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1.INTRODUCTION

Poverty is a multidimensional issue that cannot be fully understood using income-based measures alone. Traditional approaches to poverty measurement often fail to capture important aspects of human well-being such as education, health, and living standards. To address these limitations, the **Multidimensional Poverty Index (MPI)** was developed as a comprehensive framework that measures poverty across multiple dimensions. MPI provides a broader understanding of deprivation by combining indicators related to health, education, and standard of living.

Multidimensional poverty analysis has become increasingly important for socio-economic planning and policy formulation. Poverty levels vary significantly across **urban and rural areas**, between **subnational regions**, and among **world regions**, making it necessary to analyze poverty beyond national averages. Identifying these disparities helps policymakers and development agencies design targeted interventions and allocate resources more effectively.

This project analyzes multidimensional poverty using **national and subnational MPI datasets**, with a focus on urban–rural inequality, regional disparities within countries, and global poverty patterns. By incorporating measures such as MPI values, headcount ratios, and intensity of deprivation, the analysis provides insight into both the spread and severity of poverty.

The analysis is implemented using **Power BI**, which enables efficient data modeling, interactive visualizations, and dynamic filtering through slicers and KPIs. The dashboard is structured into three analytical levels: national, subnational, and global, each addressing a specific poverty-related question. This structured approach ensures clarity, avoids redundancy, and supports meaningful data interpretation.

Overall, the project demonstrates how multidimensional poverty data can be effectively analyzed and communicated through interactive dashboards, offering valuable insights into complex socio-economic challenges.

2. Source of Dataset

The dataset used in this project was obtained from **Kaggle**, a widely recognized open-data platform that hosts datasets contributed by researchers, analysts, and organizations across various domains. Kaggle is commonly used for academic projects, data analytics practice, and applied research due to the availability of well-documented and publicly accessible datasets.

The dataset is available at the following link:
https://www.kaggle.com/datasets/billhuang0/mpidata/data

This dataset contains **Multidimensional Poverty Index (MPI)** data compiled from reliable international sources. It provides information at both **national** and **subnational** levels, making it suitable for multi-level poverty analysis. The data is provided in **CSV (Comma-Separated Values)** format, which allows easy import into analytical tools such as Power BI.

The dataset includes indicators related to multidimensional poverty, such as MPI values, headcount ratios, and intensity of deprivation. It also distinguishes between **urban and rural poverty levels** at the national level and provides **regional-level poverty indicators** for subnational analysis. This structure enables detailed examination of poverty disparities across different population groups and geographic regions.

The availability of separate national and subnational datasets allows for comparative analysis at multiple levels of granularity. Additionally, the presence of country names, region names, and world region classifications supports geographic and regional analysis using maps and slicers within Power BI.

The dataset was selected for this project because of its **relevance, completeness, and analytical depth**. Its structured format and rich socio-economic indicators make it appropriate for studying multidimensional poverty patterns and for building interactive dashboards that support data-driven insights.

3. Dataset Preprocessing

Dataset preprocessing is a crucial stage in any data analytics project, as the quality of analysis and visualization depends heavily on how well the data is prepared and structured. In this project, preprocessing was performed using **Power BI Power Query** and the **Model view**, focusing primarily on data organization, correct categorization, and relationship management rather than extensive data cleaning.

3.1 Data Import

The MPI datasets were imported into Power BI in **CSV format** directly from the downloaded Kaggle files. Separate datasets representing **national-level MPI data** and **subnational-level MPI data** were loaded into Power BI. Power Query was used to review the structure of each dataset and verify column names, data types, and overall completeness.

During import, no rows were removed or altered, as the dataset was already structured and did not contain invalid or corrupted records that would affect the analysis.

3.2 Column Review and Data Categorization

After importing the datasets, all columns were carefully reviewed in Power Query to understand their purpose and analytical relevance. Special attention was given to **geographic fields**, as they are critical for mapping and filtering operations in Power BI.

The **Data Category** property was manually updated for the following fields:

- The **Country** column was categorized as *Country*
- The **Region** column was categorized as *State/Province/Region*

These changes ensured that Power BI correctly recognized geographic fields, enabling accurate rendering of map visuals and improving the reliability of geographic filtering. This step was particularly important for visualizations involving national and subnational spatial analysis.

3.3 Data Modeling and Table Structure

Instead of performing heavy row-level transformations, preprocessing focused on building a **clean and logical data model**. The datasets were organized into a structured model consisting of fact and dimension tables, which improves performance and analytical clarity.

The following logical structure was used:

- **Fact tables** to store MPI indicators and measures
- **Dimension tables** to store descriptive information such as country and region names

To support subnational analysis, a **Region_Key** was created to uniquely identify regions and avoid ambiguity caused by duplicate region names across different countries. This key played a critical role in establishing correct relationships between tables.

3.4 Relationship Management

Relationships between tables were created and refined in the **Model view**. Incorrect or ambiguous relationships were removed, and appropriate **one-to-many relationships** were established to ensure accurate filtering and aggregation.

Care was taken to:

- Avoid many-to-many relationships

- Prevent circular filtering paths
- Maintain correct granularity for national and subnational analysis

This step ensured that slicers and visuals behaved predictably across different pages of the dashboard.

3.5 Feature Enhancements for Dashboard Navigation

As part of preprocessing and report preparation, **page navigation buttons** were added to the dashboard. These buttons enable users to move seamlessly between different analytical pages, improving usability and overall user experience.

No additional data manipulation or artificial transformations were introduced beyond what was required for modeling and visualization. This approach ensured that the analysis remained faithful to the original dataset while still supporting meaningful insights.

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4. Analysis on Dataset

4.i General Description

The analysis phase of this project focuses on deriving meaningful insights from the **Multidimensional Poverty Index (MPI)** datasets at **national, subnational, and global levels**. The primary objective is to understand how multidimensional poverty varies across population groups and geographic regions, with particular emphasis on **urban–rural disparities**, **regional inequality**, and **global deviation patterns**.

At the national level, the analysis compares **urban and rural poverty across countries** to identify whether deprivation is predominantly rural or if urban poverty also plays a significant role. By examining MPI values together with headcount ratios and intensity of deprivation, the analysis captures both the **extent and severity** of poverty, offering a more comprehensive perspective than single-indicator measures.

The subnational analysis extends this approach by examining **regional disparities within countries**. Since poverty is rarely uniform across national boundaries, this level of analysis helps identify **high-risk regions** that may be overlooked when relying solely on national averages. It also enables meaningful comparisons between regions within the same country and across world regions.

At the global level, the analysis aggregates patterns across **world regions** to identify broader trends and extreme cases. Comparing regional MPI values against **global benchmarks** highlights regions that perform significantly above or below the global average, providing insight into global inequality and poverty concentration.

The analysis is designed to be **interactive and exploratory**, supported by KPIs, charts, maps, and relational visuals. Slicers for country and world region allow dynamic filtering, ensuring a logical progression from national analysis to subnational detail and finally to global insights. This framework establishes a clear foundation for detailed computation, interpretation, and visualization in subsequent sections.

4.ii Specific Requirements, Functions and Formulas

This subsection describes the analytical requirements of the project and the **measures created using DAX (Data Analysis Expressions)** in Power BI. The purpose of these measures is to derive meaningful insights from the MPI datasets by transforming raw indicators into interpretable metrics. All calculations were implemented as **measures** to ensure correct aggregation, dynamic filtering, and interactive analysis across visuals.

4.ii.1 Measures for National-Level Analysis

To analyze poverty at the national level and compare urban and rural deprivation, separate measures were created for urban and rural MPI values.

- **Average MPI (Urban)**
  This measure calculates the average multidimensional poverty index for urban populations. It is used to assess poverty conditions in urban areas and to compare them against rural poverty levels.
- **Average MPI (Rural)**
  This measure calculates the average MPI for rural populations. It plays a crucial role in identifying whether poverty is more concentrated in rural areas across countries.

To evaluate inequality between urban and rural populations, a comparative measure was required.

- **Urban–Rural MPI Gap**
  This measure represents the difference between rural MPI and urban MPI values. A higher gap indicates greater inequality between rural and urban areas within a country. This measure is particularly important for identifying countries with strong spatial inequality in poverty distribution.

4.ii.2 Measures for Subnational Analysis

For subnational analysis, measures were created to capture poverty characteristics at the regional level.

- **Average Regional MPI**
  This measure calculates the average MPI across subnational regions. It is used to compare poverty levels between different regions within and across countries.
- **Average Headcount Ratio (Regional)**
  The headcount ratio represents the proportion of the population experiencing multidimensional poverty. This measure helps determine how widespread poverty is within a region.
- **Average Intensity of Deprivation (Regional)**
  This measure captures the severity of deprivation experienced by the poor population in a region. It complements the headcount ratio by explaining how intense poverty is among affected individuals.

Together, these measures allow the analysis to distinguish between regions where poverty is widespread and regions where poverty is less common but more severe.

4.ii.3 Global Benchmark and Deviation Measures

To support global-level comparison, benchmark and deviation-based measures were introduced.

- **Global Average Regional MPI**
  This measure calculates the overall average of regional MPI values across all regions. It serves as a global benchmark for comparison.
- **MPI Deviation from Global Average**
  This measure calculates the difference between a region's MPI and the global average MPI. Positive deviation values indicate regions performing worse than the global average, while negative values indicate relatively better performance.

Deviation-based analysis is essential for identifying regions that significantly differ from global norms and for understanding structural inequality.

4.ii.4 Poverty Severity Measures

To move beyond individual indicators, a composite measure was created to represent overall poverty severity.

- **Poverty Severity Score**
  This measure combines MPI values with intensity of deprivation to represent both the spread and depth of poverty. It provides a single metric for identifying regions experiencing extreme deprivation.

To support extreme-value analysis, additional measures were created:

- **Maximum Poverty Severity**
  Identifies the highest observed poverty severity across regions.

- **Minimum Poverty Severity**
  Identifies the lowest observed poverty severity, representing best-performing regions.

These measures are used to highlight extreme cases and support global insight generation.

4.ii.5 Rationale for Measure-Based Analysis

All calculations were implemented as **DAX measures instead of calculated columns** to ensure that results respond dynamically to slicers and filters. This approach improves analytical accuracy, supports interactive exploration, and maintains consistency across multiple visuals and dashboard pages.

The measures defined in this section form the computational backbone of the dashboard and enable systematic analysis across national, subnational, and global levels.

4.iii Analysis Results

The analysis of the **Multidimensional Poverty Index (MPI)** datasets reveals clear disparities across countries, regions, and population groups. By examining MPI values alongside headcount ratios and intensity of deprivation, the results highlight not only the **prevalence of poverty** but also its **depth and severity**.

At the national level, comparisons between **urban and rural MPI values** show that poverty is predominantly concentrated in rural areas across most countries. Rural MPI values consistently exceed urban MPI values, indicating limited access to education, healthcare, and basic living standards in rural regions. However, the size of the urban–rural gap varies across countries, reflecting differing levels of spatial inequality.

The **urban–rural MPI gap** further emphasizes inequality within countries. Larger gaps indicate strong rural disadvantage, while smaller gaps suggest more balanced poverty levels between urban and rural populations. This finding underscores the importance of

spatially targeted poverty reduction strategies rather than uniform national interventions.

Subnational analysis reveals substantial **regional disparities within countries**. Although national averages may indicate moderate poverty levels, several subnational regions exhibit significantly higher MPI values. These regions often combine high headcount ratios with high intensity of deprivation, confirming that poverty is unevenly distributed within national boundaries and that subnational analysis is essential for identifying high-risk areas.

The relationship between **headcount ratio and intensity of deprivation** highlights distinct poverty patterns. Some regions experience widespread poverty with moderate intensity, while others show lower headcount but severe deprivation. This distinction demonstrates that reducing poverty incidence does not always reduce poverty severity.

At the global level, comparisons against **global average MPI benchmarks** reveal strong regional deviations. Certain world regions perform consistently worse than the global average, contributing disproportionately to global poverty severity, while others perform significantly better.

Overall, the results show that multidimensional poverty is influenced by **spatial, regional, and structural factors**, reinforcing the need for multi-level analysis and the combined use of multiple poverty indicators to achieve a comprehensive understanding of deprivation patterns.

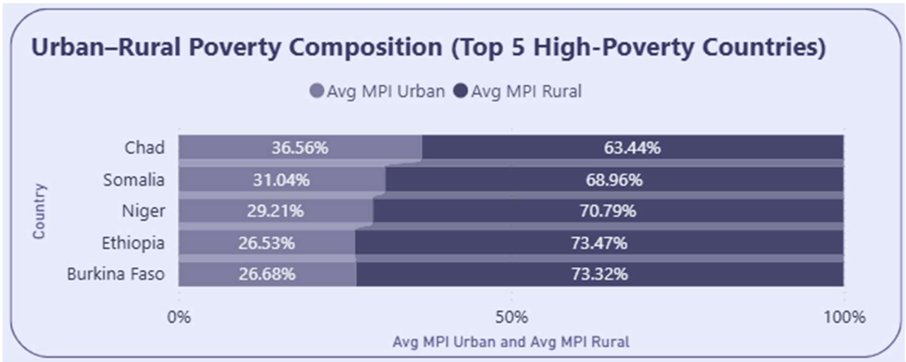
4.iv.1 Page 1 – National-Level Urban and Rural Poverty Analysis

The first page of the dashboard presents a **national-level overview of multidimensional poverty**, with a specific focus on comparing **urban and rural poverty patterns across countries**. The objective of this page is to highlight spatial inequality in poverty distribution and identify whether deprivation is predominantly urban or rural in nature.

At the top of the page, **KPI cards** summarize key national indicators, including **Average Rural MPI**, **Average Urban MPI**, and the **Urban–Rural MPI Gap**. These indicators provide an immediate snapshot of overall poverty conditions and the extent of inequality between urban and rural populations.

The visualizations on this page are designed to support **comparative analysis**, **geographic context**, and **pattern identification**, while keeping the layout clean and interpretable.

Visualization 1: Urban–Rural Poverty Composition (Top 5 High-Poverty Countries)



Key Insights:

- Rural poverty contributes the **largest share of total MPI** in all five high-poverty countries.
- Countries such as **Burkina Faso and Ethiopia** show rural contributions exceeding **70%**, indicating strong rural disadvantage.
- Urban poverty forms a smaller but non-negligible component, highlighting the presence of deprivation even in urban areas.
- The visual confirms that poverty in high-risk countries is **predominantly rural in nature**.

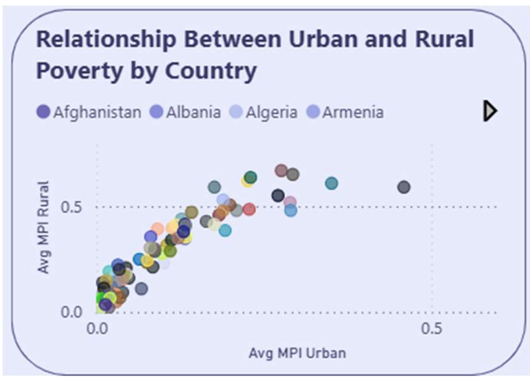
Visualization 2: Geographic Coverage of Countries in the Analysis

Key Insights:

- The map shows that the dataset covers countries across **Africa, Asia, Europe, and Latin America**.

- A higher concentration of countries appears in **Africa and South Asia**, regions known for higher MPI values.
- This visual provides geographic context and validates the **global scope** of the analysis.
- It supports intuitive filtering when combined with country slicers.

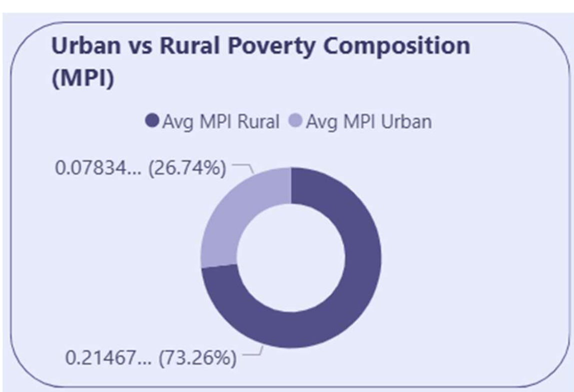
Visualization 3: Urban vs Rural MPI Relationship by Country



Key Insights:

- A strong positive relationship is observed between urban and rural MPI values.
- Countries with high rural MPI generally also show higher urban MPI, though rural values remain consistently higher.
- Some countries deviate from the general trend, indicating uneven development patterns.
- The scatter plot helps identify **outliers and inequality extremes**.

Visualization 4: Urban vs Rural Poverty Composition (Overall)



Key Insights:

- Rural poverty accounts for the **majority share** of overall multidimensional poverty.
- Urban poverty contributes a smaller proportion but remains significant.
- The chart reinforces findings from the stacked bar chart at an aggregate level.
- This visualization simplifies complex data into a **high-level summary**.

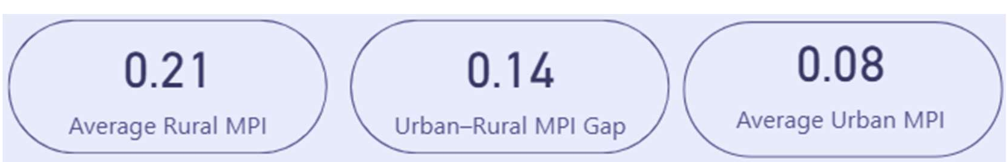
Visualization 5: Country-wise MPI Summary Table

Country	Avg MPI Rural	Avg MPI Urban	MPI Urban Rural Gap
Afghanistan	0.35	0.13	0.22
Albania	0.01	0.00	0.00
Algeria	0.01	0.00	0.01
Armenia	0.00	0.00	0.00
Azerbaijan	0.04	0.01	0.03
Bangladesh	0.23	0.10	0.13
Barbados	0.00	0.00	0.00
Belize	0.03	0.01	0.02

Key Insights:

- The table provides exact numerical values for **Avg MPI Urban**, **Avg MPI Rural**, and **Urban–Rural MPI Gap**.
- Countries can be directly compared based on the magnitude of inequality.
- Conditional formatting helps quickly identify **high-gap and low-gap countries**.
- This visual supports validation of trends observed in other charts.

Visualization 4: KPIs – National-Level Urban and Rural Poverty



These KPI cards provide a concise overview of national multidimensional poverty patterns, highlighting the contrast between urban and rural deprivation.

- Average Rural MPI (0.21)

This indicator shows that rural populations experience moderate to high multidimensional poverty on average. It confirms that rural areas are the primary contributors to overall poverty, serving as a key benchmark for comparing rural deprivation across countries.

- Average Urban MPI (0.08)

The relatively low urban MPI indicates better living conditions in urban areas, including improved access to education, healthcare, and basic services. While urban poverty exists, it is less severe compared to rural poverty.

- Urban–Rural MPI Gap (0.14)

The positive gap highlights a clear inequality between rural and urban poverty levels. A higher gap reflects stronger rural disadvantage, making this metric crucial for identifying countries with pronounced spatial inequality.

Interactive Elements

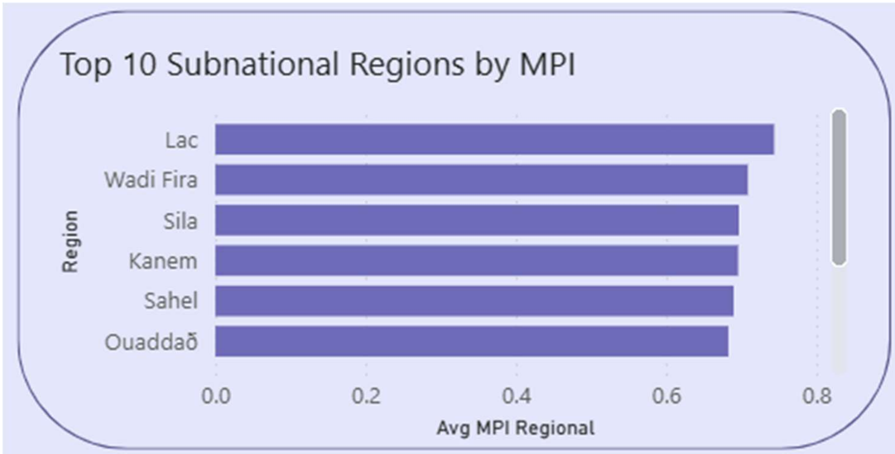
- **Country slicer** allows users to focus on specific countries.
- All visuals on this page respond dynamically to slicer selections.
- KPI cards update automatically based on applied filters.

4.iv.2 Page 2 – Subnational Poverty Patterns and Regional Inequality

The second page of the dashboard focuses on **subnational poverty analysis**, highlighting disparities **within countries and across regions**. While national averages provide a broad view of poverty, this page reveals how deprivation varies significantly at the regional level. The objective is to identify **high-risk subnational regions**, understand regional inequality, and examine how poverty depth and spread differ across world regions.

KPI cards on this page summarize key subnational indicators, including **Average Regional Headcount**, **Average Poverty Intensity**, and **Average Subnational MPI**, offering a concise overview of regional poverty conditions.

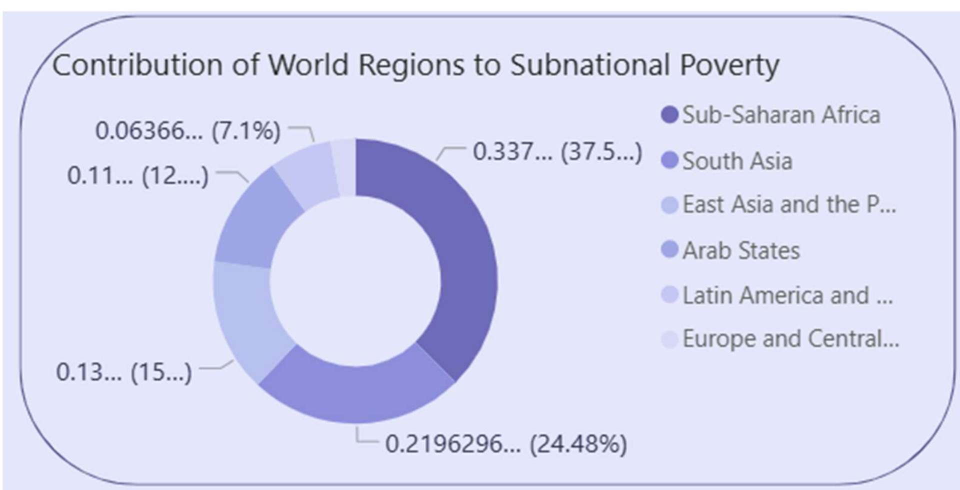
Visualization 1: Top 10 Subnational Regions by MPI



Key Insights:

- The chart identifies the **most deprived subnational regions** based on MPI values.
- Regions such as **Lac, Wadi Fira, and Sila** exhibit exceptionally high MPI levels.
- These regions significantly exceed average subnational poverty levels.
- The ranking highlights **localized poverty hotspots** that may not be visible at the national level.
- This visualization supports targeted regional intervention planning.

Visualization 2: Contribution of World Regions to Subnational Poverty

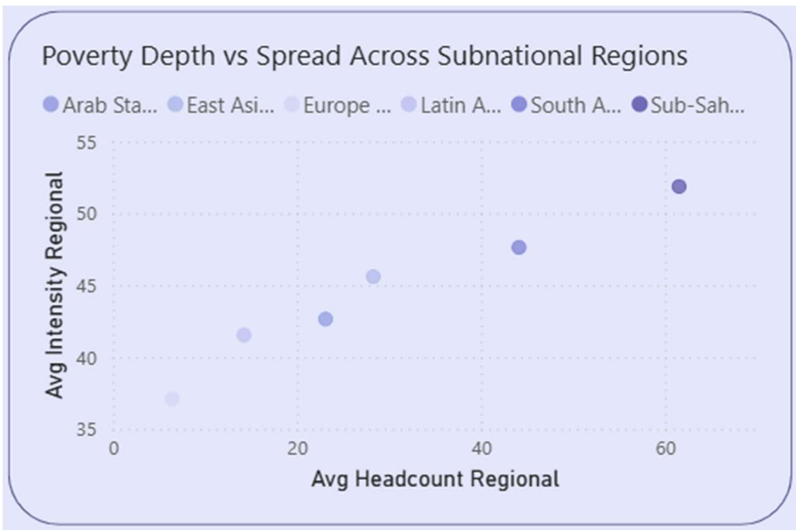


Key Insights:

- **Sub-Saharan Africa** contributes the largest share to overall subnational poverty.

- **South Asia** is the second-largest contributor, reinforcing its vulnerability.
- Other world regions contribute relatively smaller proportions.
- The chart shows that global subnational poverty is **highly concentrated in specific regions**.
- This visualization provides a global context for regional poverty distribution.

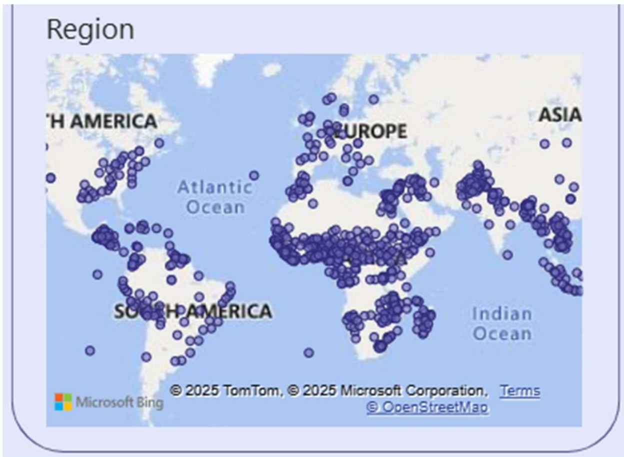
Visualization 3: Poverty Depth vs Spread Across Subnational Regions



Key Insights:

- A positive relationship is observed between **headcount ratio** and **intensity of deprivation**.
- Regions with a higher proportion of poor populations often experience more severe deprivation.
- Some regions show **moderate spread but high intensity**, indicating deep poverty among fewer people.
- Other regions show **high spread but lower intensity**, suggesting widespread but less severe poverty.
- This visual helps distinguish between different **types of poverty challenges**.

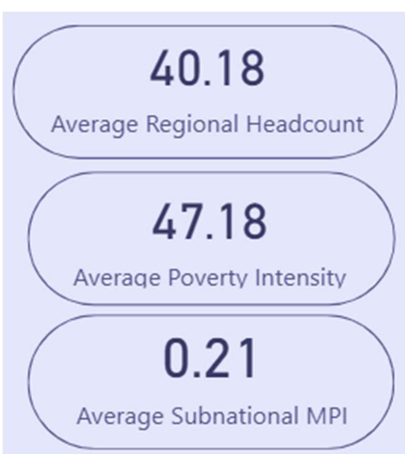
Visualization 4: Geographic Distribution of Subnational Regions



Key Insights:

- High-MPI subnational regions are geographically concentrated in **Africa and South Asia**.
- The map reveals strong **spatial clustering** of poverty hotspots.
- Regions with similar poverty levels often appear close geographically.
- This visualization enhances spatial understanding of subnational poverty patterns.
- It complements numerical charts by adding **geographic context**.

Visualization 5: Subnational Poverty Summary KPIs



These KPI cards summarize subnational poverty conditions, focusing on the spread, intensity, and overall severity of multidimensional poverty at the regional level.

- Average Regional Headcount (40.18)

This indicator represents the average proportion of the population experiencing multidimensional poverty across subnational regions. The relatively high value indicates that poverty is widespread within several regions, even when national averages appear moderate.

- Average Poverty Intensity (47.18)

This KPI reflects the severity of deprivation among the poor population at the subnational level. A higher intensity value indicates that individuals experiencing poverty face multiple and overlapping deprivations, highlighting deep-rooted regional disadvantages.

- Average Subnational MPI (0.21)

The average subnational MPI combines both headcount and intensity, providing a single measure of overall regional poverty severity. This value confirms that subnational poverty levels remain significant and often exceed national averages, reinforcing the importance of regional-level analysis.

Interactive Elements

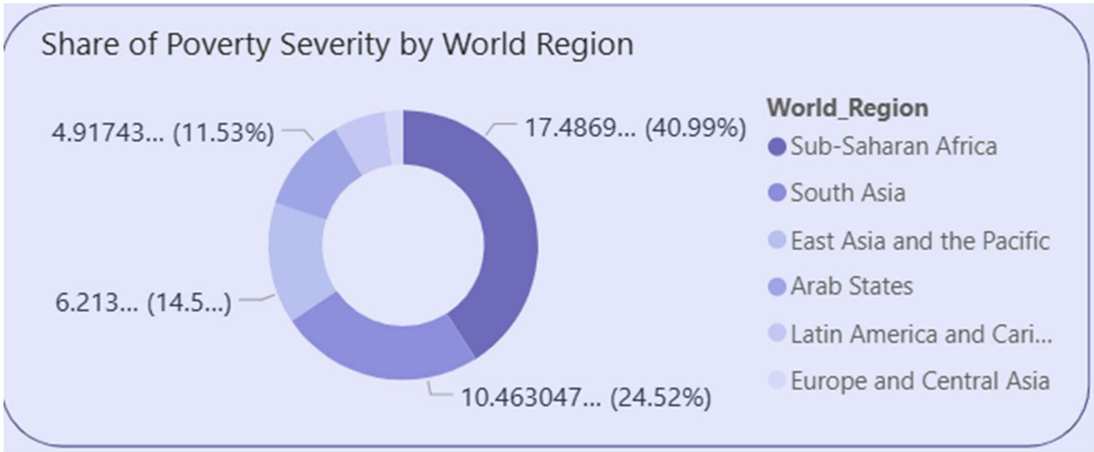
- **World Region slicer** allows users to isolate regional patterns.
- **Country slicer** enables focused subnational analysis within selected countries.
- All visuals update dynamically, ensuring consistent interpretation across the page.

4.iv.3 Page 3 – Global Poverty Patterns, Deviations, and Extremes

The third page of the dashboard provides a **global-level synthesis** of multidimensional poverty patterns. Unlike the previous pages, which focus on comparison and distribution, this page emphasizes **deviation from global benchmarks**, **poverty severity**, and **extreme cases**. The objective is to identify which world regions and subnational areas contribute most to global poverty severity and how far they deviate from global averages.

KPI cards on this page establish global reference points, while advanced analytical visuals such as scatter plots, donut charts, and detailed tables support deeper interpretation of global inequality.

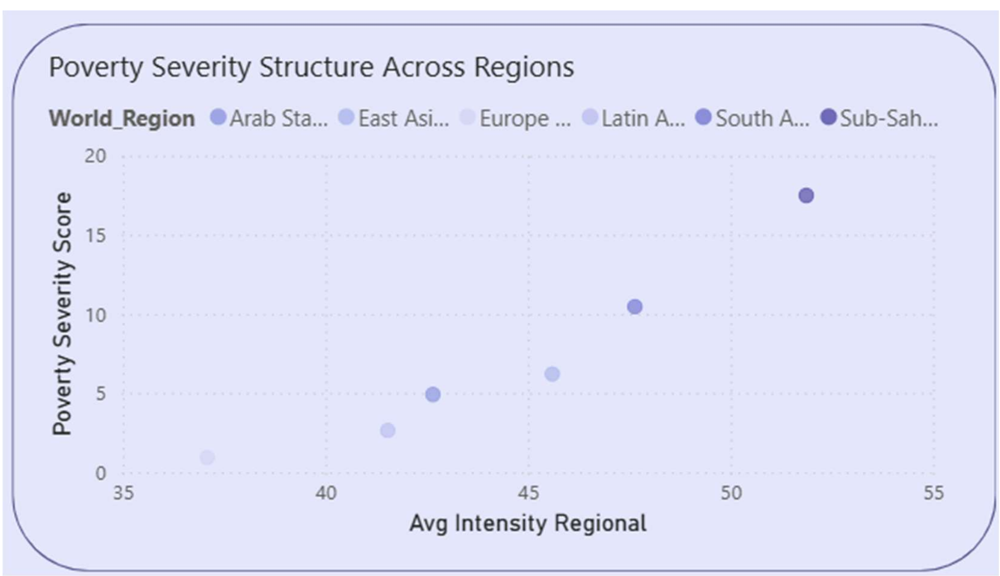
Visualization 1: Share of Poverty Severity by World Region



Key Insights:

- **Sub-Saharan Africa** contributes the largest share of global poverty severity.
- **South Asia** is the second-largest contributor, indicating high severity combined with wide spread.
- Other regions contribute comparatively smaller shares.
- The chart shows that global poverty severity is **highly concentrated**, not evenly distributed.

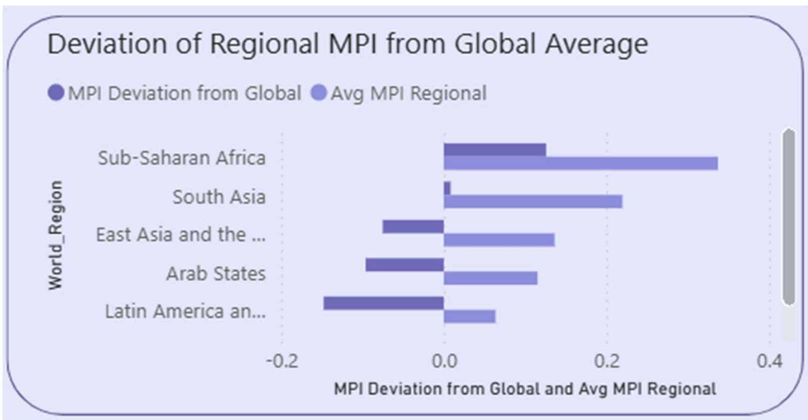
Visualization 2: Poverty Severity Structure Across Regions



Key Insights:

- A positive relationship exists between **intensity of deprivation** and **poverty severity score**.
- Regions with higher deprivation intensity experience disproportionately higher severity.
- Sub-Saharan Africa stands out as an **extreme case** with both high intensity and high severity.
- This chart explains *why* some regions dominate global poverty statistics.

Visualization 3: Deviation of Regional MPI from Global Average



Key Insights:

- Sub-Saharan Africa shows the largest positive deviation, indicating significantly higher multidimensional poverty than the global average.
- South Asia also exhibits a positive deviation, confirming persistent regional poverty challenges.
- East Asia and the Pacific lies close to the global benchmark, suggesting moderate poverty levels relative to the global average.
- Arab States and Latin America and the Caribbean display negative deviations, indicating better-than-global-average poverty performance.
- The visual clearly distinguishes over-performing and under-performing regions, making global inequality patterns easy to interpret.

Visualization 4: Regions with Extreme Poverty Severity

Regions with Extreme Poverty Severity

World_Region	Region	Avg MPI Regional	Poverty Severity Score
Arab States	Abyan	0.14	6.22
Arab States	Aden	0.06	2.55
Arab States	Al-Anbar	0.05	1.94
Arab States	Al-Baidha	0.19	9.61
Arab States	Aldhalae	0.20	9.42
Arab States	Alexandria	0.00	0.13
Arab States	Al-Hodiedah	0.34	18.90
Arab States	Al-Jawf	0.21	9.87
Arab States	Al-Mhrah	0.11	5.12
Arab States	Al-Mhweit	0.35	18.85

Key Insights:

- The table lists subnational regions with the **highest poverty severity scores**.
- Several regions within the same world region appear repeatedly, indicating **localized clusters of extreme poverty**.
- Even regions with moderate MPI can exhibit high severity when deprivation intensity is high.
- This visual supports evidence-based identification of **priority regions for intervention**.

Visualization 1: Summary KPIs – Global Poverty Insights

56.47

Highest Poverty Severity

0.21

Global Avg Regional MPI

These KPI cards provide global benchmarks for assessing multidimensional poverty severity and regional performance relative to world averages.

- Highest Poverty Severity (56.47)

This indicator represents the maximum observed poverty severity score across all regions. It highlights the presence of extreme deprivation hotspots globally, where high poverty incidence is combined with severe intensity of deprivation.

- Global Average Regional MPI (0.21)

This KPI serves as a global benchmark for comparing regional MPI values. Regions with MPI values above this level perform worse than the global average, while those below it exhibit relatively better poverty outcomes.

Interactive Elements

- **World Region slicer** allows isolation of specific global regions.
- All visuals dynamically update to reflect selected regions.
- This interactivity supports focused global analysis without overwhelming the user.

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5. Conclusion

This project demonstrates the effective use of data analytics and visualization techniques to examine **multidimensional poverty** from national, subnational, and global perspectives. By using the **Multidimensional Poverty Index (MPI)**, the analysis moves beyond income-based measures and captures deprivation across health, education, and living standards.

At the national level, the analysis reveals a consistent **urban–rural disparity**, with rural populations experiencing significantly higher poverty levels. The urban–rural MPI gap highlights spatial inequality and emphasizes the need for targeted rural-focused policies. Subnational analysis further shows that poverty is **unevenly distributed within countries**, with several regions exhibiting high MPI values despite moderate national averages.

At the global level, the results indicate a strong **concentration of poverty severity** in regions such as Sub-Saharan Africa and South Asia. Deviation and severity-based measures clearly identify regions that contribute disproportionately to global poverty, enabling meaningful comparison against global benchmarks.

The use of **Power BI** supported efficient data modeling, interactive filtering, and clear visual storytelling. Overall, the project illustrates how multidimensional poverty data can be transformed into **actionable insights**, reinforcing the importance of multi-level analysis for informed policy formulation and development planning.

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6. Future Scope

While this project provides valuable insights into multidimensional poverty using national, subnational, and global MPI data, there is significant scope for further enhancement. One important extension would be the inclusion of **time-series data**, which would enable trend analysis and help assess how poverty levels change over time and respond to policy interventions.

The analysis could also be strengthened by integrating **additional socio-economic indicators** such as employment, literacy, healthcare access, or public expenditure. Combining these factors with MPI would support deeper understanding of the underlying drivers of poverty.

From a technical perspective, future work could incorporate **advanced analytical techniques** such as regional clustering or predictive modeling to estimate future poverty severity. Visualization enhancements, including custom visuals, drill-through pages, and narrative annotations, could further improve interpretability and user engagement.

Additionally, integrating **regularly updated or real-time data sources** from international organizations would improve data relevance and allow the dashboard to function as a continuous poverty monitoring tool. Overall, expanding data depth, analytical complexity, and interactivity would make the analysis more actionable and policy-oriented.

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7. References

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8. Screenshots