

# International Aid Allocation

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## Unsupervised Learning on Country Data - Strategic Aid Allocation for HELP International

- Analysis of 167 countries
- \$10 million humanitarian fund allocation
- Machine Learning approach: K-Means Clustering



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# Problem Statement

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## **Objective**

HELP International needs to allocate \$10 million strategically to countries in greatest need.

## **Challenge**

How to identify priority countries objectively?

## **Approach**

Unsupervised learning to categorize countries based on socio-economic and health indicators.

# Dataset Overview

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## Source

<https://www.kaggle.com/datasets/rohan0301/unsupervised-learning-on-country-data/code>

## Scope

167 countries, 10 features, 9 development indicators

## Features

- **country:** 167 countries
- **child\_mort:** Child mortality rate (deaths per 1000 live births under age 5)
- **exports:** Exports as % of GDP per capita
- **health:** Health spending as % of GDP per capita
- **imports:** Imports as % of GDP per capita
- **income:** Net income per person (USD)
- **inflation:** Annual GDP growth rate (%)
- **life\_expec:** Life expectancy at birth (years)
- **total\_fer:** Fertility rate (children per woman)
- **gdpp:** GDP per capita (USD)

## Key Features

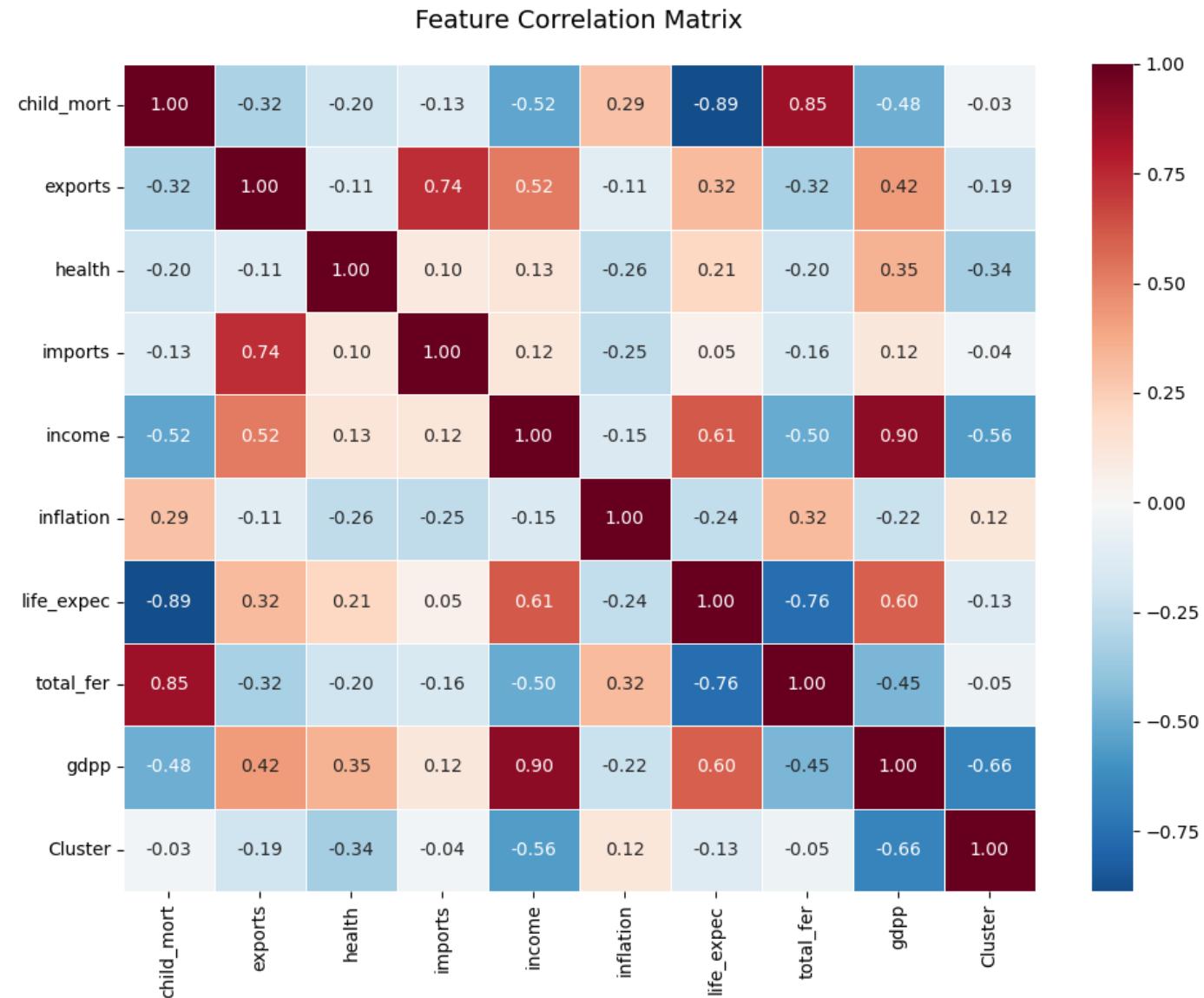
- **Health:** child\_mort, life\_expec, health spending
- **Economic:** income, gdpp, exports, imports
- **Demographic:** total\_fer, inflation

## Dataset Characteristics:

- No missing values (167/167 complete)
- All numerical features (except country name)
- Appropriate data types (float64)
- No duplicates

country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

# Correlation Analysis



## Strong Negative Correlations:

- child\_mort  $\leftrightarrow$  life\_expec ( $r = -0.89$ )
- total\_fer  $\leftrightarrow$  life\_expec ( $r = -0.76$ )

## Strong Positive Correlations:

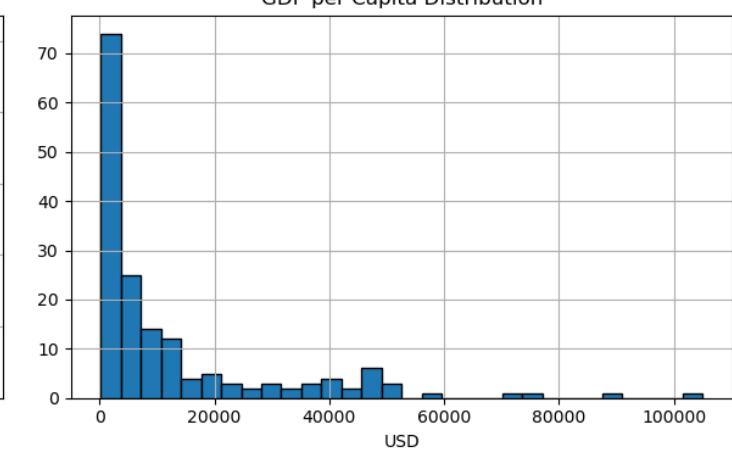
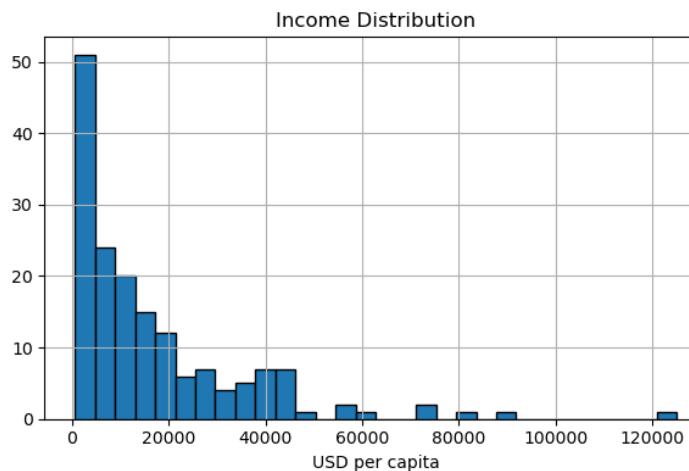
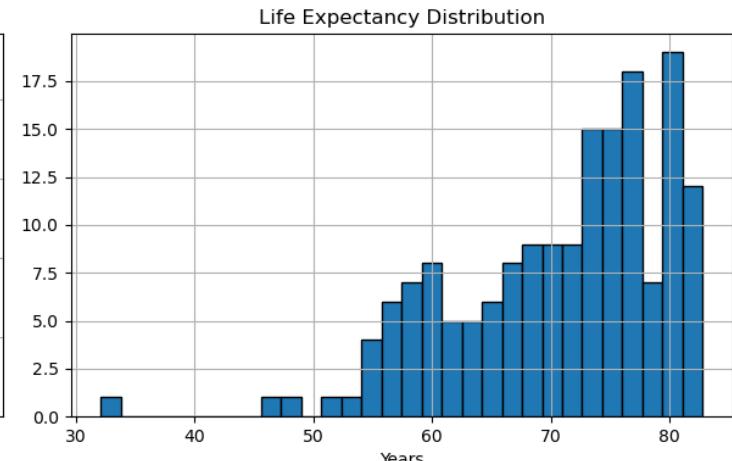
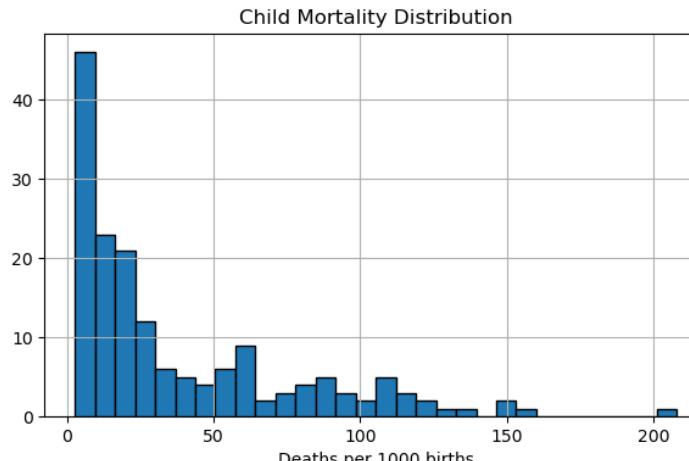
- income  $\leftrightarrow$  gdpp ( $r = 0.90$ )
- child\_mort  $\leftrightarrow$  total\_fer ( $r = 0.85$ )

These correlations suggest that child mortality, income, GDP, and life expectancy form the primary indicators of development status.

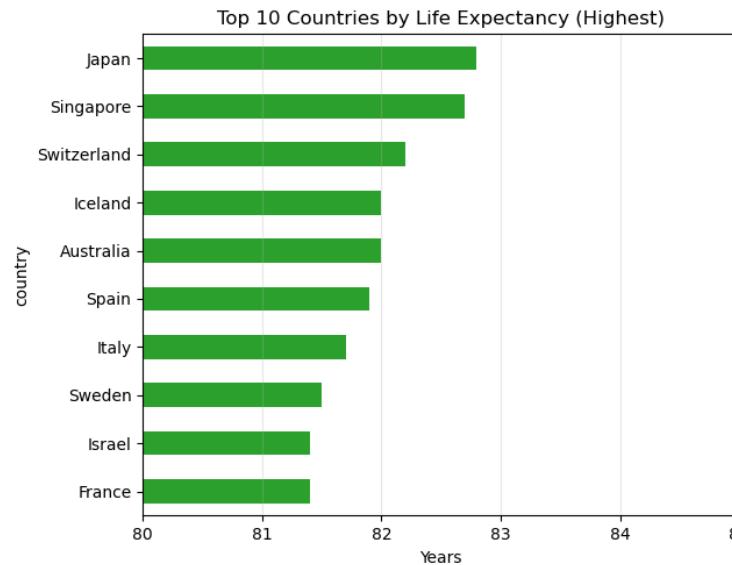
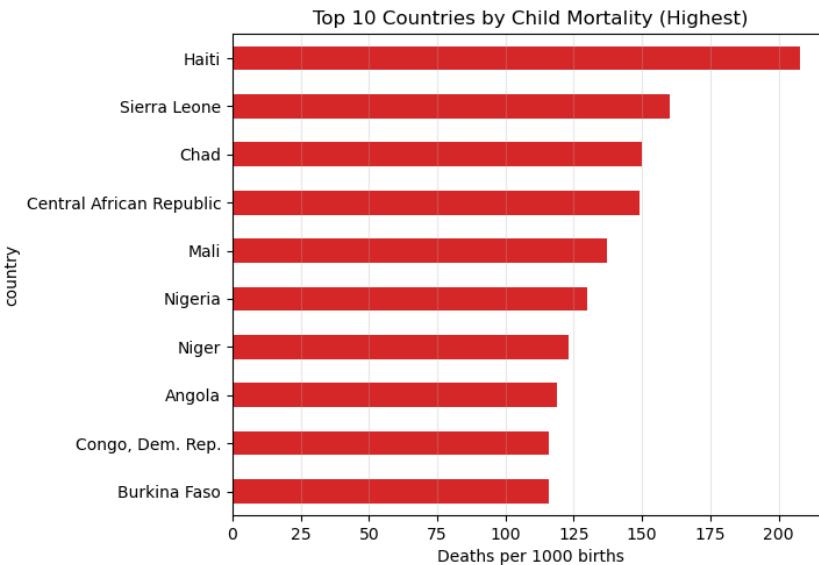
# Feature Distributions

## Key Observations:

- Right-skewed distributions for income and GDP
- Wealth concentration in fewer nations
- High variability across all indicators
- Clear need for clustering



# Extreme Values



## Child Mortality (highest)

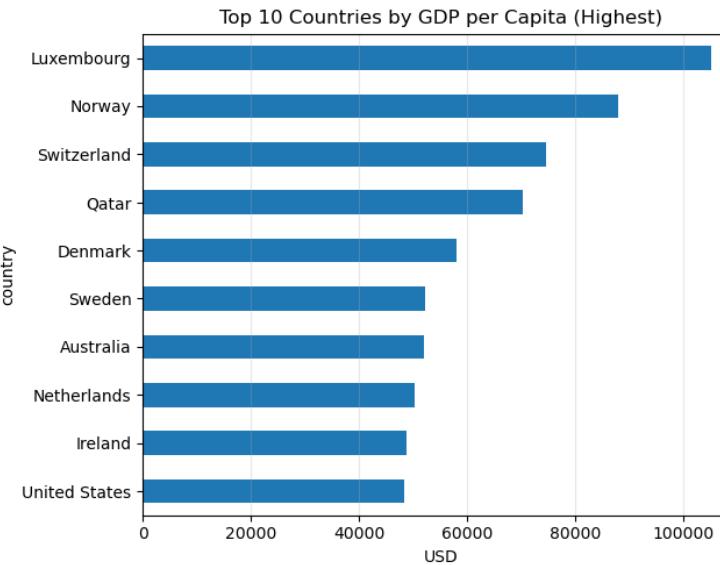
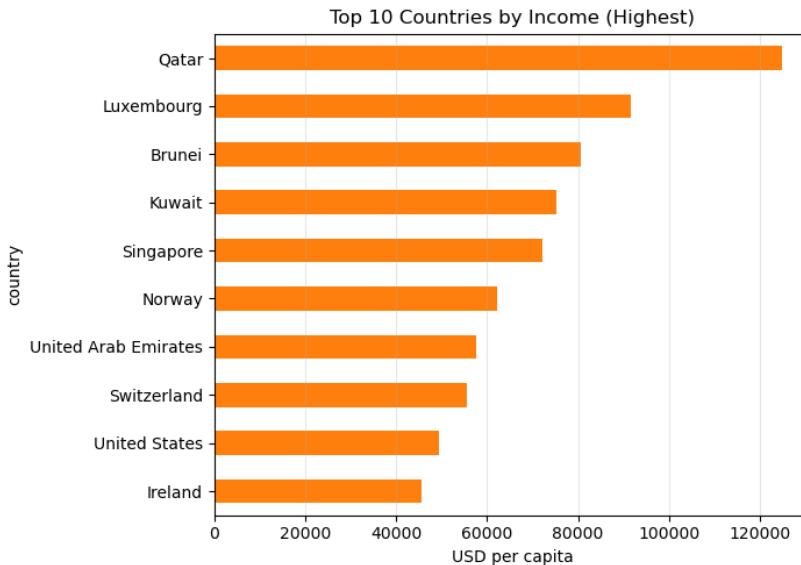
Average: >100 deaths per 1000 births

## Life Expectancy (highest)

Range: 81-83 years

## Income and GDP Disparities (highest)

Exceed \$40,000 per capita



# Data Preprocessing

**Standardization** required. Why?

- Features have vastly different scales (GDP: thousands, Inflation: percentages)
- Distance-based algorithms need equal feature contribution

## Method

StandardScaler (mean=0, std=1)

Before scaling

country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
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After scaling

country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
Afghanistan	1.291532	-1.138280	0.279088	-0.082455	-0.808245	0.157336	-1.619092	1.902882	-0.679180
Albania	-0.538949	-0.479658	-0.097016	0.070837	-0.375369	-0.312347	0.647866	-0.859973	-0.485623
Algeria	-0.272833	-0.099122	-0.966073	-0.641762	-0.220844	0.789274	0.670423	-0.038404	-0.465376
Angola	2.007808	0.775381	-1.448071	-0.165315	-0.585043	1.387054	-1.179234	2.128151	-0.516268
Antigua and Barbuda	-0.695634	0.160668	-0.286894	0.497568	0.101732	-0.601749	0.704258	-0.541946	-0.041817

# Methodology Overview

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## Clustering Approach:

### 1. K-Means (primary)

- Partitions data into spherical clusters
- Minimizes within-cluster variance
- Best for evenly distributed data

### 2. DBSCAN (comparison)

- Density-based clustering
- Identifies outliers automatically
- Tests for non-spherical patterns

### 3. Hierarchical (comparison)

- Shows nested relationships
- No random initialization
- Validates K-Means results

## Why Multiple Algorithms?

- Cross-validation of results
- Each algorithm has different assumptions
- Ensures clustering is not method-specific artifact

## Evaluation: Silhouette Score

- Measures cluster quality (cohesion + separation)
- Range: -1 to +1 (higher = better)
- Objective metric for comparing algorithms

# K-Means Algorithm

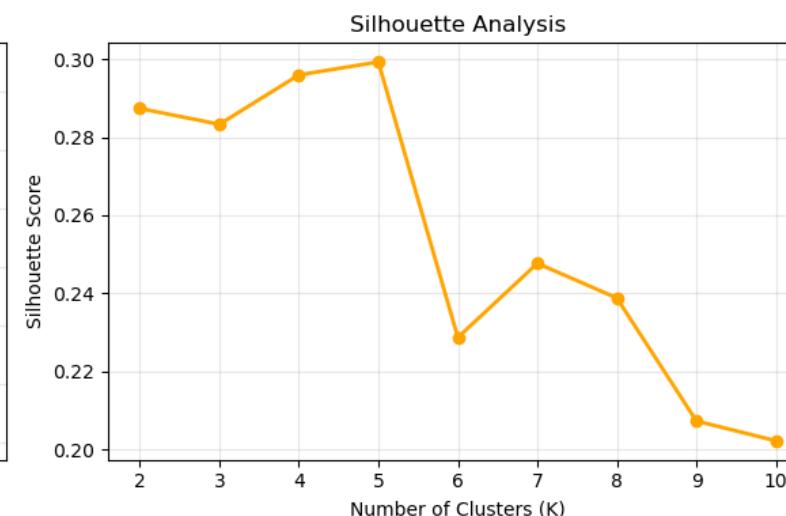
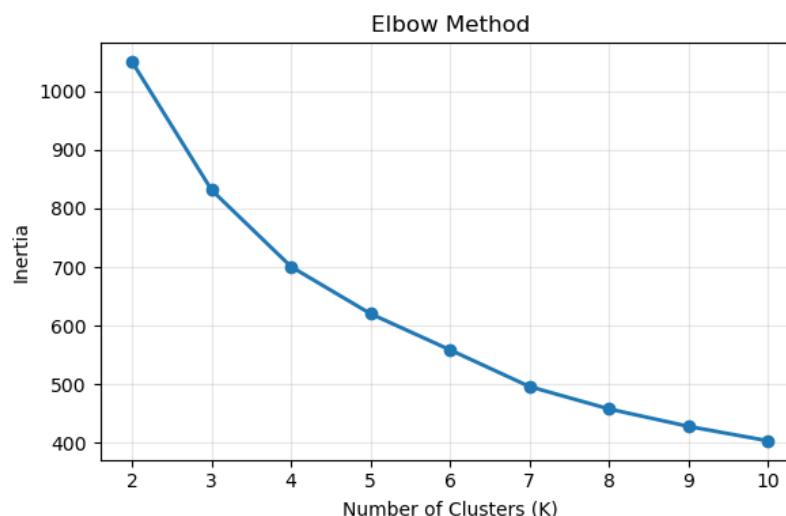
**Elbow Method:** Identify point of diminishing returns

**Silhouette Analysis:** Measure cluster separation quality

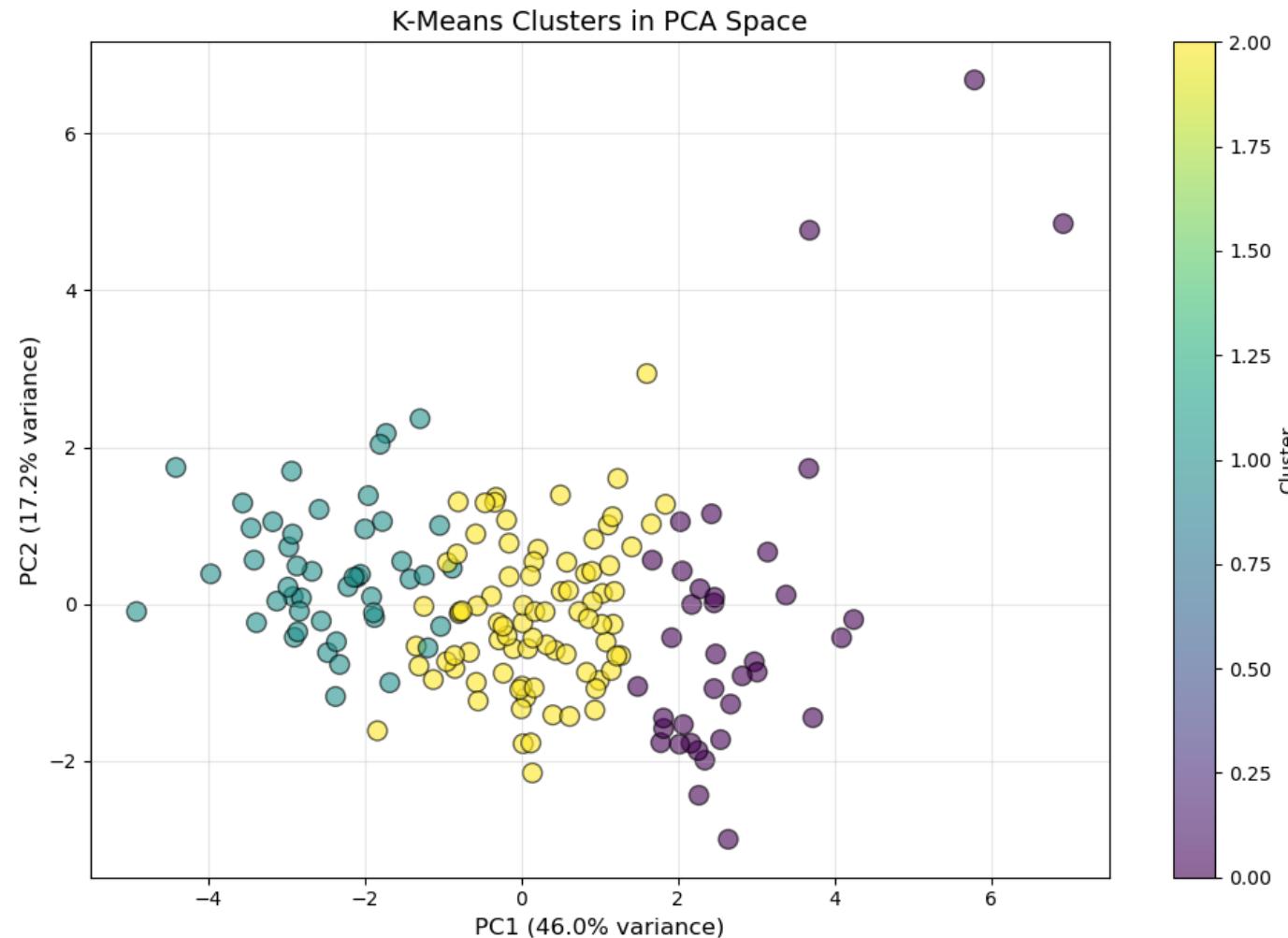
Scores obtained: K=5 (0.299), K=4 (0.296), K=3 (0.283)

**Chosen value:** K=3 for the following reasons:

- The difference between K=5 and K=3 is only 0.016 (5.3% improvement)
- Good cluster separation even with K=3
- K=3 provides clear, actionable categories: Developed, Developing, Underdeveloped
- Balance between granularity and simplicity



# PCA Visualization



## Purpose:

- Visual validation of cluster separation
- Confirm distinct country groupings

**Dimensionality Reduction:** 9D  $\rightarrow$  2D

**Variance Explained:** ~63% (PC1 + PC2)

**PC1:** Development gradient  
(underdeveloped  $\rightarrow$  developed)

**PC2:** Secondary variation  
(trade balance, resource distribution)

## Observation:

Clear separation between clusters  
validates K=3 choice

# Cluster Statistics

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Three distinct groups identified:

**Cluster 0 - Developed Nations:** Low child mortality (<10 per 1000), high life expectancy (>75 years), substantial income (>\$40,000), and high GDP. These nations are self-sufficient.

**Cluster 1 - Underdeveloped Nations:** Characterized by high child mortality (>80 per 1000), low life expectancy (<60 years), minimal income (<\$5,000), and low GDP. These countries require immediate humanitarian intervention.

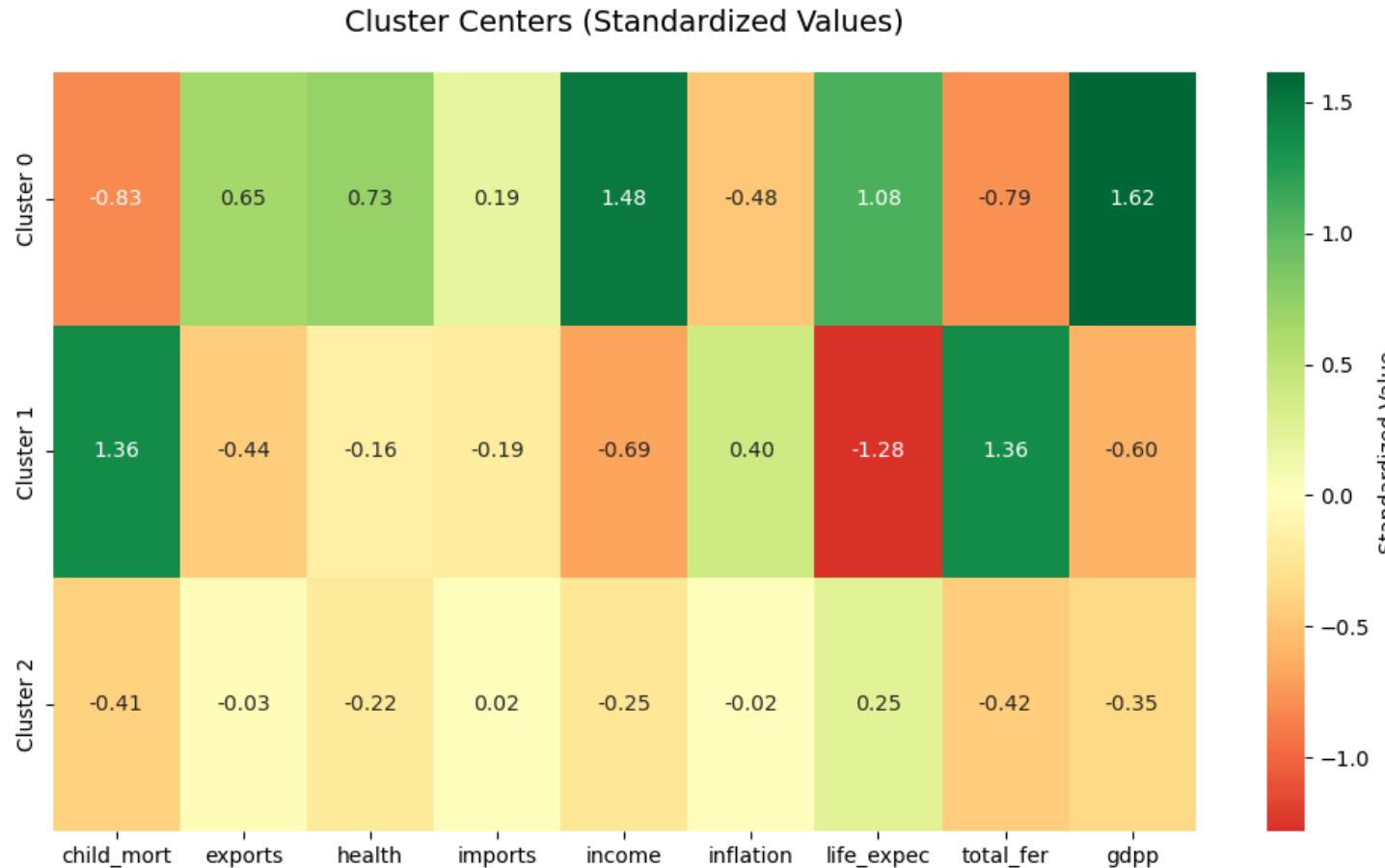
**Cluster 2 - Developing Nations:** Moderate indicators with child mortality between 20-80 per 1000, life expectancy 60-75 years, and GDP \$5,000-\$20,000. These countries are transitioning but need targeted support.

Cluster Profiles (Original Scale):						
Cluster	child_mort	life_expec	income	gdpp	health	total_fer
0	5.00	80.13	45672.22	42494.44	8.81	1.75
1	92.96	59.19	3942.40	1922.38	6.39	5.01
2	21.93	72.81	12305.60	6486.45	6.20	2.31

Cluster	n_countries
0	36
1	47
2	84

# Cluster Centers Heatmap



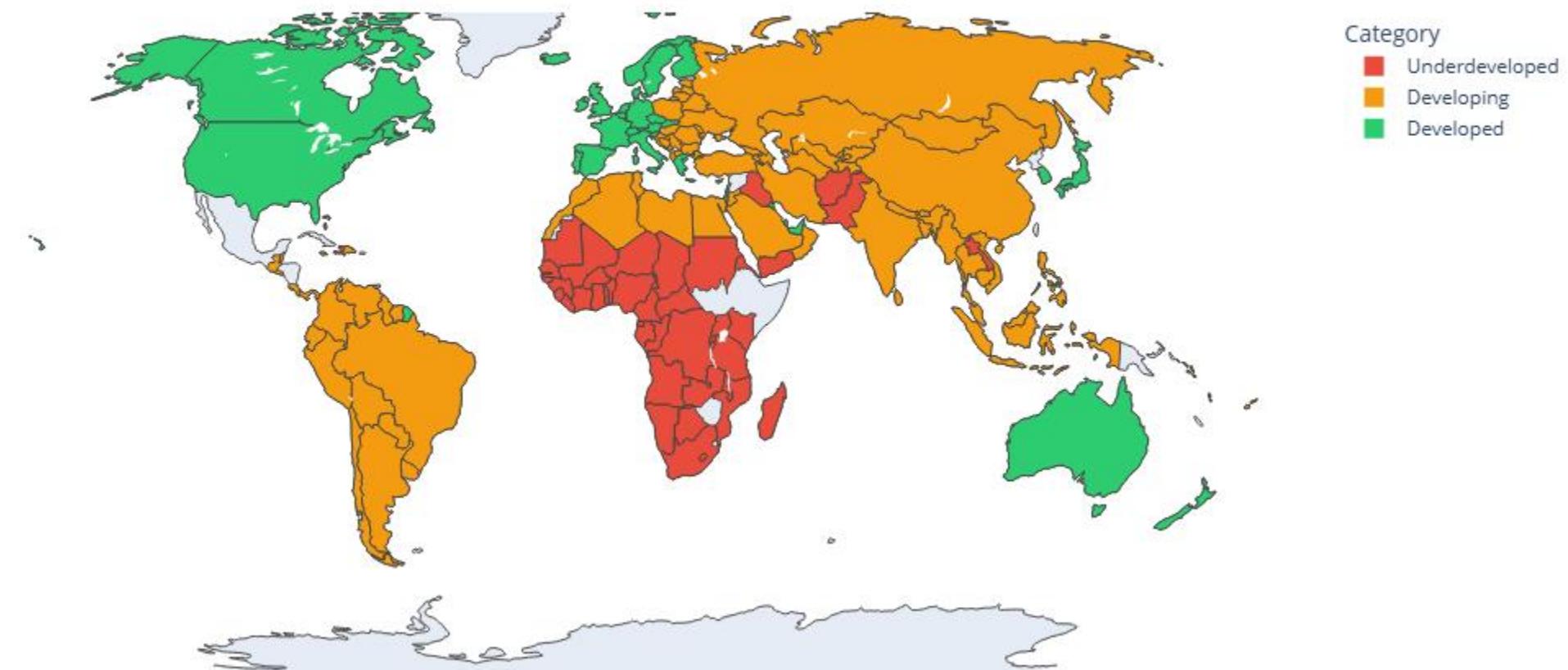
**Standardized Centroids of each cluster:**

- **Green:** Above-average values
- **Red:** Below-average values
- **White:** Near global mean

# Geographic Distribution

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Global Distribution of Country Development Clusters



# Priority Countries

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High-Need Cluster: 1

Total countries requiring aid: 47

Top 15 Priority Countries:

		Child Mort:	Life Exp:	GDP: \$
1.	Haiti	208.0	32.1	662
2.	Sierra Leone	160.0	55.0	399
3.	Chad	150.0	56.5	897
4.	Central African Republic	149.0	47.5	446
5.	Mali	137.0	59.5	708
6.	Nigeria	130.0	60.5	2,330
7.	Niger	123.0	58.8	348
8.	Angola	119.0	60.1	3,530
9.	Burkina Faso	116.0	57.9	575
10.	Congo, Dem. Rep.	116.0	57.5	334
11.	Guinea-Bissau	114.0	55.6	547
12.	Cote d'Ivoire	111.0	56.3	1,220
13.	Benin	111.0	61.8	758
14.	Equatorial Guinea	111.0	60.9	17,100
15.	Guinea	109.0	58.0	648

Ranked by child mortality rate (highest to lowest)

# Alternative Algorithm - DBSCAN

## Density-Based Clustering

**How it works:** Groups high-density regions, marks outliers

**Result:** Underperformed (Silhouette: varies)

## Why?

Country development follows a continuous gradient without clear density gaps. DBSCAN excels at finding isolated clusters (e.g., customer segments), but our data lacks these distinct separations. Result: either one massive cluster or excessive noise points.

**Business impact:** We need to classify ALL countries for aid allocation. DBSCAN's outlier detection leaves some countries unclassified, making it unsuitable for our purpose.

```
1 # DBSCAN with parameter search
2 best_score = -1
3 best_params = None
4
5 for eps in np.arange(2.0, 4.5, 0.5):
6     for min_samples in [4, 5, 6]:
7         dbscan = DBSCAN(eps=eps, min_samples=min_samples)
8         labels = dbscan.fit_predict(data_scaled)
9
10        n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
11        if n_clusters >= 2:
12            mask = labels != -1
13            if mask.sum() > 0:
14                score = silhouette_score(data_scaled[mask], labels[mask])
15                if score > best_score:
16                    best_score = score
17                    best_params = (eps, min_samples, n_clusters)
18
19 if best_params:
20     print(f"Best DBSCAN: eps={best_params[0]:.1f}, min_samples={best_params[1]}")
21     print(f"Clusters found: {best_params[2]}, Silhouette: {best_score:.3f}")
22     dbscan_score = best_score
23 else:
24     print("DBSCAN: No valid clustering found")
25     dbscan_score = -1.0
✓ 0.1s
DBSCAN: No valid clustering found
```

# Alternative Algorithm - Hierarchical

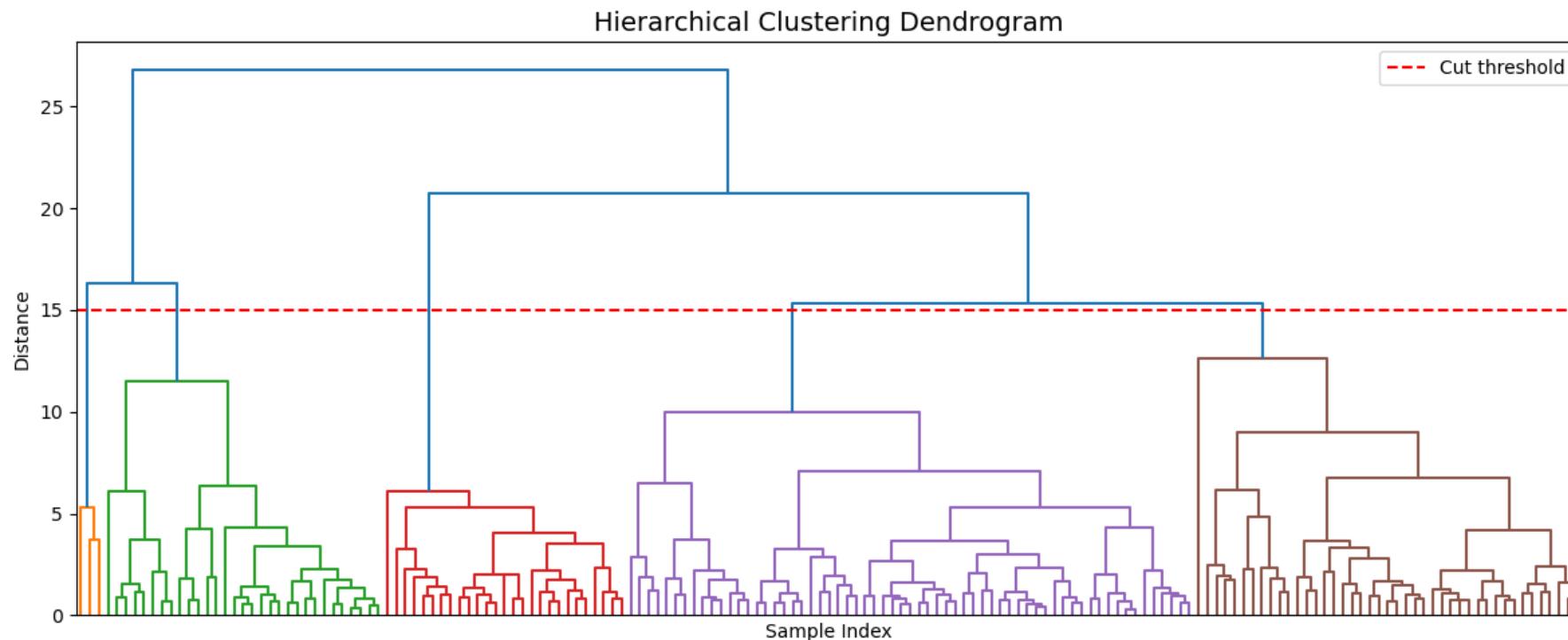
## Agglomerative Clustering

**How it works:** builds tree by merging similar clusters

**Result:** similar to K-Means (Silhouette: 0.246)

**Advantage:** shows nested relationships

**Limitation:** less practical for flat categorization



# Model Comparison

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**Model Selection:** K-Means is selected as the final model based on:

1. **Highest silhouette score** indicating well-separated clusters
2. **Complete country coverage** enabling comprehensive aid allocation
3. **Interpretable centroids** providing clear cluster definitions
4. **Computational efficiency** and reproducibility

**DBSCAN**'s lower performance suggests country development exists on a continuous spectrum rather than as distinct density-based groups.

**Hierarchical** clustering produces similar results but lacks explicit cluster centers.

Algorithm Performance Comparison:

Algorithm	Silhouette Score	N Clusters	Complete Coverage
K-Means	0.283296	3	Yes
Hierarchical	0.245630	3	Yes
DBSCAN	-1.000000	0	No

# Strategic Fund Allocation

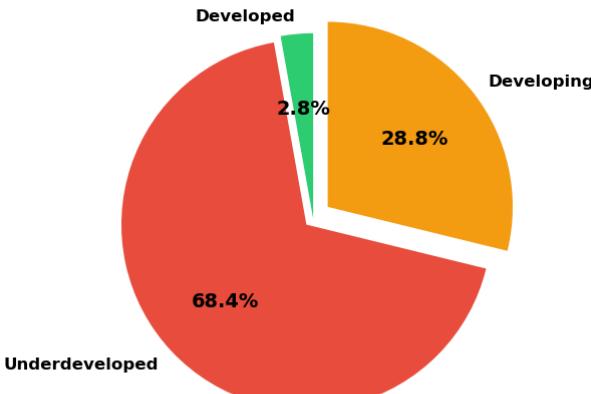
STRATEGIC FUND ALLOCATION - \$10,000,000							
Cluster	Category	Countries	Avg Child Mortality	Need Score	Allocation (\$)	Per Country (\$)	Percentage (%)
0	Developed	36	5.00	180.0	281635	7823	2.8
1	Underdeveloped	47	92.96	4369.0	6836107	145449	68.4
2	Developing	84	21.93	1842.0	2882258	34313	28.8

Total Allocated: \$10,000,000

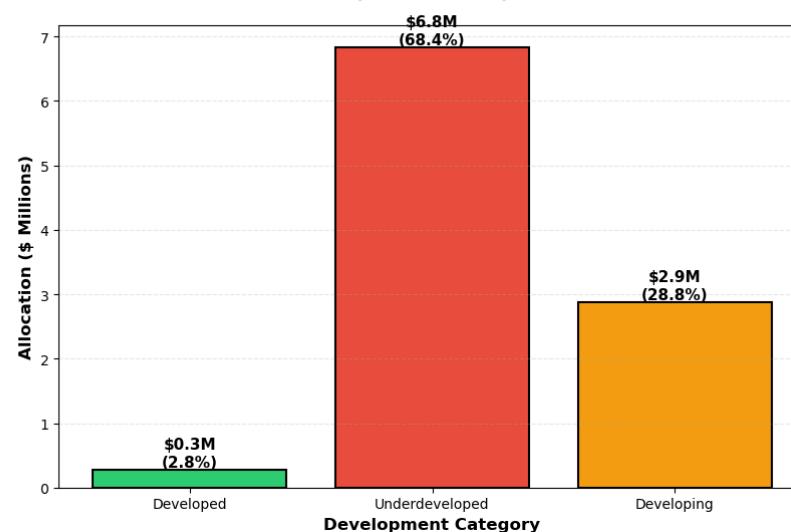
Allocation Strategy:

- Proportional to (Child Mortality Rate × Number of Countries)
- Ensures both severity and scale are considered
- Developed nations (Cluster 0) receive minimal/no funding

Budget Allocation by Development Category  
(\$10 Million Total)



Budget Allocation by Category  
(Millions USD)



# Conclusions

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## Key Findings

- **Three distinct development clusters** identified among 167 countries
- **High-need cluster** contains countries with child mortality rates exceeding 80 per 1000 births
- **Strong correlation** between economic indicators (income, GDP) and health outcomes (child mortality, life expectancy)
- **K-Means clustering** outperforms alternative algorithms for this dataset

## Limitations

- Analysis limited to socio-economic indicators; political stability and governance quality not considered
- Static dataset does not capture temporal changes
- Equal weighting of features may not reflect true importance for aid effectiveness
- Outliers within clusters may require individual assessment

## Conclusion

This unsupervised learning analysis successfully identified three distinct country development categories, enabling data-driven allocation of humanitarian aid. K-Means clustering with K=3 provides the optimal balance of statistical performance and practical interpretability. The results align with established development classifications and offer actionable insights for HELP International's strategic decision-making.

Future work should incorporate additional variables (political stability, corruption indices), explore temporal dynamics, and validate recommendations through cost-benefit analysis.

# Thank You!

Contact:

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Full Python notebook:

<https://github.com/mtvz42/International-Aid-Allocation/tree/main>