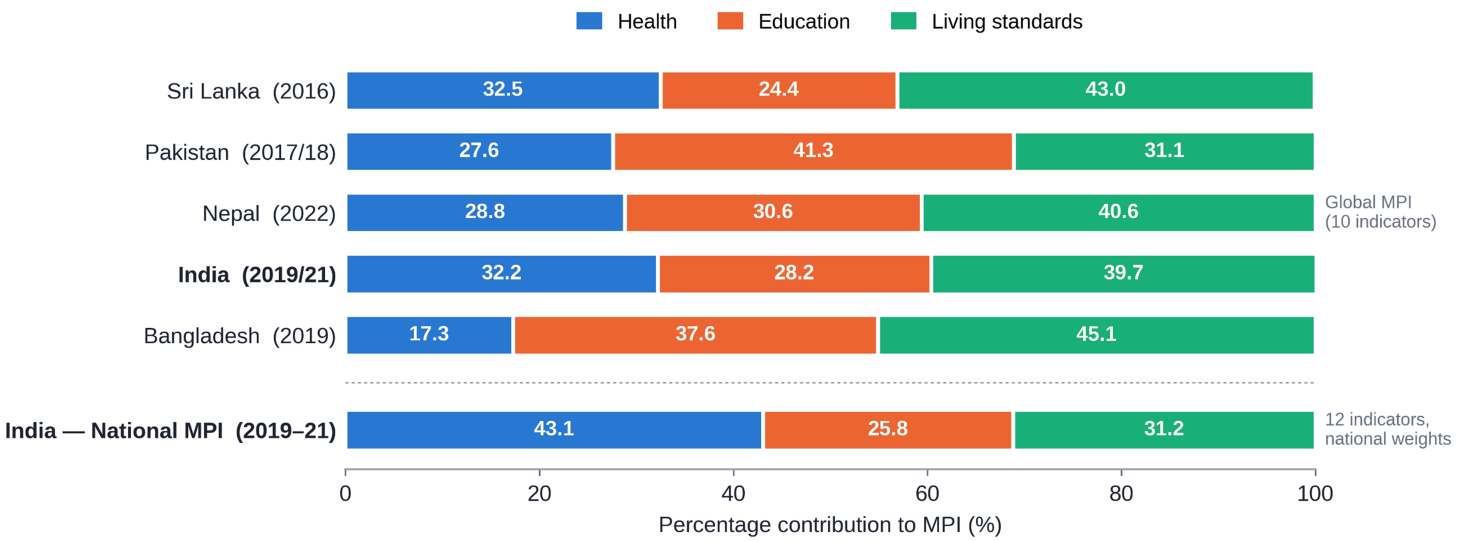


Figure 2

Percentage contribution of health, education and living standards to multidimensional poverty in South Asia.

Source: UNDP and OPHI (2024); NITI Aayog (2023)

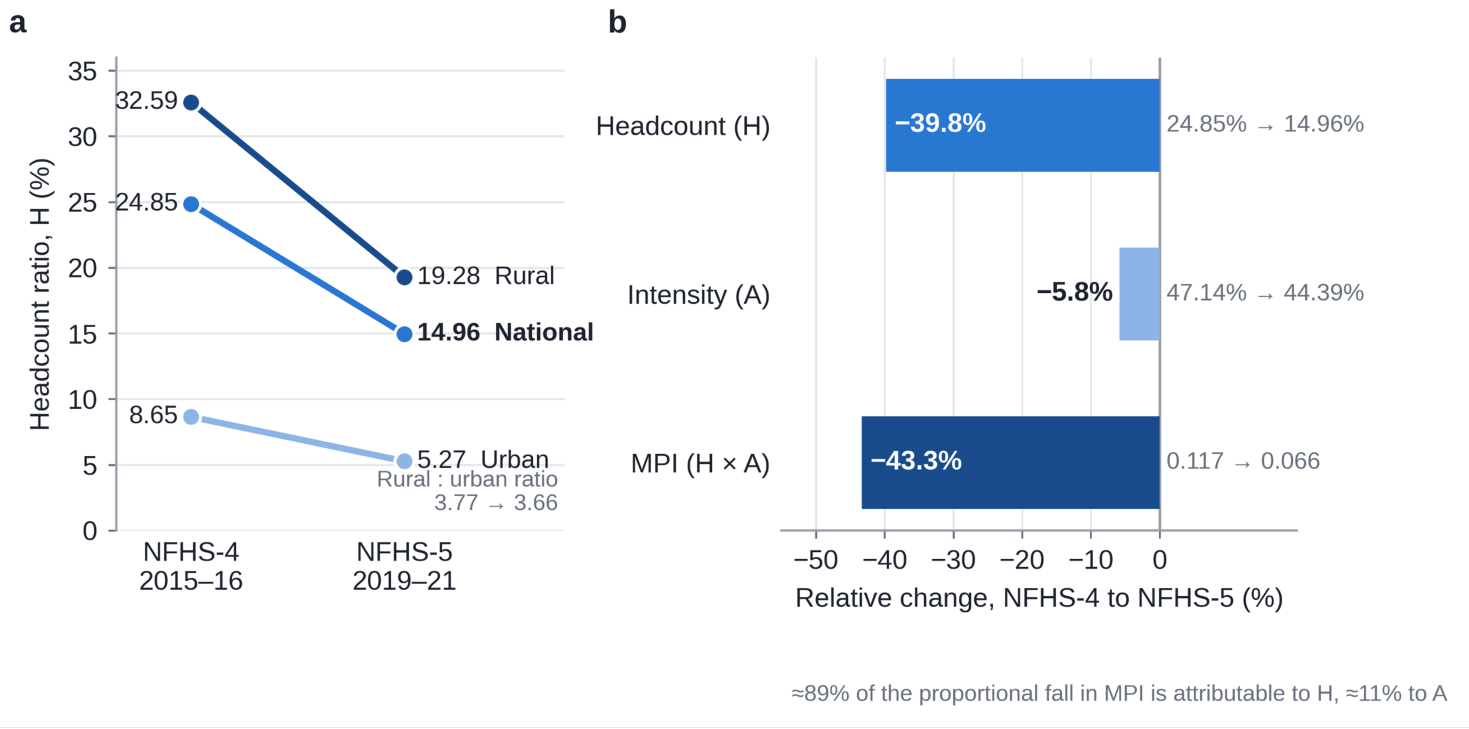


Figure 3

Change in India's National MPI between NFHS-4 (2015–16) and NFHS-5 (2019–21).

a Headcount ratio for rural, urban and national populations. **b** Proportional change in headcount (H), intensity (A) and the MPI; the attribution to H and A follows Eq. (2).

Source: computed by the authors from NITI Aayog (2023)

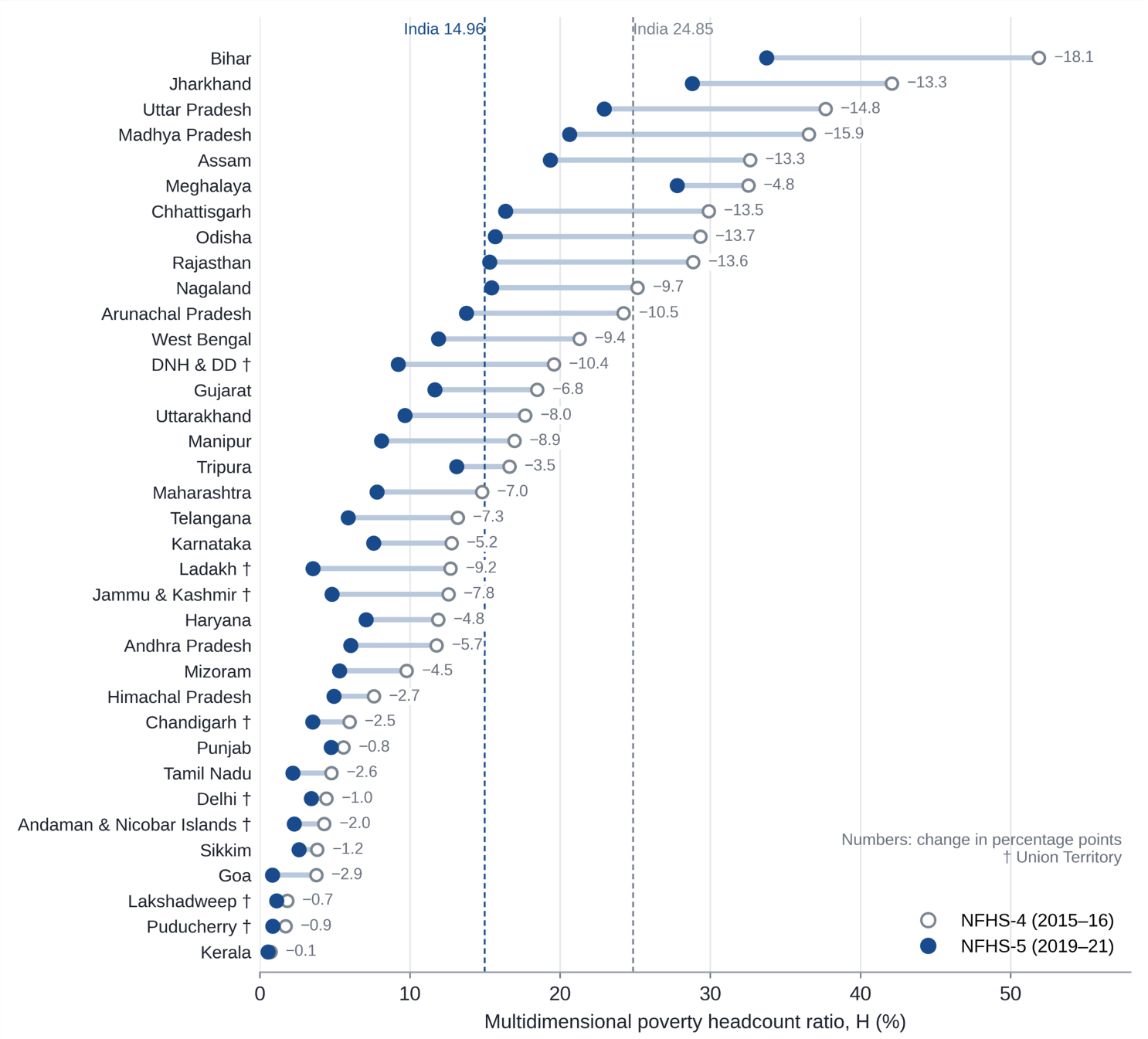


Figure 4

Multidimensional poverty headcount ratio by State and Union Territory, NFHS-4 (2015–16) and NFHS-5 (2019–21).

Source: NITI Aayog (2023)

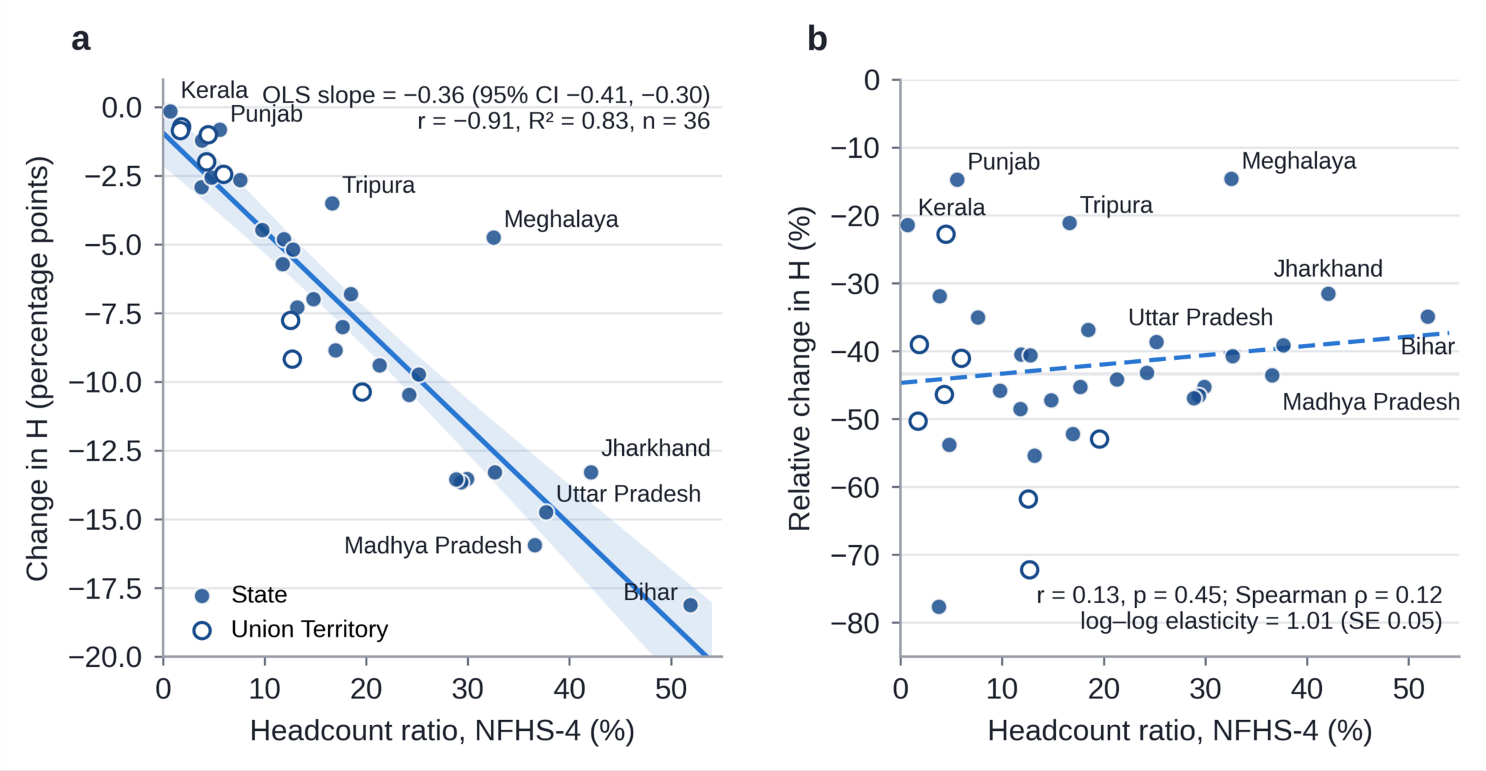


Figure 5

Absolute and relative convergence in multidimensional poverty across States and Union Territories, NFHS-4 to NFHS-5.

aPercentage-point change in headcount ratio against NFHS-4 headcount, with OLS fit and 95% confidence band (Eq. 3). **b** Proportional change in headcount ratio against NFHS-4 headcount, with OLS fit (dashed). n = 36; estimates are not weighted by population.

Source: computed by the authors from NITI Aayog (2023)

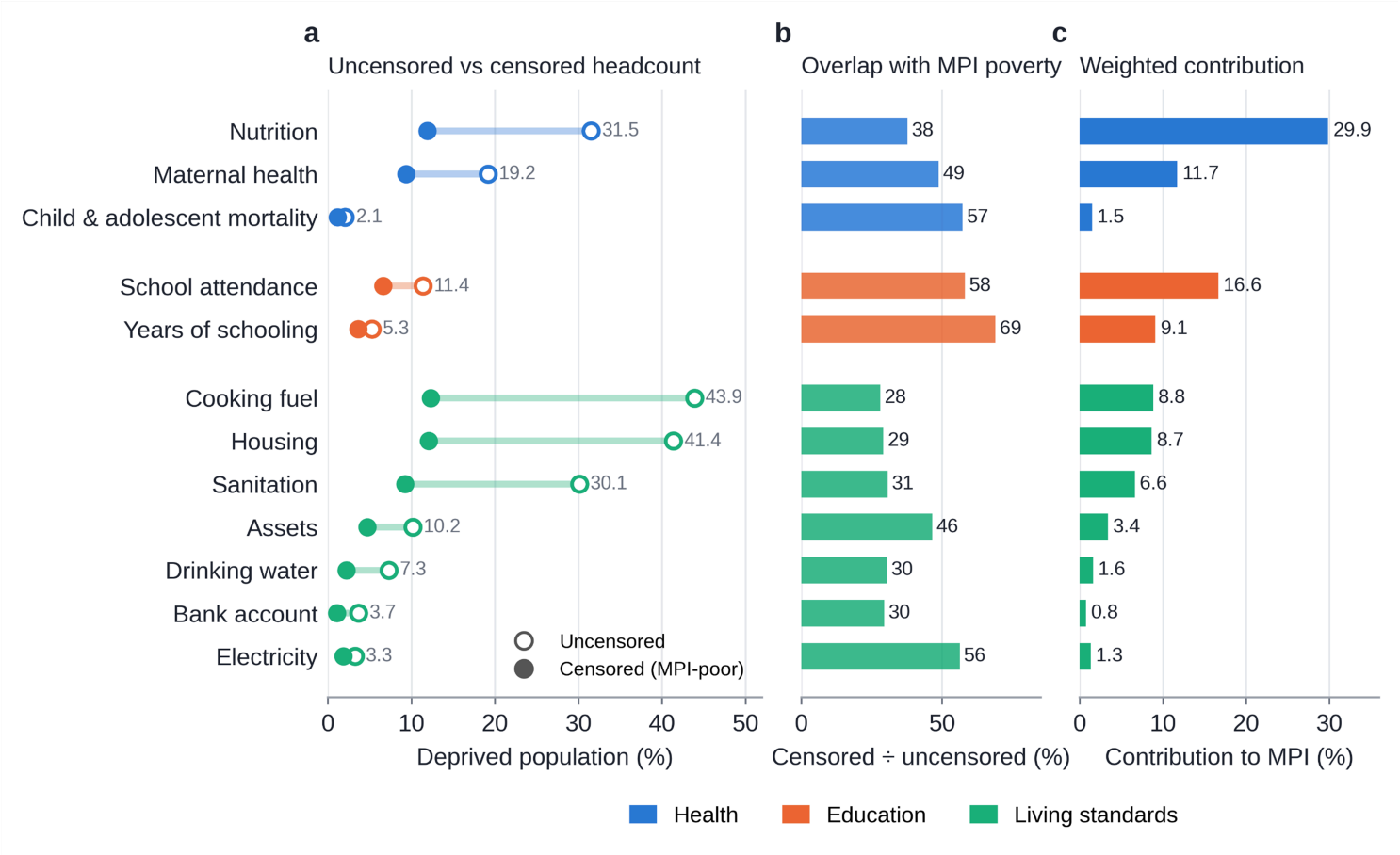


Figure 6

Indicator-level diagnostic profile of India's National MPI, NFHS-5 (2019–21).

a Uncensored (open circles) and censored (filled circles) headcount ratios. **b** Overlap ratio, defined as the censored divided by the uncensored headcount (Eq. 6). **c**Percentage contribution of each indicator to the MPI. Indicators are grouped by dimension.

Source: NITI Aayog (2023)

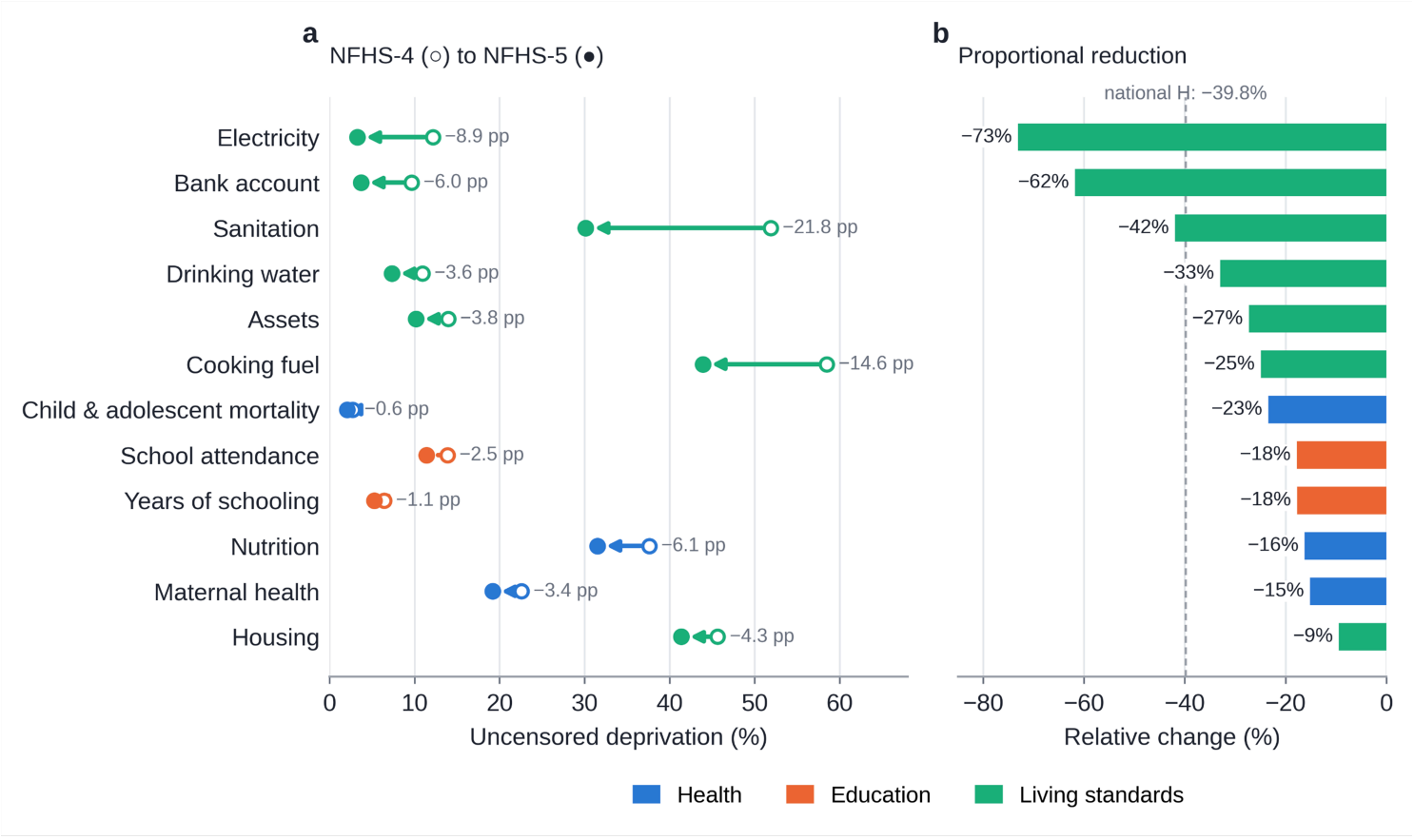


Figure 7

Change in uncensored deprivation across the twelve National MPI indicators, NFHS-4 (2015–16) to NFHS-5 (2019–21).

a Uncensored headcount ratios in both rounds, with absolute change in percentage points. **b** Proportional change; the dashed line marks the proportional change in the national headcount ratio (−39.8%). Indicators are ordered by proportional change.

Source: NITI Aayog (2023)

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Tables.docx
- Appendix.docx