



Layers of Deprivation:

Multidimensional Poverty
in Myanmar

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Executive Summary

Myanmar's socio-economic landscape is shaped by overlapping pressures, including prolonged conflict, macroeconomic instability, recurrent natural hazards and the additional impact of the March 2025 earthquake. In such conditions, conventional monetary poverty measures have become increasingly difficult to estimate due to inflation volatility, market fragmentation and disrupted livelihoods. At the same time, income alone does not fully capture how crises affect household well-being, particularly where access to services, infrastructure and livelihoods has deteriorated.

While monetary poverty measures whether households have sufficient income or consumption to meet basic needs, multidimensional poverty captures overlapping deprivations across education, health and living standards. In crisis settings such as Myanmar, these dimensions do not always move together. Households may retain some income while losing access to healthcare, education, adequate housing or basic services. This report complements monetary analysis by applying an adapted Multidimensional Poverty Index (MPI) to nationwide household data from the People's Pulse Survey (PPS 2025). The analysis identifies where deprivations are most concentrated, how structural household vulnerabilities and contextual pressures interact to shape poverty outcomes, and which population groups face the highest risk. Together, these findings provide a timely evidence base for understanding poverty in Myanmar's current crisis context and for informing more differentiated, context-sensitive responses.

Multidimensional poverty is widespread, deep and persistent. Nearly one in three people in Myanmar (approximately 17.9 million people) are multidimensionally poor. A further 19.5 million are vulnerable to falling into multidimensional poverty, bringing the total share of the population experiencing or at risk of multidimensional deprivation to two-thirds (37.5 million). Poverty reflects overlapping deficits across health, living standards and education, rather than income constraints alone. Addressing multidimensional poverty therefore requires strengthening household capabilities alongside improving income security.

Poverty patterns vary by geography, requiring attention to both severity and scale. In states experiencing heightened insecurity and access constraints, such as Kayah and Rakhine, poverty is exceptionally severe, combining very high incidence with deep deprivation. At the same time, the largest numbers of MPI-poor households are located in populous states/regions such as Ayeyarwady, Sagaing, Mandalay and Shan. Effective responses must therefore balance reducing the depth of deprivation in severely affected areas with addressing the large-scale burden of poverty in more populous regions.

Structural household vulnerabilities and contextual pressures shape different poverty dynamics across Myanmar. Structural factors, including low education, insecure employment and weak income positions, interact with contextual pressures such as conflict, displacement, market disruption and

service fragmentation. In some states/regions, poverty is driven primarily by long-standing household disadvantages. In others, particularly conflict-affected areas, contextual pressures significantly elevate deprivation beyond what household characteristics alone would predict. These differences imply that poverty responses need to combine area-based approaches in context-dominated settings with targeted household-level interventions where structural disadvantages prevail.

Repeated shocks amplify deprivation and erode household resilience. Economic shocks affect more than half of households nationally, while natural hazard shocks affect around one in five. Conflict shocks, although geographically concentrated, are associated with the highest levels of multidimensional poverty. As shocks accumulate, households with limited coping capacity experience worsening health, declining service access and deteriorating living conditions, reinforcing cycles of deprivation.

Poverty risk is concentrated among specific socio-economic groups. Households in the lowest income quintiles, those relying on casual labour and those headed by individuals with limited education consistently face the highest multidimensional deprivation. Migrant households and vulnerable urban populations also exhibit elevated poverty risk due to settlement instability, informal employment and limited access to services. Effective targeting therefore requires recognizing the differentiated vulnerabilities faced by these groups.

Poverty composition varies by context, pointing to different intervention priorities. Living standards and health drive the national picture, but the dimensional composition of poverty shifts systematically across contexts. In states/regions where survival-related deprivations dominate (Rakhine, Kayah, Chin, Kachin and Ayeyarwady), health and living standards together dominate the index, with education compressed. In others, such as Sagaing, Mon, Mandalay and Nay Pyi Taw, education's share is comparatively higher, signalling a transition from survival deprivations to human-capital constraints. The remaining states and regions fall between these patterns. Income quintile decomposition reveals a structural deprivation trap, with the bottom two quintiles displaying nearly identical compositional structures: modest income gains alone are unlikely to reshape the underlying deprivation profile.

Taken together, these findings point to four strategic directions. First, geographic responses need to balance depth-focused engagement in severely affected areas, where contextual pressures drive poverty far above structural predictions, with scale-oriented coverage in populous regions where the absolute number of poor remains large. Second, programming design should distinguish between context-dominant settings, where area-based restoration of markets, services and safe mobility is the primary entry point, and structure-dominant settings, where sustained household-level investment in education, employment and livelihoods addresses the foundations of deprivation; latent vulnerability in urban areas calls for resilience-building interventions that reach households before poverty transitions occur. Third, strengthening resilience to repeated and overlapping shocks is central to preventing transitions into deeper and more persistent poverty, with responses calibrated to the different amplification pathways of economic, conflict-related, natural hazard and health shocks. Finally, the composition of deprivation matters as much as poverty levels themselves. In areas where survival-related deprivations dominate, restoring services and basic infrastructure is the primary lever. Where education's share rises, human capital investment carries greater leverage. Where states and regions fall between these two patterns, livelihood restoration and economic resilience carry particular leverage, since rising incomes reduce the depth of deprivation even where they do not change its underlying composition.

1 Introduction

Myanmar is navigating a period of compounding pressures. Prolonged conflict, macroeconomic instability and recurrent natural hazards have disrupted livelihoods, fragmented markets and strained service delivery across much of the country, with the March 2025 earthquake adding further strain to an already fragile environment. In this context, understanding how poverty and deprivation are evolving, and where they are most concentrated, is essential for informing humanitarian response, recovery efforts and longer-term development programming.

Conventional monetary poverty measures have become increasingly difficult to apply in Myanmar's current crisis environment. Rapid and uneven inflation, widening spatial price differences, and disrupted labour markets have reduced the comparability of income and expenditure data across locations. At the same time, updated consumption-based poverty estimates require detailed household expenditure modules that cannot be implemented through rapid telephone surveys. Myanmar's most recent comprehensive consumption-based poverty estimate dates to the 2017 Myanmar Living Conditions Survey,¹ conducted under fundamentally different macroeconomic and security conditions. In the absence of more recent large-scale consumption data, monetary poverty analysis increasingly relies on assumptions and models that may not fully capture rapidly changing realities in areas affected by displacement, conflict and market disruption.

Even where income data are available, they do not fully capture household well-being during protracted crises. Households may experience disruptions in education, healthcare, water, sanitation and housing even when their reported incomes remain above a monetary poverty threshold. These non-monetary deprivations can significantly affect well-being, resilience and recovery prospects, particularly where service systems are fragmented or infrastructure has deteriorated.

Monetary poverty measures whether households can meet basic needs, while multidimensional poverty captures overlapping deprivations in areas such as education, health and living standards. In Myanmar's crisis context, the two do not always align.

Monetary poverty measures whether households have sufficient income or consumption to meet basic needs, while multidimensional poverty captures overlapping deprivations across essential aspects of well-being such as education, health and living standards. In crisis settings, such as Myanmar, these dimensions do not always move together. Households may retain some income while losing access to services,

education or adequate living conditions, while others may experience low incomes without severe non-monetary deprivation. The analysis therefore aims to provide a more timely and comprehensive evidence base for understanding poverty in Myanmar's current crisis context and for informing more differentiated, context-sensitive responses.

¹ CSO, UNDP and World Bank (2017). Myanmar Living Conditions Survey 2017: Key Indicators Report.

This report responds to these measurement and interpretation challenges by applying a multidimensional approach to poverty analysis in Myanmar. Drawing on the nationwide People's Pulse Survey (PPS 2025), it uses an adapted Multidimensional Poverty Index (MPI) to assess overlapping deprivations across education, health and living standards. The objectives are threefold: to identify where deprivations are most concentrated geographically; to examine how poverty is shaped by structural household characteristics, contextual conditions and exposure to shocks; and to profile who is most affected, in terms of socio-economic and demographic groups. Structural factors refer to persistent household-level characteristics, including education, employment type, income position and demographic composition, while contextual factors refer to area-level conditions such as conflict, geographic isolation, market disruption, service availability and natural hazard shocks that shape poverty beyond household characteristics alone.

The report is organized as follows.

Section 2 examines where poverty is concentrated, presenting national, urban–rural, state/region and township-level patterns and distinguishing between the severity and the scale of deprivation. Section 3 examines how poverty is generated and amplified, distinguishing structural and contextual drivers and analyzing the role of shocks.

Section 4 profiles who is most affected, examining variation across income groups, employment categories, education levels, migration status and gender. Section 5 goes beyond headcount to examine what kind of poverty these households experience, showing how the composition of deprivation shifts predictably across contexts and why similar MPI scores can reflect fundamentally different poverty dynamics. Section 6 translates these findings into four strategic directions covering geographic targeting, response design, shock resilience, and dimensional composition as a programming diagnostic. Section 7 concludes.

In Myanmar, a household's poverty risk depends not only on its income and education, but on where it lives, who controls that area, and what shocks it has absorbed. The combination of these forces explains why similar households face very different outcomes across the country.

1.1 Data and Methodology

The analysis draws on UNDP's People's Pulse Survey (PPS 2025), a nationwide telephone-based survey of 7,463 households across all 15 states/regions of Myanmar.² The survey was designed to capture household well-being during a period of compounding pressures, including conflict, displacement and the March 2025 earthquake, with sampling stratified independently across urban and rural areas to support disaggregation by geography and socio-economic status. PPS 2025 captures emerging deprivations such as inability to access healthcare, deterioration in household food security, disruptions in schooling, and changes in access to basic services. These features make the PPS 2025 a valuable instrument for crisis-responsive monitoring and programme adaptation.

Three limitations should be noted. First, phone-based sampling may under-represent households without functioning phones, who are more likely to be extremely poor or living in remote or conflict-affected areas. Second, self-reported housing and asset information may also be less detailed than information collected through in-person observation. Third, the sampling frame does not adequately reach stateless and displaced populations, including Rohingya populations in Rakhine, who face particular constraints on phone access and on participation in standard sampling frames; the

² Myanmar is administratively divided into seven States (Kachin, Kayah, Kayin, Chin, Mon, Rakhine and Shan) and seven Regions (Sagaing, Tanintharyi, Bago, Magway, Mandalay, Yangon and Ayeyarwady). Nay Pyi Taw constitutes a separate 'Union Territory', but for simplicity, this report refers to them collectively as "states/regions".

multidimensional poverty estimates presented for Rakhine therefore likely understate true deprivation in the state. These limitations are acknowledged throughout the analysis but do not affect the relative comparisons across geographies, household groups and shock-exposure categories that are central to the report’s findings.

The Myanmar MPI follows the global Alkire–Foster methodology³ and retains the standard structure of three equally weighted dimensions, namely education, health and living standards, with two adaptations to reflect Myanmar’s context and the constraints of phone-based data collection. First, the global MPI’s nutrition indicator is replaced by the Livelihood Coping Strategy Index (LhCSI),⁴ which captures the use of stress, crisis and emergency strategies in response to food and income shortfalls and serves as a behavioural proxy for food- and consumption-related stress in the absence of anthropometric data. Second, the child mortality indicator is replaced by an indicator capturing whether households face barriers to accessing healthcare, which better reflects current service-disruption realities and the constraints of the PPS instrument. The cooking fuel indicator is omitted as it is not collected in PPS 2025, with the remaining living-standards indicator weights adjusted accordingly while preserving the equal one-third dimension weighting. The full set of indicators, weights and deprivation thresholds is shown in Table 1.

Table 1 PPS adapted MPI indicators

Dimension (Weight)	Indicator (Weight)	Deprived if...
Education (1/3)	Years of schooling (1/6)	No household member aged 11+ has completed six years of schooling
	School attendance (1/6)	Any school-age child (5–17) is not attending school in 2024–2025
Health (1/3)	Livelihood coping strategy index (1/6)	Household has LhCSI classified as “stressed” or above (crisis, emergency)
	Inability to access healthcare (1/6)	Household reports at least one barrier to accessing health services
Living Standards (1/3)	Lighting (1/15)	Household relies on non-reliable lighting sources
	Sanitation (1/15)	Household uses non-improved sanitation facilities
	Drinking water (1/15)	Household uses non-improved drinking water in either season
	Housing quality (1/15)	Household resides in non-stable housing
	Assets (1/15)	Household owns fewer than one basic asset

A deprivation profile is constructed for each household across all nine indicators, recording whether the household is deprived in each indicator according to the thresholds set out in Table 1. Household deprivation scores are then calculated by summing the weighted deprivations across the nine indicators. Following global MPI conventions, households are classified according to their deprivation scores: MPI vulnerable (20–<33%), MPI poor (≥33%) and MPI severely poor (≥50%). The MPI headcount ratio (H) represents the share of population classified as MPI poor; intensity (A) is the average proportion of weighted deprivations among MPI poor households; and the overall MPI score is the product of incidence and intensity (H × A). Standard treatment rules apply to non-eligible indicators (for example, households without school-age children are classified as non-deprived in school attendance).

3 Alkire, S., Mishra, R., Selden, L., and Suppa, N. (2025). A methodological note on the Global Multidimensional Poverty Index (MPI) 2025 changes over Time Results for 88 countries

4 The Livelihood Coping Strategy Index (LhCSI) is a food-security–related indicator that captures the use of stress, crisis and emergency coping strategies in response to insufficient food or income. While it is not a direct measure of nutritional status, LhCSI is widely used in humanitarian and crisis contexts as a proxy for acute consumption- and nutrition-related stress when anthropometric data are unavailable. The deprivation threshold is set at “stressed or above” (i.e. households classified as stressed, crisis or emergency). This threshold was chosen because households already adopting stress-level coping strategies, such as reducing meal frequency, drawing down savings or selling productive assets, have compromised their food security and longer-term resilience in ways that align with the MPI’s intent to capture meaningful deprivation rather than marginal or transitory stress.

2 Severity and Scale: Geographic Distribution of Multidimensional Poverty

Key Messages

01

Poverty in Myanmar is widespread and deep, with vulnerability extending well beyond the poor:

32.6 percent of the population (approximately 17.9 million people) is multidimensionally poor, and a further 19.5 million are vulnerable, meaning two-thirds of the population are either poor or at risk of falling into poverty.

02

Rural areas carry a disproportionate share of the poverty burden, but urban vulnerability is underestimated by averages:

Nearly four in five MPI-poor people live outside cities, and rural headcount (36.7%) is near double the urban rate (21.7%). Yet Yangon alone hosts 1.73 million MPI-poor people, concentrated in peri-urban areas that urban averages mask.

03

Conflict-affected states face poverty so severe that poor households are deprived in roughly half of all indicators simultaneously:

In Rakhine and Kayah, more than two in three people are multidimensionally poor and intensity exceeds 48 percent, a combination that signals not just widespread poverty but acute, overlapping deprivation requiring area-based responses.

04

Severity and scale point in different directions, and both matter for programming:

The states with the most MPI-poor people in absolute terms (Ayeyarwady, Sagaing, Mandalay and Shan together account for over half the national count) record only moderate MPI scores, while the most severely deprived states have smaller populations. Effective responses require distinguishing between where poverty is deepest and where it is most numerous.

Multidimensional poverty in Myanmar is unevenly distributed across space. Two complementary dimensions help interpret this spatial pattern: severity, captured by the overall MPI score as a combined measure of headcount (H) and intensity (A); and scale, captured by the absolute number of MPI-poor people, reflecting both poverty incidence and population size. These two lenses often point in different directions. A state may record a high MPI score yet contain relatively few people in absolute terms, or it may record a moderate MPI score but account for a large share of the national poverty count simply because of its population. Distinguishing severity from scale is analytically important because it shapes what kind of programmatic response is needed: whether targeted crisis intervention or broad coverage strategies. This distinction is returned to in Section 6.

2.1 National Level: The Overall Burden

Two in three people in Myanmar are either multidimensionally poor or one shock away from becoming so. Poverty here is not a condition affecting a minority; it is the baseline reality for most of the population.

One in three people in Myanmar is multidimensionally poor (32.6%), living in households that are deprived in at least one-third of the weighted indicators across education, health and living standards. Among those identified as MPI-poor, the average intensity of deprivation is 46.1 percent, indicating that poor individuals lived in households experiencing nearly half of all

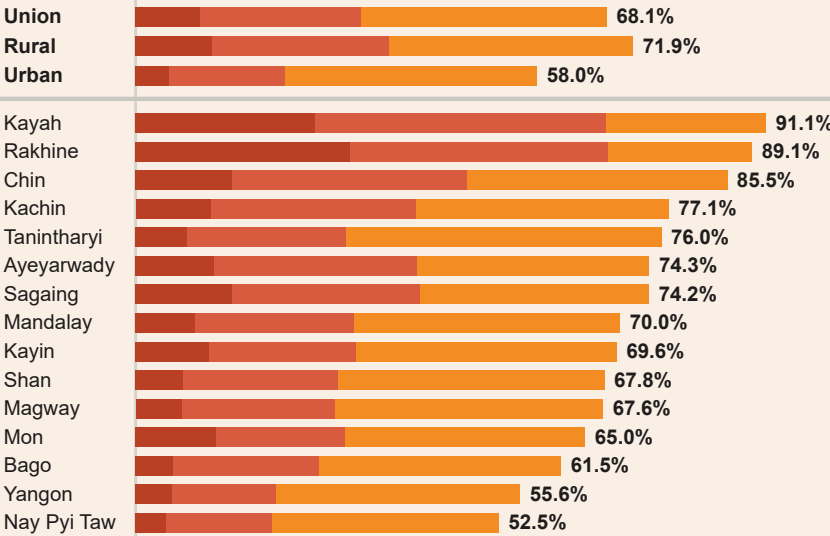
possible deprivations captured in the index simultaneously. The resulting national MPI score is 0.15, reflecting both the scale of poverty and the depth of overlapping deficits affecting household well-being.

Figure 1 Multidimensional poverty and vulnerability in Myanmar

Of every 100 people, 68 are multidimensionally poor or vulnerable

By area and state/region

Severely poor Other MPI poor Vulnerable



National snapshot

Severely poor

5.2m

9.4% of population

MPI poor (total)

17.9m

32.6% of population
Includes 5.2m severely poor

Vulnerable

19.5m

35.5% of population
At risk, not yet poor

Source: PPS 2025 (UNDP)

Vulnerability extends well beyond those classified as poor. An additional 35.5 percent of the population, or approximately 19.5 million people, is MPI-vulnerable, living in households that face deprivations but have not yet crossed the poverty threshold. Within the poor population, 9.4 percent of the national population, or about 5.2 million people, are severely poor.

Taken together, 68.1 percent of the population, or roughly 37.5 million people, are either vulnerable or multidimensionally poor. This distribution highlights the large share of the population living close to the poverty threshold and at risk of falling deeper into deprivation in the event of additional shocks.

2.2 Urban and Rural: The First Spatial Cut

Before examining state and region patterns, the urban–rural divide provides an essential first-order spatial cut. At the national level, poverty is predominantly rural in both severity and scale. Rural areas record an MPI headcount of 36.7 percent, compared to 21.7 percent in urban areas, with slightly higher deprivation intensity (46.4% versus 44.8%). In absolute terms, approximately 14.6 million MPI-poor people live in rural areas, compared with 3.3 million in urban areas, out of a total population of about 55 million. This means that nearly four out of five MPI-poor individuals reside outside major urban centres.

Yangon has the lowest MPI score of any state or region in Myanmar, yet it hosts 1.73 million multidimensionally poor people. A low average conceals a city where poverty is concentrated, invisible and growing at its edges.

Table 2 MPI headcount, intensity, MPI score and population (by geography)

	MPI poor			MPI poor (Population)
	Headcount (H)	Intensity (A)	MPI score	
Union	32.6%	46.1%	0.150	~17.9 million
Urban	21.7%	44.8%	0.097	~3.3 million*
Rural	36.7%	46.4%	0.170	~14.6 million*

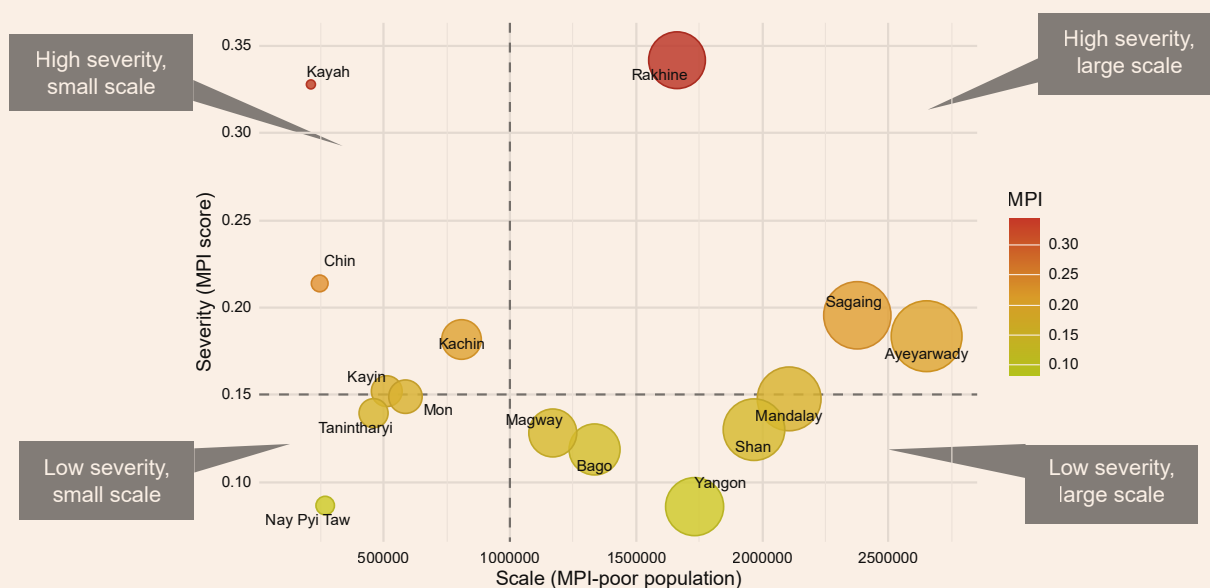
* The urban and rural population figures are derived by applying the survey-implied urban/rural composition in PPS 2025 (27.5% urban, 72.5% rural) to the national population. This composition is consistent, within expected sampling variation, with the 2019 Inter-Censal Survey, which reported an urban population share of 28.8 percent.

However, urban poverty should not be interpreted as marginal. Although incidence is lower, urban areas contain large populations, and deprivation is often concentrated in informal settlements and peri-urban zones where housing insecurity, informal employment, and weak social protection intersect. Urban dominant areas such as Yangon and Nay Pyi Taw record the lowest MPI scores nationally (Yangon 0.092, Nay Pyi Taw 0.087). Yet Yangon, with a population of approximately 8.5 million, still contains around 1.73 million MPI-poor people, with a deprivation intensity of 45.3 percent among those who are poor. This peri-urban concentration within large cities is a pattern examined at township level in Section 2.4. The urban–rural divide thus sets the broad spatial frame: rural poverty dominates in scale and severity, while urban poverty manifests in localized pockets, a distinction that becomes sharper when disaggregated to the state/region and township level.

2.3 States and Regions: Severity versus Scale

Figure 2 maps states and regions along two dimensions: severity, measured by the overall MPI score on the vertical axis, and scale, measured by the absolute number of MPI-poor people on the horizontal axis. Bubble colour reinforces severity. Dashed reference lines mark the national MPI and the average MPI-poor population across states and regions, dividing the figure into four analytical quadrants. This structure allows states and regions to be read not only by how severe poverty is, but by how much they contribute to the national poverty count, two signals that do not always align.

Figure 2 Multidimensional poverty across states/regions: severity and scale



Source: PPS 2025 (UNDP)

High severity, large scale: Rakhine, Sagaing, Ayeyarwady

These three states and regions share the distinction of combining above-average MPI scores with large affected populations, though the underlying poverty dynamics differ considerably across them.

In Rakhine, more than two in three people are multidimensionally poor and poor households are deprived in roughly half of all indicators at once. For many, poverty is not a single unmet need. It is the simultaneous collapse of shelter, healthcare, schooling and livelihood.

Rakhine records the highest MPI score nationally (0.342), with a headcount of 68.4 percent and approximately 1.66 million MPI-poor people. Poverty in Rakhine is pervasive, reflecting the intersection of prolonged insecurity, restricted mobility, weak market integration, and constrained access to health and education services. The situation of stateless and displaced populations, including barriers related to documentation, freedom of movement, and service entitlement, constitutes a central structural feature of the poverty

landscape, distinguishing Rakhine's profile from other high-poverty areas.

Sagaing (MPI score 0.196) has approximately 2.38 million MPI-poor people. Its poverty profile reflects the compounding of longstanding structural disadvantages, namely weak rural infrastructure, agricultural dependency, and limited service coverage, with acute conflict-related disruption that has fractured livelihoods and displaced communities across the region.

Ayeyarwady has the largest MPI-poor population nationally (approximately 2.65 million), yet its comparatively moderate severity (MPI score 0.183) indicates a poverty profile shaped more by long-standing agrarian conditions than acute conflict-driven crisis. A large agrarian population with limited livelihood diversification, high exposure to natural hazard shocks, and constrained access to services explains why Ayeyarwady contributes so substantially to national poverty counts despite not recording the highest deprivation levels.

High severity, small scale: Kayah, Chin, Kachin, Kayin

These states record above-average MPI severity but have smaller populations, so their aggregate contribution to national poverty counts is more limited. The defining analytical feature of this quadrant is the disjuncture between the depth of deprivation and the scale of the affected population.

Kayah records the second-highest MPI score nationally (0.328) with a headcount of 68.1 percent, yet only approximately 0.21 million MPI-poor people. The concentration of severe outcomes within a small population makes Kayah's poverty profile one of severity rather than scale, a pattern that distinguishes it analytically from high-severity, high-scale contexts such as Rakhine.

Chin (MPI score 0.220) has approximately 0.25 million MPI-poor people. Poverty here reflects structural isolation, such as limited road connectivity, weak service infrastructure, and geographic barriers to market integration, rather than conflict-driven deterioration alone, though the two interact in parts of the state.

Kachin (MPI score 0.188) has approximately 0.81 million MPI-poor people. The state's overall severity sits above the national average, yet remains lower than Kayah and Chin, reflecting a poverty profile shaped by the intersection of conflict-related disruption and geographic isolation across rural and border areas.

Kayin (MPI score 0.153) has approximately 0.51 million MPI-poor people. Its position near the quadrant boundary reflects a poverty profile where conflict-related disruption overlaps with structural access constraints, producing moderate but persistent deprivation across a relatively small population.

Low severity, large scale: Mandalay, Shan, Bago, Magway, Yangon

These states and regions record below-average MPI severity but above-average numbers of MPI-poor people, making them the primary drivers of the national poverty headcount. Aggregate poverty burdens here reflect scale effects rather than the depth of individual household deprivation.

Mandalay (MPI score 0.148) and Shan (MPI score 0.131) each contain approximately two million MPI-poor people. Despite moderate severity, their population size means poverty outcomes carry considerable weight in national aggregates. Bago and Magway similarly combine moderate MPI scores (0.118 and 0.128 respectively) with sizeable affected populations of approximately 1.34 million and 1.17 million, driven largely by structural rural livelihood vulnerabilities and uneven service coverage.

Yangon presents a particularly distinctive profile within this quadrant. An MPI headcount of 20.4 percent (the third-lowest nationally) translates into approximately 1.73 million MPI-poor people within

the country's largest urban centre. Poverty in Yangon is concentrated in peri-urban townships,⁵ where informal employment, migrant and displaced populations, housing precarity, and constrained access to formal safety nets generate a deprivation profile structurally distinct from rural poverty elsewhere, yet one that aggregates city-level figures can obscure and that the township analysis in Section 2.4 examines.

Low severity, small scale: Nay Pyi Taw, Tanintharyi, Mon

Nay Pyi Taw records the lowest MPI score nationally (0.087) with approximately 0.27 million MPI-poor people. Tanintharyi (MPI score 0.140) and Mon (MPI score 0.149) record moderate headcounts with approximately 0.46 million and 0.59 million MPI-poor people respectively.

The comparatively lower severity in this quadrant should not be read as an absence of significant deprivation. Both Mon and Tanintharyi record deprivation intensity above the national average among those who are poor, indicating that households classified as MPI-poor in these states experience multiple overlapping deficits even where overall incidence is more contained. The gap between headcount and intensity is the analytically important signal here: aggregate MPI scores understate the depth of poverty among those who are affected.

Table 3 Multidimensional poverty profiles (by geography)

	State/Region	MPI score (H x A)	MPI Headcount (H)	MPI intensity (A)	MPI-poor pop.	Predominant deprivation profile
	Union	0.150	32.6%	46.1%	~17.9 m	—
High severity, large scale	Rakhine	0.342	68.4%	50.1%	1.66 m	High conflict exposure; pervasive deprivation; stateless and displaced populations
	Sagaing	0.196	41.2%	47.5%	2.38 m	Structural deficits; high conflict exposure
	Ayeyarwady	0.183	40.7%	45.0%	2.65 m	Structural rural vulnerability across large agrarian population
High severity, small scale	Kayah	0.328	68.1%	48.2%	0.21 m	High conflict exposure; severity concentrated in small population
	Chin	0.220	47.9%	45.9%	0.25 m	Structural isolation; geographic and connectivity barriers
	Kachin	0.188	40.5%	46.3%	0.81 m	Conflict exposure intersecting with geographic isolation
	Kayin	0.153	31.9%	47.8%	0.51 m	Conflict and structural access constraints; moderate but persistent
Low severity, large scale	Mandalay	0.148	31.7%	46.6%	2.11 m	Moderate structural deprivation; large population weight
	Shan	0.131	29.3%	44.6%	1.97 m	Moderate structural deprivation; large population weight
	Magway	0.128	28.9%	44.3%	1.17 m	Rural livelihood vulnerability; uneven service coverage
	Bago	0.118	26.5%	44.6%	1.34 m	Rural livelihood vulnerability; uneven service coverage
	Yangon	0.092	20.4%	45.3%	1.73 m	Urban and peri-urban concentration; low incidence, high scale
Low severity, small scale	Mon	0.149	30.4%	49.2%	0.59 m	Moderate incidence; above-average intensity among the poor
	Tanintharyi	0.140	30.5%	45.8%	0.46 m	Moderate incidence; above-average intensity among the poor
	Nay Pyi Taw	0.087	19.7%	44.2%	0.27 m	Lowest severity nationally; small scale

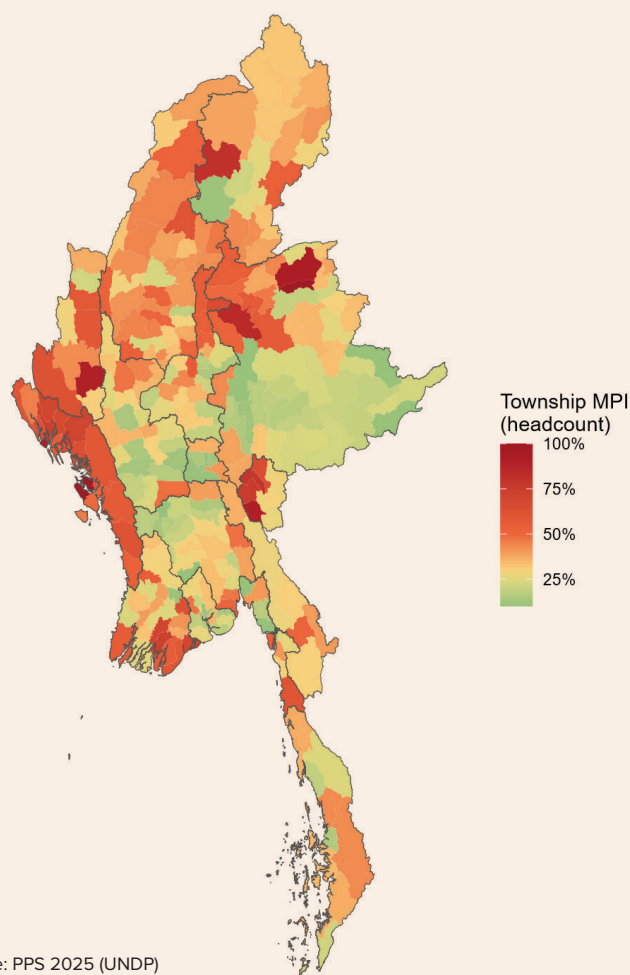
5 UNDP (2025). Urban Poverty: Unpacking Yangon.

2.4 Townships: Within-State Variation and Poverty Clustering

The state/region quadrant analysis in Section 2.3 characterizes poverty at an administrative level, but the averages underlying each quadrant position conceal substantial variation within states. Township-level estimates reveal that the within-state range of MPI headcounts is often as analytically significant as the between-state differences, and that the quadrant assignment of a state reflects the balance of its internal distribution rather than a uniform poverty profile.

Township MPI headcounts are estimated using a model-based small area estimation approach⁶ that combines PPS 2025 household data with township-level auxiliary information and benchmarks results to state totals. These estimates should be interpreted as indicative comparisons that support geographic prioritization rather than precise measurements of poverty levels. The full township MPI estimates are presented in Appendix Table 5.

Figure 3 Township-level distribution of multidimensional poverty (MPI Headcount)



Source: PPS 2025 (UNDP)

⁶ Township-level MPI headcounts are estimated using a unit-level small area estimation (SAE) approach. A generalized linear mixed model (GLMM) with a binomial logit link is fitted to PPS 2025 household data, with MPI poverty status as the binary outcome, township-level random intercepts, and five township-level auxiliary covariates: night-time light intensity (proxy for economic activity), a Vulnerability to Conflict Index derived from ACLED event data, flood risk, forest cover (proxy for remoteness and geographic isolation), and mining area. All covariates are log-transformed and standardized. For townships with 30 or more sampled households, the predicted headcount is the weighted mean of household-level predicted probabilities from the full model. For townships with fewer than 30 sampled households or no sample, a synthetic prediction based on fixed effects only is used. All township estimates are then benchmarked to the directly observed state/region MPI from PPS 2025 by applying a proportional scaling factor, ensuring internal consistency between the township and state/region levels. Uncertainty is estimated via a 500-iteration parametric bootstrap that propagates uncertainty in both fixed effects and random intercepts, with benchmarking applied in each replicate.

Conflict clusters: Acute deprivation concentrated in high-severity states

Within the high-severity states/regions identified in Section 2.3, township-level estimates show that extreme deprivation is not evenly distributed but concentrated in specific localities where conflict exposure, displacement, and restricted mobility are most acute. In Kayah, which records the second-highest state MPI nationally, headcount reaches 89.9 percent in Hpasawng, compared to 29.4 percent in Bawlake, a range of over 55 percentage points within a single state. In Chin, Mindat records 89.6 percent and Paletwa 61.9 percent, while other townships record considerably lower levels. In Kachin, Hpakant (80.4%) contrasts sharply with Mohnyin (11.5%), two townships in the same state separated by nearly 70 percentage points. These contrasts confirm that state-level MPI scores, even when high, aggregate over localities with different poverty conditions. Where services have collapsed and mobility is restricted, poverty clusters sharply. The conflict-affected townships with the highest MPI headcounts, particularly in Rakhine, Kayah, Kachin and Chin, broadly correspond to areas classified at Level 3 (highest access constraints) in OCHA's October 2025 access severity monitoring, though the two frameworks measure different phenomena: MPI captures household deprivation outcomes while access severity reflects operational constraints faced by humanitarian actors.⁷

Structurally depressed localities: Uneven distribution within large-scale rural regions

In the large-scale regions of the lower-left and lower-right quadrants (Figure 2), such as Ayeyarwady, Magway, Bago, and parts of Mandalay, township variation reflects structural household vulnerabilities interacting with local economic and geographic conditions rather than acute conflict exposure. In Ayeyarwady, township MPI headcount ranges from 10.7 percent in Danubyu to 72.8 percent in Mawlamyinegyun, with Wakema (70.2%) and Dedaye (69.3%) also among the highest in the region. Despite belonging to the same delta region, these townships differ markedly in their exposure to flooding, access to markets, and livelihood diversification. In Magway, headcount ranges from 44.6 percent in Myaing to 14.0 percent in Salin. In Bago (East), from 14.9 percent in Taungoo to more than 50 percent in Kawa. This internal dispersion explains why regions with moderate state-level MPI scores, placing them in the lower-severity quadrants, nonetheless contain townships with deprivation levels approaching those seen in the highest-severity states/regions.

Peri-urban pockets: Latent vulnerability in Yangon and other urban centres



In peri-urban Yangon, MPI headcounts in townships such as Hlaingtharya (East) reach 40 percent, higher than many rural townships elsewhere, exposing a hidden poverty concentrated among migrants and informal workers at the city's edge.

Yangon's position in the low-severity, large-scale quadrant reflects region-level aggregation that obscures sharp spatial differentiation within the urban area. In the urban core, MPI headcounts remain below five percent in townships such as Kyauktada and Pabedan. In contrast, peri-urban townships such as Hlaingtharya (East) (39.9%), Thaketa (36.4%), Dagon Myothit (South) (36.3%), and Thanlyin (35.2%) exhibit substantially higher

deprivation, levels that exceed those recorded in many rural townships elsewhere. These peri-urban zones combine informal settlements, high concentrations of migrant and displaced populations, insecure and informal employment, and limited access to public services or social protection. The result is that urban poverty in Myanmar manifests less as widespread city-level deprivation and more as localized clusters of vulnerability at the urban periphery, areas highly sensitive to economic

⁷ OCHA (2025). Myanmar Humanitarian Access Severity Overview, October 2025.

downturns, inflationary pressures, and disruptions in employment or service provision. That these MPI headcounts are lower than Yangon's income poverty rate reflects a genuine feature of urban poverty: proximity to schools, clinics and markets provides a partial buffer against non-monetary deprivations that keeps income-poor households out of MPI poverty even where incomes remain insufficient.⁸ This is why the MPI headcount alone understates urban vulnerability: households currently outside the poverty threshold carry the structural risk profiles of the poor and remain highly sensitive to transitions into multidimensional deprivation when access to available services is constrained or withdrawn.

Across all three township patterns, namely conflict clusters, structurally depressed localities, and peri-urban pockets, the analytical implication is consistent: geographic targeting at the state or region level is a necessary but insufficient guide to where poverty is most acute. Within-state heterogeneity is large enough that township-level evidence materially changes the prioritization picture.

8 UNDP (2025). Urban Poverty: Unpacking Yangon.

3 Drivers and Amplifiers of Poverty

Key Messages

01

Poverty reflects structural and contextual factors acting together:

Nationally, observed MPI headcount (32.6%) closely matches predicted probability (32.1%), indicating that long-standing household characteristics, such as low education, insecure work and limited income, explain most baseline deprivation. In conflict-affected areas, however, poverty levels are far higher than household characteristics alone would suggest.

02

Conflict and access constraints push poverty far beyond structural predictions:

In Kayah (68.1% observed versus 51.1% predicted) and Rakhine (68.4% observed versus 39.3% predicted), conflict, displacement and restricted mobility substantially raise poverty above what household characteristics alone would predict.

03

Shocks deepen poverty, with conflict shocks carrying the heaviest burden:

More than half of households report economic shocks and around one in five face natural hazard shocks; conflict shocks affect fewer households, around one in ten, but are associated with the highest poverty levels, with over half of conflict-affected households classified as multidimensionally poor. As shocks accumulate, poverty risk rises sharply.

3.1 Drivers of Poverty: Context versus Structure

Multidimensional poverty in Myanmar is shaped by the interaction of two distinct factors: **structural household vulnerabilities** and **contextual conditions**. Structural vulnerabilities refer to persistent socio-economic characteristics, encompassing educational attainment, employment type, income position and demographic composition, that shape a household's underlying risk of deprivation. Contextual conditions refer to area-level factors beyond household control, including conflict intensity, geographic isolation, infrastructure quality, market access and service availability.

In some areas, poverty is largely explained by these household characteristics. In others, poverty far exceeds what household profiles would predict, indicating that conflict, displacement, isolation or other area-level pressures elevate deprivation well beyond structural baselines. In a third group, households possess risk profiles typically associated with high poverty, but currently record lower deprivation levels, suggesting that favourable area-level conditions are moderating, though not eliminating, underlying vulnerability.

To distinguish these patterns, observed MPI headcount was compared with predicted probabilities from a survey-weighted logistic regression model⁹ based solely on household characteristics. This comparison reveals three distinct poverty patterns:¹⁰

- **Context-dominant poverty:** Where observed poverty substantially exceeds predicted levels, area-level pressures, such as conflict, displacement, geographic isolation, infrastructure gaps or market disruption, push deprivation far beyond what household characteristics alone would produce.
- **Structure-dominant poverty:** Where observed and predicted poverty align closely, deprivation is primarily driven by entrenched household characteristics. Long-standing disadvantages, including low education, precarious employment, and limited income, explain the poverty pattern, rather than recent contextual shocks.
- **High structural vulnerability (latent risk):** Where predicted poverty exceeds observed levels, households carry high risk profiles (informal employment, low assets, limited education) but are partially protected by favourable area-level conditions, such as dense markets, service infrastructure, economic opportunities. These households are not currently classified as poor but remain vulnerable to deteriorating conditions.

Union and urban-rural patterns

At the national level, observed MPI headcount (32.6%) closely matches predicted probability (32.1%), indicating that structural household characteristics explain most aggregate deprivation. This national alignment, however, masks sharp divergence between urban and rural areas.

9 The predicted MPI headcount is estimated from a survey-weighted logistic regression model predicting MPI poverty status (binary outcome) from household characteristics alone: household head age, education level, employment type and occupation, household size, presence of school-age and pre-school children, and asset ownership. The model includes survey weights to account for PPS 2025 sampling design. For each household, survey-weighted predicted probabilities of being MPI-poor are calculated based on their characteristics. These predicted probabilities are then aggregated to the geographic unit (urban/rural, state/region) to produce predicted MPI headcount rates. The comparison between observed (directly measured from data) and predicted (model-based, holding area-level conditions constant) headcount isolates the structural component of poverty and makes explicit the contribution of contextual factors through the residual gap.

10 States/regions are classified based on the gap between observed and predicted MPI headcount (observed minus predicted), compared against a statistically informed threshold. The standard error of the predicted headcount is derived from the 95 percent confidence interval of the logistic regression model. States/regions are classified as context-dominant poverty if the gap exceeds +1.5 standard errors, as high structural vulnerability (latent risk) if the gap is less than -1.5 standard errors, and as structure-dominant poverty if the gap falls within the ± 1.5 standard error range.

Urban areas illustrate the high structural vulnerability (latent risk) profile: observed MPI headcount falls substantially below the predicted level (21.7% observed against 28.6% predicted), a gap of nearly seven percentage points. Urban households carry **high structural vulnerability**, including informal employment and limited asset buffers, that is partly offset by favourable contextual conditions such as better infrastructure, denser markets, service availability and more diverse employment opportunities. In contrast, rural areas exhibit a **context-dominant** profile, where observed MPI exceeds the predicted level (36.7% observed against 33.6% predicted). Weaker infrastructure, service gaps, and market constraints raise rural deprivation beyond what household characteristics alone would produce. However, this urban-rural distinction masks considerable state/region variation in how contextual factors mediate structural deprivation.

Table 4 Predicted and observed MPI headcount, union and urban/rural

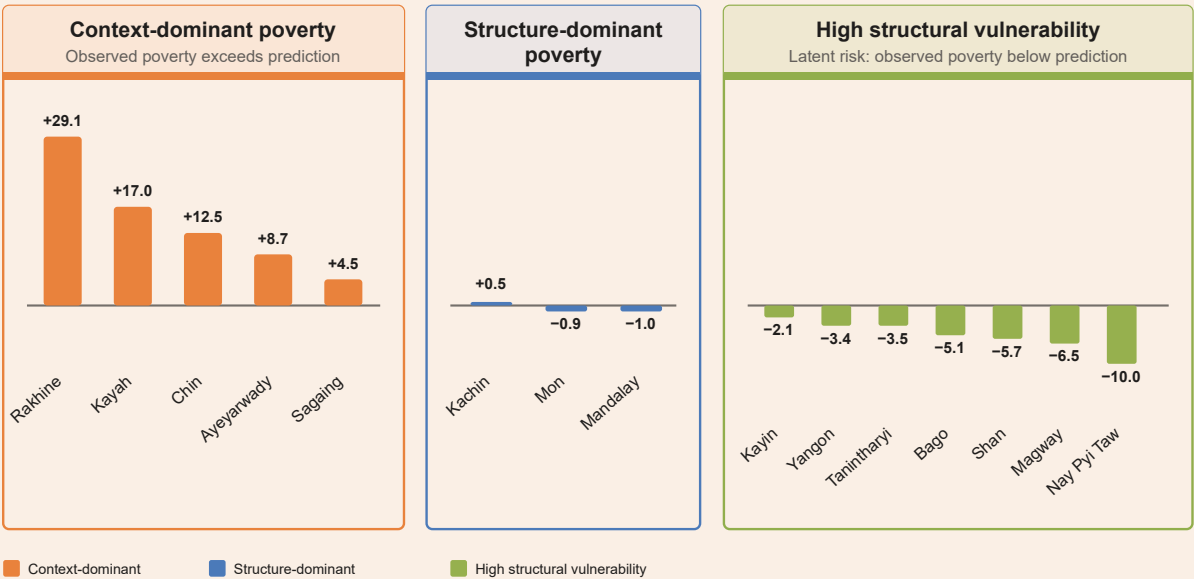
	Predicted MPI headcount	Observed MPI headcount	Gap (percentage point)
Union	32.1%	32.6%	0.5
Urban	28.6%	21.7%	-6.8
Rural	33.6%	36.7%	3.1

State and region profiles

Three poverty profiles emerge across states/regions, reflecting varying combinations of structural and contextual conditions. The classification is based on the direction and magnitude of the gap between observed and predicted poverty.

Figure 4 Poverty profiles across states/regions: Observed versus predicted MPI headcount gap

Observed MPI headcount minus predicted MPI headcount (percentage points)



Source: PPS 2025 (UNDP)

(I) CONTEXT-DOMINANT POVERTY

In several states/regions, the observed MPI headcount significantly exceeds the predicted levels, indicating that contextual factors, such as conflict exposure, displacement, restricted mobility, infrastructure damage, market fragmentation and disrupted service delivery, substantially raise poverty above what household characteristics alone would generate.

The largest gaps appear in Rakhine and Kayah, where around two thirds of households are multidimensionally poor, far above what the structural characteristics of their populations would predict. In Rakhine, prolonged access restrictions, displacement and the cumulative effects of conflict compound deprivation well beyond household-level risk factors. In Kayah, repeated displacement cycles, insecurity and market fragmentation produce a similar pattern.

In Kayah and Rakhine, poverty is 25 percentage points or more above what household characteristics alone would predict. The households are not unusually disadvantaged in their education or employment. What sets them apart is where they live and what has happened around them.

Notably, Ayeyarwady shows a nine-percentage-point gap that exceeds the statistical threshold, indicating a substantial context-dominant pattern. This is consistent with the state's exposure to recurrent flooding, geographic isolation in delta areas, and market constraints that raise deprivation above what household characteristics alone would explain.

Persona 1:

Context-dominant poverty¹¹

Khu Bua Reh is living in Kayah and has been displaced multiple times due to conflict. With primary education, Khu Bua Reh relies on irregular agricultural and casual labour. Despite being willing and able to work, livelihood options are severely constrained by insecurity and repeated displacement. Agricultural activities are frequently interrupted by access restrictions, land abandonment and damage to tools and inputs. Casual labour opportunities are sporadic and often unsafe to reach due to mobility constraints. Markets operate intermittently, leading to shortages and price volatility that force the household to reduce food consumption and rely on negative coping strategies. Access to healthcare is highly constrained, with facilities distant, under-resourced or inaccessible during periods of heightened insecurity. Schooling for children is repeatedly disrupted by displacement and school closures, undermining educational continuity regardless of household or parental preferences.

¹¹ The three personas presented in this section, namely Khu Bua Reh (context-dominant), U Myaing (structure-dominant), and Ma Nu (high structural vulnerability), are composite representations based on patterns identified in the PPS 2025 survey data. They are not portraits of actual individuals but are constructed from survey responses to illustrate how the three poverty profiles manifest in lived experience across different geographic and social contexts.

(II) STRUCTURE-DOMINANT POVERTY

In a second group of states/regions, observed and predicted poverty align closely, indicating that deprivation largely reflects entrenched household characteristics, notably educational deficits, agricultural dependence, limited livelihood diversification, and low-income security, rather than acute contextual shocks. Here, poverty is not primarily a product of conflict or geographic isolation but of long-standing human capital constraints and livelihood patterns. Reducing poverty in these contexts requires sustained investment in education, skills development, livelihood diversification and service quality, interventions that address the structural foundations of deprivation.

Persona 2:

Structure-dominant poverty

U Myaing is living in a rural township of Mandalay, located in Myanmar's central dry zone. With no formal education, U Myaing cultivates a small plot of rain-fed land, growing sesame and groundnut during the monsoon and depending on casual agricultural labour during the dry months. Rainfall is erratic and concentrated in a short wet season; in years of poor rains, crop yields fall sharply and no irrigation is available to compensate. U Myaing owns no livestock and has limited savings to invest in improved seeds or fertiliser, so productivity remains low from season to season. Landlessness is widespread in neighbouring households, and competition for casual labour keeps daily wages low. The nearest market town is accessible but offers few non-agricultural employment opportunities for workers without formal education. Children in the household attend primary school, though older children are regularly withdrawn during planting and harvest to supplement household labour. Housing is basic, marked by earth floors, thatch roofing and no improved sanitation, reflecting decades of low investment capacity rather than recent deterioration. U Myaing's poverty is persistent and structural: it predates the current crisis and would remain even if contextual conditions improved, because the binding constraints are education, skills and productive assets.

(III) HIGH STRUCTURAL VULNERABILITY (LATENT RISK)

In these states/regions, predicted poverty exceeds the observed MPI headcount, indicating that many households exhibit structural characteristics associated with a higher underlying risk of multidimensional poverty than current measurements reflect. These households possess structural risk factors, including informal employment, low asset buffers, and limited education, that are partially moderated by favourable area-level conditions. They are not currently classified as multidimensionally poor but are highly sensitive to shocks and economic disruption.

Two sub-patterns emerge within this group. In Yangon and Nay Pyi Taw, urban economic infrastructure, such as market density, service availability, and employment diversity, buffers households whose structural profiles would otherwise place them at considerably higher risk. In Magway and Bago, agricultural market access, particularly Magway's oil-crop production for a domestic market that remains import-dependent, moderates the expression of underlying vulnerability without eliminating it. In Shan, Tanintharyi and Kayin, proximity to international borders adds remittance flows and cross-border trade as additional moderating channels. Identifying this group is analytically and programmatically important. Lower observed MPI outcomes reflect area-level averages and do not imply resilience for individual households, particularly migrants, informal workers or those without asset buffers. These households sit close to the poverty threshold and are vulnerable to transitions into multidimensional poverty when conditions change, through economic contraction, conflict spillover, natural hazards or the withdrawal of moderating infrastructure. Resilience-building interventions targeting this group can reduce future poverty transitions and avoid reversals in well-being that are costly and difficult to reverse once they occur.

Persona 3:

High structural vulnerability (latent risk)

Ma Nu is living in a peri-urban area of Yangon as a migrant. With secondary education, Ma Nu works in informal, short-term employment. Ma Nu benefits from proximity to markets, services and employment opportunities, allowing basic needs to be met during periods of stable income. Children attend school and healthcare is physically accessible, though often costly. Housing is informal and insecure, and Ma Nu has little savings or access to formal social protection. Income fluctuates month to month. When daily work is unavailable or wages are delayed, rent payments are postponed and utility bills accumulate. Food purchases are adjusted first, with reduced meal diversity and quantity, while healthcare visits are delayed unless absolutely necessary. Although schools and clinics are physically accessible, out-of-pocket expenses and lost work time limit consistent use. Housing insecurity and the absence of savings mean Ma Nu has little capacity to absorb even short disruptions.

3.2 Amplifiers of Poverty: Shock Exposure

This section examines how shocks interact with existing structural and contextual vulnerabilities to deepen deprivation and accelerate transitions into multidimensional poverty.

While structural and contextual drivers shape baseline patterns of multidimensional poverty, shocks act as amplifiers: they deepen deprivation among already vulnerable households and accelerate transitions into poverty for those at the margin. The analytical question is not whether shocks matter, but how to differentiate their effects. Shocks differ in how widely they reach, in how strongly they amplify poverty per exposed household, and in how their effects accumulate over time. Understanding these differences matters for programming design because the most prevalent shock is not necessarily the one that does the most damage to an individual household, and the response required to break the cycle differs accordingly.

This section presents three findings. First, prevalence and intensity rank inversely across shock types: economic shocks reach the largest number of households, but conflict shocks carry the largest amplification effect per exposed household. Second, the effects of repeated economic and natural hazard shocks accumulate steadily, eroding coping capacity in ways that can move structurally protected households into deep deprivation. Third, conflict differs from economic and natural hazard shocks in that it creates a persistent elevated-risk context rather than acting as a single discrete event.

Geographic distribution of shock exposure

The three shock types, economic, natural hazard, and conflict-related, differ markedly in how widely and where they reach.¹² Figure 5 shows household exposure across union, urban-rural and state/region levels.

Economic shocks are systemic. At the union level, around 57 percent of households report at least one economic shock, and exposure exceeds 40 percent in every state and region. The highest rates are in Kayah (90%), Kachin (86%), Rakhine (75%) and Magway (67%), but even the least-exposed area, Mon, records around 43 percent. The urban-rural gap is narrow (54% urban, 57% rural), reflecting that income volatility and price pressures reach households across the income and geographic distribution.

Natural hazard shocks are geographically concentrated. Around 20 percent of households are exposed at the union level, with rural households more than twice as likely to be affected as urban (23% versus 10%). Exposure is highest in Kayah (52%), Bago (32%), Kayin (30%) and Magway (30%), areas with significant rain-fed agriculture, flood-prone terrain or both. At the other end, exposure is well under 10 percent in Tanintharyi (4%) and Yangon (7%).

Conflict shocks are the most geographically concentrated. Around 10 percent of households nationally report direct conflict or displacement exposure, but two states account for the bulk of this: Kayah (68%) and Rakhine (52%). Chin (21%), Kachin (21%) and Sagaing (20%) follow at substantially lower

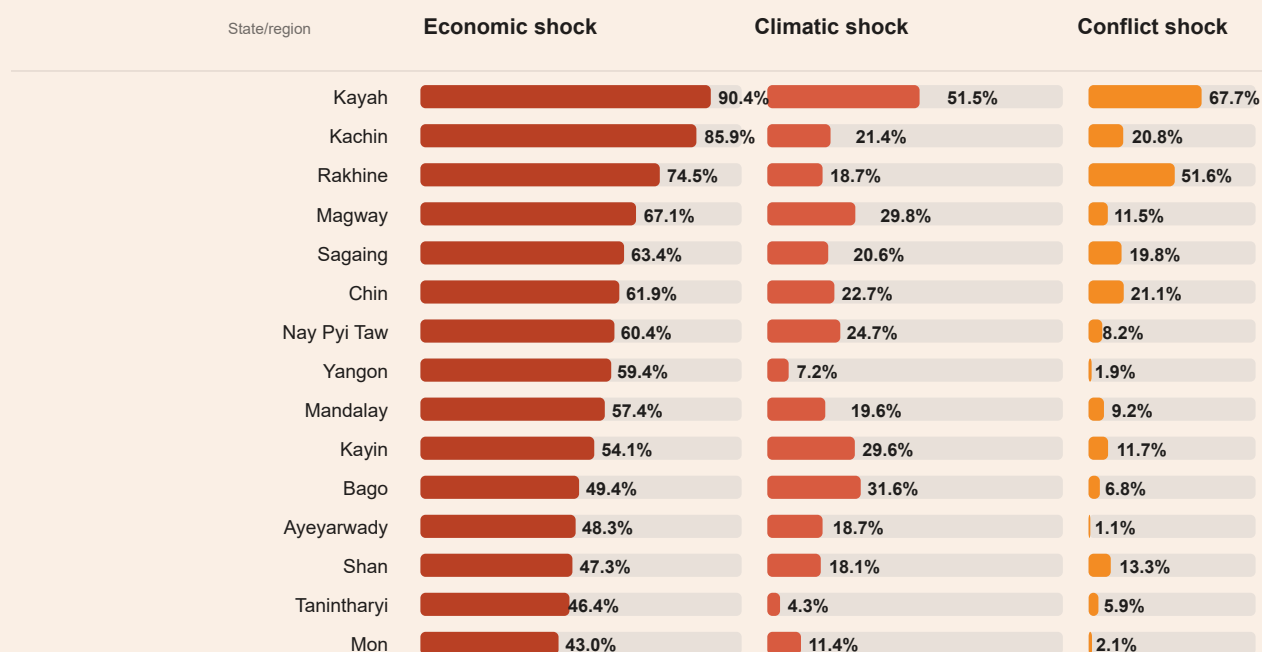
¹² A shock refers to self-reported negative impacts experienced by a household during the preceding 12 months. The three shock categories are based on the PPS 2025. Natural hazard shocks include drought, heavy rain or hail, floods, cyclones or tornadoes, earthquakes, tsunamis, landslides, fire, lightning, and crop pests or diseases. Economic shocks include low agricultural prices, high food prices, reduced non-agricultural business earnings, and loss of employment or reduced earnings. Conflict shocks include direct exposure to conflict and displacement. As with shock-recall modules in household surveys more broadly (i.e., living standard measurement study), categories are self-reported and not mutually exclusive: a household's reported loss of employment or reduced earnings, for example, may itself result from a conflict or natural hazard shock rather than reflecting an independent economic trigger.

but still elevated levels. In Mon, Yangon and Ayeyarwady, exposure is at or below two percent. The geographic concentration of conflict shocks reinforces the analytical point developed below: the rarest shock at the national level is the most concentrated locally, and, as the next subsection shows, the most damaging per exposed household.

Figure 5 Household exposure to economic, natural hazard and conflict shocks (by geography)

Share of households reporting exposure, by state/region (%)

Kayah records the highest exposure to all three shocks:
economic 90.4% · climatic 51.5% · conflict 67.7%



Source: PPS 2025 (UNDP)

Differentiating shocks by intensity

To isolate the effect of each shock type from underlying household vulnerability, predicted MPI headcounts were compared between households exposed to a given shock and otherwise similar households not exposed, holding structural characteristics constant.¹³ The resulting amplification effect, that is the percentage-point increase in predicted poverty associated with shock exposure, captures the contribution of the shock itself, separate from the structural risk profile of the household. Table 5 summarizes the three estimates.

¹³ The amplification effects are estimated from a survey-weighted logistic regression that includes structural household characteristics, namely household size, sex of head, education of head, employment of head, per capita income quintile and migrant status, alongside three binary shock indicators (natural, economic, conflict). Predicted probabilities are computed for each household at observed values of the structural variables, separately for shock-exposed and unexposed scenarios, and averaged across the sample. The amplification effect is the difference between these two averaged predicted probabilities, with confidence intervals derived from the model's standard errors.

Table 5

Amplification effect of each shock type on predicted MPI poverty

Shock type	Prevalence (% households exposed)	Predicted MPI poverty if not exposed	Predicted MPI poverty if exposed	Amplification effect (pp)	95% CI	Aggregate contribution to national MPI (pp)
Conflict	10%	30.6%	44.8%	14.2	9.9 – 18.5	1.4
Economic	57%	25.6%	36.7%	11.1	9.5 – 12.7	6.3
Natural hazard	20%	31.3%	35.0%	3.8	1.0 – 6.5	0.8

Source: PPS 2025 (UNDP)

Conflict exposure carries the largest amplification effect at 14.2 percentage points, raising predicted MPI headcount from around 31 percent for unexposed households to 45 percent for those exposed, comparable to the 43.5 percent observed among households headed by someone with no formal education. Economic exposure produces an amplification effect of 11.1 percentage points, somewhat smaller per household but still substantial. Natural hazard shocks add 3.8 percentage points, a statistically significant but more modest effect, partly because much of the vulnerability associated with environmental hazards is already absorbed into the structural baseline through agricultural employment, low income and rural location.

However, the shocks that affect the most households are not those that damage most severely per exposed household. Economic shocks are the most pervasive, affecting 57 percent of households nationally; conflict shocks are the most concentrated, reaching 10 percent; and natural hazard shocks fall between the two at 20 percent. This inverse relationship between scale and severity points toward different programming responses. Economic shocks, operating through market and employment channels, warrant broad-based interventions because they reach the largest share of households. Conflict shocks warrant the most intensive and targeted support because they cause the deepest poverty among those affected, acting simultaneously across livelihoods, mobility and service access. Natural hazard shocks are concentrated among agriculture-dependent households and operate through production and asset-level channels, namely crop loss, physical damage and livelihood disruption, that overlap substantially with those of economic shocks. Although the survey instrument distinguishes the two, for farming households a drought or flood that destroys a harvest is simultaneously an income loss, an asset depletion and a food price pressure. For both shock types, addressing the underlying risk, not only responding once it materializes, requires investment beyond the household level: climate-resilient infrastructure, market stabilization and employment protection operate at community, market and policy level and are addressed further under Section 6.

Cumulative shock exposure erodes coping capacity

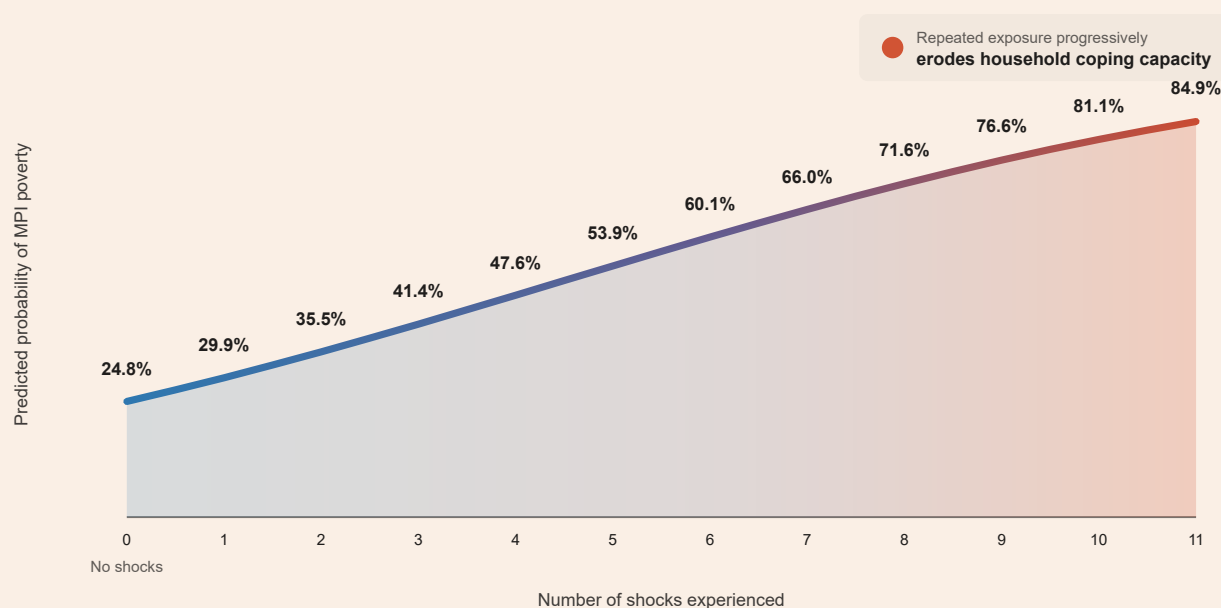
The amplification effects in Table 5 capture the impact of each shock type individually. But households rarely experience shocks in isolation: economic, natural hazard and conflict pressures often co-occur and compound over time. Figure 6 shows how predicted MPI poverty rises with total shock count, holding structural characteristics constant.¹⁴

¹⁴ The cumulative trajectory is estimated from a Firth-penalized logistic regression fitted on the full sample, using a count of all shocks reported by the household (natural hazard, economic and conflict combined) as the independent variable. The model includes structural controls, namely household size, sex of head, education of head, employment of head, per capita income quintile, migrant status, together with state/region and urban/rural indicators. Predicted probabilities are averaged across the full sample at observed values of the controls for each shock count value from zero to ten.

Figure 6

Predicted multidimensional poverty (by cumulative shock exposure)

Predicted probability of MPI poverty, holding structural household characteristics constant



From no shocks to ten shocks: predicted poverty rises by about 56 percentage points

Source: PPS 2025 (UNDP)

With zero shocks, predicted poverty stands at around 25 percent. Each additional shock adds roughly five percentage points, with the curve rising to 41 percent after three shocks, 54 percent after five, and 81 percent after ten. The pattern is consistent: repeated exposure, regardless of shock type, progressively erodes coping capacity, as assets are depleted, savings exhausted, and household buffers diminished, pushing households deeper into deprivation with each successive event.

Conflict is the most powerful amplifier of poverty, because unlike other shocks, conflict affects multiple dimensions of well-being at once.

Each shock type damages the same channels through which households maintain well-being, such as income, assets, food security and service access, but does so through different entry points and at different speeds. Economic shocks act primarily through income volatility, with deprivation cascading from household budgets into food and service consumption. Natural hazard shocks act through physical damage to crops, housing and infrastructure, with effects often concentrated geographically and seasonally. Conflict shocks act simultaneously across all channels, disrupting livelihoods, markets, mobility and service delivery at once, which is why the per-household amplification is largest. The cumulative analysis adds a temporal dimension: even when individual shocks are modest, their repeated effects on the same household can produce levels of deprivation as severe as those caused by a single acute event such as conflict.

Taken together, the evidence in this section shows that poverty in Myanmar is structurally embedded and contextually shaped, with shocks amplifying both household and area-level vulnerabilities. Two states/regions or household groups with similar MPI headcount levels may face very different poverty dynamics, with one driven primarily by structural disadvantage, another by contextual pressures, and another by repeated shock exposure, each requiring a different programmatic response. Section 4 turns from how poverty is generated to who experiences it most acutely, profiling multidimensional poverty across income, employment, education, migration and gender.

4 Socio-Economic Profiles of Poverty

Key Messages

01

Multidimensional poverty in Myanmar is concentrated

among specific household profiles where income insecurity, labour conditions and exposure to shocks intersect and reinforce one another.

02

Nearly half of households in the lowest income quintile are multidimensionally poor,

and deprivation deepens sharply where low income coincides with insecure work, limited education and repeated shock exposure. (Households in Q1 show an MPI headcount of 52.2% and an score of 0.255, nearly fourfold higher than Q5 (MPI score 0.067).

03

Labour insecurity is a central transmission channel of poverty, not just a correlate:

households relying on casual labour show some of the highest poverty rates and intensities, reflecting irregular earnings, weak buffers and limited capacity to absorb shocks once livelihoods are disrupted (MPI headcount 48.5% and MPI score 0.228, among the highest across employment groups).

04

Conflict exposure and migration are acute amplifiers:

conflict-affected households record the highest poverty of any group (MPI headcount 56.5%, MPI score 0.271); migrant households are close behind (MPI headcount 50.2%, MPI score 0.241), with deprivation shaped by displacement, institutional barriers, documentation gaps and settlement instability.

05

Education remains a key structural driver:

households headed by individuals with no formal education or primary education record nearly identical headcounts (around 44%) and MPI scores (around 0.211), suggesting primary education alone provides little protective effect. Both groups face deprivation more than double that of higher-educated households (MPI score 0.089).

06

Health shocks act as an acute poverty trigger:

households experiencing serious illness or accident record an MPI headcount of around 46.6 percent and a score of 0.220, reflecting how a single health event can rapidly deplete assets and income for households already operating with thin margins.

07

Gender differences are expressed more in the depth of deprivation than in incidence:

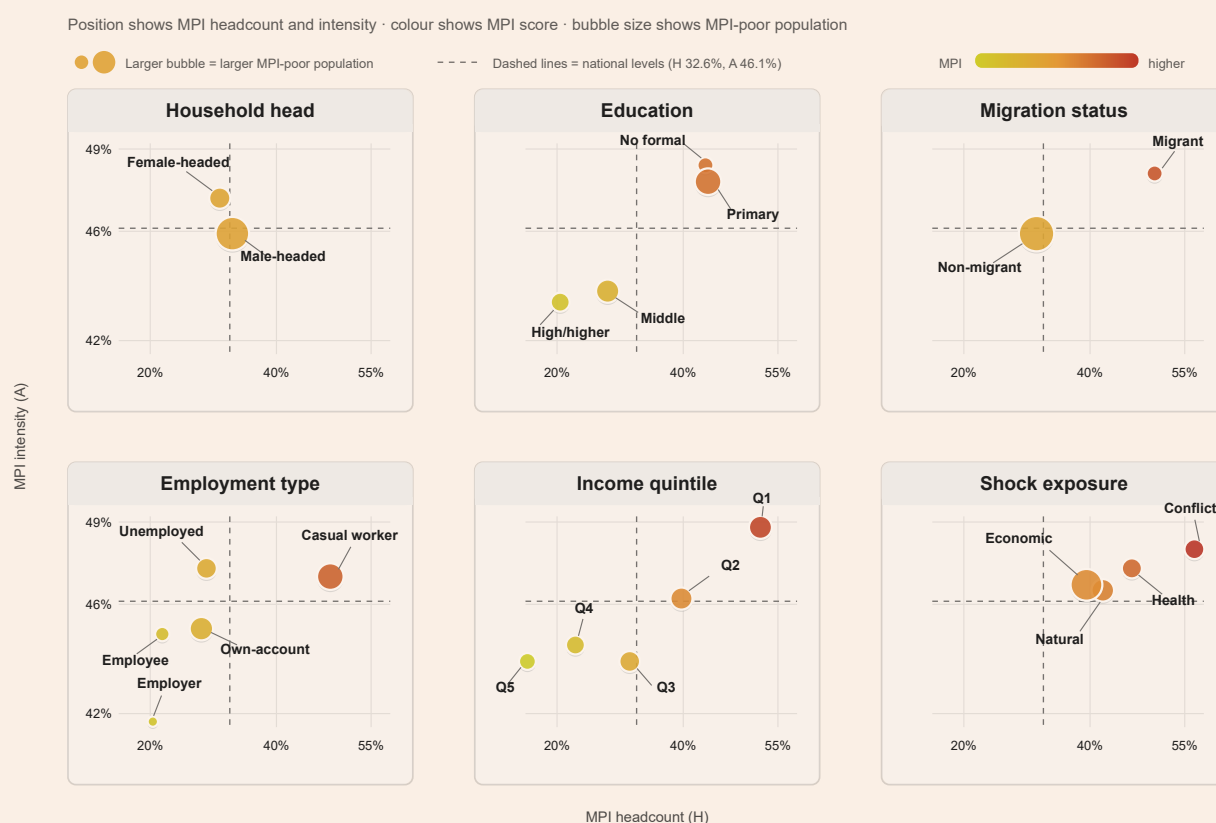
woman-headed households record a modestly lower headcount (31.0%) than man-headed households (33.0%), but higher deprivation intensity (47.2% versus 45.9%). The gaps are small, but the directional reversal is analytically meaningful: women who fall into poverty face deeper deprivation than their male-headed counterparts, a pattern consistent with the disproportionate care burdens and labour-market constraints that limit recovery capacity for woman-headed households.

4.1 A People-Centred Lens

The preceding sections examined poverty through a geographic and structural lens: where deprivation is concentrated, what contextual and structural factors drive it, and how shocks amplify it. Section 4 turns to a people-centred perspective, asking who bears the greatest burden of multidimensional poverty across income, employment, education, migration status and household type.

Figure 7 compares household groups across three dimensions simultaneously. The horizontal axis shows how many are poor (incidence), the vertical axis shows how deeply poor they are (intensity), and bubble size reflects the absolute number of MPI-poor households in each group. Groups in the upper-right quadrant face the worst outcomes: both widespread and deep poverty. Groups with large bubbles carry the greatest share of the national poverty burden, even when their MPI score is not the highest.

Figure 7 Multidimensional poverty across household types



Source: PPS 2025 (UNDP)

In practice, many of these characteristics overlap, as migrant households are often income-poor, reliant on casual labour and exposed to shocks, reinforcing the compounding nature of multidimensional poverty. The following sections examine these intersections, moving from structural traps to acute amplifiers to gendered dimensions of deprivation.

4.2 Structural Trap: Where Vulnerabilities Intersect

Poverty deepens sharply where multiple vulnerabilities coincide. Low income, insecure employment and limited education do not operate independently: they form interlocking constraints that reduce a household's capacity to invest, diversify and recover, producing a structural trap that persists even in the absence of acute shocks.

Income as the foundation of vulnerability



Income growth can reduce poverty, but escaping the structural poverty trap requires improvements in health, education and living standards as well.

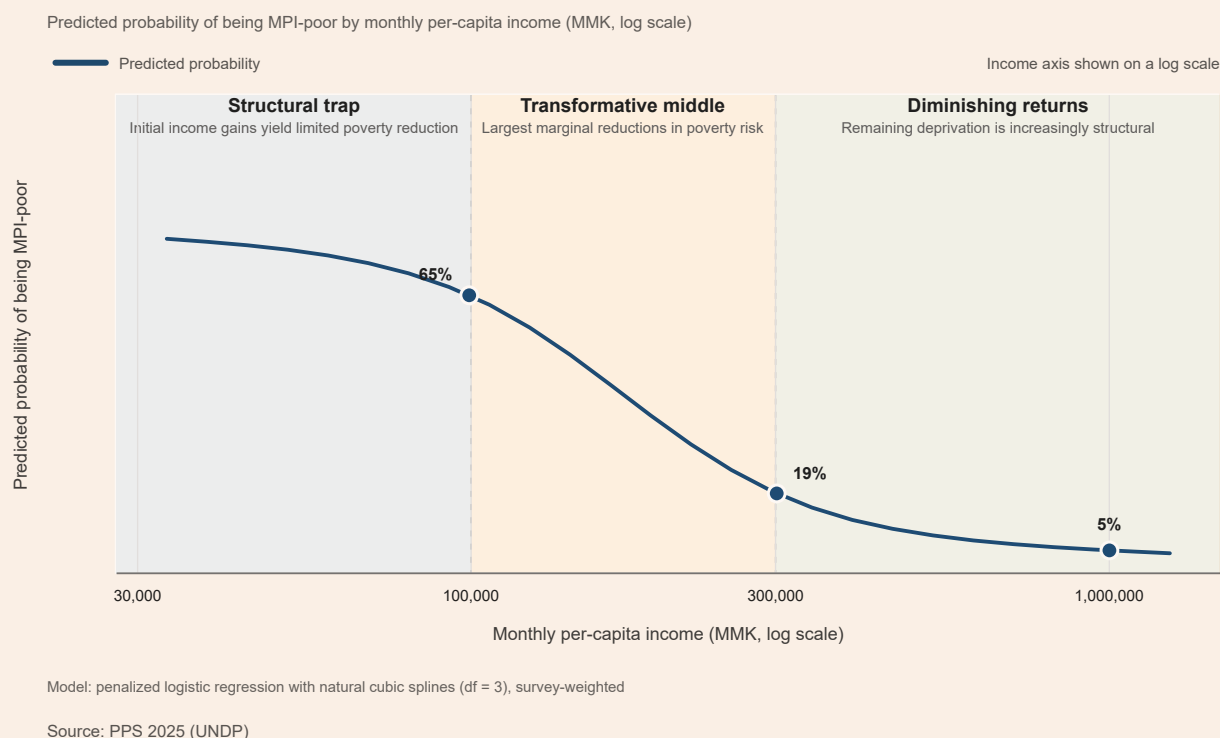
Income-poor households are concentrated in the upper-right quadrant of Figure 7, combining high poverty incidence with deep overlapping deprivations. Households in Q1 record an MPI headcount of 52.2 percent and a score of 0.255. Poverty declines steadily across quintiles, reaching an MPI score of

0.067 in Q5. While poverty headcount declines steadily, MPI intensity is very close for Q3 to Q5.

The relationship between income and multidimensional poverty is non-linear and follows an S-shaped curve commonly observed in poverty transitions. Figure 8 sheds light on this pattern. At very low income levels, marginal increases in income translate into only modest reductions in multidimensional poverty, as households remain constrained by structural deprivations (e.g., poor access to services, weak assets, limited resilience). As income rises into a middle range, the curve steepens sharply. In this transformative middle the incremental gains in income enable households to overcome key thresholds, such as securing stable food consumption, accessing basic services, or investing in productive assets. In this range, income support generates the largest marginal reductions in poverty risk. However, this segment is also characterized by fragility. Households have partially escaped deprivation but lack sufficient buffers, making them highly vulnerable to shocks and at risk of slipping back into poverty. At higher income levels, the curve flattens again, as additional income yields diminishing reductions in multidimensional poverty once core deprivations have already been addressed.

Figure 8 illustrates why income growth alone is insufficient at the bottom of the distribution: the curve is flat and high at low income levels, meaning that initial income gains, from extreme to merely low income, barely shift the probability of being MPI-poor, because housing, sanitation and health access deficits are not directly resolved through marginal income increases. The probability of being MPI-poor falls steeply only in the middle income range, before flattening again at higher income levels, where remaining poverty is driven by structural deficits in health, education and living conditions that income growth alone does not resolve. This pattern is consistent with Figure 7: deprivation intensity falls more noticeably from Q2 to Q3 than within the bottom two quintiles, indicating that reaching a moderate income level is where income growth starts to translate into reduced depth of deprivation, not only reduced headcount.

Figure 8 Non-linear relationship between income and multidimensional poverty¹⁵



Labour insecurity as a transmission channel

Employment type reinforces income vulnerability. Households relying on casual labour record an MPI headcount of 48.5 percent and a score of 0.228, among the highest across all employment groups. Figure 9 illustrates the gradient across employment types. The mechanism is not simply low wages: casual work provides no employment protection, no income continuity and no buffers against disruption. When livelihoods are interrupted by illness, conflict or natural hazards, casual workers have no savings or formal safety nets to draw on. Labour insecurity is therefore a transmission channel through which income shocks cascade into multidimensional deprivation.

By contrast, households headed by employees show markedly lower levels of multidimensional poverty (MPI headcount 21.9%, MPI score 0.098). Employer-headed households, defined as those whose head runs a business with at least one hired worker, record the lowest poverty of any employment group (MPI headcount 20.4%, MPI score 0.085) and the lowest intensity (41.7%). The poverty gradient across employment types runs from employer to employee to own-account to casual worker, consistent with the interpretation that capital accumulation and the capacity to hire labour are stronger poverty buffers than wage employment alone. Own-account workers occupy a distinct intermediate position (MPI headcount 28.1%, MPI score 0.127): better protected than casual workers but meaningfully more vulnerable than either employees or employers, reflecting the absence of employment security and the thin buffers typical of self-employment in Myanmar's informal economy.

¹⁵ The x-axis uses a log scale to reflect the right-skewed distribution of monthly per capita income in Myanmar: most households are clustered at low incomes with a long upper tail. The log scale spreads out the lower range where most households are concentrated, making the steep poverty decline more clearly visible. The regression model is fitted on log-transformed income using a natural cubic spline (three degrees of freedom) with Firth penalization to capture the non-linear relationship between income and MPI poverty risk. Income is measured in Myanmar Kyat (MMK) per capita per month.

Figure 9 MPI score by employment types of household head

MPI score by employment category compared with the national level



Source: PPS 2025 (UNDP)

Education as a structural divider

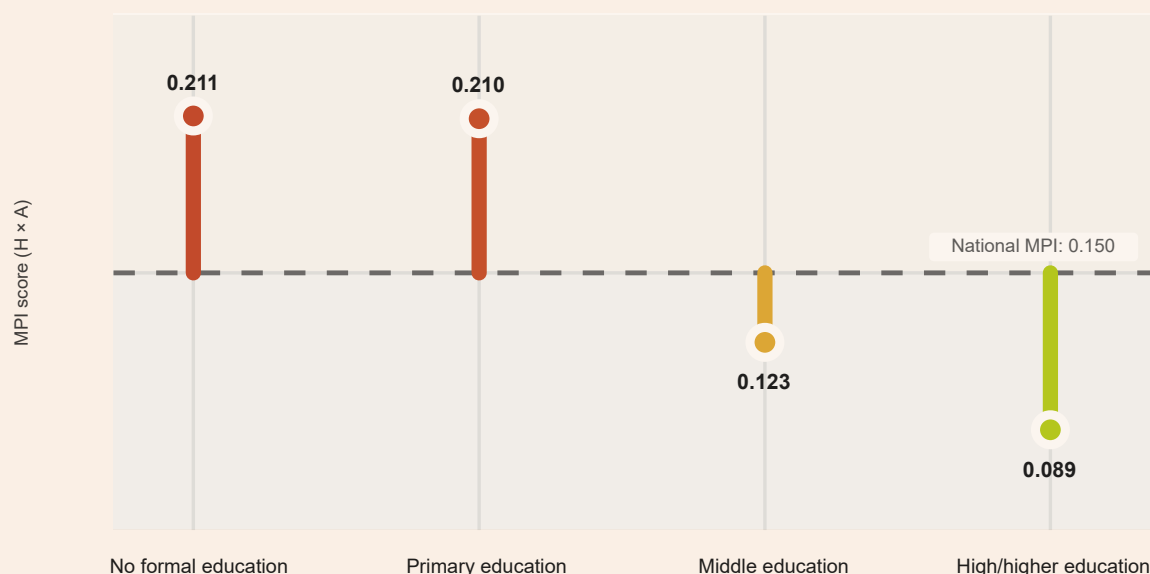
Education of the household head strongly differentiates poverty outcomes. Figure 7 shows no formal education and primary education as distinct groups, though their poverty levels are nearly identical: both record headcounts close to 44 percent and a score of around 0.211, more than double that of households headed by someone with higher education (MPI score 0.089). This near-equivalence suggests that even one level of formal schooling provides little protective effect against multidimensional poverty when it remains at primary level only. Figure 10 illustrates the gradient

Households headed by someone with only primary education are nearly as likely to be multidimensionally poor as those with no education at all. One level of schooling, without further investment, provides almost no protection against poverty in Myanmar today.

directly: the MPI score drops sharply only from middle education onward. Poverty declines markedly with middle education (MPI score 0.123). Education's role is structural: it shapes livelihood options, access to information and services, and capacity to navigate shocks across generations. Where educational attainment is low, the structural trap is hardest to escape.

Figure 10 MPI score by education level of household head

Independent category comparisons show meaningful protection emerging beyond primary education



Source: PPS 2025 (UNDP)

4.3 Conflict, Displacement and Migration as Acute Amplifiers

Beyond structural disadvantage, conflict exposure and migration amplify multidimensional poverty through acute, often compounding mechanisms such as displacement, institutional barriers, documentation gaps and settlement instability. These pressures intensify deprivation well beyond what income or employment status alone would produce.

Conflict exposure

Conflict-affected households record the highest poverty of any group with an MPI headcount of 56.5 percent and a score of 0.271. As shown in Table 5, conflict carries the largest amplification effect of any shock type (14.2 percentage points), acting simultaneously across livelihoods, markets, mobility and service delivery. Displacement, disrupted services and livelihood loss compound existing vulnerabilities rather than acting as isolated events.

Conflict-affected households record the highest multidimensional poverty of any group in this report: 56.5 percent. Conflict does not simply reduce income. It simultaneously dismantles the livelihoods, markets, services and mobility that households depend on to stay out of poverty.

Migration and urban vulnerability

Migrant households record an MPI headcount of 50.2 percent and a score of 0.241, placing them among the most deprived groups nationally. Around half of migrant households (50.7%) are conflict-induced migrants¹⁶, highlighting the intersection of migration and conflict-related vulnerabilities. This share has risen substantially since 2023, which recorded 18 percent conflict-driven migration using data collected before the October 2023 conflict escalation and the February 2024 activation of the conscription law.¹⁷

Deprivation among migrants reflects not only income insecurity but also institutional and access barriers: documentation gaps, informal settlement, reliance on precarious work and weaker social networks that constrain coping capacity. Lost documents and burdensome recovery procedures¹⁸ further limit employment and education options beyond the informal sector. These findings are consistent with the concentration of migrant and displaced populations in peri-urban Yangon, the primary destination for 31 percent of all internal migrants,¹⁹ where informal employment, housing precarity and limited access to social protection in these peri-urban areas generate particularly acute deprivation among migrant households.²⁰

Health shocks as an acute poverty trigger

Health shocks, namely serious illness or accident of a household member, appear in Figure 7 as a distinct group positioned in the upper-right quadrant, with an MPI headcount of around 46.6 percent and a score of 0.220. Unlike structural disadvantages that develop gradually, health shocks trigger immediate income loss, asset depletion and increased out-of-pocket expenditure simultaneously. For households already operating with thin margins, such as low income, casual employment, and limited savings, a single health event can push them across the poverty threshold rapidly and durably. Health shocks thus function as an acute amplifier that intersects with and deepens structural vulnerability, particularly among households that lack formal social protection or health insurance.

4.4 Gender: Depth Over Incidence

Gender differences in multidimensional poverty are expressed more in the depth of deprivation than in incidence. As Figure 7 shows, woman-headed households record a slightly lower MPI

Woman-headed households are slightly less likely to be multidimensionally poor than man-headed households. But among those who are poor, women experience deeper and more overlapping deprivations. Counting who is poor understates what women in poverty are living through.

headcount (31.0%) than man-headed households (33.0%). However, their deprivation intensity is higher (47.2% compared with 45.9%), resulting in a marginally lower MPI score (0.146 versus 0.151). Although fewer woman-headed households are classified as multidimensionally poor, those who are poor experience deeper and more overlapping deprivations.

16 "Conflict-induced migrants" refers to households that self-reported conflict or displacement as their primary reason for migration in PPS 2025. This is a behavioural category based on self-reported migration reason, not a legal status. It is distinct from economic migrants (households that moved primarily for livelihood or employment reasons), Internally Displaced Persons (IDPs, a legal/humanitarian status under the UN Guiding Principles on Internal Displacement), and refugees (persons who have crossed an international border and hold formal protection status under UNHCR).

17 UNDP (2024). Moving to Cope: Migration in Myanmar.

18 According to the 2014 Myanmar Population and Housing Census and related analyses, almost one-third of the population (approximately 17–18 million people) did not possess any form of identity documentation such as an NRC card. The census counted over 9 million internal migrants (about 18–20 % of the population) and nearly 2.9 million Myanmar nationals living abroad.

19 UNDP (2024). Moving to Cope: Migration in Myanmar.

20 UNDP (2025). Urban Poverty: Unpacking Yangon.

This pattern aligns with findings from UNDP and UN Women's 2026 report, which show that woman-headed households do not differ significantly from man-headed households in overall food insecurity incidence, yet are more likely to adopt severe negative coping mechanisms when faced with food security challenges.²¹ Unpaid care burdens, weaker labour-market opportunities and more limited access to community support structures compound the severity of deprivation among young women and women in general.²² These findings underscore the importance of interventions that address the intensity of deprivation. When caregiving responsibilities for children or elderly dependents compel women to leave stable employment, the resulting loss of regular income deepens deprivation. Access to childcare, social protection, livelihoods support and community-based services directly address this transmission channel, rather than focusing solely on poverty incidence.

Table 6 Socio-economic profiles of multidimensional poverty

Household profile	MPI headcount	MPI score	Key vulnerability mechanism
Income-poor households (Q1)	52.2%	0.255	Low and unstable income, limited asset buffers and constrained access to services
Income Q2 households	39.7%	0.183	Structural vulnerability and limited returns to small income gains
Casual-worker households	48.5%	0.228	Irregular earnings, job insecurity and absence of employment protection
Low education household head (none or primary)	44%	0.211	Limited human capital, livelihood diversification and restricted service utilization
Migrant households	50.2%	0.241	Informal employment, settlement insecurity, weaker social networks and documentation barriers
Conflict-exposed households	56.5%	0.271	Displacement, disrupted services and livelihood loss
Woman-headed households (among the poor)	31.0%	0.146	Higher deprivation depth linked to care burdens and labour-market constraints

The household-group analysis establishes who carries the highest poverty burden: low-income households, casual and informal workers, migrants, conflict-affected households, and households whose head has limited or no formal education. These groups overlap and reinforce one another, with deprivation deepening sharply where multiple vulnerabilities coincide. Identifying who is poor and how deeply, across income, employment, education, migration and conflict exposure, is the first step. The next question is what kind of deprivation these households experience: whether it is driven by health deficits, inadequate living standards, or lack of education. Section 5 addresses this by decomposing the MPI into its three component dimensions: education, health and living standards.

²¹ UNDP & UN WOMEN (2026). Uneven Burdens: Women in Myanmar's Crisis Economy.

²² UNDP (2025). A Generation on Hold: Youth Employment and Education.

5 Beyond Headcount: What the Composition of Deprivation Reveals

Key Messages

01

Health and living standards drive the national deprivation picture:

Nationally, health (39.3%) and living standards (41.3%) together account for over 80 percent of the MPI score, with education contributing 19.4 percent. The urban–rural gap is a gap in the level of poverty, not its type: the compositional shares are nearly identical across both areas.

02

Dimensional composition varies by context, not poverty level alone:

In states/regions where survival-related deprivations dominate (Rakhine, Kayah, Chin, Kachin and Ayeyarwady), health and living standards compress education's share. In states/regions where education's share is comparatively higher (Sagaing, Mon, Mandalay and Nay Pyi Taw), the transition from survival deprivations to human-capital constraints has direct implications for which interventions carry the most leverage.

03

The poorest households face a structural deprivation trap that income gains alone cannot dislodge:

The two lowest income quintiles display nearly identical dimensional structures dominated by health and living standards. Income shifts the level of poverty across the distribution without shifting its dimensional structure, because housing, sanitation and health access deficits are not directly resolved through marginal income increases.

04

Dimensional composition is the diagnostic that headcount alone cannot provide:

Mon and Kayin record nearly identical MPI scores but face different binding constraints, Kayin's higher health share points to healthcare access, Mon's higher living-standards share points to infrastructure first. More broadly, where survival-related deprivations dominate, service restoration is the primary lever; where human-capital constraints dominate, education investment carries greater leverage; and where states and regions fall between these two patterns, livelihood restoration and economic resilience carry particular leverage, since rising incomes reduce the depth of deprivation even where they do not change its underlying composition.

Sections 2 to 4 have established where multidimensional poverty is concentrated, how it is generated and amplified, and who experiences it most acutely. This section turns to a final diagnostic question: what kind of poverty do these households experience? The MPI score decomposes into three mutually exclusive dimensional contributions (education, health and living standards) whose shares sum to 100 percent by construction; comparing these shares across contexts and household groups reveals shifts in the underlying structure of deprivation. Four findings emerge: health and living standards drive the national picture; dimensional composition varies by context, pointing to different intervention priorities; and similar MPI scores can mask fundamentally different poverty dynamics. Together, these findings indicate that contexts and groups with similar headline poverty levels often face very different compositional structures of deprivation, with direct implications for which interventions are likely to reduce poverty most effectively.

5.1 The National Picture: Health and Living Standards Dominate

Nationally, Myanmar's MPI score of 0.150 is composed of deprivations in living standards (0.062, or 41.3% of the index), health (0.059, or 39.3%) and education (0.029, or 19.4%). Living standards captures deficits in housing quality, sanitation, water access and electricity; health captures access to healthcare and food security stress (measured through the Livelihood Coping Strategy Index - LhCSI); education captures schooling attendance and attainment. Together, the first two dimensions account for more than four fifths of national multidimensional poverty, indicating that the binding constraints on household well-being are basic living conditions and service access rather than education access itself.

The urban-rural decomposition reinforces this finding. The rural MPI score (0.170) and urban MPI score (0.097) differ substantially in level, but the compositional shares are nearly identical: in rural areas, education accounts for 19.4 percent of the index, health 38.7 percent and living standards 42.0 percent; in urban areas, the corresponding shares are 19.7 percent, 42.1 percent and 38.2 percent. The urban-rural gap is a gap in overall poverty, not in its dimensional structure. This stable national composition serves as the reference against which variation across states/regions, household types and shock exposure is read in the sections below.

5.2 Variation Across States and Regions

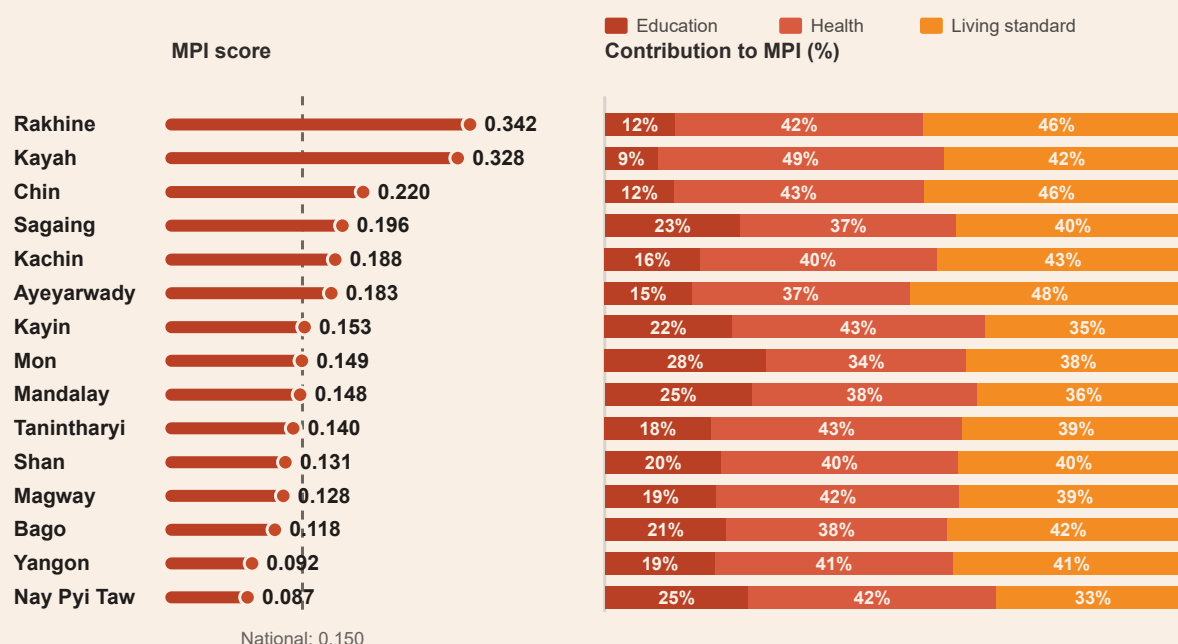
Dimensional composition varies across states and regions. Figure 11 shows both the MPI score (top panel) and the dimensional composition (bottom panel) for each state and region, sorted by MPI score. While MPI scores fall steadily from Rakhine (0.34) to Nay Pyi Taw (0.09), the dimensional composition does not shift in lockstep: each state has its own compositional profile reflecting its specific service environment, infrastructure conditions and schooling access.

This cross-state variation in dimensional composition is significant, and it is not a product of MPI score itself. State-level MPI score is driven overwhelmingly by headcount, the share of the population that is multidimensionally poor, rather than by intensity, the average depth of deprivation among the poor: headcount ranges widely across states and regions, from 19.7 percent (Nay Pyi Taw) to 68.4 percent (Rakhine), while intensity varies only narrowly, from 44.2 percent (Nay Pyi Taw) to 50.1 percent (Rakhine) (Table 3). In other words, states and regions differ widely in how many people are poor, but the poor in any given state or region are, on average, similarly deep in poverty. Each

Figure 11

Dimensional composition of MPI (by geography) (percentage contribution)

MPI scores vary widely across states/regions, while dimensional composition differs by local context



Source: PPS 2025 (UNDP)

state's compositional profile, shown in Figure 11, therefore reflects contextual differences in service infrastructure, conflict exposure, livelihood patterns and access, rather than tracking each state's position in the MPI severity ranking.

Some states/regions, such as Rakhine, Kayah, Chin, Kachin and Ayeyarwady, exhibit compositions where health and living standards together dominate, with education compressed. Others, such as Sagaing, Mon, Mandalay and Nay Pyi Taw, show more balanced contributions across all three dimensions. Still others fall between these patterns. These compositional differences, determined by geography rather than MPI score, establish the foundation for determining which interventions are likely to carry the greatest leverage in each setting. However, it should be noted that a lower education share in a given state/region does not imply an absence of education deficits; rather, it indicates that health and living standards account for a larger proportion of each household's total deprivation, making service restoration and infrastructure investment the most efficient entry points for poverty reduction in those settings.

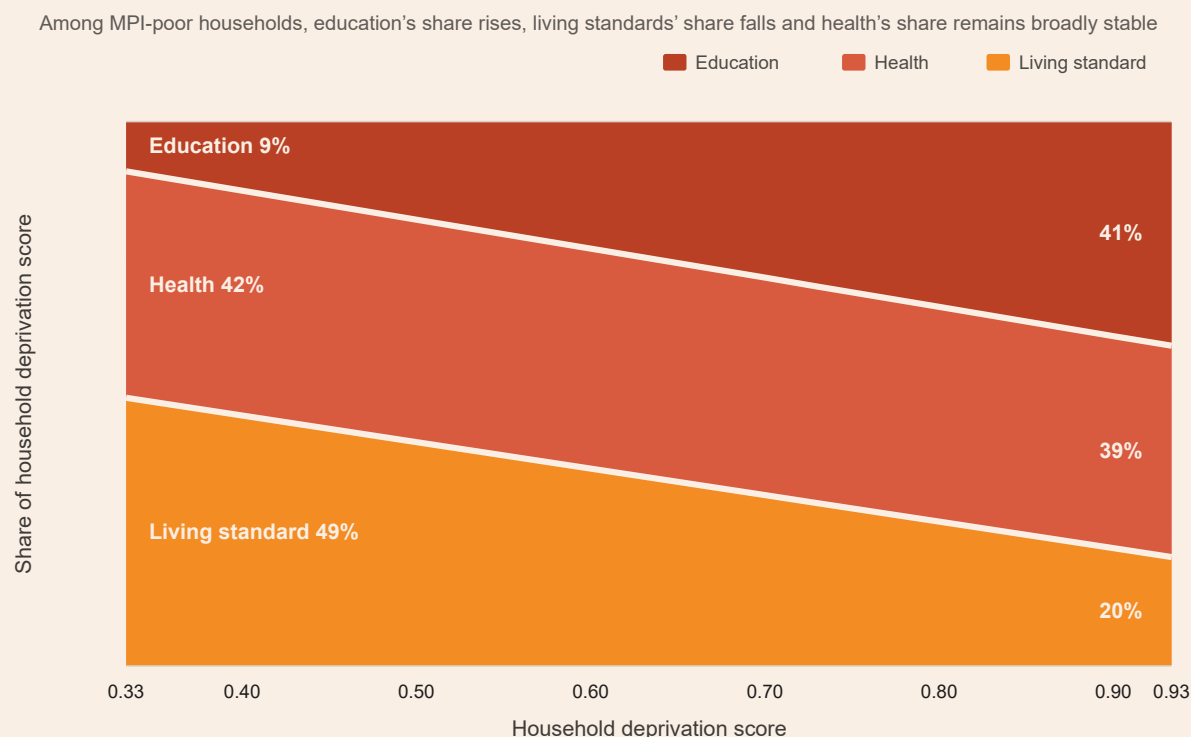
Health is the most stable dimension across all states/regions, ranging from 34 percent (Mon) to 49 percent (Kayah) without a consistent relationship to overall MPI level.

5.3 The Household-Level Gradient: Composition Shifts as Deprivation Deepens

Section 5.2 shows that dimensional composition across states and regions does not track state-level MPI severity, since MPI score is driven by headcount rather than intensity. This section turns to a different question: not where households are, but how the structure of their deprivation changes as poverty deepens.

Figure 12 plots the share of each dimension in the household deprivation score for MPI-poor households across the full range of deprivation depth. This score is each household's own measure of how deprived it is overall, on the same scale used to determine whether a household is MPI-poor in the first place and differs from intensity (A) in Section 5.2, which is an average of this score across all poor households in a state or region. Although average intensity is similar across states and regions, it varies considerably among individual households, and it is this household-level variation that drives the compositional shifts examined below.

Figure 12 Dimensional composition of MPI (by household deprivation score)



Source: PPS 2025 (UNDP)

Living standards is the dominant dimension at the lower end of the deprivation distribution, accounting for around 49 percent of the deprivation score for households with minimal poverty, and remaining substantial throughout the deprivation range. As deprivation deepens, however, living standards' share falls steadily, reaching around 20 percent for the most deprived households. Education runs in the opposite direction: its share starts at around nine percent among less-deprived households and rises to around 41 percent the most deprived. The two dimensions cross at around a deprivation score of 0.73, at which point education's share overtakes living standards as the largest share. Health remains comparatively stable throughout, declining only modestly from around 42 percent among less-deprived households to around 39 percent among the most deprived.

This may appear to conflict with Section 5.2, where living standards' share was highest in the states and regions where survival-related deprivations dominate (Rakhine, Kayah, Chin, Kachin and Ayeyarwady), several of which also carry the highest MPI scores. The two findings operate on different axes and are not in tension. Section 5.2 reflects context: states/regions with weaker infrastructure and service environments show a high living-standards share across most of their poor households, regardless of how deep each household's own deprivation is, because baseline living-standards deficits are widespread there. Figure 12 reflects sequence: within any household, in any state or region, living standards is typically the first dimension to bind, and education becomes a larger share only as

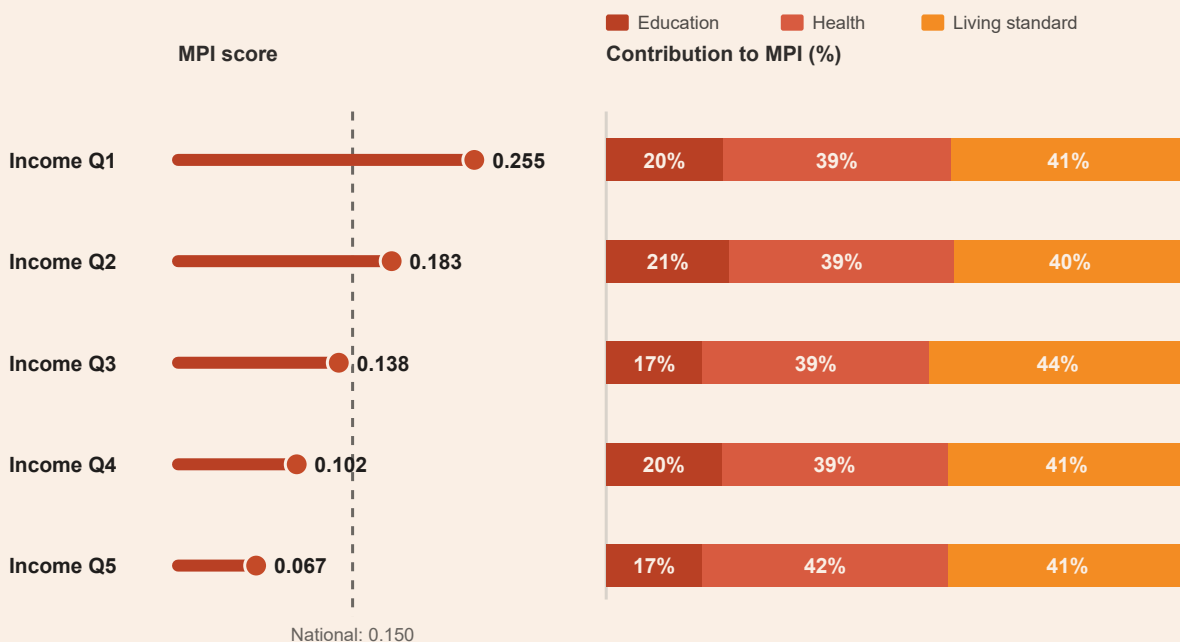
additional deprivations accumulate. Since intensity barely varies across states/regions (Section 5.2), most poor households, including those in high-MPI states/regions, sit at broadly similar points along this depth gradient; what differs by state/region is not how deep poverty runs, but how widespread the underlying living-standards deficit is to begin with.

This pattern reveals the sequence in which deprivations accumulate. Living standards deficits are nearly universal among MPI-poor households, affecting even those with minimal poverty. As deprivation deepens and households experience multiple concurrent deprivations, education deficits become increasingly prominent, suggesting that education-related deprivations intensify only when households are already suffering from other constraints. The deepest deprivation is characterized not by dominance of any single dimension, but by the accumulation of disadvantage across all three dimensions, with education carrying as much weight as living standards.

Household characteristics shift where households sit along this gradient without changing the gradient itself. Income quintile decomposition illustrates the distinction clearly. MPI scores fall substantially across the quintiles, from 0.255 in Q1 to 0.067 in Q5, yet the dimensional composition remains broadly stable across all five quintiles. Households at the bottom of the income distribution and households at the top exhibit similar shares of education, health and living standards deprivation, even as the overall depth of their poverty differs by nearly fourfold. Income shifts where households sit along the deprivation distribution; it does not shift what their deprivation is made of. The same logic applies to employment type, education of head, migration status and shock exposure: these characteristics shift the depth of poverty, but the dimensional gradient they sit on is determined by deprivation depth, not by the characteristic itself.

Figure 13 MPI score and dimensional composition (by income quintile)

MPI is lower in higher-income quintiles, while dimensional composition remains broadly stable



Source: PPS 2025 (UNDP)

The implication is direct: because living standards deficits are the first and most widespread to bind, service and infrastructure investment is the primary entry point for poverty reduction across all deprivation levels, addressing deficits that affect nearly all poor households. Human-capital investment becomes increasingly important for households experiencing multiple deprivations, complementing rather than replacing infrastructure priorities.

5.4 Synthesis: Similar MPI Scores, Different Poverty Dynamics

Similar MPI scores do not imply similar poverty problems. Mon and Kayin record nearly identical MPI scores (0.149 and 0.153 respectively), yet their dimensional structures differ substantially: Mon's education share is 27.5 percent against Kayin's 21.8 percent, while Kayin's health share is 43.1 percent against Mon's 34.3 percent. Two states at the same poverty level face fundamentally different binding constraints. This divergence reflects the finding from Section 5.2: dimensional composition is determined by geographic context, not by poverty level alone, so two states with similar MPI scores can face structurally different poverty problems.

Section 5.3 adds a second dimension to this picture. Household characteristics (employment type, income position, education of head, migration status) shift the level of poverty without shifting its dimensional structure. The implication is that compositional differences between contexts are driven primarily by geography, not by the socio-economic profile of the households within them. Area-level conditions (service environment, infrastructure and schooling access) shape what kind of poverty residents experience; household characteristics shape how deeply poor they are.

Taken together, the two findings establish dimensional composition as a diagnostic that headcount alone cannot provide, and one with direct practical reading. Where living standards and health dominate, as in Rakhine, Kayah, Chin, Kachin and Ayeyarwady, service restoration and infrastructure investment carry the greatest leverage, since these are the deficits affecting the largest share of poor households regardless of how deep their poverty runs. Where education's share is comparatively higher, as in Sagaing, Mon, Mandalay and Nay Pyi Taw, human-capital investment becomes a more relevant complement, though never a substitute for infrastructure priorities given Section 5.3's finding that living standards deficits remain the most widespread starting point nationally. Mon and Kayin illustrate why this distinction matters in practice: despite near-identical MPI scores, Kayin's higher health share points toward healthcare access as a priority alongside infrastructure, while Mon's lower health and higher living-standards share point toward a different sequencing of the same two priorities. Section 6 draws out these programming implications in full.

6 Strategic Directions: From Evidence to Action

The preceding analysis shows that multidimensional poverty in Myanmar is not only widespread but highly differentiated, by geography, by the interplay of structural and contextual drivers, by shock accumulation, and by the dimensional composition of deprivation. Similar poverty levels can arise from fundamentally different combinations of constraints, and similar interventions will not produce similar results across these contexts. Four strategic directions follow from this evidence. Each corresponds to a distinct analytical finding; together, they point toward responses calibrated to the specific poverty dynamics identified in this report rather than to aggregate headcount figures alone.

The evidence points to four strategic directions:

01

Differentiated geographic targeting: severity and scale require different responses.

Where poverty is deepest, intensive and targeted engagement is needed; where it is most numerous, broad coverage approaches are appropriate.

02

Area-based recovery or household investment: matching the response to the driver.

Where contextual pressures dominate, restoring markets, services and mobility is the primary entry point; where structural disadvantages dominate, investment in livelihoods, education and employment addresses the foundations of deprivation.

03

Strengthen livelihood and community resilience to compounding shocks.

Address the specific pathways through which economic, conflict, natural hazard and health shocks translate into deprivation, recognizing that humanitarian, recovery and development responses need to run simultaneously across contexts.

04

Programme to the deprivation profile, not the headcount alone.

Use the dimensional breakdown of the MPI to identify whether service restoration, human capital investment or livelihood support carries the greatest leverage in each context.

01

Differentiated geographic targeting: Severity and scale require different responses

The analysis identifies a systematic tension in geographic prioritization between severity and scale that cannot be resolved by ranking states/regions on a single indicator. In Kayah and Rakhine, poverty is exceptionally severe: MPI headcounts exceed 68 percent, and poor households are deprived in roughly half of all indicators simultaneously. These are the clearest cases of context-dominant poverty, where conflict, displacement, mobility restrictions and fragmented services push deprivation far beyond what household characteristics alone would predict. In these settings, area-based responses that restore essential services, basic living conditions and local markets are the primary entry point; household-level targeting alone will not address the contextual pressures driving the gap between observed and predicted poverty.

In Rakhine specifically, responses must additionally account for the situation of stateless and displaced populations, including barriers related to documentation, freedom of movement and service entitlement, which standard area-based programming is unlikely to reach without explicit design adjustments. As noted in Section 1.1, the MPI estimates for Rakhine almost certainly understate true deprivation given these populations' limited representation in the survey frame, meaning the scale of need is greater than the figures in this report reflect.

The scale of need in Rakhine is almost certainly greater than the figures in this report reflect. Stateless and displaced populations, including those facing barriers related to documentation and freedom of movement, fall outside standard survey frames, making them the hardest to count and the hardest to reach.

The largest absolute concentrations of MPI-poor people, however, are not in Kayah or Rakhine. Ayeyarwady (2.65 million MPI-poor), Sagaing (2.38 million), Mandalay (2.11 million) and Shan (1.97 million) together account for roughly half of the 17.9 million poor nationally, despite recording only moderate MPI scores. In these regions, the scale of poverty reflects large populations with widespread but moderate deprivation. Scale-oriented approaches, including broad-based rural development, livelihood expansion and service coverage, are appropriate here alongside targeted household-level support.

Township-level evidence reinforces the importance of within-state geographic differentiation. Poverty clustering within states/regions means that state-level averages conceal townships with substantially higher deprivation: in Ayeyarwady, for example, Mawlamyinegyun and Wakema exceed 70 percent MPI headcount, a severity comparable to the worst-affected townships in Rakhine and Kayah, despite the region's moderate state-level score. Geographic targeting should therefore operate at sub-state level, not solely on state/region rankings.

02

Area-based recovery or household investment: Let the driver decide

Multidimensional poverty in Myanmar arises from two distinct but interacting sources, namely structural household disadvantages and contextual area-level conditions, and the relative weight of each varies considerably across states/regions. Identifying which driver dominates in a given context is not an academic distinction: it determines whether area-based or household-level responses are likely to produce the larger reduction in poverty.

Where contextual pressures dominate, as in Kayah, Rakhine and Ayeyarwady, observed poverty substantially exceeds what household characteristics alone would predict. In these settings, the primary entry point is area-based: restoring local market systems, essential service infrastructure, access to productive inputs, and safe mobility conditions creates the enabling environment within which households can begin to recover. Household-level support, including livelihood inputs, productive asset restoration, skills development and access to services, retains value but cannot substitute for area-level recovery; structural disadvantages within these households will persist even with targeted support if the operating environment remains severely constrained.

Where poverty is predominantly structural, as in Kachin, Mon and Mandalay, deprivation is explained by long-standing household characteristics: limited education, precarious employment, agricultural dependency and low asset buffers. Here, sustained investment in human capital, livelihood diversification and service quality addresses the foundations of deprivation. Households relying on casual labour face particularly high poverty (MPI headcount 48.5%, MPI score 0.228) due to irregular earnings and the absence of employment protection; supporting livelihood stability, self-employment and small enterprise development directly addresses this channel. Similarly, households headed by individuals with no formal or primary education record poverty levels more than double those of higher-educated households (MPI score of around 0.211 versus 0.089), reflecting education's role as a structural divider of livelihood options, access to services and intergenerational mobility.

A third group, including urban areas such as Yangon and Nay Pyi Taw, exhibits high structural vulnerability that is currently moderated by favourable area-level conditions. These households are not yet classified as poor but carry risk profiles (informal employment, limited savings, and housing insecurity) that make them highly sensitive to disruption. Responses targeting this latent vulnerability group should focus on building resilience before poverty transitions occur, particularly as urban costs and economic instability continue to put pressure on informal household budgets. Because this vulnerability is unevenly distributed within cities, township-level and profile-based programming is needed to identify and reach pockets of deprivation that urban averages conceal.

03 Strengthen livelihood and community resilience to compounding shocks

Shock exposure is the primary pathway through which structural and contextual vulnerability translates into acute multidimensional deprivation. The analysis shows not only that each shock type deepens poverty, but that shocks accumulate: each additional shock raises poverty risk sharply, and households with limited coping capacity move quickly from vulnerable to poor to severely poor as shocks compound.

Economic shocks are the most pervasive, affecting more than half of households nationally. Income losses, price increases and employment disruption directly constrain the ability to maintain consumption and service access. Strengthening livelihood stability, through diversification, employment protection and access to savings mechanisms, reduces exposure to this most widespread shock pathway.

Conflict-related shocks, while geographically concentrated, carry the highest amplification effect of any shock type: a 14.2-percentage-point increase in predicted poverty, acting simultaneously across livelihoods, mobility, markets and service delivery. Poverty reduction in conflict-affected contexts requires conflict-sensitive approaches that support the recovery of local markets, service systems and institutions alongside direct humanitarian response, recognizing that humanitarian, recovery and development assistance need to run simultaneously across contexts.

Natural hazard shocks are concentrated in rural and agriculture-dependent areas, where they disrupt livelihoods, damage housing and degrade infrastructure. In Myanmar's current context, where natural hazard shocks frequently compound with economic stress and conflict-related disruption, reducing exposure requires investment in livelihood diversification, agricultural input support and local infrastructure rehabilitation, including resilient and low-carbon design where feasible, that can be delivered in constrained access environments. Climate-resilient agricultural systems, early warning mechanisms and basic infrastructure investment retain value in reducing both the frequency and severity of livelihood disruption from this shock type but depend on functioning market and mobility conditions to translate into protective action.

Health shocks, as serious illness or accident, act as acute poverty triggers, particularly for households already operating with thin margins. Unlike structural disadvantages that develop gradually, a single health event simultaneously produces income loss, asset depletion and increased out-of-pocket expenditure. Reducing the poverty impact of health shocks requires action on both demand and supply sides: expanding social protection coverage and reducing financial barriers to healthcare access addresses the household's exposure to catastrophic costs, while strengthening health service availability and community-based care reduces the probability and severity of the shock itself.

04 Programme to the deprivation profile, not the headcount alone

The fourth direction departs from the three preceding ones in a critical way: it is not a domain-specific direction but a diagnostic principle. As Section 5 demonstrates, dimensional composition, that is the share of each dimension in the overall MPI, is the indicator that translates poverty measurement into programming specificity. Two states/regions or household groups may record similar MPI scores yet require entirely different interventions, because the deprivations driving their poverty are different. Headcount alone cannot make this distinction; dimensional composition can.

A compositional gradient emerges from the data, derived from the state-level dimensional composition analysis in Section 5.2, distinguishing states and regions by which dimension accounts for a disproportionately large share of their MPI score. In states/regions where survival-related deprivations dominate such as Rakhine, Kayah, Chin, Kachin and Ayeyarwady, health and living standards together dominate the index, with education compressed. In these settings, area-based restoration of basic services and infrastructure is the primary entry point; education investment retains long-term value but will not reduce the index substantially until survival-level deprivations are addressed. In states/regions where education's share is comparatively higher, such as Sagaing, Mon, Mandalay and Nay Pyi Taw, human-capital investment carries greater leverage for poverty reduction alongside continued investment in health and living standards. The remaining states/regions fall between these two patterns, without education compressed as sharply as in the first group or as elevated as in the second. Here, livelihood restoration, employment support and income resilience carry particular leverage, since rising incomes reduce the depth of deprivation even where they do not change its underlying composition.

Within any geographic context, the dimensional composition of an individual household's deprivation also shifts as poverty deepens. Living standards deficits, such as inadequate housing, sanitation or water access, are typically the first to bind and remain the largest single contributor to deprivation for the majority of MPI-poor households. As deprivation deepens, education's share rises, overtaking living standards once a household's deprivation score passes approximately 0.73; the most severely deprived households face accumulating disadvantage across all three dimensions, with education

and health each carrying a larger share than living standards at that point. This sequence holds broadly regardless of states and regions, since average deprivation depth (intensity) varies little between them. For programming, this implies that living-standards interventions, namely housing, water and sanitation, address the binding constraint for most MPI-poor households, while education investment carries growing weight specifically among the most severely deprived, who require multi-sectoral support across all three dimensions simultaneously.

Dimensional composition also clarifies the limits of income-focused approaches for the most deprived households. The bottom two income quintiles display nearly identical compositional structures, with the same combined health and living-standards share described above, meaning that income shifts the level of poverty across the distribution without shifting its dimensional structure. Housing, sanitation and health access deficits cannot be resolved through marginal income increases alone; direct investment in basic services and living conditions is required to alter the underlying composition of deprivation.

The same principle applies across specific household groups. For migrant households, where living standards account for 46 percent of the MPI score, settlement insecurity and institutional barriers require responses beyond income transfers alone. Gender adds a further dimension: woman-headed households record lower poverty incidence than man-headed households but higher deprivation intensity among those who are poor, a directional reversal consistent with findings on food security from the independent evidence.²³ As the crisis has deepened, women in Myanmar have taken on additional caregiving and household responsibilities without reducing their existing economic ones and without emerging care support-public, private or communal. This creates a double trap of income poverty and time poverty, leaving women without sufficient time to meet essential household responsibilities and without sufficient resources to purchase market-based substitutes. This depth-over-incidence pattern indicates that interventions need to address the intensity of deprivation, including access to childcare, social protection and community-based services, not only coverage, if they are to reduce poverty among women-headed households effectively.

Taken together, these four directions reflect a single analytical conclusion. Myanmar's multidimensional poverty is too differentiated to yield to uniform responses. Effective poverty reduction requires approaches calibrated to where poverty is severe versus where it is large-scale, to whether it is structurally embedded or contextually driven, to which shocks are compounding vulnerability, and to which dimension dominates in a given geographical context. Dimensional composition is the diagnostic that makes this calibration possible, translating multidimensional poverty evidence into context-specific programming across area-based recovery, livelihoods, resilience and human capital investment.

23 UNDP & UN WOMEN (2026). *Uneven Burdens: Women in Myanmar's Crisis Economy*.

7 Conclusion

Myanmar's multidimensional poverty is widespread and affects nearly two-thirds of Myanmar's population either directly or through vulnerability to future poverty. One in three people (32.6%, approximately 17.9 million) are multidimensionally poor, and a further 19.5 million are at risk. Applying an adapted MPI to the PPS 2025 data moves beyond income measurement to capture the overlapping deprivations, encompassing education, health and living standards, which shape household well-being during a period of compounding conflict, macroeconomic instability and recurrent natural hazards. The analysis establishes not only where poverty is concentrated and how deep it runs, but what kind of poverty households experience and why similar poverty levels demand different responses in different contexts. That last question, what kind, is the analytical contribution that headline headcount figures cannot provide.

Poverty in Myanmar is shaped by a tension between severity and scale, requiring attention to both the deepest deprivation and the largest concentrations of poor people. Rakhine and Kayah record the highest poverty incidence and intensity nationally, with over 68 percent of their populations multidimensionally poor and poor households deprived in roughly half of all indicators simultaneously. But the largest absolute concentrations of poor people are found in Ayeyarwady, Sagaing, Mandalay and Shan, which together account for roughly half of the 17.9 million MPI-poor nationally despite recording only moderate MPI scores. Effective responses require balancing depth-focused engagement in the most severely affected areas with scale-oriented coverage where poverty is widespread but less acute. Township-level evidence further shows that state-level averages conceal substantial within-state disparity, with poverty clustering in specific sub-areas regardless of the broader state/region profile.

Poverty is driven by different combinations of structural disadvantages, contextual pressures and repeated shocks. The analysis distinguishes two interacting drivers, namely structural household disadvantages and contextual area-level conditions, whose relative weight varies considerably across states/regions. In Kayah, Rakhine and Ayeyarwady, observed poverty substantially exceeds what household characteristics alone would predict, indicating that conflict, displacement, restricted mobility and disrupted services are the binding constraints. In Kachin, Mon and Mandalay, poverty aligns closely with structural predictions, indicating that long-standing disadvantages in education, employment and income are the primary drivers rather than acute contextual shocks. A third pattern, high structural vulnerability partially moderated by favourable area-level conditions, characterizes urban areas such as Yangon, where households are not currently classified as poor but are highly sensitive to disruption. Repeated shocks compound all three patterns: economic shocks affect more than half of households nationally; conflict shocks carry the highest amplification effect of any shock type; and the cumulative effects of economic, natural hazard, conflict and health shocks erode coping capacity and accelerate transitions from vulnerability into deep poverty.

Multidimensional poverty is concentrated where socio-economic vulnerabilities overlap and reinforce one another. Households in the lowest income quintiles, those relying on casual labour and those headed by individuals with limited or no formal education face the highest poverty incidence and intensity. Migrant households, half of whom are conflict-induced, experience particularly acute deprivation reflecting institutional barriers, such as documentation gaps, informal settlement and weak social networks, alongside income insecurity. Gender differences are visible in depth rather than incidence: woman-headed households record a modestly lower poverty headcount than man-headed households but higher deprivation intensity among those who are poor, a directional reversal consistent with independent evidence on food security. This pattern points to the importance of interventions that address the severity of deprivation, not only its prevalence.

The composition of poverty matters as much as its prevalence. Nationally, health and living standards account for over four-fifths of the MPI, with education contributing to less than one fifth, indicating that deficits in housing, sanitation, water access and healthcare, rather than schooling per se, are the binding constraints on household well-being. This does not diminish education's importance: because human-capital deficits accumulate and persist across generations, education investment remains essential for breaking the cycle of poverty in the longer term, even where it is not the most immediate lever for reducing current MPI scores. At the national level this composition is stable, but it shifts across contexts: in states/regions where survival-related deprivations dominate (Rakhine, Kayah, Chin, Kachin and Ayeyarwady), health and living standards together dominate the index and education's share is compressed; in others, such as Sagaing, Mon, Mandalay and Nay Pyi Taw, education's share is comparatively higher, marking a shift toward human-capital constraints. At the household level, the bottom two income quintiles display nearly identical dimensional structures, with the same combined health and living-standards share described above, meaning that income shifts the level of poverty across the distribution without shifting its dimensional structure: the structural deprivation trap can only be broken through simultaneous investment in basic services, living conditions and human capital.

Reducing poverty requires more than raising incomes. Taken together, the findings suggest that multidimensional poverty in Myanmar is not simply a household income problem. In some areas, poverty is primarily driven by conflict, displacement and service disruption; in others by long-standing deficits in education, livelihoods and living standards; and in still others by high levels of vulnerability that remain masked by relatively favourable local conditions. The implication is that poverty reduction requires a combination of household support, strengthened community systems, more resilient local economies and greater capacity to withstand and recover from shocks. Where contextual factors dominate, strengthening local service delivery, community institutions and social cohesion becomes as important as addressing household-level deprivation. Where structural factors dominate, investments in human capital, livelihoods and economic opportunities become increasingly important.

Community resilience, local economic recovery and effective local institutions are critical pathways out of poverty. Households do not experience shocks in isolation. Conflict, economic disruption, climate hazards and service failures interact through local systems, markets and institutions. The strongest poverty reductions are therefore likely to emerge where interventions simultaneously strengthen community capacities, expand economic opportunities, improve access to essential services and build resilience to future shocks.

Understanding what kind of poverty people experience is essential for designing effective responses. Myanmar's multidimensional poverty is too differentiated to yield to uniform responses. The analysis shows where poverty is concentrated, how it is driven, which households carry the highest risk, and what dimensional structure it takes all vary systematically across contexts, and that each dimension of variation has direct implications for what kind of response is most effective. The MPI, applied to crisis-responsive survey data such as PPS 2025, provides an evidence base that monetary poverty measures cannot easily replicate under current conditions: it identifies the specific dimensional profile of deprivation, tracks how that profile shifts under shock exposure, and signals when headcount-focused programming is likely to address the wrong constraint. It also highlights the importance of understanding poverty as a multidimensional resilience challenge that extends beyond households to the systems, institutions and environments within which they live. Sustaining this kind of multidimensional evidence as Myanmar's context evolves remains essential for informing recovery programming, protecting human well-being and supporting progress toward reducing poverty in all its dimensions.

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Appendix

Appendix Table 1

Multidimensional Poverty Status and Intensity
(by geography)

	MPI vulnerable			MPI poor			MPI severe		
	H	A	MPI	H	A	MPI	H	A	MPI
Union	0.355	0.259	0.092	0.326	0.461	0.150	0.094	0.599	0.056
Urban	0.363	0.257	0.093	0.217	0.448	0.097	0.048	0.587	0.028
Rural	0.352	0.259	0.091	0.367	0.464	0.170	0.111	0.601	0.067
Ayeyarwady	0.335	0.250	0.084	0.407	0.450	0.183	0.114	0.584	0.067
Bago	0.350	0.259	0.091	0.265	0.446	0.118	0.055	0.589	0.033
Chin	0.376	0.262	0.099	0.479	0.459	0.220	0.140	0.593	0.083
Kachin	0.366	0.251	0.092	0.405	0.463	0.188	0.110	0.593	0.065
Kayah	0.230	0.264	0.061	0.681	0.482	0.328	0.260	0.600	0.156
Kayin	0.376	0.266	0.100	0.319	0.478	0.153	0.106	0.616	0.066
Magway	0.386	0.267	0.103	0.289	0.443	0.128	0.067	0.572	0.038
Mandalay	0.384	0.254	0.097	0.317	0.466	0.148	0.086	0.612	0.052
Mon	0.346	0.257	0.089	0.304	0.492	0.149	0.116	0.624	0.073
Nay Pyi Taw	0.328	0.249	0.082	0.197	0.442	0.087	0.044	0.604	0.027
Rakhine	0.208	0.273	0.057	0.684	0.501	0.342	0.311	0.603	0.187
Sagaing	0.330	0.263	0.087	0.412	0.475	0.196	0.140	0.621	0.087
Shan	0.385	0.264	0.102	0.293	0.446	0.131	0.069	0.588	0.041
Tanintharyi	0.455	0.260	0.118	0.305	0.458	0.140	0.075	0.603	0.046
Yangon	0.352	0.260	0.091	0.204	0.453	0.092	0.054	0.586	0.031

	MPI vulnerable			MPI poor			MPI severe		
	H	A	MPI	H	A	MPI	H	A	MPI
Household head characteristics									
Woman-headed	0.366	0.260	0.095	0.310	0.472	0.146	0.100	0.600	0.060
Man-headed	0.353	0.258	0.091	0.330	0.459	0.151	0.092	0.599	0.055
High/higher education	0.335	0.258	0.087	0.205	0.434	0.089	0.041	0.568	0.023
Middle education	0.405	0.256	0.104	0.280	0.438	0.123	0.056	0.582	0.033
No formal education	0.309	0.265	0.082	0.435	0.484	0.211	0.173	0.598	0.104
Primary education	0.331	0.262	0.087	0.439	0.478	0.210	0.151	0.612	0.092
Employer	0.328	0.252	0.083	0.204	0.417	0.085	0.025	0.579	0.014
Employee	0.375	0.260	0.097	0.219	0.449	0.098	0.055	0.588	0.032
Own-account	0.373	0.256	0.096	0.281	0.451	0.127	0.066	0.603	0.040
Casual worker	0.324	0.262	0.085	0.485	0.470	0.228	0.155	0.602	0.093
Unemployed	0.369	0.260	0.096	0.289	0.473	0.137	0.102	0.594	0.060
Household type									
Non-migrant	0.359	0.258	0.093	0.315	0.459	0.145	0.090	0.599	0.054
Migrant	0.300	0.269	0.081	0.502	0.481	0.241	0.164	0.602	0.099
Household income									
Income Q1	0.301	0.267	0.080	0.522	0.488	0.255	0.209	0.605	0.126
Income Q2	0.391	0.261	0.102	0.397	0.462	0.183	0.112	0.606	0.068
Income Q3	0.385	0.255	0.098	0.315	0.439	0.138	0.058	0.581	0.033
Income Q4	0.386	0.260	0.100	0.229	0.445	0.102	0.050	0.591	0.030
Income Q5	0.310	0.252	0.078	0.153	0.439	0.067	0.035	0.582	0.020
Household shock exposure									
Natural shock	0.364	0.262	0.095	0.420	0.465	0.195	0.130	0.592	0.077
Economic shock	0.368	0.261	0.096	0.394	0.467	0.184	0.121	0.599	0.073
Conflict shock	0.287	0.270	0.078	0.565	0.480	0.271	0.197	0.602	0.119
Health shock	0.370	0.265	0.098	0.466	0.473	0.220	0.148	0.614	0.091

Appendix Table 3

Dimensional Contributions to the MPI
(by geography)

	MPI	Absolute contribution			Percentage contribution		
		Education	Health	Living standards	Education	Health	Living standards
Union	0.150	0.029	0.059	0.062	19.4%	39.3%	41.3%
Rural	0.170	0.033	0.066	0.071	19.4%	38.7%	42.0%
Urban	0.097	0.019	0.041	0.037	19.7%	42.1%	38.2%
Ayeyarwady	0.183	0.027	0.068	0.088	14.8%	37.2%	47.9%
Bago	0.118	0.025	0.045	0.049	20.8%	37.6%	41.6%
Chin	0.220	0.026	0.094	0.100	11.9%	42.5%	45.6%
Kachin	0.188	0.030	0.076	0.081	16.2%	40.4%	43.4%
Kayah	0.328	0.030	0.160	0.138	9.1%	48.8%	42.1%
Kayin	0.153	0.033	0.066	0.054	21.8%	43.1%	35.1%
Magway	0.128	0.024	0.053	0.051	19.1%	41.5%	39.4%
Mandalay	0.148	0.037	0.057	0.054	25.2%	38.5%	36.3%
Mon	0.149	0.041	0.051	0.057	27.5%	34.3%	38.2%
Nay Pyi Taw	0.087	0.021	0.037	0.029	24.5%	42.3%	33.1%
Rakhine	0.342	0.041	0.145	0.156	12.1%	42.3%	45.6%
Sagaing	0.196	0.045	0.072	0.078	23.2%	36.8%	40.0%
Shan	0.131	0.026	0.053	0.052	19.9%	40.3%	39.7%
Tanintharyi	0.140	0.025	0.060	0.054	18.2%	43.0%	38.9%
Yangon	0.092	0.017	0.037	0.037	18.9%	40.6%	40.5%

Dimensional Contributions to the MPI (by Household Characteristics and Shock Exposure)

	MPI	Absolute contribution			Percentage contribution		
		Education	Health	Living standards	Education	Health	Living standards
Household head characteristics							
Woman-headed	0.146	0.031	0.059	0.057	21.1%	40.3%	38.7%
Man-headed	0.151	0.029	0.059	0.063	19.1%	39.0%	41.9%
High/higher education	0.089	0.010	0.040	0.039	11.0%	45.5%	43.5%
Middle education	0.123	0.018	0.050	0.054	14.7%	41.1%	44.3%
No formal education	0.211	0.050	0.080	0.081	23.5%	38.2%	38.3%
Primary education	0.210	0.050	0.076	0.084	23.8%	36.2%	39.9%
Casual worker	0.228	0.047	0.085	0.097	20.5%	37.1%	42.4%
Employer	0.085	0.014	0.035	0.036	16.2%	41.6%	42.1%
Employee	0.098	0.012	0.043	0.043	12.7%	43.7%	43.6%
Own-account	0.127	0.025	0.051	0.051	19.7%	40.0%	40.3%
Unemployed	0.137	0.027	0.056	0.054	19.6%	40.7%	39.7%
Household type							
Migrant	0.241	0.036	0.094	0.111	15.0%	39.0%	46.0%
Non-migrant	0.145	0.029	0.057	0.059	19.9%	39.3%	40.8%
Household income							
Income Q1	0.255	0.051	0.100	0.103	20.1%	39.2%	40.6%
Income Q2	0.183	0.039	0.071	0.074	21.3%	38.6%	40.1%
Income Q3	0.138	0.023	0.054	0.061	16.6%	39.0%	44.4%
Income Q4	0.102	0.020	0.040	0.042	19.9%	38.9%	41.2%
Income Q5	0.067	0.011	0.029	0.028	16.5%	42.5%	41.0%
Household shock exposure							
Natural shock	0.195	0.033	0.082	0.080	17.1%	42.1%	40.8%
Economic shock	0.184	0.033	0.076	0.075	17.7%	41.2%	41.1%
Conflict shock	0.271	0.043	0.112	0.116	15.8%	41.2%	42.9%
Health shock	0.220	0.039	0.092	0.089	17.6%	41.8%	40.6%

State/ Region	Township	MPI estimate	State/Region	Township	MPI estimate	State/ Region	Township	MPI estimate
Rakhine	Kyaukpyu	1.00	Magway	Yenangyaung	0.37	Shan (South)	Monghsu	0.23
Shan (North)	Hseni	1.00	Mandalay	Patheingyi	0.37	Shan (South)	Kunhing	0.23
Shan (North)	Kutkai	0.92	Sagaing	Wetlet	0.37	Shan (East)	Mongyawng	0.22
Rakhine	Sittwe	0.91	Tanintharyi	Yebyu	0.37	Shan (North)	Hopang	0.22
Kayah	Hpasawng	0.90	Ayeyarwady	Kyaiklat	0.37	Shan (East)	Mongton	0.22
Chin	Mindat	0.90	Chin	Tonzang	0.37	Chin	Tedim	0.22
Shan (North)	Kyaukme	0.85	Tanintharyi	Bokpyin	0.36	Mandalay	Myingyan	0.22
Kachin	Hpakant	0.80	Kachin	Khaunglanhpu	0.36	Tanintharyi	Kawthoung	0.22
Kayah	Demoso	0.79	Yangon	Thaketa	0.36	Kachin	Mogaung	0.21
Kayah	Hpruso	0.75	Yangon	Dagon Myothit (South)	0.36	Mandalay	Myittha	0.21
Ayeyarwady	Mawlamyinegyun	0.73	Kayin	Thandaunggyi	0.36	Yangon	Hmawbi	0.21
Rakhine	Ponnagyun	0.72	Nay Pyi Taw	Tatkon	0.36	Bago (West)	Nattalin	0.21
Rakhine	Minbya	0.71	Magway	Yesagyo	0.36	Bago (West)	Paukkhaung	0.21
Ayeyarwady	Wakema	0.70	Tanintharyi	Launglon	0.36	Bago (West)	Monyo	0.20
Rakhine	Kyauktaw	0.70	Mandalay	Wundwin	0.35	Shan (East)	Mongping	0.20
Ayeyarwady	Dedaye	0.69	Sagaing	Salingyi	0.35	Bago (West)	Zigon	0.20
Rakhine	Mrauk-U	0.67	Magway	Sidoktaya	0.35	Shan (South)	Laihka	0.20
Mandalay	Mogoke	0.66	Magway	Pwintbyu	0.35	Shan (East)	Monghsat	0.20
Kayah	Loikaw	0.65	Yangon	Thanlyin	0.35	Shan (North)	Lashio	0.20
Rakhine	Myebon	0.64	Shan (North)	Tangyan	0.35	Magway	Myothit	0.19
Ayeyarwady	Nyaungdon	0.62	Magway	Pakokku	0.35	Magway	Mindon	0.19
Rakhine	Rathedaung	0.62	Tanintharyi	Kyunsu	0.35	Bago (East)	Oktwin	0.19
Chin	Paletwa	0.62	Shan (North)	Mongyai	0.35	Mandalay	Yamethin	0.19
Rakhine	Thandwe	0.62	Mandalay	Aungmyaythazan	0.34	Shan (South)	Mongnai	0.19
Sagaing	Banmauk	0.60	Shan (North)	Kunlong	0.34	Shan (East)	Kengtung	0.19
Mon	Ye	0.60	Shan (North)	Matman	0.34	Mandalay	Nyaung-U	0.19
Mandalay	Chanmyathazi	0.59	Bago (East)	Bago	0.34	Yangon	Twantay	0.19
Rakhine	Maungdaw	0.59	Shan (North)	Pangwaun	0.34	Sagaing	Khin-U	0.19
Ayeyarwady	Pyapon	0.59	Sagaing	Wuntho	0.33	Tanintharyi	Thayetchaung	0.19
Chin	Hakha	0.59	Sagaing	Myinmu	0.33	Bago (East)	Nyaunglebin	0.19
Rakhine	Ann	0.59	Ayeyarwady	Kyangin	0.33	Mon	Mawlamyine	0.18
Chin	Falam	0.58	Ayeyarwady	Thabaung	0.33	Shan (South)	Loilen	0.18
Shan (North)	Hsipaw	0.56	Yangon	Hlegu	0.33	Bago (West)	Paungde	0.18

²⁴ Township MPI headcounts are derived using a model-based small area estimation approach that combines PPS 2025 household data with township-complete auxiliary information and benchmarks results to PPS state and region MPI totals. The estimates should be interpreted as comparative, model-based approximations designed to support geographic prioritization.

State/ Region	Township	MPI estimate	State/Region	Township	MPI estimate	State/ Region	Township	MPI estimate
Rakhine	Toungup	0.56	Shan (North)	Narphan	0.33	Mandalay	Thazi	0.18
Shan (North)	Namhsan	0.56	Shan (North)	Konkyan	0.33	Yangon	Seikgyikanaungto	0.18
Mandalay	Tada-U	0.56	Kachin	Machanbaw	0.33	Shan (South)	Pindaya	0.18
Ayeyarwady	Ngapudaw	0.55	Magway	Tilin	0.33	Yangon	Kyauktan	0.18
Ayeyarwady	Bogale	0.55	Ayeyarwady	Myaungmya	0.33	Mandalay	Amarapura	0.18
Rakhine	Pauktaw	0.55	Bago (East)	Kyauktaga	0.33	Mandalay	Sintgaing	0.18
Mandalay	Thabeikkyin	0.55	Kachin	Momauk	0.33	Mon	Thaton	0.18
Ayeyarwady	Lemyethna	0.55	Sagaing	Tamu	0.32	Shan (South)	Hopong	0.17
Shan (North)	Mabein	0.54	Shan (South)	Hsihseng	0.32	Bago (West)	Padaung	0.17
Kachin	Waingmaw	0.54	Kachin	Putao	0.32	Shan (South)	Nansang	0.17
Sagaing	Pale	0.54	Kachin	Sumprabum	0.32	Bago (West)	Thegon	0.17
Mandalay	Singu	0.53	Kachin	Nawngmun	0.32	Yangon	Dala	0.17
Rakhine	Gwa	0.53	Mandalay	Meiktila	0.32	Magway	Sinbaungwe	0.17
Mandalay	Madaya	0.52	Bago (West)	Okpho	0.31	Tanintharyi	Myeik	0.16
Sagaing	Kale	0.51	Sagaing	Ayadaw	0.31	Shan (South)	Kalaw	0.16
Sagaing	Hkamti	0.51	Sagaing	Lahe	0.31	Yangon	Dagon Myothit (Seikkan)	0.16
Mon	Chaungzon	0.51	Mandalay	Pyawbwe	0.31	Yangon	Kayan	0.15
Shan (North)	Nawngkhio	0.51	Mandalay	Mahlaing	0.31	Mandalay	Kyaukse	0.15
Sagaing	Taze	0.50	Kayin	Hlaingbwe	0.31	Shan (South)	Nyaungshwe	0.15
Bago (East)	Kawa	0.50	Mandalay	Ngazun	0.30	Bago (East)	Taungoo	0.15
Sagaing	Tabayin	0.50	Chin	Kanpetlet	0.30	Nay Pyi Taw	Oke Ta Ra Thi Ri	0.15
Kayin	Kawkareik	0.50	Kayin	Kyainseikgyi	0.30	Magway	Minbu	0.15
Sagaing	Sagaing	0.50	Ayeyarwady	Myanaung	0.30	Yangon	Insein	0.15
Shan (North)	Mongmit	0.49	Magway	Magway	0.30	Magway	Salin	0.14
Rakhine	Ramree	0.49	Mon	Thanbyuzayat	0.30	Bago (West)	Shwedaung	0.14
Magway	Aunglan	0.48	Bago (West)	Letpadan	0.30	Nay Pyi Taw	Zay Yar Thi Ri	0.13
Bago (East)	Kyaukkyi	0.48	Shan (North)	Mongmao	0.29	Yangon	Hlaingtharya (West)	0.13
Magway	Pauk	0.48	Kayah	Bawlake	0.29	Magway	Minhla	0.13
Yangon	Htantabin	0.47	Sagaing	Shwebo	0.29	Yangon	Dagon Myothit (East)	0.12
Yangon	Cocokyun	0.47	Magway	Seikphyu	0.29	Shan (South)	Taunggyi	0.12
Bago (East)	Thanatpin	0.47	Bago (East)	Phyu	0.29	Magway	Taungdwingyi	0.12
Sagaing	Katha	0.47	Ayeyarwady	Ingapu	0.29	Kachin	Mohnyin	0.12
Shan (North)	Namtu	0.46	Bago (West)	Gyobingauk	0.29	Nay Pyi Taw	Det Khi Na Thi Ri	0.11
Rakhine	Munaung	0.46	Chin	Thantlang	0.29	Yangon	Kyeemyindaing	0.11
Rakhine	Buthidaung	0.45	Sagaing	Kalewa	0.28	Ayeyarwady	Danubyu	0.11

State/ Region	Township	MPI estimate	State/Region	Township	MPI estimate	State/ Region	Township	MPI estimate
Sagaing	Budalin	0.45	Bago (East)	Htantabin	0.28	Nay Pyi Taw	Lewe	0.11
Sagaing	Kani	0.45	Kachin	Chipwi	0.28	Yangon	Mayangone	0.11
Magway	Myaing	0.45	Yangon	Taikkyi	0.28	Mandalay	Pyigyitagon	0.10
Sagaing	Paungbyin	0.44	Ayeyarwady	Hinthada	0.28	Bago (West)	Thayarwady	0.10
Sagaing	Homalin	0.44	Magway	Gangaw	0.28	Mandalay	Mahaaungmyay	0.09
Mandalay	Natogyi	0.44	Kayah	Shadaw	0.28	Yangon	Mingaladon	0.09
Shan (North)	Namhkan	0.44	Bago (East)	Daik-U	0.28	Shan (South)	Lawksawk	0.09
Kachin	Shwegu	0.43	Kayin	Hpa-An	0.28	Nay Pyi Taw	Poke Ba Thi Ri	0.09
Shan (South)	Ywangan	0.43	Ayeyarwady	Zalun	0.27	Shan (East)	Tachileik	0.09
Sagaing	Ye-U	0.43	Kayin	Hpapun	0.27	Yangon	Kamaryut	0.09
Sagaing	Chaung-U	0.43	Bago (West)	Minhla	0.27	Shan (East)	Mongyang	0.08
Tanintharyi	Palaw	0.43	Yangon	Kawhmu	0.27	Yangon	Hlaing	0.08
Tanintharyi	Tanintharyi	0.43	Kayah	Mese	0.27	Mandalay	Chanayethazan	0.08
Chin	Matupi	0.43	Mon	Kyaikmaraw	0.27	Mon	Kyaikto	0.08
Kachin	Bhamo	0.43	Mandalay	Kyaukpadaung	0.26	Bago (West)	Pyay	0.08
Sagaing	Indaw	0.42	Magway	Ngape	0.26	Yangon	Sanchaung	0.07
Sagaing	Tigyaing	0.42	Magway	Natmauk	0.26	Yangon	Pazundaung	0.07
Sagaing	Mawlaik	0.42	Ayeyarwady	Labutta	0.26	Yangon	Botahtaung	0.07
Sagaing	Mingin	0.42	Yangon	Kungyangon	0.26	Yangon	Tamwe	0.07
Sagaing	Kawlin	0.42	Yangon	Shwepyithar	0.26	Yangon	North Okkalapa	0.07
Ayeyarwady	Maubin	0.42	Shan (North)	Pangsang	0.26	Yangon	Thingangyun	0.07
Kachin	Tsawlaw	0.41	Ayeyarwady	Einme	0.26	Yangon	Dagon Myothit (North)	0.07
Nay Pyi Taw	Pyinmana	0.41	Kachin	Myitkyina	0.26	Yangon	Dawbon	0.07
Sagaing	Kanbalu	0.41	Sagaing	Monywa	0.25	Yangon	South Okkalapa	0.07
Mon	Mudon	0.40	Shan (North)	Muse	0.25	Yangon	Mingalar Taungnyunt	0.06
Mon	Bilin	0.40	Shan (South)	Mawksmai	0.25	Yangon	Ahlone	0.06
Mandalay	Taungtha	0.40	Magway	Saw	0.25	Shan (East)	Mongla	0.06
Ayeyarwady	Kangyidaunt	0.40	Yangon	Thongwa	0.24	Yangon	Bahan	0.06
Yangon	Hlaingtharya (East)	0.40	Mandalay	Pyinoolwin	0.24	Yangon	Yankin	0.06
Kayin	Myawaddy	0.40	Ayeyarwady	Pantanaw	0.24	Mon	Paung	0.06
Sagaing	Nanyun	0.39	Ayeyarwady	Yegy	0.24	Nay Pyi Taw	Za Bu Thi Ri	0.06
Bago (East)	Yedashe	0.39	Magway	Chauk	0.24	Yangon	Latha	0.05
Ayeyarwady	Kyonpyaw	0.39	Bago (East)	Waw	0.24	Yangon	Lanmadaw	0.05
Sagaing	Pinlebu	0.39	Tanintharyi	Dawei	0.24	Yangon	Pabedan	0.05
Bago (East)	Shwegyin	0.39	Magway	Kamma	0.24	Yangon	Kyauktada	0.04
Shan (South)	Pinlaung	0.39	Ayeyarwady	Pathein	0.24	Yangon	Dagon	0.04

State/ Region	Township	MPI estimate	State/Region	Township	MPI estimate	State/ Region	Township	MPI estimate
Ayeyarwady	Kyaunggon	0.39	Shan (South)	Mongpan	0.23			
Shan (North)	Laukaing	0.38	Shan (South)	Kyethi	0.23			
Kachin	Tanai	0.38	Shan (East)	Monghpyak	0.23			
Kachin	Mansi	0.38	Sagaing	Yinmarbin	0.23			
Kachin	Injangyang	0.38	Shan (South)	Mongkaing	0.23			
Shan (North)	Manton	0.38	Magway	Thayet	0.23			
Sagaing	Myaung	0.38	Shan (South)	Langkho	0.23			
Shan (South)	Pekon	0.38	Sagaing	Kyunhla	0.23			
Sagaing	Layshi	0.37	Shan (East)	Mongkhet	0.23			

