Beyond GDP: The True Indicators of Extreme Poverty

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1 Abstract

Despite decades of global efforts to eradicate poverty, the gap between wealthy and impoverished nations continues to widen, exposing the limitations of traditional metrics like GDP in capturing the true state of human well-being. This paper seeks to move beyond GDP by analyzing the Multidimensional Poverty Index (MPI) as a more comprehensive indicator of extreme poverty. Using SAP's dataset, we investigate the underlying factors contributing to persistent poverty in countries with MPI values exceeding 0.15. By focusing on actionable insights, this study aims to equip national governments and international institutions, such as the World Bank and IMF, with strategies to foster sustainable development and alleviate extreme poverty effectively. Ultimately, our findings underscore the urgent need for new indicators and approaches that go beyond GDP to accurately reflect the lived experiences of the world's most vulnerable populations.

2 Introduction

In 1992, representatives from across the globe gathered at the United Nations, united by a bold vision: to eradicate poverty and declare October 17th the International Day for its elimination. Three decades later, the crisis is yet to be resolved.

It is easy to be fooled by rising GDP figures worldwide into assuming that conditions are improving for countries all over the world. However, they mask a harsh reality: wealth is accumulating at the top, while entire populations in the Global South continue to struggle with food insecurity, inadequate institutions, political instability, and lack of opportunity. The world's most impoverished nations have remained trapped in economic stagnation, with little benefit from the prosperity enjoyed by more developed countries. This growing divide exposes the failure of GDP as a true measure of progress and highlights the urgent need for new indicators that reveal the real state of extreme poverty.

This paper seeks to uncover why the world's poorest nations have continued to fail in alleviating poverty. In particular, it will analyze SAP's dataset to uncover the true indicators of extreme poverty as indicated by the Multidimensional Poverty Index (MPI). Based on these insights, the paper will propose targeted policy recommendations—both for national governments and international institutions like the World Bank and the IMF—to drive more effective and lasting solutions in the global fight against poverty. In particular, the following important questions are considered:

1. What key indicators that best capture different dimensions of poverty ?
2. Which indicators contribute most significantly to poverty levels ?
3. What policy interventions can be proposed to the most affected countries ?

In section 3, we describe the methodology used in data cleaning, feature selection, and model development. In section 4, the answers to each of the questions above are provided along with visualizations and summary statistics.

3 Methodology

3.1 Assumptions

During our initial exploration of the dataset, we noticed a problem: the majority of entries were missing for the Multidimensional Poverty Index (MPI). At first glance, it appeared that data was scarce—only 110 nation-year pairs were available for the UNDP's MPI indicator, while the World Bank's MPI indicator covered just 964 out of 6,360 possible pairs. However, upon closer examination, we realized the problem wasn't primarily due to missing data but rather because many countries reported an MPI value of 0. This revelation introduced a new challenge: any country with an MPI value of 0 was automatically deemed "perfect" by the index, regardless of its actual economic or social conditions. As a result, nations with vastly different standards of living and economic profiles, such as Singapore and Belarus, were both classified as having no poverty according to the MPI.

To gain a more accurate understanding of the indicators of extreme poverty and propose actionable policies, we decided to focus exclusively on countries with MPI values greater than 0. Specifically, this paper investigates the factors contributing to extreme poverty in countries where the MPI exceeds 0.15. Additionally, it explores potential policy measures that these nations could implement to reduce their MPI to below 0.15. The threshold of 0.15 was selected because it serves as a meaningful cutoff point around the median, as shown in 4.

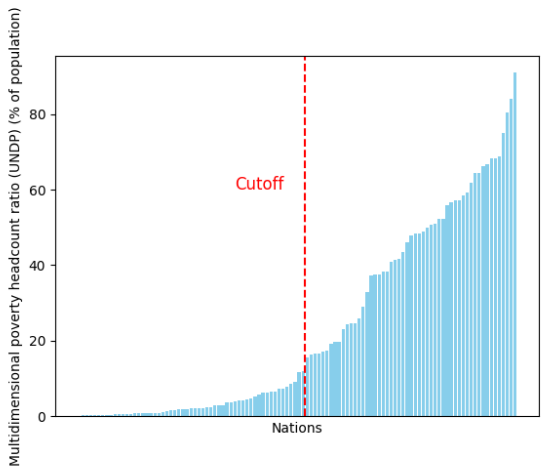


Figure 1: Visualization of cutoff

3.2 Data Cleaning and Preprocessing

A significant portion of data was missing across multiple indicators in the dataset. Before analysis, we transformed the dataset from a wide to a long format, meaning that each row now represents a nation-year pair in this section. Out of 88 features, we found that just 3 had data for every nation-year row (2), with the median availability being less than 50 percent.

Since our approach focused on relationships between different features, missing data posed a significant challenge. For example, if we were using two features that were each available for less than 50% of all rows, we could expect that the number of direct row-to-row comparisons that could be made for the two features would be less than 50% of the total possible comparisons that could have been made if both datasets contained no missing values. As such, addressing these gaps was crucial in ensuring our analysis was meaningful.

Fortunately, we discovered that a large percentage of the missing values present in our long-format data was due to several indicators not reporting annually. When counting the number of nations present for each feature, we found that the median feature included at least one year row for 70 to 80 percent of nations, and that, ignoring one outlier, the worst features still included at least a quarter of the 265 nations provided (3a). As the dataset included constituent countries (e.g. Aruba) and world regions (e.g. Arab World) as nations, we realized that many rows that were missing from features were reporting on data from non-UN member nations (3b).

We found that one way to alleviate the problem of missing years, taking into account the presence of data across nations when years are ignored, was to leverage mean substitution and backfill-forward filling. The median standard deviation of an indicator for one nation, across all years, was 2.22, so mean substitution across years was a convenient move that kept data mostly consistent.

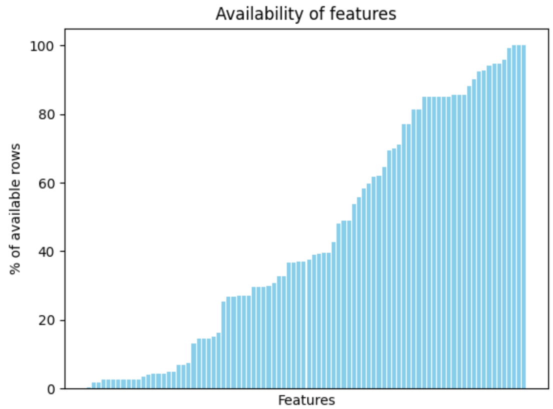
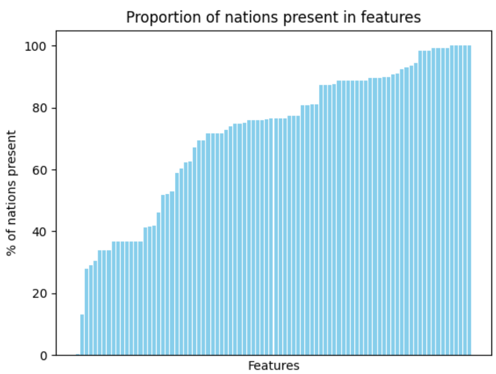
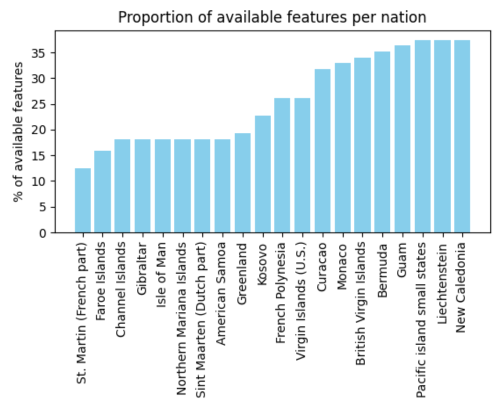


Figure 2: Total availability of features



(a) Total availability of features



(b) Total availability of features

Finally, to ensure that the dataset was suitable for Extreme Gradient Boosting regression analysis, we underwent several preprocessing steps:

1. Redundant columns such as country code, short description, long description, unit of measure, topic, and indicator code were removed to focus on more relevant features.

2. Blank MPI cells were filled with the other MPI source. For example, if the World Bank had a blank MPI cell at Afghanistan in the year 2015 and the UNDP had data for that cell, we would replace the blank cell with UNDP data, and vice versa. Completely blank MPI rows were replaced with 0, as we learned from **??**.

3. Missing values were addressed by first sorting the data chronologically and then applying forward and backward filling within each country-indicator pair's time series to impute gaps under the assumption of temporal continuity, as discussed in 3.2.

4. The dataset was pivoted into a fully wide format, with indicators being used as columns alongside years 2000 through 2023.

5. We unpacked the year columns into rows, converting the data into a format where each row contained a unique combination of country name, year, and indicator values (for that year).

The final cleaned dataset was saved as "cleaned_dataset.csv", ready for our machine learning tasks.

3.3 Feature Selection/Data Engineering

After conducting exploratory data analysis and PCA on the original dataset, the following variables are included in our final training, testing and validating datasets:

1. Urban population (% of total population)
2. Multilateral debt service (% of public and publicly guaranteed debt service)
3. Adjusted savings: education expenditure (current US$)
4. Political stability and absence of violence/terrorism: estimate
5. Literacy rate, adult total (% of people ages 15 and above)
6. Access to electricity (% of population)
7. Control of Corruption: estimate
8. Adjusted net national income per capita (current US$)
9. Access to clean fuels and technologies for cooking, rural (% of rural population)
10. People using at least basic drinking water services (% of population)
11. Compensation of employees (current LCU)
12. Terms of trade adjustment (constant LCU)
13. School enrollment, primary (gross), gender parity index (GPI)
14. Current health expenditure (% of GDP)
15. Women who were first married by age 18 (% of women ages 20-24)

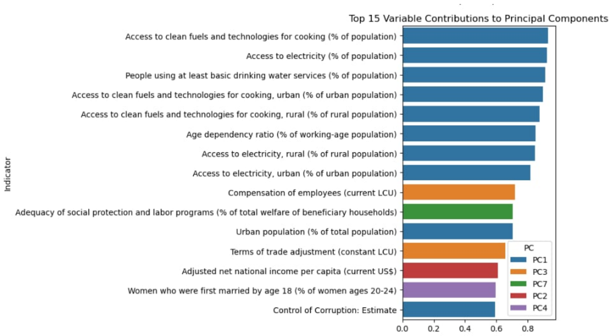


Figure 4: Principal Component Analysis on all features for all countries

We also created a modified version of cleaned_dataset.csv, as described in Section 3.2, by integrating the Human Development Index (HDI) dataset (hdr_general.csv), which covers 195 countries from 1990 to 2022. This merged dataset, named cleaned_with_hdi.csv, is used for benchmarking, as discussed later in Section 3.6.

Finally, the typical approach in normalizing numeric values is used in our analysis, namely:

$$\mathbf{x} \mapsto \frac{\mathbf{x} - \mu}{\sigma},$$

where μ is the mean and σ is the standard deviation of $\mathbf{x}$.

3.4 Building a Multidimensional Index

The main objective of this task is to identify the features which correlate to the poverty indices to determine the main causes of poverty, and conceptualize policies that would target those features. There were three main problems that needed to be addressed:

1. A significant amount of data was missing, which we will describe in more detail in 3.2. We decided to use mean substitution to fill in gaps in data for each country.

2. There were two poverty metrics, one by UNDP and another by the World Bank. We decided to create two different models, one corresponding to each metric, and compare their results.

3. Some of the data in the provided dataset were highly redundant and correlated. In extreme cases, there were items with $r^2 > 0.99$ (5). In our preliminary stages, we analyzed extremely high ($r^2 > 0.80$) intercorrelations and removed one item per pair.

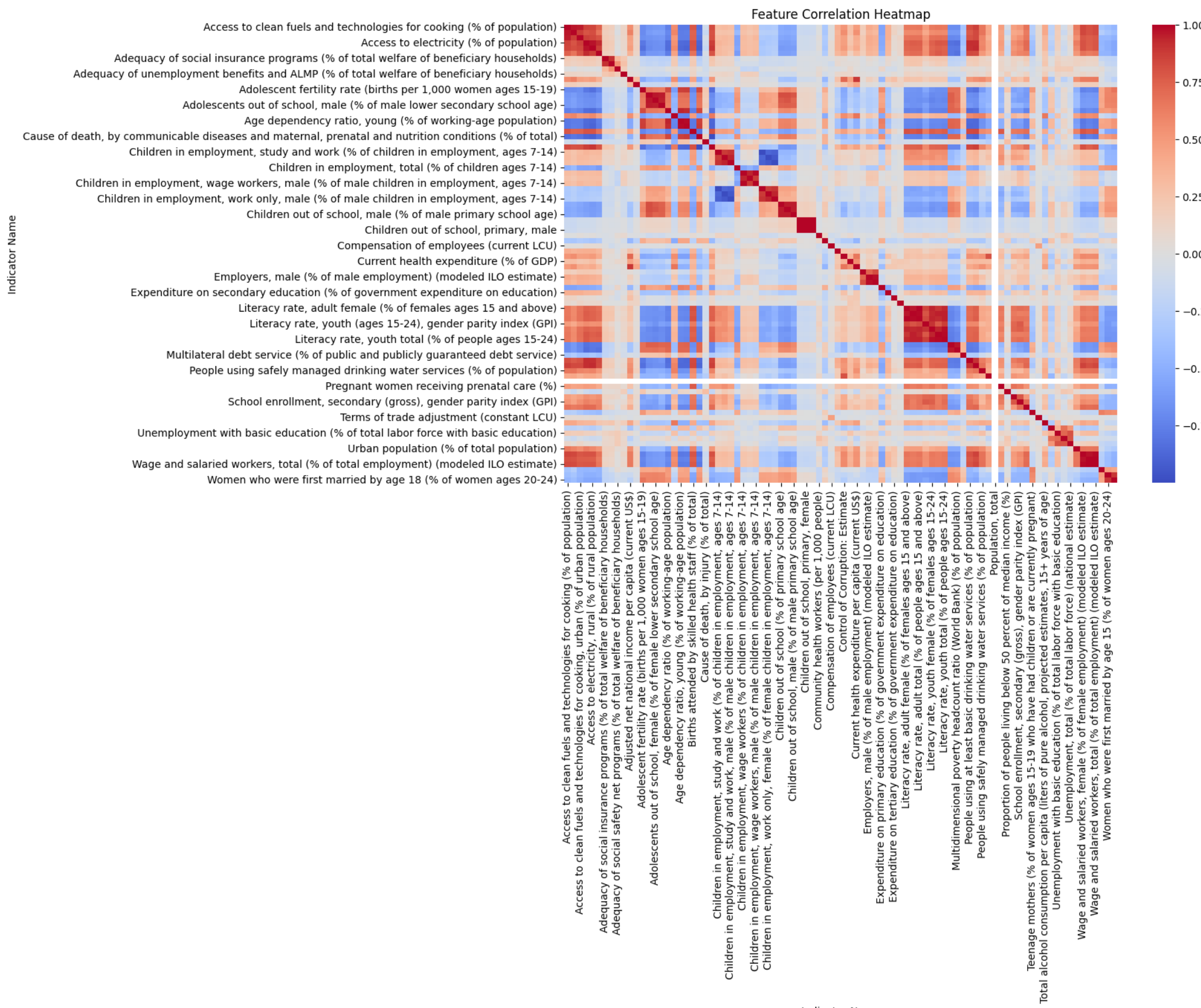


Figure 5: Feature Correlation Heatmap

After addressing these initial hurdles and running data preprocessing (3.2), we performed the following procedure to create a model for each MPI metric:

1. Run the XGBoost regression model between all features and the used MPI metric.

2. Use SHAP to visualize and interpret the results.

3. Based on feature importance analysis, pick off the top 20 features.

After finding the top 20 features in each model, we take their intersection and restart this procedure. This time, we train the models on a reduced feature set consisting of just the indicators in the shared top 20 of prior models.

3.5 Finding data-driven policies

A list of countries with MPI less than or equal to 15% in at least four of the last 5 years (2018-2023) are deemed the most affected. The list consists of 53 out of 296 countries and territories represented in the original dataset. PCA is then conducted on this subset of data to find the main contributors to poverty.

3.6 Training, Validating, and Testing Sets

After performing data cleaning, feature selection, and data engineering, we split the dataset into training set (70%), validating set (15%), and testing set 150%). We benchmarked our model against the United Nations' Human Development Index (HDI), which is a summary measure of development that provides a useful portrayal of a country's economic and social well-being.

3.7 Prediction Model

The model that we mainly use in this paper is the Extreme Gradient Boosting Regressor (XGBoost Regressor) [?]. We found that it outperformed several other tested regression models, including Linear and Ridge, and performed similar to random forest without risking overfitting. Furthermore, the model provides feature importance ranking for the independent variables, allowing ease of feature analysis.

4 Experiments and Results

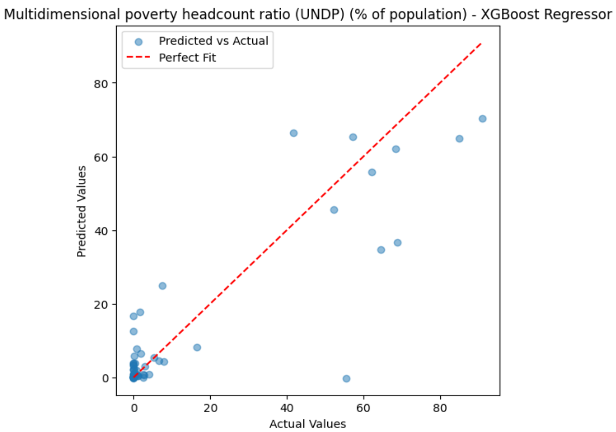
4.1 Multidimensional Index

4.1.1 Building Models

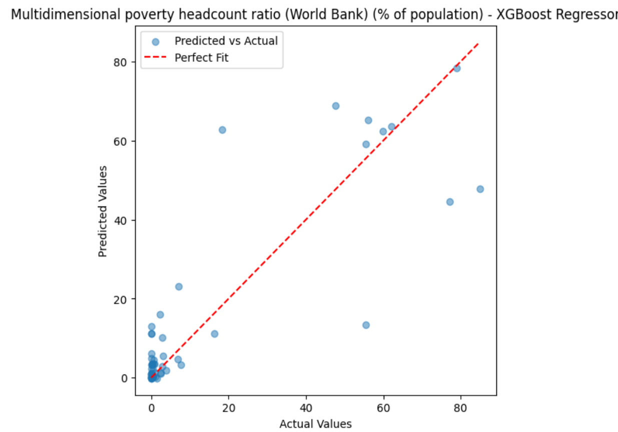
From 3.4, we produced two XGBoost regression models, as displayed in 6. When compared to other regression models trained on the same data, it was between XGBoost and random forest for the models with the best fit (10). We ultimately decided to use the XGBoost model out of ease of analysis and to prevent overfitting.

Next, we found the top-contributing features.
After identifying the top contributing features for each of the two models (8), we found the intersection of the top 20 features from both models:

- Pregnant women receiving prenatal care (%)
- International migrant stock, total
- Compensation of employees (% of expense)
- Employers, female (% of female employment) (modeled ILO estimate)
- Adjusted savings: education expenditure (current US$)
- Adjusted net national income per capita (current US$)
- Teenage mothers (% of women ages 15-19 who have had children or are currently pregnant)
- Access to clean fuels and technologies for cooking (% of population)

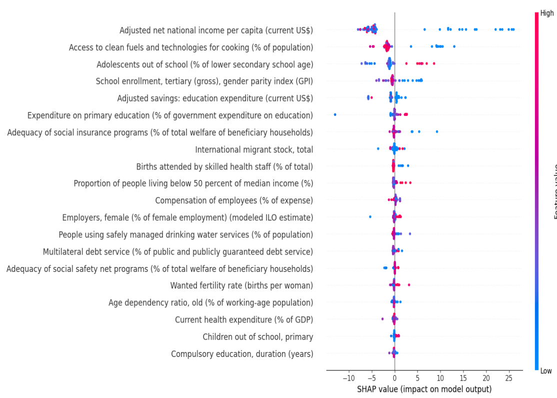


(a) UNDP model

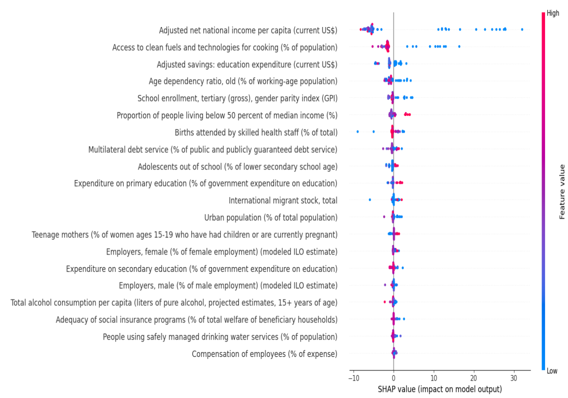


(b) World bank model

Figure 6: XGBoost regression models



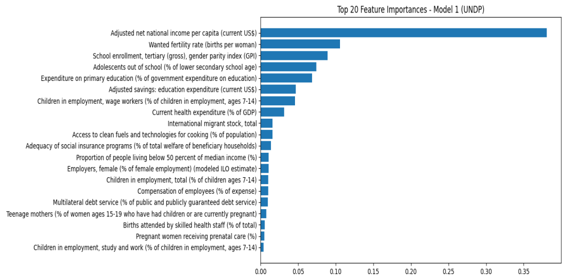
(a) UNDP SHAP



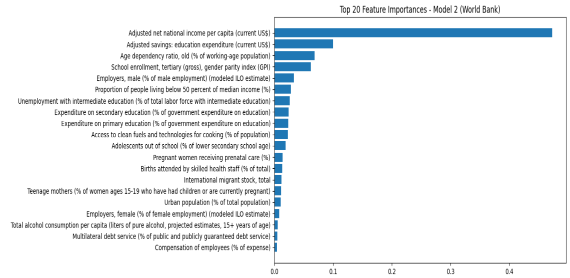
(b) World bank SHAP

Figure 7: Model SHAP

- Adolescents out of school (% of lower secondary school age)
- Births attended by skilled health staff (% of total)
- School enrollment, tertiary (gross), gender parity index (GPI)
- Multilateral debt service (% of public and publicly guaranteed debt service)
- Expenditure on primary education (% of government expenditure on education)
- Proportion of people living below 50 percent of median income (%)

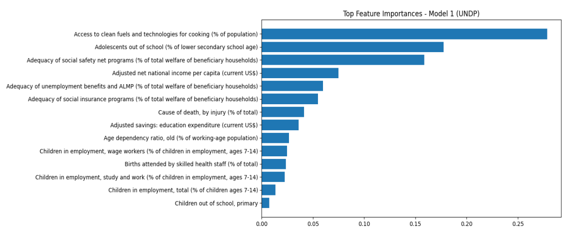


(a) UNDP feature importances

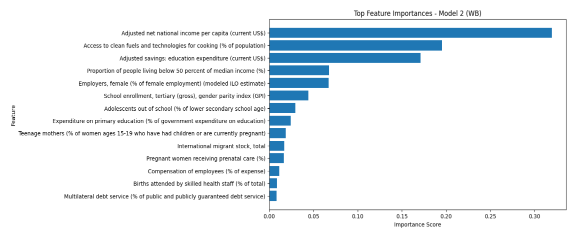


(b) World bank feature importances

Figure 8: Model feature importances



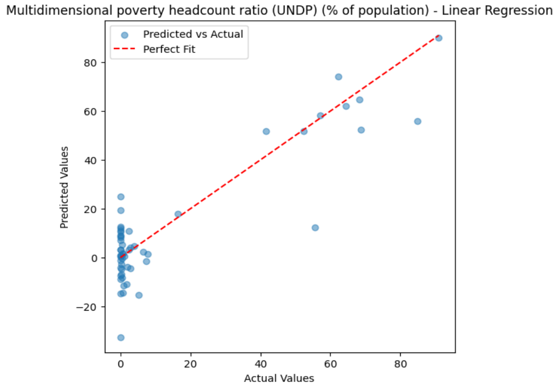
(a) UNDP feature importances, reduced version



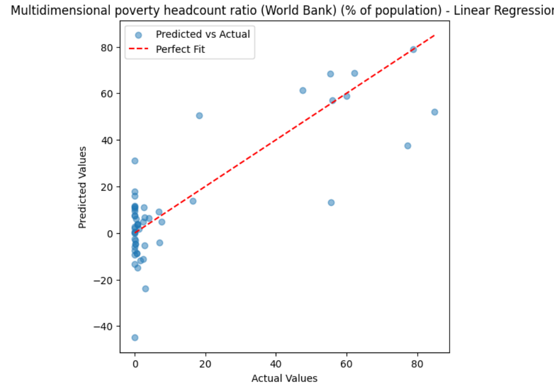
(b) World bank feature importances, reduced version

Figure 9: Reduced model feature importances

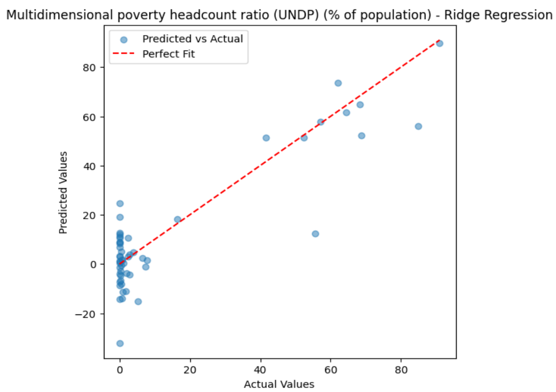
After identify the shared features, we then reran the same XGBoost regression model on just the features. Surprisingly, we obtained different data for feature importances on this iteration (9): while our highest feature used to be adjusted net income, it was now dwarfed by several features relating to political and societal health. One explanation for this phenomenon could be that there were several other features associated with political and societal health that didn't make it into our feature cutoff, but contributed heavily into our initial model.



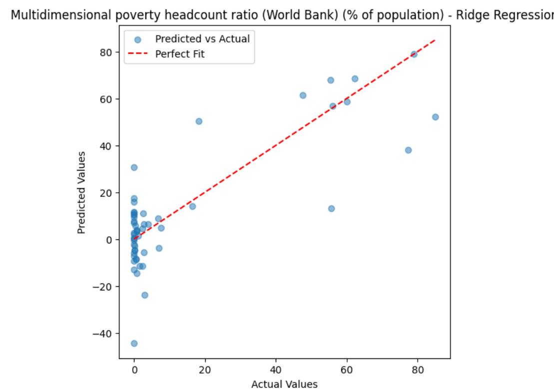
(a) UNDP linear model



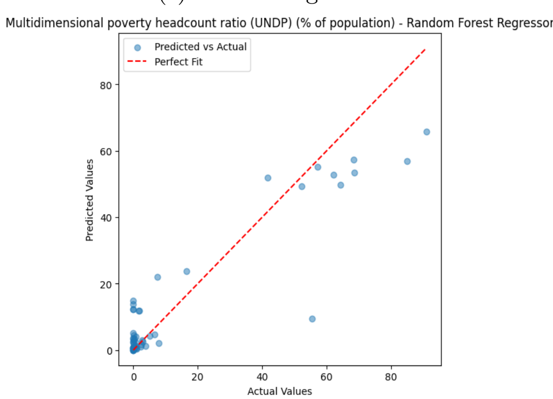
(b) World bank linear model



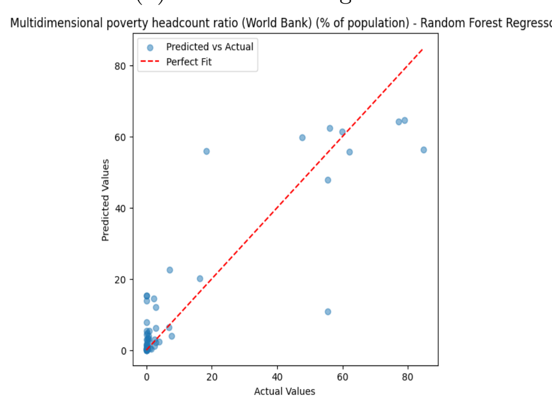
(c) UNDP ridge model



(d) World bank ridge model



(e) UNDP random forest model



(f) World bank randomforest model

Figure 10: Other regression models

The model obtained was the following:

```
  Poverty Index (WB) =
+ 0.3197 × Adjusted net national income per capita (current US$)
- 0.0441 × School enrollment, tertiary (gross), gender parity index (GPI)
+ 0.0294 × Adolescents out of school (% of lower secondary school age)
+ 0.0244 × Expenditure on primary education (% of government expenditure on education)
- 0.1712 × Adjusted savings: education expenditure (current US$)
- 0.0169 × International migrant stock, total
- 0.1952 × Access to clean fuels and technologies for cooking (% of population)
```

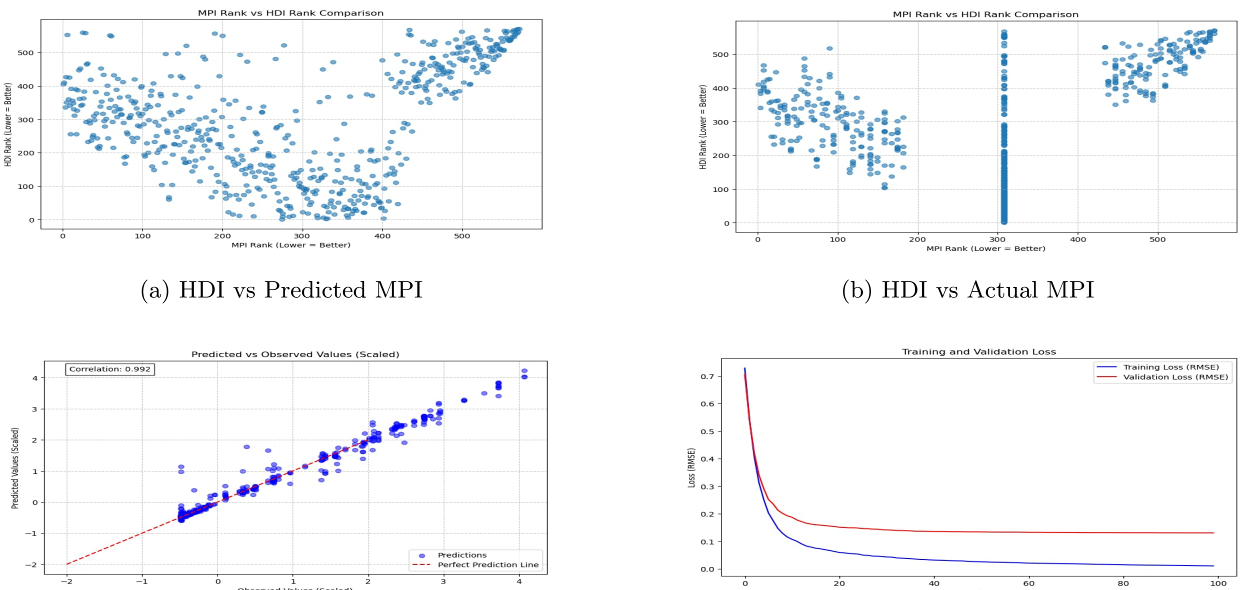
```
+ 0.0678 × Proportion of people living below 50 percent of median income (%)
- 0.0672 × Employers, female (% of female employment) (modeled ILO estimate)
- 0.0115 × Compensation of employees (% of expense)
+ 0.0083 × Multilateral debt service (% of public and publicly guaranteed debt service)
+ 0.0187 × Teenage mothers (% of women ages 15-19 who have had children or are currently pregnant)
- 0.0089 × Births attended by skilled health staff (% of total)
+ 0.0167 × Pregnant women receiving prenatal care (%)
```

4.2 The Most Influential Indicators

4.2.1 Building Models

From Section 3.3, we extracted the top 15 most important features from the top 5 Principal Components. These features are then used as the independent variables for XG Boosting Regressor with the dependent variable being either: Multidimensional poverty headcount ratio (UNDP) (% of population) or Multidimensional poverty headcount ratio (World Bank) (% of population).

Once the predicted MPI values have been calculated, we assigned predicted MPI rankings to the countries associated with each predicted MPI value. Benchmarking is done against the cleaned_with_hdi.csv as outlined in Section 3.6.



(a) HDI vs Predicted MPI

(b) HDI vs Actual MPI

(c) Actual vs Predicted MPI

(d) Training vs Validating Loss

Figure 11: The results for 4.2: The Most Influential Indicators

4.2.2 Results and Findings

From Figures 10a and 10b, for countries with rankings around 400-500 in the top right corner in both figures, the poorest countries by MPIs, our model does relatively well since it captures the correct rankings for the poorest countries.
We fit an Extreme Gradient Boosting Regressor on the training dataset, validate against the validating dataset, and test on the testing dataset. The metric being used is mean squared absolute error to account for outliers. We have tuned the hyperparameters to get the optimal number of estimators, maximum depth, learning rate, and minimum child weight before making predictions.
The gap between training and validation loss is expected and normal in machine learning models. What's crucial is that both curves show substantial improvement from their starting points (around 0.7) and converge to much lower values. The validation loss decreases by over 80% from its initial value, demonstrating significant learning.
The early convergence (around 40-50 iterations) indicates efficient training without wasting computational resources. The stable validation curve from iterations 40-100 suggests the model has found a robust solution rather than memorizing the training data.
The Root Mean Squared Error (RMSE) between predictions of testing data and actual values is approximately 0.127

4.3 Targeted Poverty Alleviation

Using 3.5, we found a list of 53 countries to target with possible policies to alleviate poverty. Using PCA similar to what we did in 4.2, we determined certain metrics that needed to be focused on. Our PCA analysis produced several main features to improve, as shown in figure 12.

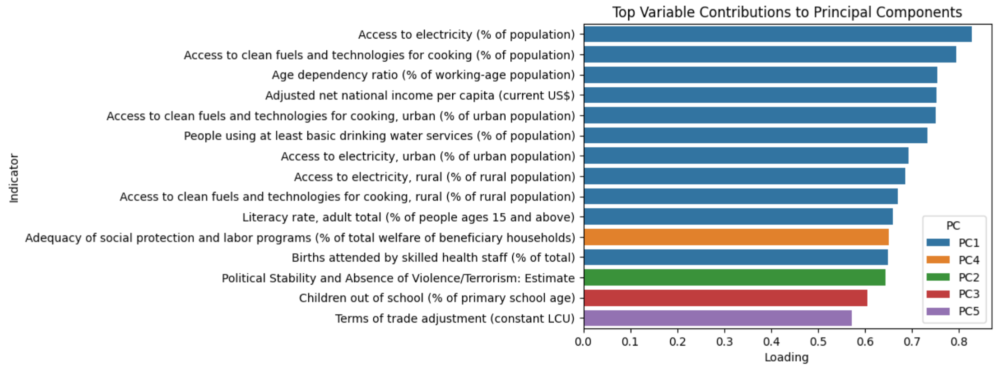


Figure 12: Top-contributing features to poverty in selected nations, chart

We can group these features into three main categories: access to services and infrastructure (including access to electricity, clean fuels and technologies for cooking, basic drinking water services, and skilled health staff for births), economic health (including net income per capita and terms of trade adjustment), and socio-political indicators (including age dependency ratio, literacy rate, children out of primary school, political stability, and adequacy of social protection and labour programs). Next, we will expand on policy suggestions.

4.3.1 Expanding Access to Services and Infrastructure

One of the most effective ways to combat poverty is to ensure that all individuals, especially in rural and underdeveloped areas, have access to reliable electricity. Governments and international organizations should prioritize electrification through affordable and sustainable means, such as renewable energy sources like solar power, wind turbines, and hydropower. Decentralized solutions, including solar microgrids, can be a cost-effective approach, particularly in areas that are not connected to the main power grid. Furthermore, these systems can be scaled to meet the needs of the population over time.

The relationship between access to electricity and poverty reduction is well-established. Electricity can improve quality of life by enabling people to access essential services, such as education, healthcare, and financial services. For example, electrification can increase study hours for students, improve healthcare outcomes through refrigerated medicines, and support entrepreneurship through energy access. According to Banerjee, Duflo, and Qian (2015), access to electricity leads to higher productivity, income generation, and employment opportunities, which directly impacts poverty levels.

As a case study, the World Bank's Lighting Africa initiative has successfully expanded electricity access to millions of people in Sub-Saharan Africa by providing affordable solar energy products. The initiative not only contributes to reducing poverty but also mitigates environmental damage by replacing kerosene lamps with clean, renewable energy sources.

4.3.2 Improving Economic Health

To promote economic growth and development, several key policies can be implemented. First, low-interest microfinance programs should be established to support small enterprises, alongside startup grants specifically targeting local businesses in sectors such as agriculture, technology, and manufacturing. Additionally, to attract foreign investment, tax incentives could be offered to companies investing in sustainable industries, while special economic zones (SEZs) with reduced regulatory barriers can further encourage investment. Like before, infrastructure development is also critical; funds should be allocated to improve essential services like roads, electricity, and internet connectivity to enhance trade and productivity. Moreover, partnerships with private firms for public infrastructure projects, through Public-Private Partnership (PPP) models, can provide efficient and innovative solutions for long-term infrastructure needs.

To strengthen economic growth and trade, several strategic policies should be pursued. First, fair trade agreements should be negotiated to improve the terms of trade for local producers, while reducing dependency on raw material exports by incentivizing local processing and manufacturing. In parallel, efforts should be made to diversify exports by investing in value-added industries such as textile production, agricultural processing, and technology services. Subsidies can also be provided to industries developing competitive export products. Furthermore, fostering a digital economy is essential; promoting digital literacy programs and expanding internet accessibility will support e-commerce and remote work opportunities. Additionally, establishing regulations to support fintech and online banking will enhance financial inclusion and empower more people to participate in the digital economy.

To strengthen economic stability and development, several targeted policy actions should be taken. Negotiating with international financial institutions for reduced debt repayment terms can alleviate fiscal pressures, while attracting grants from international organizations will support healthcare and infrastructure development. In addition, sustainable taxation policies should be implemented, including progressive taxation with incentives for sustainable businesses and measures to reduce tax evasion through stronger tax collection systems. Moreover, fostering partnerships with NGOs and the private sector is crucial; collaboration with non-profit organizations can enhance education, health, and entrepreneurship programs, while establishing corporate social responsibility (CSR) initiatives with multinational companies operating in the country will ensure that businesses contribute positively to social and environmental goals.

4.3.3 Socio-Political Indicators

To address the age dependency ratio, governments should implement family-friendly policies, including paid parental leave, subsidized childcare, and support for elder care. These initiatives can alleviate the economic burden that dependents (such as children and the elderly) place on the working-age population. Encouraging balanced population growth through these measures can help improve productivity, ultimately benefiting the nation's economic stability and long-term development.

Improving literacy rates requires increased government funding for primary and secondary education, particularly in rural and underserved areas. Expanding access to quality education, alongside investing in teacher training and resources, will directly impact literacy levels. A higher literacy rate contributes to a more skilled workforce, driving productivity and innovation, and reducing income inequality by ensuring that all citizens have access to basic educational opportunities.

To reduce the number of children out of primary school, policies should focus on providing free or subsidized primary education and addressing barriers such as transportation, child labor, and cultural practices that prevent children from attending school. Ensuring universal access to education is critical for human capital development, enabling future generations to contribute meaningfully to the economy. These efforts will also help break the cycle of poverty and promote social mobility for underserved communities.

Political stability is fundamental for sustained growth and development. Governments can enhance stability by strengthening democratic institutions, promoting transparency, and encouraging active citizen participation in political processes. Measures such as fair elections, protection of civil liberties, and effective governance mechanisms can foster trust in public institutions. A stable political environment attracts investment, reduces risks of conflict, and provides the foundation for a thriving, secure society.

To improve the adequacy of social protection and labor programs, governments should expand social safety nets, including unemployment benefits, disability support, and pension systems. These programs provide a crucial buffer against economic shocks and poverty, particularly for vulnerable populations. A comprehensive social protection system can also stimulate economic growth by promoting social stability and allowing citizens to engage more effectively in the labor market, knowing that their basic needs are safeguarded.

Promoting gender equality in education and workforce participation is essential for economic and social progress. Governments should create initiatives that encourage equal access to education and employment opportunities for women and girls, such as offering scholarships, mentorship programs, and workplace diversity incentives. By empowering women and ensuring their active participation in the workforce, economies can tap into a wider talent pool, boost productivity, and foster a more inclusive and equitable society.

Finally, strengthening labor market policies is vital to ensure the working-age population is prepared for the evolving job market. This can be achieved by implementing job creation programs, vocational training, and skills development initiatives. By equipping workers with the necessary skills and creating opportunities for employment, these policies can reduce unemployment and underemployment, ultimately improving the age dependency ratio by increasing the proportion of the population that is actively employed.

Fostering peace and security is a cornerstone of political stability. Governments should invest in conflict resolution, law enforcement, and the protection of human rights to ensure a peaceful environment conducive to development. A secure society allows for the effective implementation of economic policies and encourages both domestic and foreign investment, while reducing the likelihood of violence and instability that can hinder progress.

We notice that one factor unites all of these policy suggestions: these suggestions are all improvements to the institutions of a nation, which matches the conclusions driven by Acemoglu and Robinson's Nobel prize-winning work (2012) on what makes nations fail. This reinforces the undeniable truth that robust, inclusive institutions are the key to a nation's success and long-term prosperity.

5 Conclusion

In conclusion, this study underscores the critical need to move beyond traditional metrics like GDP in understanding and addressing the complexities of extreme poverty. By analyzing the Multidimensional Poverty Index (MPI) and leveraging advanced machine learning techniques such as XGBoost , we have developed a robust index that captures the multidimensional nature of deprivation more accurately than conventional measures. Our findings reveal that factors such as access to electricity, unemployment rates, national income per capita, and social safety nets are key contributors to poverty levels, particularly in countries with MPI values exceeding 0.15. These insights provide a clear roadmap for targeted policy interventions aimed at fostering sustainable development and improving the lives of the world's most vulnerable populations.

Through rigorous data cleaning, feature selection, and cross-validation with benchmarks like the Human Development Index (HDI), we ensured the reliability and relevance of our results. The creation of an index that aligns well with established indicators highlights the potential of data-driven approaches to inform evidence-based policymaking. Furthermore, our analysis emphasizes the importance of addressing systemic issues such as inadequate infrastructure, economic inequality, and limited access to essential services like healthcare and education.

Looking ahead, the global fight against poverty requires a paradigm shift toward more comprehensive and nuanced measures of human well-being. By adopting multidimensional frameworks like the one proposed in this study, national governments and international institutions can design and implement policies that not only reduce poverty but also promote long-term resilience and equity. As the world continues to grapple with persistent inequalities, this research serves as a call to action for stakeholders to prioritize innovative solutions that reflect the lived realities of those most affected by extreme poverty. Ultimately, our work demonstrates that progress is possible—but only if we are willing to look beyond outdated metrics and embrace new ways of measuring and addressing the challenges of our time.

The issues addressed in the report are important because they allow decision-makers to answer the following important questions

1. What key indicators that best capture different dimensions of poverty ?
2. Which indicators contribute most significantly to poverty levels ?
3. What policy interventions can be proposed to the most affected countries ?

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