

Zakaria Chbani

A Master's Thesis

AGU 2021

PRIORITY REGIONS FOR
DEVELOPMENT ASSISTANCE FOR
HEALTH: AN EVIDENCE-BASED
APPROACH

A THESIS

SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL
ENGINEERING

AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE
OF ABDULLAH GUL UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF
MASTER OF SCIENCE

By

Zakaria Chbani

March 2021

PRIORITY REGIONS FOR DEVELOPMENT
ASSISTANCE FOR HEALTH: AN EVIDENCE-
BASED APPROACH

A THESIS

SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING
AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE OF
ABDULLAH GUL UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF
MASTER OF SCIENCE

By

Zakaria Chbani

March 2021

SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document have been obtained in accordance with the academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

Zakaria CHBANI

A handwritten signature in blue ink, appearing to be 'Zakaria Chbani', written in a cursive style.

REGULATORY COMPLIANCE

M.Sc. thesis titled “**PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH**” has been prepared in accordance with the Thesis Writing Guidelines of the Abdullah Gül University, Graduate School of Engineering & Science.

Prepared By

Zakaria CHBANI



Advisor

Assis. Prof. Muhammed SÜTÇÜ

Head of the Industrial Engineering Graduate Program

Prof. İbrahim AKGÜN

ACCEPTANCE AND APPROVAL

M.Sc. thesis titled “**PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH**” and prepared by Zakaria CHBANI has been accepted by the jury in the Industrial Engineering Graduate Program at Abdullah Gül University, Graduate School of Engineering & Science.

..... / / 2021

JURY:

Assis.Prof. Muhammed SÜTÇÜ :.....
Assis.Prof. Selçuk GÖREN :.....
Prof. Seçkin POLAT :.....

APPROVAL:

The acceptance of this M.Sc. thesis has been approved by the decision of the Abdullah Gül University, Graduate School of Engineering & Science, Executive Board dated / / and numbered

..... / /

Graduate School Dean

Prof. Hakan USTA

ABSTRACT

PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH

Zakaria CHBANI

MSc. in Industrial Engineering

Advisor: Assis. Prof. Muhammed SÜTÇÜ

March 2021

Eligibility and allocation criteria of development assistance for health have received much attention in the last years. Critical issues have been raised on the usage of GNI per capita (GNIpc) as a sole indicator for this task. The major critics emphasize the GNIpc overlooks the changes in characteristics of middle-income countries (MICs). These countries now have the highest proportion of poor people and disease burden, combined with significant inequalities. Various alternative frameworks have been suggested that tried to avoid the issues GNIpc failed to take into account. This thesis attempts to build on previous works and introduce a data-driven methodology of developing a framework that guides eligibility and aid allocation decisions. The framework combines health status measures (estimating the level of wellness and illness of a population) and measures of capacity of response to the disease burden. We use Disability Adjusted Life Years (DALYs) as a measure of health status. To determine the measures of capacity, the starting point was to assemble relevant indicators in the literature. Using these indicators, feature selection then allowed to choose a minimal set of discriminative ones. Finally, an aggregate of chosen indicators enables ranking countries by order of priority. Comparing the framework with GNIpc and other frameworks show its potential usefulness. It is better than most other frameworks in targeting countries with a high disease burden and populations in extreme poverty. Moreover, it integrates some concerns other frameworks failed to address.

Keywords: development assistance for health, aid eligibility, allocation criteria, feature selection, inequality

ÖZET

SAĞLIK İÇİN KALKINMA YARDIMINDA ÖNCELİKLİ BÖLGELER: KANITA DAYALI BİR YAKLAŞIM

Zakaria CHBANI

Yüksek Lisans. Endüstri Mühendisliği

Tez Danışmanı: Dr.Öğr.Üyesi Muhammed SÜTÇÜ

Mart 2021

Son yıllarda sağlık alanında kalkınma yardımlarının uygunluğu ve hangi kriterlere göre belirleneceği büyük ilgi görmektedir. Bu alanda yapılan çalışmalarda, kişi başına Gayri Safi Milli Hasıla (GSMH)'nin tek indikatör olarak kullanılmasından dolayı kritik sorunlar ortaya çıkmıştır. Bu konudaki en kritik eleştiri, kişi başına düşen GSMH'nin orta gelirli ülkelerin analizlerinde çok büyük sapmalara sebep olmasıdır. Bu ülkeler önemli dezavantajlara sahip olmakla birlikte en yüksek yoksulluk ve hastalık yüküne sahip ülkelerdir. Kişi başına GSMH'nin hesaba katmadığı bazı alternatif çalışmalar literatürde önerilmiştir. Bu tez, önceki çalışmaları temel alarak, kalkınma yardımlarının uygunluğu ve tahsis kararlarında kullanılan verilere dayalı bir metodoloji sunmaktadır. Bu metodoloji, sağlık durumu ölçütlerini (bir nüfusun sağlık ve hastalık düzeyini tahmin eden) ve hastalık yüküne tepki kapasitesi ölçütlerini birleştirir. Bu çalışmada Yeti Yitimine Ayarlanmış Yaşam Yılı sağlık durumunun bir ölçüsü olarak kullanılmaktadır. Kapasite ölçülerini belirlemek için öncelikli olarak literatürde kullanılan ilgili göstergeleri kapsayan bir gösterge kümesi oluşturulmuştur. Bu gösterge kümesini kullanarak, öznelik seçimi metodu ile daha küçük ve tanımlayıcı gösterge alt kümesi oluşturulmuştur. Son olarak, seçilen göstergelerin modelde kullanılması ile ülkeler için öncelik sıralamayı elde edilmiştir. Önerilen metodoloji, kişi başına GSMH ve önceki çalışmalarla karşılaştırılarak, önerilen metodolojinin üstünlükleri gösterilmiştir. Önerilen yeni hesaplama metodolojisi “hastalık yükü yüksek ülkeleri” ve “aşırı yoksulluk içindeki nüfusu” hedefleyen diğer birçok metodolojiden daha iyidir. Ayrıca, önerilen metodoloji önceki çalışmalarda ele alınmayan yada çözülemeyen bazı endişeleri de kapsamaktadır.

Anahtar Kelimeler: sağlık için kalkınma yardımı, yardım uygunluğu, tahsis kriterleri, öznelik seçimi, eşitsizlik

Acknowledgements

First and foremost, I would like to thank my advisor Dr. Muhammed Sütçü for his support throughout the period of my master studies, without which none of what is to follow would have been possible.

I want to thank my thesis committee members: Dr. Seçkin Polat and Dr. Selçuk Gören, for their support and patience.

Also special thanks to AGU IE academic staff who have taught me several courses and provided their support in various forms toward the accomplishment of my studies and development of my career afterward.

My thanks go out to all the students and professors in AGU whom I met and learned from.

Table of Contents

| | |
|---|-----------|
| 1. INTRODUCTION | 9 |
| 2. RELATED WORKS..... | 13 |
| 3. METHODOLOGY | 19 |
| 3.1 MEASURING THE BURDEN OF DISEASE..... | 19 |
| 3.2 MEASURING THE CAPACITY OF RESPONSE | 22 |
| 3.3 DATA | 23 |
| 3.3.1 <i>Data sources</i> | 23 |
| 3.3.2 <i>Data cleaning</i> | 23 |
| 3.4 GROUPING OF COUNTRIES | 26 |
| 3.5 FEATURE SELECTION..... | 28 |
| 4. RESULTS | 39 |
| 4.1 CLUSTERS OF COUNTRIES..... | 39 |
| 4.2 SELECTED INDICATORS | 41 |
| 4.3 COUNTRIES SCORES..... | 43 |
| 4.4 FRAMEWORK EVALUATION..... | 46 |
| 4.5 THE FRAMEWORK AT A SUBNATIONAL LEVEL | 49 |
| 4.5.1 <i>Brazil</i> | 49 |
| 4.5.2 <i>Mexico</i> | 50 |
| 4.5.3 <i>The United States</i> | 52 |
| 5. CONCLUSIONS AND FUTURE PROSPECTS | 54 |
| 5.1 CONCLUSIONS..... | 54 |
| 5.2 SOCIETAL IMPACT AND CONTRIBUTION TO GLOBAL SUSTAINABILITY | 55 |
| 5.3 FUTURE PROSPECTS | 56 |
| 6. BIBLIOGRAPHY | 57 |
| 7. APPENDIX 1: FEATURE SELECTION RESULTS..... | 63 |
| 8. APPENDIX 2: INDICATORS VALUES AND RANKS COMPARISON | 64 |

List of Figures

| | |
|--|----|
| Figure 1.1: Development assistance for health by recipient region, 1990–2019..... | 11 |
| Figure 2.1: Health spending, population, and disability-adjusted life years by World bank income group, 2017 | 14 |
| Figure 3.1: DALY rates from communicable, neonatal, maternal & nutritional diseases, 2016 | 20 |
| Figure 3.2: DALY rates from non-communicable diseases (NCDs), 2016..... | 21 |
| Figure 3.3: DALY rates from injuries, 2016 | 21 |
| Figure 3.4: Flowchart of wrapper-based vs filter-based feature selection..... | 29 |
| Figure 3.5: SVM optimal hyperplane | 33 |
| Figure 3.6: Random Forest algorithm..... | 34 |
| Figure 3.7: Multilayer perceptron for earthquake magnitude classification..... | 35 |
| Figure 3.8: Ensemble feature selection approach | 38 |
| Figure 4.1: Sankey diagram for clustering – HDI correspondance | 39 |
| Figure 4.2: Domestic general government health expenditure per capita, PPP (current international \$), 2016..... | 42 |
| Figure 4.3: People using at least basic drinking water services (% of people), 2016..... | 42 |
| Figure 4.4: People using at least basic sanitation services (% of people), 2016 | 43 |
| Figure 4.5: Mean years of schooling, 2016 | 43 |
| Figure 4.6: Scatter plot describing the relationship between GNI countries’ rank and ranks resulting from our framework..... | 45 |
| Figure 4.7: Scatter plot describing the relationship between HDI countries’ rank and ranks resulting from our framework..... | 46 |
| Figure 4.8: Spearman correlation of frameworks with fundamental indicators | 47 |
| Figure 4.9: Treemap of rank change while moving from GNIpc to our framework for populations in extreme poverty..... | 48 |
| Figure 4.10: Brazilian states scores with our framework | 49 |
| Figure 4.11: Mexican states scores with our framework | 51 |
| Figure 4.12: Scores of states of the United States with our framework | 52 |

List of Tables

| | |
|--|----|
| Table 1.1: Total health spending and health spending by source, 2017 | 12 |
| Table 2.1: Frameworks proposed by the Equitable Access Initiative..... | 15 |
| Table 3.1: List of indicators | 24 |
| Table 3.2: Clustering algorithms comparison..... | 27 |
| Table 3.3: Classification experiment results..... | 31 |
| Table 4.1: Resulting clusters and centers..... | 40 |
| Table 4.2: Countries rank change when moving from original weights (rank1) to equal weights (rank2) | 44 |
| Table 4.3: Changes for countries with high populations of people in extreme poverty with performing frameworks when moving from GNIpc..... | 48 |
| Table 4.4: Spearman correlation of frameworks with key indicators for Brazilian states.... | 50 |
| Table 4.5: Spearman correlation of frameworks with key indicators for Mexican states | 51 |
| Table 4.6: Spearman correlation of frameworks with key indicators for states of the United States | 52 |

List of Abbreviations

| | |
|----------|---|
| AdaBoost | Adaptive Boosting |
| ANN | Artificial Neural Networks |
| CART | Classification and Regression Trees |
| CLARA | Clustering Large Applications |
| DAC | Development Assistance Committee |
| DAH | Development Assistance for Health |
| DALY | Disability Adjusted Life Year |
| DALYR_AS | Age-standardized Disability Adjusted Life Year Rate |
| DIANA | Divisive Analysis |
| DTP | Diphtheria, Tetanus, Pertussis |
| EAI | Equitable Access Initiative |
| GDP | Gross Domestic Product |
| GHEpc | Government health expenditure per capita |
| GNIpc | Gross National Income per capita |
| HALE | Health Adjusted Life Expectancy |
| HDI | Human Development Index |
| HIV | Human Immunodeficiency Virus |
| HIVR | Prevalence of HIV |
| IHME | Institute of Health Metrics and Evaluation |
| ILE | Inequality in Life Expectancy |
| Income40 | Income share held by bottom 40% |
| IQ | Intelligence Quotient |
| kNN | k-Nearest Neighbors |
| LE | Life Expectancy |
| MAR | Missing at Random |
| MCAR | Missing Completely at Random |
| MICs | Middle-Income Countries |
| MDGs | Millennium Development Goals |

| | |
|--------|--|
| MMR | Maternal Mortality Ratio |
| MPL | Multi-Layer Perceptron |
| NB | Naive Bayes |
| NCD | Non-Communicable Disease |
| NIPH | Norwegian Institute of Public Health |
| OOPP | Out-Of-Pocket Payments |
| PAM | Partition Around Medoids |
| PPP | Purchasing Power Parity |
| RF | Random Forest |
| SBA | Skilled Birth Attendance rate |
| SDGs | Sustainable Development Goals |
| SOM | Self-Organizing Map |
| SVM | Support Vector Machine |
| TBR | Tuberculosis Prevalence Rate |
| THEpc | Total Health Expenditure per capita |
| U5MR | Under-five mortality rate |
| U60MR | Under-sixty mortality rate |
| UNAIDS | United Nations Programme on HIV/AIDS |
| UNDP | United Nations Development Programme |
| UNFPA | United Nations Population Fund |
| UNICEF | United Nations International Children's Emergency Fund |
| WHO | World Health Organization |
| YLD | Years Lost due to Disability |
| YLL | Years of Life Lost |

Chapter 1

Introduction

A swift transformation in human health has marked the last 150 years. People in most parts of the world live longer and healthier lives [1]. The enjoyment of the highest attainable health standard is now considered a fundamental right for everyone [2].

Nevertheless, the importance of health cannot be taken separately. Apart from being a right, health is also a means for economic, social, and political development [3,4]. Poor population health conditions among working-age adults reduce labor supply and productivity, thus decreasing economic growth and government revenues. Besides, healthcare consumes resources that could instead be directed to other sectors. The HIV/AIDS pandemic is a pertinent example of these effects. Across Africa, the pandemic has reduced average national growth rates by 2-4% a year [5]. Conversely, improved population health has favorable economic outcomes. A review of historical studies [6] deduced that health improvements in terms of decline in adult mortality in low-income and middle-income countries were responsible for around 11% of economic growth during the period 1960-2000.

Poor health can also deteriorate educational outcomes. Children suffering from infectious diseases, disabilities, and malnutrition, are disposed to reduced school enrollment, increased absenteeism, retardation in cognitive and physical development, and poor school performance. A common health problem found in school-age children in low-income countries is worms. They infect around 169 million children, and due to this, each child loses some 3.75 IQ points. Iron-deficiency anemia is another health condition that touches some 300 million children, costing them around 6 IQ points per child. Hunger is still a significant obstacle to education; some 66 million children go to school hungry. The above health conditions alone translate into an equivalent loss of between 200 million and 500 million days of school in low-income countries each year [7,8].

The impact of health goes beyond economic growth and education. The current COVID-19 pandemic is a perceptible example of the extent to which population health can

affect the political and social stability of countries, international relations, and many other spheres.

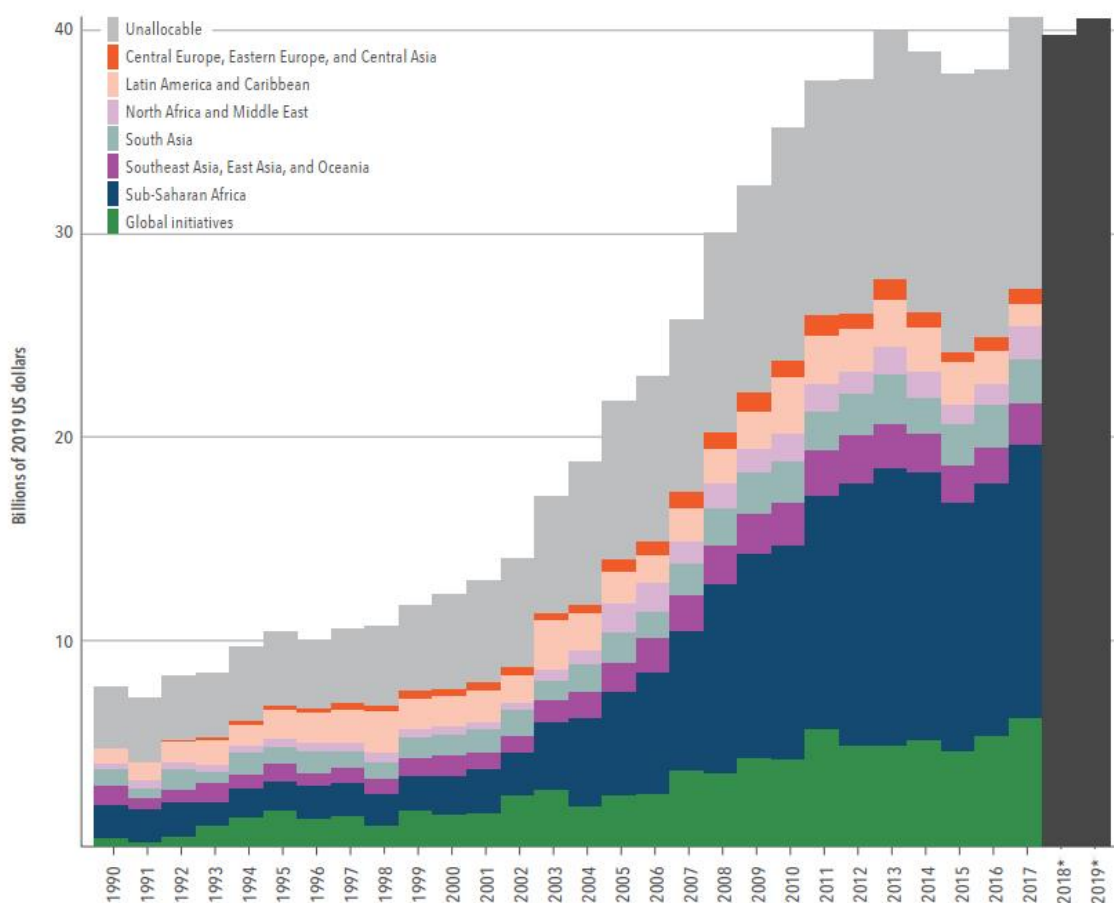
Given its importance, health was central to the Millennium Development Goals (MDGs), an unprecedented commitment by the world's leaders to address the most basic forms of injustice and inequality in our world. Health was expressed in three of the eight MDGs with six targets. Despite a remarkable acceleration towards health targets in many countries since the adoption of the MDGs, the world fell far from meeting health goals by the 2015 deadline [9,10].

The Sustainable Development Goals (SDGs) came in 2015 to tackle the unfinished agenda of the MDGs and extend global agreement and cooperation to other dimensions. Health represented by Goal 3: Ensure healthy lives and promote well-being for all at all ages, acquired more attention with 13 ambitious targets that cover various health matters [11,12]. With ten years left to finish the 2030 SDGs agenda, additional efforts are needed from the global community to reach the defined targets. Many countries may miss several health targets, but more financial resources, cooperation, and better policies could make reaching the targets possible [13]. One instrument that could help accelerate the progress is development assistance for health (DAH). An increase in development assistance and amelioration of its management will support poor countries in providing health services and sustaining their health reform efforts [14].

In 2017, development assistance for health totaled around \$41 billion, a considerable increase from 2010, when it was \$35 billion (15.40% percentage change). It made triple the value of \$14 billion in 2000 (the year when the Millennium Development Goals (MDGs) were adopted) (Figure 1.1 [15]). DAH accounted for about 27.7% of 2017 health spending in low-income countries. Out-of-pocket spending is, however, more prevailing for health financing in lower-middle-income countries (55.0% of 2017 health spending). Besides, government and prepaid private spending are more relied upon in upper-middle-income and high-income countries (66.9% and 86.0%, respectively) [15] (Table 1.1).

Nevertheless, while their humanitarian peers provide assistance based on assessed needs, development aid actors' decisions are subject to multiple or conflicting objectives [16]. Donor self-interest is a factor that adds to recipient needs and merit for all bilateral donors [17-19]. In a prominent work on this topic in the literature, Alesina and Dollar

contend that foreign aid is more governed by political, historical, and strategic determinants than by the recipients' needs. Hoeffler and Outram [19] investigated aid patterns for the five principal members of the Development Assistance Committee (DAC) over the period 1980-2004. The DAC provided 95% of bilateral aid over the given period. The five countries' shares in the total DAC contribution are 24% for the US, Japan (24%), France (12%), Germany (12%), and the UK (5%). All five donors provide more aid to trade partners. The UK and the US, in particular, devote more aid to recipients who vote with them at the UN. France and the UK provide substantial foreign aid to their ex-colonies. Only the UK and Japan provide more aid to countries with higher democracy scores. Moreover, Germany, France, and Japan give more to countries with fewer human rights abuses. Whereas, the US seems to place no importance on recipient merit.



*2018 and 2019 estimates are preliminary

Figure 1.1: Development assistance for health by recipient region, 1990–2019

Table 1.1: Total health spending and health spending by source, 2017 [15]

| | Health spending per person (purchasing power parity) | Health spending per gross domestic product | Government health spending per total health spending | Prepaid private spending per total health spending | Out-of-pocket spending per total health spending | Development assistance for health per total health spending |
|---------------------|--|--|--|--|--|---|
| Total | 1,418 | 9.7% | 60.7% | 20.6% | 18.5% | 0.50% |
| High-income | 5,825 | 12.2% | 62.8% | 23.2% | 14.0% | 0.00% |
| Upper-middle-income | 1,053 | 5.7% | 56.5% | 10.4% | 32.9% | 0.20% |
| Lower-middle-income | 289 | 3.9% | 32.7% | 8.9% | 55.0% | 3.50% |
| Low-income | 119 | 5.3% | 25.0% | 5.9% | 41.4% | 27.7% |

Chapter 1 represented a concise introduction to the importance of health and development assistance for health and to the biases that can intervene with its allocation, mainly for bilateral donors. Chapter 2 discusses the Gross National Income per capita (GNIpc) as a “more objective” criterion for aid eligibility and allocation adopted mainly by major multilateral donors, its limitations, and the frameworks proposed as an alternative to GNIpc. The chapter also states the problem our study is dealing with and our project’s objectives. Chapter 3 shows the methodology developed in this research to construct a new framework that we contend it represents a fairer alternative to GNIpc. Chapter 4 reveals our analysis results and presents a comparison of the framework with other frameworks in the literature. Our conclusions are drawn in the last chapter.

Chapter 2

Related works

Major multilateral development aid entities rely mainly on Gross National Income per capita (GNIpc) for determination of aid eligibility and allocation [20]. This indicator has shown, however, severe limitations. Health is a multidimensional issue, and while GNIpc measures average national accounts, it does not capture the health needs and well-being of people, nor the existing inequalities [21]. Besides, GNIpc penalizes middle-income countries (MICs) which currently have the highest proportion of poor people (mainly due to higher inequality in income distribution) [22]. Coupled with this is the current transition in disease burden in middle-income countries with the rise of non-communicable diseases (NCDs) [23,24]. MICs are not only exposed to receiving less aid than reflected by their needs but are indeed at risk of losing eligibility as they attain a GNIpc that excludes them from receiving assistance. Over a dozen of MICs are likely to surpass eligibility thresholds in the few coming years. These countries are on average in weaker macroeconomic conditions, with more vulnerable health systems, and with higher poverty and inequality than the group of countries that graduated previously [25] (Figure 2.1). These limitations raise an urgent question as to whether GNIpc should continue to dictate decisions about eligibility and allocation of development assistance for health.

The Equitable Access Initiative (EAI) [26] launched in 2015 was a groundbreaking effort in research for alternatives to GNIpc. Nine multilateral actors were behind the initiative: Gavi, the Global Fund, UNAIDS, UNDP, UNFPA, UNICEF, Unitaid, the World Bank and WHO, together with high-level experts. The conveners of the initiative assigned the task of developing potential alternative frameworks to four expert academic teams representing: The University of Oxford, the Institute of Health Metrics and Evaluation (University of Washington), the University of Sheffield/Imperial College, and the Norwegian Institute of Public Health (NIPH). The final report of each team can be accessed from [27]. The methods and findings of the NIPH were summarized in [28].

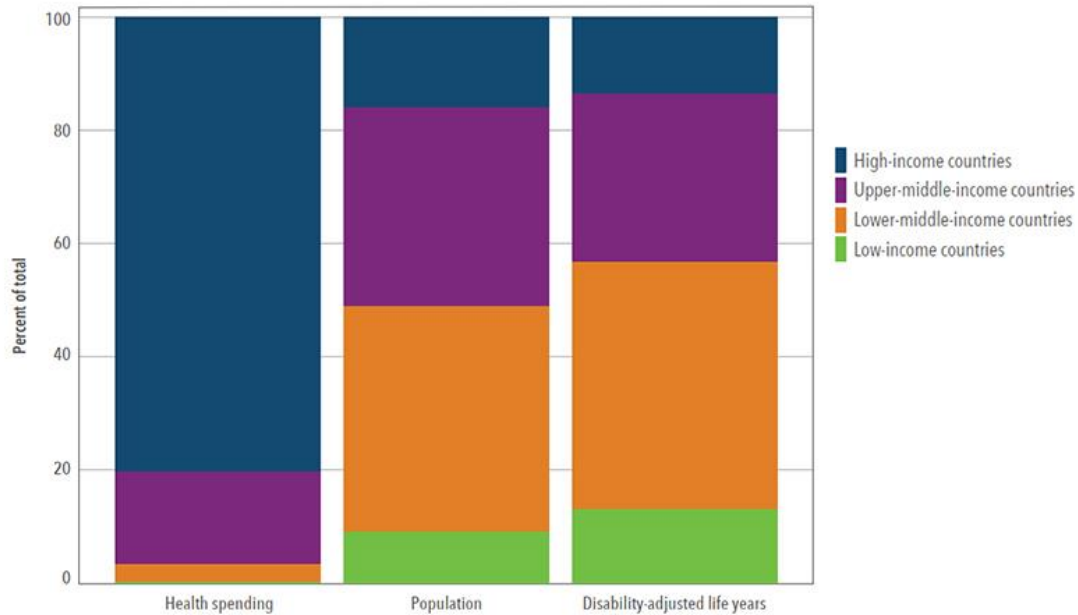


Figure 2.1: Health spending, population, and disability-adjusted life years by World bank income group, 2017 [15]

The teams agreed that a multi-criteria framework that moves beyond income levels by considering health needs, inequality in income, as well as domestic capacity and policies, should inform external health financing decisions. Furthermore, the teams proposed that a continuous arrangement framework should be used rather than discrete groupings of countries that make a country ineligible for support once it surpasses a specific GNI per capita threshold.

Nevertheless, works of the teams resulted in broadly different frameworks. The Norwegian Institute of Public Health examined 27 distinct multi-aggregate measures (e.g., average of normalized GNIpc and Life expectancy). The University of Oxford proposed five frameworks (e.g., GNI adjusted with Gini index: $GNIpc \cdot (1 - Gini)$). The team representing the University of Sheffield/Imperial College introduced three composite indices. Whereas, the Institute of Health Metrics and Evaluation approach handled health goals distinctively by measuring the gap between resources needed to reach a specific goal, a country's government expected spending, and a country's potential government spending (Table 2.1).

Table 2.1: Frameworks proposed by the Equitable Access Initiative

| Team | Frameworks | Missing * |
|--|---|-----------|
| Oxford University | GNI adjustment with GINI index: $GNIpc(1 - Gini)$ | 69 |
| | GNI adjustment with Income share of bottom 40%: $GNIpc(1 - Income40)$ | 69 |
| | GNI adjustment with Disability-Adjusted Life Years: $GNIpc(1 - DALY)$ | 9 |
| | GNI adjustment with Health Adjusted Life Expectancy: $GNIpc*HALE$ | 8 |
| | GNI adjustment with Strict Index (proposed by Sheffield): $GNIpc*Strict\ index$ | 11 |
| IHME | Gap between resources need (N) and government's expected spending (ES) | - |
| | Gap between resources need (N) and a country's potential government spending relative to peers (PS) | - |
| NIPH | Average of normalized $GNIpc$ and Under-five mortality rate (U5MR) | 6 |
| | Average of normalized $GNIpc$ and Under-sixty mortality rate (U60MR) | 9 |
| | Average of normalized $GNIpc$ and Life expectancy (LE) | 8 |
| | Average of normalized $GNIpc$ and Healthy life expectancy (HALE) | 8 |
| | Average of normalized $GNIpc$ and Disability-adjusted life year rate (DALYR) | 9 |
| | Average of normalized $GNIpc$ and Age-standardized disability-adjusted life year rate (DALYR_AS) | 9 |
| | Average of normalized $GNIpc$ and Debt service (% of GNI) (Debt) | 70 |
| | Average of normalized $GNIpc$ and Tax revenue (% of GDP) (Tax) | 44 |
| | Average of normalized $GNIpc$ and Total health expenditure per capita (THEpc) | 8 |
| | Average of normalized $GNIpc$ and Government health expenditure per capita (GHEpc) | 5 |
| | Average of normalized $GNIpc$ and Absolute improvement in under-five mortality rate (cU5MR) | 5 |
| Average of normalized $GNIpc$ and Relative improvement in under-five mortality rate (rcU5MR) | 5 | |

| | | |
|---|--|----|
| NIPP | Average of normalized GNIpc and Absolute improvement in skilled birth attendance rate (cSBA) | 75 |
| | Average of normalized GNIpc and Relative improvement in skilled birth attendance rate (rcSBA) | 75 |
| | Average of normalized GNIpc and Maternal mortality ratio (per 100,000 live births) (MMR) | 10 |
| | Average of normalized GNIpc and Prevalence of HIV (% of population ages 15-49) (HIVR) | 56 |
| | Average of normalized GNIpc and Tuberculosis prevalence rate (per 100,000 population) (TBR) | 5 |
| | Average of normalized GNIpc and Inequality in life expectancy (ILE) | 5 |
| | Average of normalized GNIpc and Gini index for income (Gini) | 69 |
| | Average of normalized GNIpc and Income share held by bottom 40% (% of total income) (Income40) | 69 |
| | Average of normalized GNIpc and Skilled birth attendance rate (% of total deliveries) (SBA) | 27 |
| | Average of normalized GNIpc and Coverage of three doses of vaccine against diphtheria, tetanus, and pertussis (% of children aged 12–23 months) (DTP3) | 6 |
| | Out-of-pocket payments (% of total health expenditure) (OOPP) | 7 |
| | LE, ILE and SBA with equal weights (MCF_EQ LE baseline) | 18 |
| | LE, ILE and SBA with weights informed by online survey (MCF_SU LE baseline) | 18 |
| | GNI, ILE and SBA with equal weights (MCF_EQ GNI baseline) | 22 |
| GNI, ILE and SBA with weights informed by online survey (MCF_SU GNI baseline) | 22 | |
| Sheffield univ. & Imp. College of London | <p>Strict health development index: $\sqrt{a * b}$</p> $a = \frac{\sqrt{ind1 * ind2}}{\max(\text{geo mean}(1,2))}$ <p>ind1: min-max normalization of skilled birth attendance (%) ind2: min-max normalization of inverse of total DALYs lost b: min-max normalization of pooled health expenditure (% total health expenditure)</p> | 7 |

- To constitute an aggregate of indicators as simple as possible for decision-makers with available and timely indicators.

This study responds to a growing debate in the literature about delivering development assistance for health. Even though we do not guarantee the resulting framework is worth considering as a better alternative to GNIpc or other frameworks, we consider our main contribution to state of the art is to offer a new perspective that may boost the discussion on this topic.

GCPRIS

Chapter 3

Methodology

Our approach focuses on incorporating two principal dimensions for assessing a country's need for development assistance for health: the burden of disease, and the capacity of response.

3.1 Measuring the burden of disease

To measure the burden of disease, we choose the Disability Adjusted Life Years (DALYs). The advantage of this measure manifests in its combination of information about mortality and morbidity in a single number. "Conceptually, one DALY is the equivalent of losing one year in good health because of either premature death or disease or disability" [29]. "The sum of these DALYs across the population, or the burden of disease, can be thought of as a measurement of the gap between current health status and an ideal health situation where the entire population lives to a late age, free of disease and disability.

DALYs for a disease or health condition are calculated as the sum of the Years of Life Lost (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) for people living with the health condition or its consequences" [30]:

$$\text{DALY} = \text{YLL} + \text{YLD}$$

$$\text{YLL} = N \times L$$

where:

N = number of deaths

L = standard life expectancy at age of death in years

$$\text{YLD} = P \times DW$$

where:

P = number of prevalent cases

DW = disability weight

The DALYs are provided for three categories: non-communicable diseases (NCDs); communicable, maternal, neonatal, and nutritional diseases; and injuries [29].

In our analysis, we consider DALYs rates related only to communicable and non-communicable diseases. Injuries, on the other hand, cover not only accidents, but also natural disasters and violence, including interpersonal violence, conflict, and terrorism [29]. These incidents are primarily subject to humanitarian and not development assistance.

DALYs' crude rates will favor countries having large old populations that naturally have a high contribution to the disease burden due to ageing-related diseases and high mortality. For this reason, we use age-standardized DALYs rates that take into consideration demographic structure differences between populations.

Figures 3.1 to 3.3 present age-standardized DALYs per 100,000 people for the three categories of DALYs across countries for the year 2016. There is a notably high burden of communicable diseases in Sub-Saharan Africa and South Asia. Rates for non-communicable diseases and injuries are more scattered and prevalent in more developed regions as well. Western Europe, Australia, Japan, and Canada, in contrast, have lower rates for the three categories.

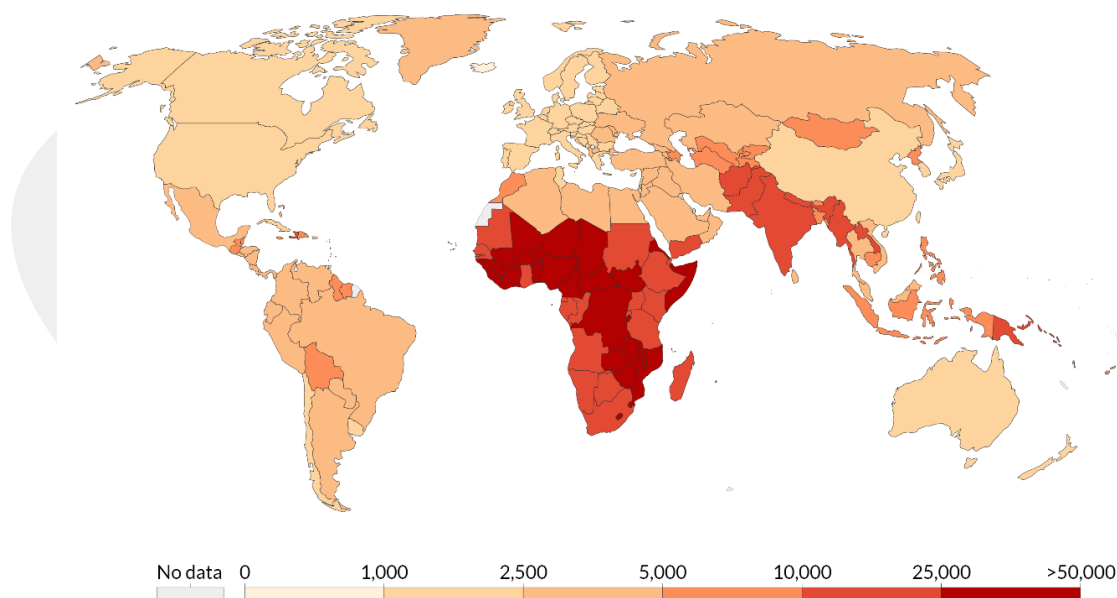


Figure 3.1: DALY rates from communicable, neonatal, maternal & nutritional diseases, 2016

Source: IHME, Global Burden of Disease [31].

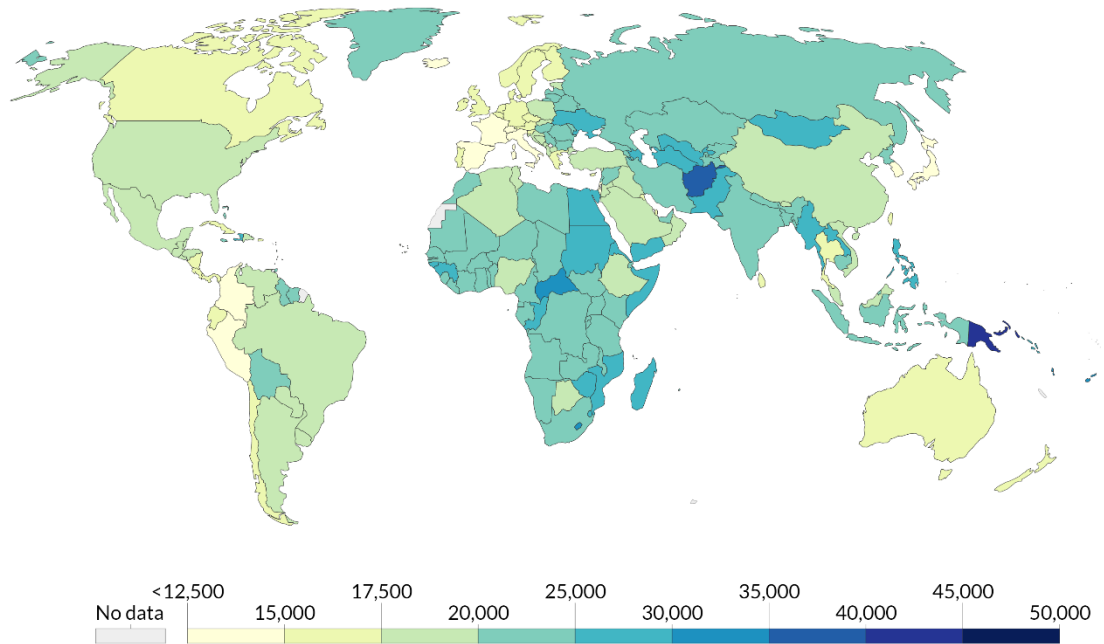


Figure 3.2: DALY rates from non-communicable diseases (NCDs), 2016

Source: IHME, Global Burden of Disease [31].

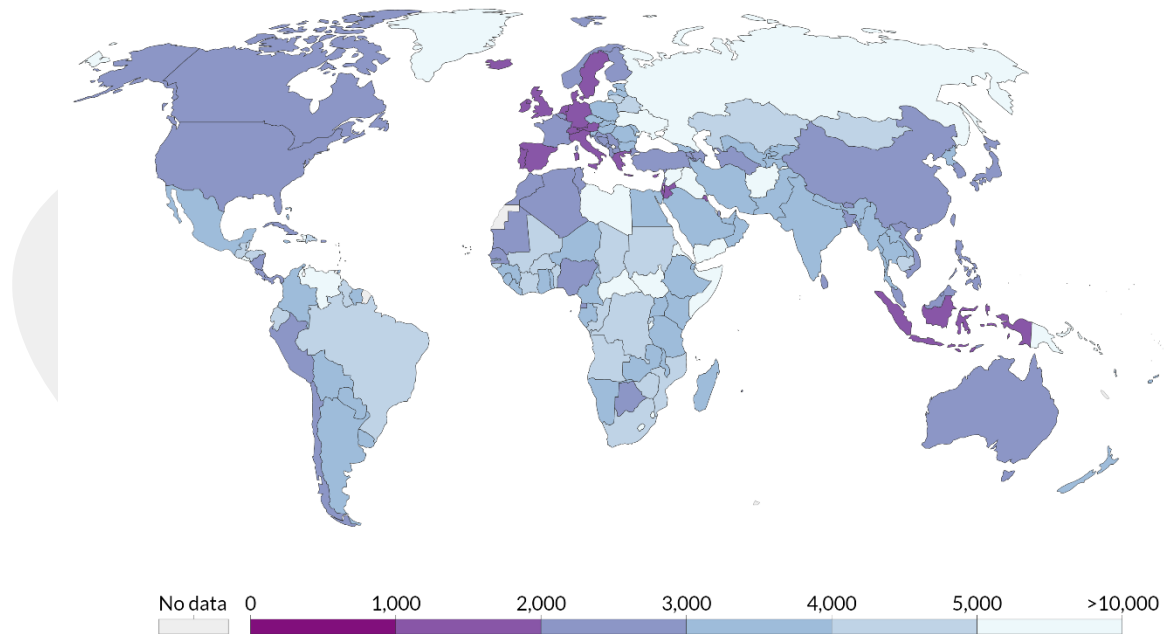


Figure 3.3: DALY rates from injuries, 2016

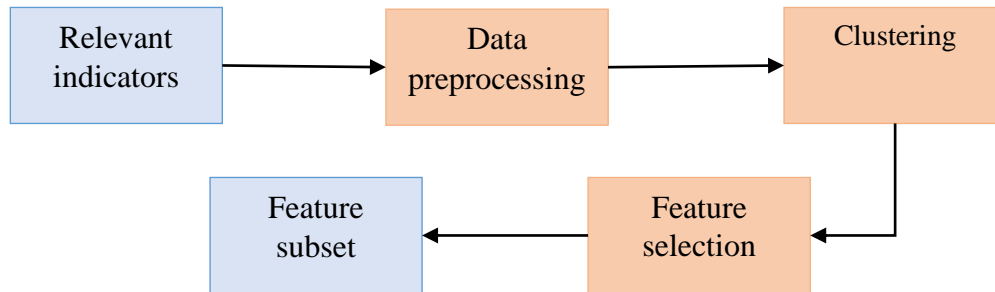
Source: IHME, Global Burden of Disease [31].

3.2 Measuring the capacity of response

A large number of factors are studied in the literature. Including all these factors for making a decision is not feasible. A limited number of factors that prove to be relevant can only be incorporated. For this purpose, we start with a broad set of indicators that gained interest in the literature, including ones the panel of experts of the Equitable Access Initiative has employed. Table 3.1 lists the chosen indicators and sources proving their relevance. We then go on an analysis to determine a small subset of these features to integrate into our framework.

Together with the burden of disease and the capacity of response dimensions, we count for the dynamic nature of the burden of disease by including three indicators for the incidence of three major health threats: HIV, tuberculosis, and malaria (see Table 3.1). The three indicators are also included in the search for the feature subset.

The search for a feature subset is carried as below, extended details of each step are given in the following parts:



We preprocess data of the initial indicators to improve their quality, then normalize the indicators' values. This task is necessary so that we can obtain high-quality clustering of countries. We cluster the countries using all the indicators so that we have countries with closer values for different indicators at the same cluster. For instance, in one of the clusters, we may have countries with the best levels for different health dimensions, and in another cluster, countries with the worst values for different indicators. The resulting clusters allow us to assign group labels that will constitute a new characteristic variable of countries instances. These labels will guide feature selection to find a small feature subset that conserves, to the best possible, the grouping of countries the clustering led to. An indicator

that is part of an optimal subset is an indicator that has useful information about the countries grouping. Finally, as we will see later, feature selection generates many and not one optimal subset. We make use of this in assigning weights to the indicators that we will include in the final aggregate used to calculate the countries' scores. These scores will serve to rank the countries by order of priority. By following this approach, we will be able to include all the indicators implicitly while using only a limited number of them in our calculations.

3.3 Data

3.3.1 Data sources

We use four main sources of quantitative data. Data were mainly extracted from the World Bank development data [32]. Data related to the burden of disease were derived from the Global Burden of Disease datasets [31]. While data regarding the Human Development were obtained from [33] and [34].

3.3.2 Data cleaning




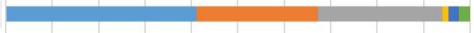
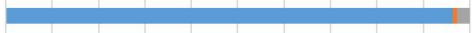



Not all countries and indicators have complete data. For this reason, we use the year 2016 as a baseline, as it is the most recent year with less missing values, and impute the missing values using data for the ten last available years (2008-17). The Little's MCAR test shows that data are missing at random (MAR).

For an indicator with missing values, we proceed as the following:

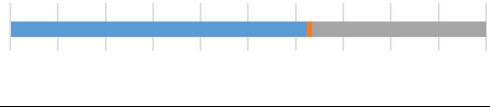
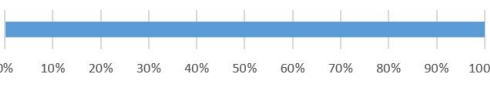
- We take complete cases for the ten years, delete the values for the baseline year (2016), build several models on each time series to predict the value for the year 2016 (linear regression, exponential smoothing with linear, multiplicative, and without trend). The method with the least sum of error for all complete cases is chosen to fill the missing values for the other cases of the given indicator.
- If there are no data points enough for interpolation or extrapolation, we use the same values as the nearest years as long as the values are from the three nearest years.
- If there is no data point for particular countries or data date to more than three years, the value is left missing.

The proportion of values for each imputation method are presented in Table 3.1. After imputation, the indicators are scaled using a min-max normalization so that they are in the same [0,1] range.

Table 3.1: List of indicators

| Indicator | Sources for relevance | Median | Data completeness |
|---|--|--------|--|
| Births attended by skilled health staff (% of total) | SDG 3.1.2, MDG 5.2, [35], NIPH, Sheffield | 97.97 |  |
| Current health expenditure per capita, PPP (current international \$) | SDG 1.a, [35], NIPH | 767.77 |  |
| Domestic general government health expenditure per capita, PPP (current international \$) | SDG 1.a.2, [35], NIPH | 373.11 |  |
| GINI index (World Bank estimate) | SDG 10.1, MDG 1.A, NIPH, Oxford | 36.70 |  |
| GNI per capita, PPP (current international \$) | SDG 8.1, HDI, MDG 1.B, NIPH, Oxford, Sheffield | 12150 |  |
| Hospital beds (per 1,000 people) | SDG 3.8.1, [35] | 2.8 |  |
| Immunization, DPT (% of children ages 12-23 months) | SDG 3.b.1, [35], NIPH, [36] | 93.5 |  |
| Incidence of HIV (per 1,000 uninfected population ages 15-49) | SDG 3.3.1, MDG 6.1, [35], NIPH | 0.2 |  |

| | | | |
|---|--|-------|--|
| Incidence of malaria (per 1,000 population at risk) ¹ | SDG 3.3.3, MDG 6.6, [35] | 0 | |
| Incidence of tuberculosis (per 100,000 people) | SDG 3.3.2, MDG 6.9, [35], NIPH | 48.5 | |
| Income share held by lowest 40% | SDG 10.1.1, MDG 1.A, NIPH, Oxford | 18.27 | |
| Nurses and midwives (per 1,000 people) | SDG 3.c.1, [35,36] | 2.91 | |
| Out-of-pocket expenditure (% of current health expenditure) | SDG 3.8.2, [35], NIPH, Sheffield, [36] | 31.17 | |
| People using at least basic drinking water services (% of population) | SDG 1.4.1, SDG 6.1, MDG 7.8, [35] | 95.61 | |
| People using at least basic sanitation services (% of population) | SDG 1.4.1 & 6.2, MDG 7.9, [35,36] | 88.73 | |
| Physicians (per 1,000 people) | SDG 3.c.1, [35,36] | 1.41 | |
| Poverty gap at \$1.90 a day (2011 PPP) (%) | SDG 1.1, MDG 1.A | 0.5 | |
| Poverty headcount ratio at \$1.90 a day (2011 PPP) (% of population) | SDG 1.1.1, MDG 1.A | 1.4 | |
| Tax revenue (% of GDP) | SDG 17.1.2, NIPH, Sheffield | 16.25 | |

| | | | |
|---------------------------------|-------------------------------------|------|--|
| Total debt service (% of GNI) | SDG 17.4, MDG 8.12, NIPH, Sheffield | 3.57 |  |
| Mean years of schooling (years) | SDG 4.1 & 4.3, MDG 2, HDI | 8.9 |  |

■ 2016 value ■ Interpolated/Extrapolated ■ Not imputed ■ 2015 or 2017 value ■ 2014 value ■ 2013 value

¹ Missing values were turned to zero value as they correspond to countries outside malaria prevalence regions.

NIPH: Norwegian Institute of Public Health report; Oxford: University of Oxford report; Sheffield: University of Sheffield/Imperial College report.

3.4 Grouping of countries

The indicators listed previously may all be considered relevant. We may not tell if an indicator proposed by an expert is better than one nominated by another expert. Conversely, considering all these indicators, we can be more confident that we covered most of the essential dimensions of the problem. A clustering of countries using these indicators may be an appropriate depiction for the grouping of countries we want, given that countries that have close values for different indicators are likely to be in the same cluster. Then, feature selection comes to find a small set of indicators that conveys much the same that grouping.

Even after imputation, we still have missing data. So, we go for clustering using the Batch k-means as it allows performing clustering with incomplete data. “The k-means algorithm is a simple iterative method to partition a given dataset into a user-specified number of clusters, k” [37]. The k-means procedure is summarized in Algorithm 3.1 [38].

For being more assured using k-means, we do a comparison experiment: We fill the remaining missing data using 3-NN (k-nearest neighbors with k=3), then evaluate k-means and other clustering algorithms for compactness, separation, and connectedness with 4 clusters and 5 clusters. The algorithms comprised in the experiment are k-means, DIANA, PAM, Model-based clustering, SOM, and CLARA. The validation measures are Dunn index [39], Silhouette Width [40], and Connectivity [41]. Higher values for Dunn index and Silhouette Width are preferred, while lower values for Connectivity are favored.

Algorithm 3.1: The k-means algorithm

Input:

- k: the number of clusters,
- D: a data set containing n objects.

Output: A set of k clusters.

Method:

- (1) arbitrarily choose k objects from D as the initial cluster centers;
- (2) repeat
- (3) (re)assign each object to the cluster to which the object is closer based on the mean value of the objects in the cluster;
- (4) update the cluster means, that is, calculate the mean value of the objects for each cluster;
- (5) until no change;

K-means topped the rank for Silhouette and connectivity measures, while DIANA scored the highest value for Dunn Index. Meanwhile, Model-based clustering was the worst. With k-means, a grouping of 4 gives better values for the three measures than a grouping of 5 (Table 3.2). Besides, a clustering of 4 allows the comparison with the Human Development Index (HDI) groups, for which we expect considerable correspondence as the HDI holds strong support as a measure of the overall development of a country. Given these points, a k=4 Batch k-means clustering is performed with incomplete data for our analysis.

Table 3.2: Clustering algorithms comparison

| | | k=4 | k=5 |
|---------|--------------|-------|--------|
| k-means | Connectivity | 54.38 | 65.22 |
| | Dunn | 0.14 | 0.14 |
| | Silhouette | 0.28 | 0.23 |
| DIANA | Connectivity | 66.47 | 68.16 |
| | Dunn | 0.15 | 0.16 |
| | Silhouette | 0.22 | 0.22 |
| SOM | Connectivity | 68.80 | 80.13 |
| | Dunn | 0.11 | 0.11 |
| | Silhouette | 0.22 | 0.18 |
| Model | Connectivity | 99.06 | 131.06 |

| | | | |
|-------|--------------|-------|-------|
| | Dunn | 0.11 | 0.08 |
| | Silhouette | 0.17 | 0.10 |
| PAM | Connectivity | 84.25 | 99.62 |
| | Dunn | 0.13 | 0.15 |
| | Silhouette | 0.18 | 0.17 |
| CLARA | Connectivity | 73.54 | 88.91 |
| | Dunn | 0.10 | 0.11 |
| | Silhouette | 0.18 | 0.17 |

3.5 Feature selection

The intent of using feature selection is to nominate a narrow subset of initial indicators that conveys a grouping of countries much the same one resulting from the clustering phase. Finding this subset of features is done by eliminating redundant indicators and less relevant ones.

Two dominant approaches are used for feature selection: filters and wrappers [42]. Filter methods rank the features by scores that are assigned to each feature using a statistical measure. The statistical measure can be intrinsic to the feature or characterizes the feature's relation with the class attribute. The features having a high rank are thus selected. For wrapper methods, a feature subset selection algorithm starts a search for a proper subset of features; the subset is then evaluated by a classifier and compared to previous combinations of features to find the combination that maximizes the performance of the model (Figure 3.4 [43]).

Filter methods are computationally efficient, thus useful for datasets with a considerable number of features. Also, they are independent of the classification algorithm. It results that feature selection needs to be done only once. A downside of filter methods is that they generally ignore feature dependencies, as they evaluate each feature separately. As a result, redundant features may still be selected. Another critical drawback of filters is that the selection criterion is not directly related to the model's performance. Besides, there is

no direct way of determining the number of features to select from the resulting ranking of features.

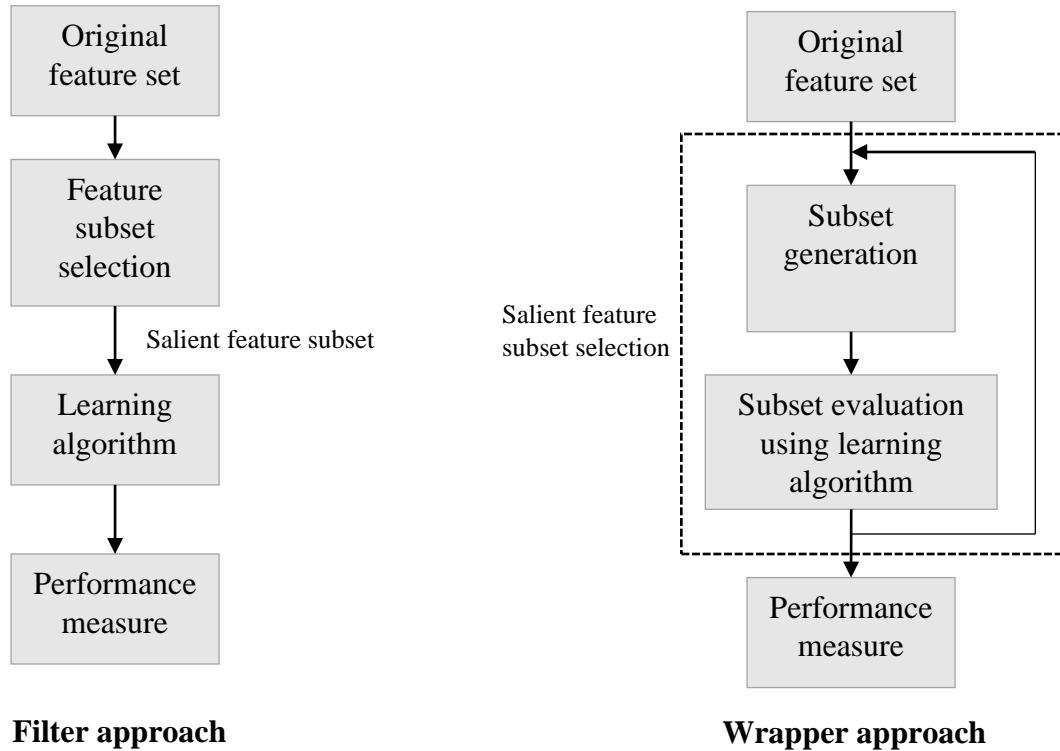


Figure 3.4: Flowchart of wrapper-based vs filter-based feature selection

Wrapper methods, on the other hand, consider feature dependencies and achieve, in most cases, a higher performance of the model as there is an interaction between the subset search algorithm and model selection. However, with wrappers, there is a higher risk of overfitting. More important is their computational cost as the number of models that need to be evaluated grows exponentially with the number of attributes. In this case, heuristic search methods are used.

Given the advantages they provide, we continue our analysis using wrappers. However, an exhaustive search in feature space is computationally intractable (with 21 indicators and using 10-fold cross-validation, 5×2^{22} models are built for each wrapping algorithm). A local optimum search algorithm, namely, Bi-directional Best-First with search termination after 10 non-improving nodes, is employed to find the best subset. A classifier is still to be specified to evaluate the subsets of features. For a more stable and

robust feature selection, we use an ensemble feature selection instead. An ensemble of wrappers allows us to exploit the strengths of the individual selectors and overcome their weaknesses [44]. The outputs of feature selectors trained on the same data are combined, and the features with the highest scores are selected.

For choosing the classifiers to use for wrapping, we start with several methods known in the literature for being among the well-performing methods with different datasets. In their highly cited paper, Wu and colleagues 2008 [37] propose 10 algorithms that are widely used for different data mining tasks. Among these, six algorithms serve for classification tasks, namely, Naive Bayes, Support Vector Machine (SVM), C4.5, Classification and regression trees (CART), k-nearest neighbors (kNN), and Adaptive Boosting (AdaBoost). In [45], the authors evaluated 179 classifiers on 121 datasets. The highest results were obtained using the Random Forest algorithm (RF) and SVM. Other algorithms achieved remarkable performance, namely, C5.0 (a successor of C4.5), multi-layer perceptron (MLP), and AdaBoost.

With the algorithms mentioned above (except C5.0 as the advantages it provides over the classical C4.5 may not apply to our problem), we run a classification experiment on Weka's Experimenter interface to see whether some classifiers are better than other ones on our dataset and whether the difference is statistically significant or not. 1R, a simple algorithm that selects one attribute that best correlates with the class attribute and splits it up to get the best classification accuracy it can, is added to the previous set of classifiers to see if there is a single attribute that is highly discriminative. The experiment is conducted based on the idea that classifiers that perform well while using all features are good candidates to use for feature selection as they may be more suited to the characteristics of the dataset.

The models are evaluated using 10-fold cross-validation with 10 repetitions. The null hypothesis (one classifier's performance is the same as the other's) is tested with a 0.05 (two-tailed) significance Paired Corrected T-Test.

Table 3.3 shows the results of the experiment with SVM as its test base. The percentage accuracy presented in the table is the mean of the 10 repetitions. Multi-Layer Perceptron achieved higher accuracy than the SVM baseline, but the difference is not statistically significant. Naïve Bayes and Random Forest have a loss against the SVM

baseline, but again one that is not statistically significant. Whilst all other classifiers performed worse. The top four algorithms will be later used for feature selection.

Table 3.3: Classification experiment results

| Algorithm | Type | Proposed by | Name in WEKA | Percentage accuracy |
|--|-----------------|-------------|----------------------|---------------------|
| Support Vector Machine (SVM) ¹ | Support vector | [46] | SMO | 92.23% |
| Multi-Layer Perceptron | Neural networks | [47] | MultilayerPerceptron | 94.18% |
| Naive Bayes (NB) | Bayesian | [48] | NaiveBayes | 89.83% |
| Random Forests | Ensemble | [49] | RandomForest | 88.67% |
| Classification and Regression Trees (CART) | Decision tree | [50] | SimpleCart | 85.14% * |
| C4.5 | Decision tree | [51] | J48 ² | 82.17% * |
| k-Nearest Neighbors (kNN) | Instance based | [52] | IBk -K 1 | 68.99% * |
| | | | IBk -K 2 | 66.93% * |
| | | | IBk -K 3 | 69.88% * |
| | | | IBk -K 4 | 65.91% * |
| 1R | Rule based | [53] | OneR | 67.46% * |
| AdaBoost | Ensemble | [54] | AdaBoostM1 | 51.05% * |

¹ The classifier is the reference in the experiment

² A Java implementation of C4.8 algorithm, a minor extension to C4.5

* Statistically significant loss against the baseline algorithm

In the next paragraphs, we provide a summary of how these algorithms function:

- **Naïve Bayes:**

Naïve Bayes is a simple classifier that uses Bayes' rule of conditional probability. The classifier supposes the conditional independence of explanatory variables. The presence or

absence of an attribute is not related to the presence or absence of all other attributes given the class [48]. The class with the highest probability is assigned to the feature vector. Indeed, features are rarely independent given the class. Still, Naïve Bayes has shown agreeable performance in cases where the features are highly correlated [55]. Due to its simplicity, Naïve Bayes is particularly useful in problems with high dimensionality.

The probability that an instance x belongs to a class c (the posterior probability) can be calculated as follows:

$$P(C = c | X = x) = \frac{P(C = c) \prod_i P(X_i = x_i | C = c)}{P(X = x)} \quad (3.1)$$

$$P(X = x) = \sum_j P(C_j) P(X = x | C_j) \quad (3.2)$$

$P(C = c)$: called the prior probability, is found by counting how many times the class c occurs in the training dataset.

Equation 3.1 is valid only if the attributes X_i are qualitative (nominal). Quantitative attributes can be handled by modelling them with a continuous probability distribution or by using discretization [56].

- **Support Vector Machine (SVM):**

SVM classifiers try to find the optimal separation of classes using one or multiple hyperplanes. In order to make the separation easier, a function (known as a kernel) maps the training instances into a high-dimensional feature space non-linearly. Different types of kernel functions can be used for separation, such as Gaussian, polynomial, and sigmoid. A hyperplane is then created within this new feature space in a way that maximizes the distance (i.e., “the margin”) between the hyperplane and the nearest instances from the opposing classes (known as the support vectors) [46,57] (Figure 3.5).

The SVM was developed initially for binary classification problems. In order to apply the SVM for situations where there are multiple classes, the multi-class problem is decomposed into several two-class problems [58].

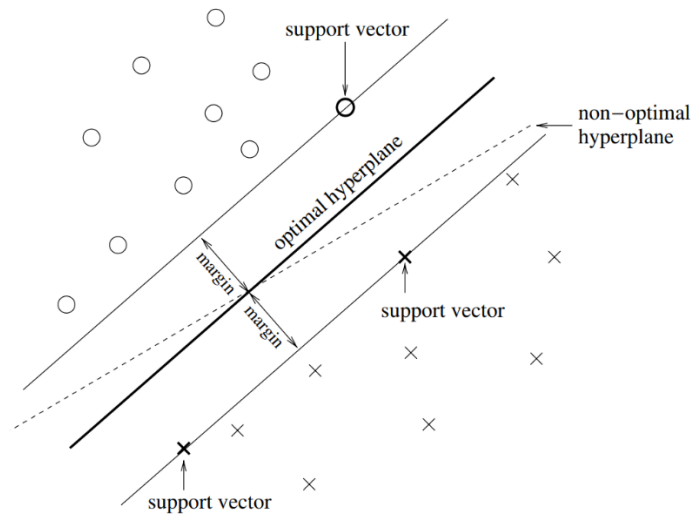


Figure 3.5: SVM optimal hyperplane [59]

SVMs are deemed to be relatively less prone to the class imbalance problem than other classification algorithms, as the boundaries between classes are determined merely in terms of the support vectors, regardless of the class sizes [60].

- **Random Forests (RF):**

Random Forests is an ensemble classification method that constructs a collection of decision trees. “Decision trees are trees that classify instances by sorting them based on feature values. Each node in a decision tree represents a feature in an instance to be classified, and each branch represents a value that the node can assume. Instances are classified starting at the root node and sorted based on their feature values”. “The feature that best divides the training data would be the root node of the tree”. For random forest, at each node of a classification tree, only a limited number of randomly chosen variables are available for the binary partitioning of the tree. The trees are fully grown and the predicted class of an observation is determined by the majority vote from the ensemble for that observation [49,61]. Figure 3.6 is a simple illustration of a random forest classifier [62].

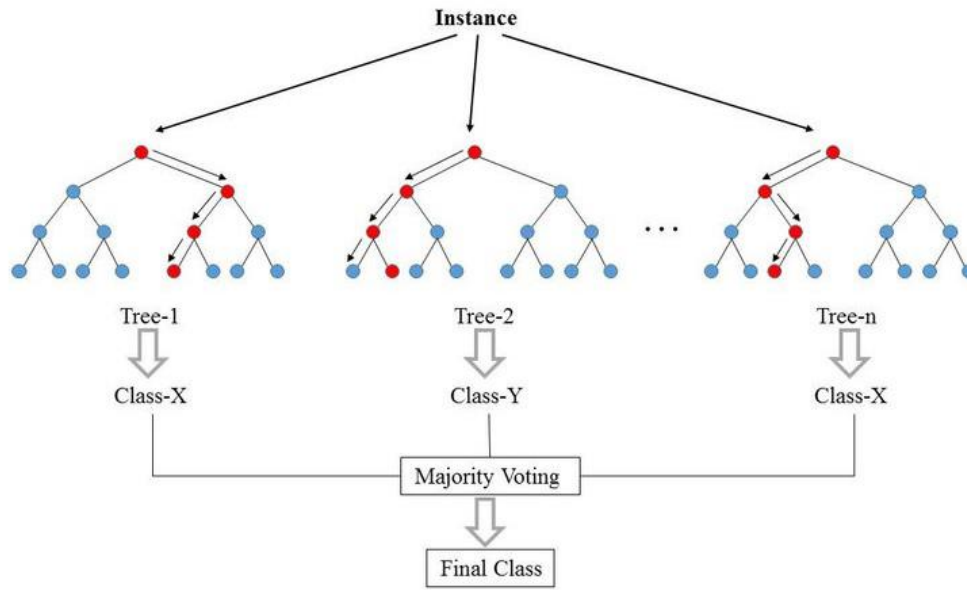


Figure 3.6: Random Forest algorithm

- **Multilayer Perceptron (MLP):**

The multilayer perceptron is the most popular artificial neural networks (ANN) classifier. An ANN is an algorithm that simulates how the biological nervous system operates, by having multiple interrelated processing elements (neurons), functioning in unity to solve a particular problem. In a single neuron, a series of features and associated weights pass through a sigmoid function. A neural network is a group of neurons connected in layers [63,64]. “An MLP is composed of several layers of neurons: an input layer, possibly one or several hidden layers and an output layer. Each neuron’s input is connected with the output of the previous layer’s neurons whereas the neurons of the output layer determine the class of the input feature vector” [59]. Figure 3.7 depicts a simple schematic of a multilayer perceptron neural network with two hidden layers for predicting a categorical variable for the magnitude of an earthquake [65].

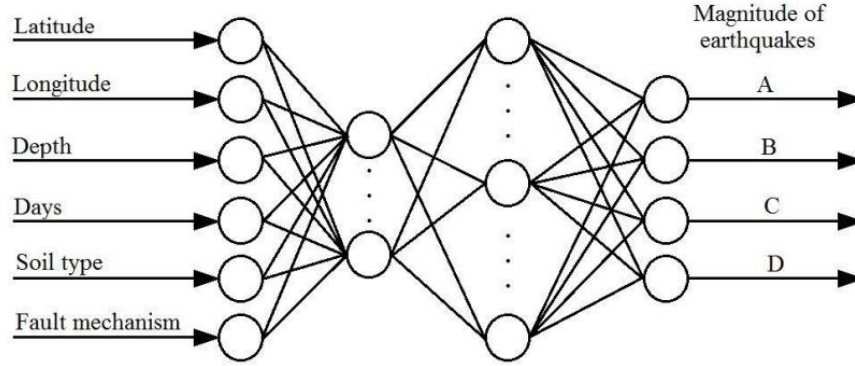


Figure 3.7: Multilayer perceptron for earthquake magnitude classification

We use the Weka Explorer to perform feature selection with the four wrapping algorithms using the "WrapperSubsetEval" technique and 10-fold cross-validation. The search method employed is the Bi-directional Best-first with search termination after 10 non-improving nodes.

Once feature selection is made, each fold and selector's outputs are combined to produce a final ranking of features. The ranking derives from the total number of times a feature takes part in an optimal subset for each fold and selector. Thus, with 10-folds and four wrapping algorithms, a feature selected in all optimal subsets will have a total score of 40 (Figure 3.8).

Thresholds of 10% and 25% of features are practical thresholds in the literature to determine the cardinality of the final set of features. Wang, Khoshgoftaar, and Napolitano 2010 [66] propose a threshold of $\log_2(n)$, where n is the number of features. A fundamental problem with these fixed thresholds is that they ignore the fact that the number of features to retain depends on the characteristics of the dataset subject to analysis. To take this into account, we go for thresholding constructed on data complexity measures. The complexity measure we have chosen is the maximum Fisher's discriminant ratio (F1). It measures the overlap between the values of the features in different classes:

$$F1 = \frac{1}{1 + \max_{i=1}^n f_i} \quad (3.3)$$

$$f_i = \frac{\sum_{i=1, j=1, i \neq j}^c p_i p_j (\mu_i \mu_j)^2}{\sum_{i=1}^c p_i \sigma_i^2} \quad (3.4)$$

where f_i is a discriminant ratio of feature i . $F1$ is basically the maximum of f_i , but in this paper, we use the inverse with values in the interval $(0,1]$ such that lower values represent an easier problem [67].

μ_i , σ_i^2 , and p_i are the mean, variance, and proportion of the i th class, respectively.

We want to minimize the fitness criterion $e[v]$:

$$e[v] = \alpha \times F1 + (1 - \alpha) \times \text{FeaturePercentage} \quad (3.5)$$

where: v : is any possible value for the threshold.

FeaturePercentage : the percentage of features retained, which should be minimized.

α : a parameter in $[0,1]$ which measures the relative relevance of the complexity measure and the feature percentage ($\alpha = 0.75$ is chosen for this work).

Using the fitness criterion, we can find the threshold using Algorithm 3.2, which we adapted from [68] to fit our method of combining feature subsets.

Features above the threshold are retained. Then, weights are assigned to features according to the proportion of their frequencies in the total number of selected features in all optimal subsets.

The final output of feature selection is a weighted sum of selected features, which afterward is combined with the DALYs in a geometric mean. The geometric mean is mainly chosen because we combine measures of different nature: health determinants, and a metric of health status. The resulted score serves as a basis for the ranking of countries:

Country score = Geometric mean (weighted sum of selected indicators, normalized DALYs).

Algorithm 3.2: Pseudocode to determine the cardinality of the final subset

Inputs:

$f = (1, \dots, i, \dots, n)$ ▶ feature vector

n ▶ number of weak selectors

F_i ▶ total frequency of selection of feature i in all folds and selectors combined

Result: S ▶ final subset of features

1 for $j = 1$ to n do

2 if $n - \frac{F_i}{10} > j$ then $v_i \leftarrow v_i + 1$

3 end if

▶ increment one vote for each feature not appearing in every 10 of the total number of optimal subsets (for a 10-fold cross-validation and n selectors, the total number of optimal subsets is $10n$)

4 end for

5 for $v = 0$ to n do

6 $Fth \leftarrow \{ \text{subset of features with number of votes} \leq v \}$

7 $F1 \leftarrow F1$ value of computed on Fth

8 $Feature\ Percentage \leftarrow$ percentage of features retained

9 $e[v] = \alpha \times F1 + (1 - \alpha) \times Feature\ Percentage$

10 end for

11 $Th \leftarrow \min(e)$ ▶ Th is the value which minimizes the error e

12 $S \leftarrow$ subset of features after removing all features with a number of votes $> Th$

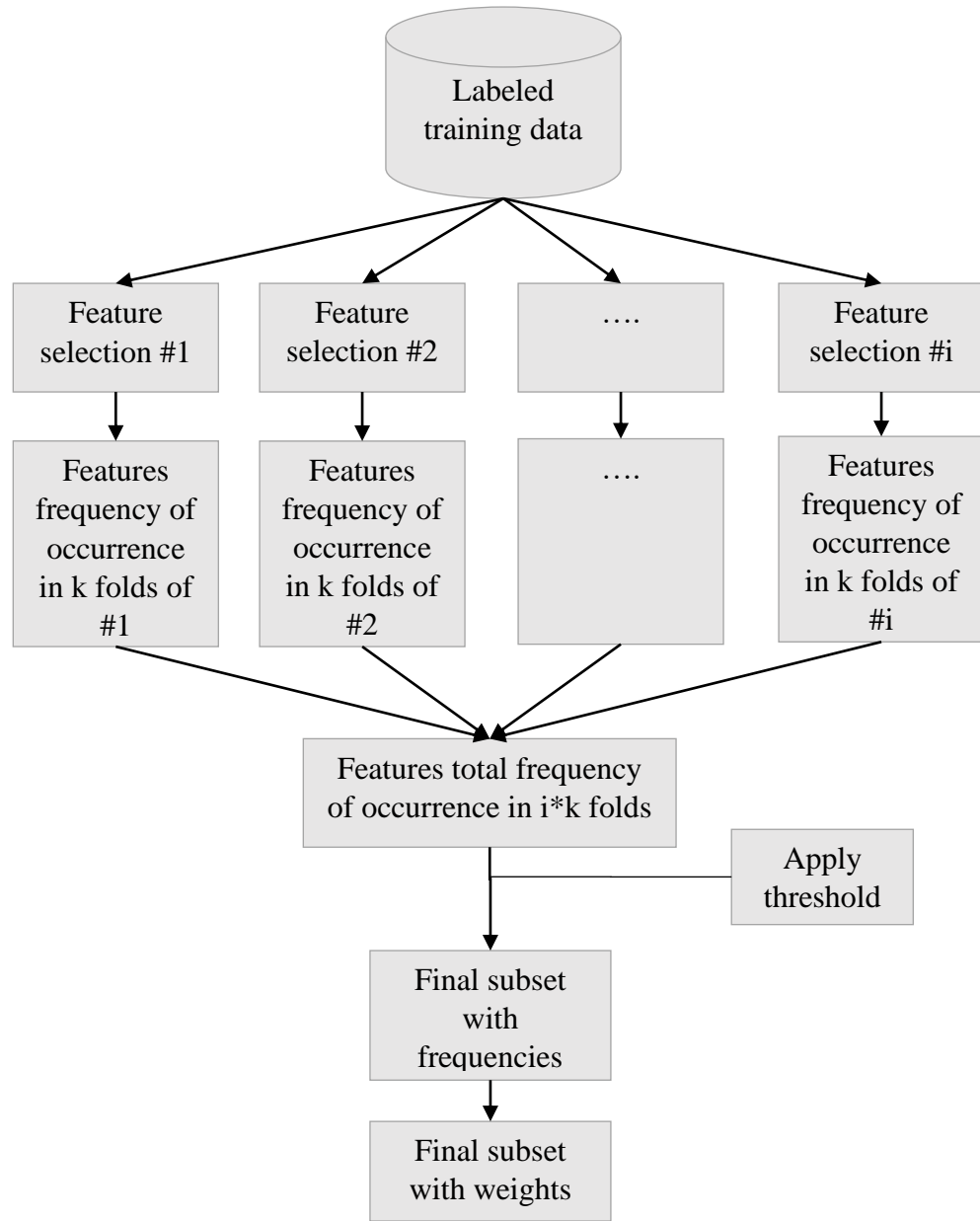


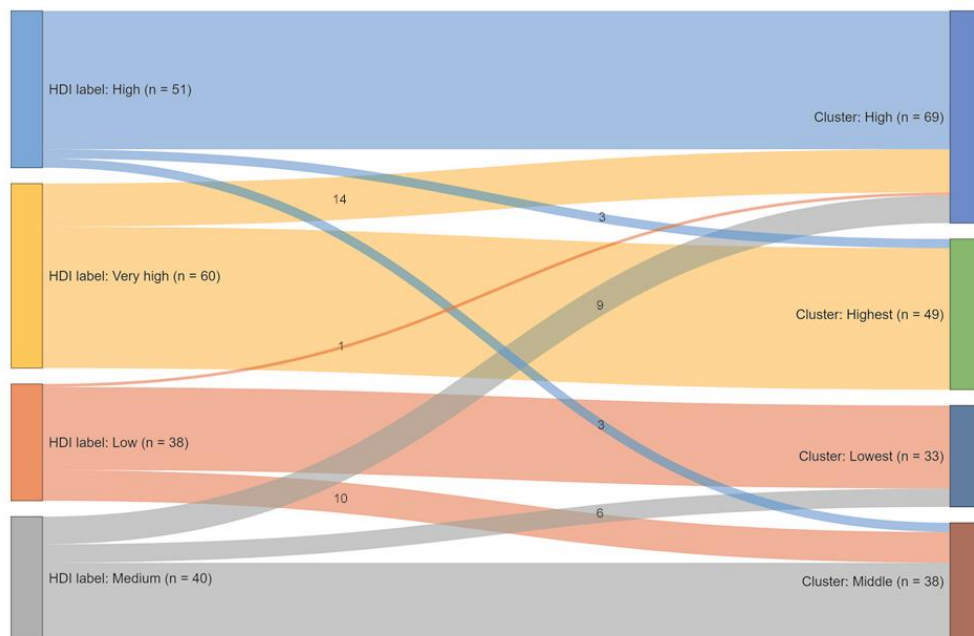
Figure 3.8: Ensemble feature selection approach

Chapter 4

Results

4.1 Clusters of countries

For three-quarters of countries, the groups of membership for the clustering are similar to their HDI groups, which may be an indication of reliable clustering (Figure 4.1).



Note: the clusters were named based on characteristics of countries dominating each cluster.

Figure 4.1: Sankey diagram for clustering – HDI correspondance

Table 4.1 shows the mean values of each feature by the cluster. Cluster 3 has the most preferred values for all measures except for total debt service. While Cluster 2 has the least favorable values for all features except for the incidence of HIV and tuberculosis. In the table, darker shades of orange represent the least preferred values, while the darker shades of blue represent the most preferred ones. The multivariate R-squared statistic shows the proportion of variance in the cluster assignment that is explained by each variable. Five

variables explain more than 70% of variation with three variables that have values of more than 80%.

Table 4.1: Resulting clusters and centers

| | Cluster 2 | Cluster 4 | Cluster 1 | Cluster 3 | R ² | p |
|---|-------------|-------------|-------------|-------------|----------------|--------|
| | n=33 17% | n=38 20% | n=69 37% | n=49 26% | | |
| Births attended by skilled health staff | 0.54 | 0.73 | 0.97 | 0.99 | 0.61 | < .001 |
| Current health expenditure per capita, PPP | 0.01 | 0.03 | 0.1 | 0.37 | 0.65 | < .001 |
| Domestic general government health expenditure per capita | 0 | 0.02 | 0.07 | 0.34 | 0.64 | < .001 |
| GINI index | 0.47 | 0.44 | 0.37 | 0.17 | 0.31 | < .001 |
| GNI per capita, PPP | 0.02 | 0.04 | 0.12 | 0.37 | 0.65 | < .001 |
| Hospital beds per 1,000 people | 0.08 | 0.11 | 0.24 | 0.37 | 0.27 | < .001 |
| Immunization DPT | 0.7 | 0.83 | 0.93 | 0.93 | 0.26 | < .001 |
| Incidence of HIV | 0.1 | 0.13 | 0.02 | 0.01 | 0.13 | 0.001 |
| Incidence of malaria | 0.41 | 0.06 | 0 | 0 | 0.63 | < .001 |
| Incidence of tuberculosis | 0.31 | 0.35 | 0.06 | 0.03 | 0.47 | < .001 |
| Income share held by lowest 40% | 0.51 | 0.52 | 0.59 | 0.8 | 0.28 | < .001 |
| Nurses and midwives per 1,000 people | 0.03 | 0.09 | 0.2 | 0.5 | 0.65 | < .001 |
| Out-of-pocket expenditure | 0.51 | 0.43 | 0.47 | 0.25 | 0.16 | < .001 |
| People using at least basic drinking water services | 0.3 | 0.71 | 0.93 | 0.98 | 0.84 | < .001 |
| People using at least basic sanitation services | 0.21 | 0.54 | 0.91 | 0.98 | 0.86 | < .001 |
| Physicians per 1,000 people | 0.02 | 0.06 | 0.26 | 0.45 | 0.66 | < .001 |
| Poverty gap at \$1.90 a day | 0.48 | 0.08 | 0.01 | 0.01 | 0.74 | < .001 |
| Poverty headcount ratio at \$1.90 a day | 0.65 | 0.16 | 0.02 | 0 | 0.85 | < .001 |
| Tax revenue (% of GDP) | 0.34 | 0.44 | 0.47 | 0.49 | 0.08 | 0.001 |
| Total debt service (% of GNI) | 0.08 | 0.1 | 0.2 | 0.68 | 0.49 | < .001 |
| Mean years of schooling | 0.23 | 0.38 | 0.64 | 0.81 | 0.73 | < .001 |

The p-values demonstrate that all the variables are significant in explaining the cluster assignment.

Now each country has a class label, which is the cluster to which it was assigned. Feature selection can allow then to define a subset of features that delivers much the same grouping.

4.2 Selected indicators

The process of feature selection led to selecting an optimal subset of features for each of the 10 folds for each of the four wrapping methods. Hence, a feature selected in every fold will have a total frequency of 40 in the total number of optimal subsets. The results reveal that four indicators have a frequency greater than or equal 30, nine features with frequencies in the interval [20,30), five features in the interval [10,20), and the remaining three features with frequencies less than 10. The frequency of each feature's selection in optimal subsets for each selection method with their total frequencies are provided in Appendix 1.

The application of a selection threshold suggests to retain the top four features; weights are assigned to these features according to the proportion of their frequencies in the total number of selected features in all folds and methods (see Appendix 1). The selected indicators and associated weights are:

- 0.25 × Domestic general government health expenditure per capita, PPP
- 0.26 × People using at least basic drinking water services (% of population)
- 0.26 × People using at least basic sanitation services (% of population)
- 0.23 × Mean years of schooling (years)

An ensemble filter feature selection proposes the same four features. However, the ranks of other features are considerably different. Figures 4.2 to 4.5 display the values of the four selected indicators across countries for the year 2016.

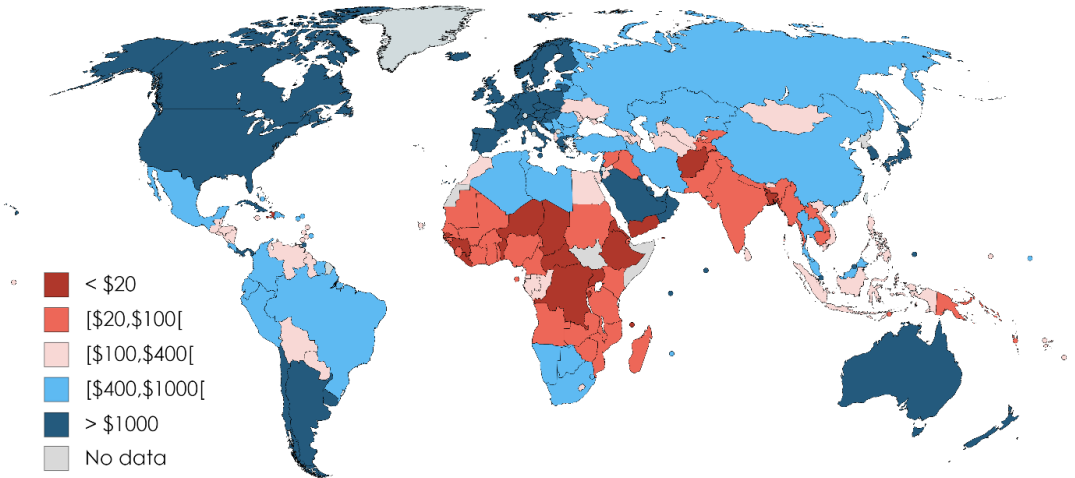


Figure 4.2: Domestic general government health expenditure per capita, PPP (current international \$), 2016

Data source: World Bank [32].

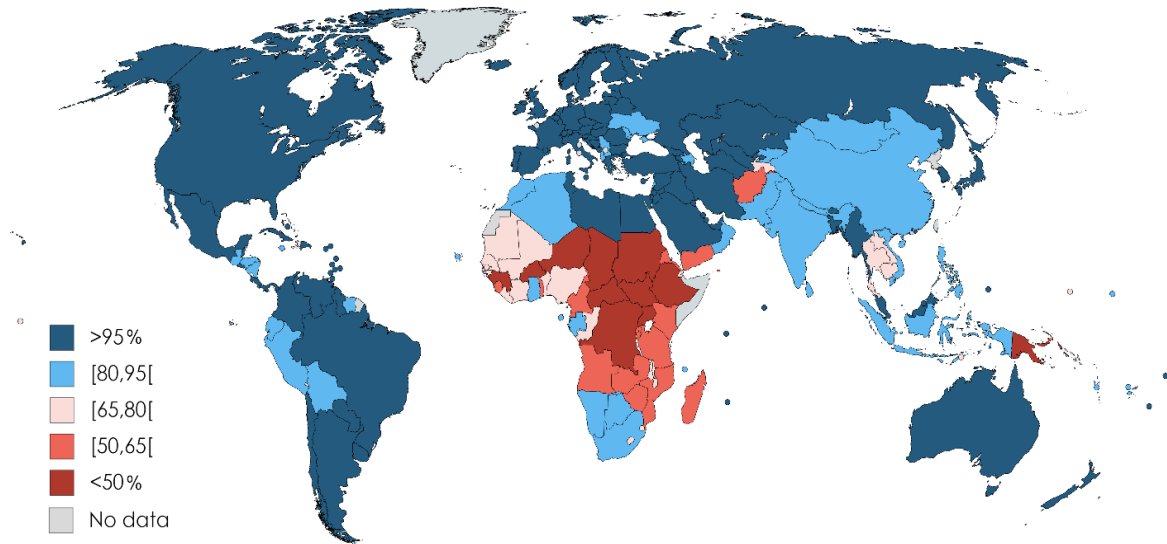


Figure 4.3: People using at least basic drinking water services (% of people), 2016

Data source: World Bank [32].

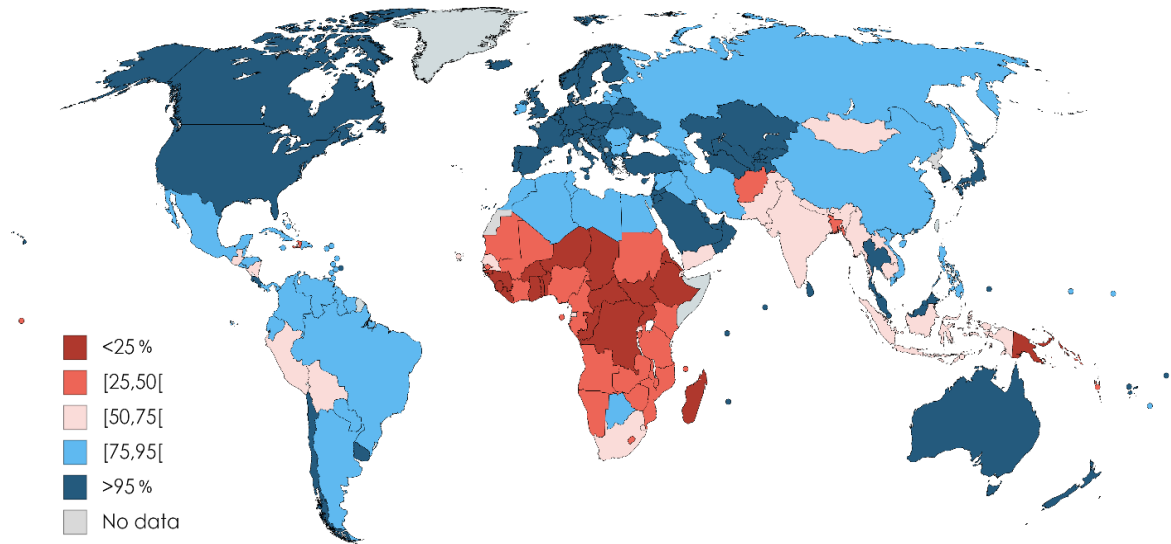


Figure 4.4: People using at least basic sanitation services (% of people), 2016

Data source: World Bank [32].

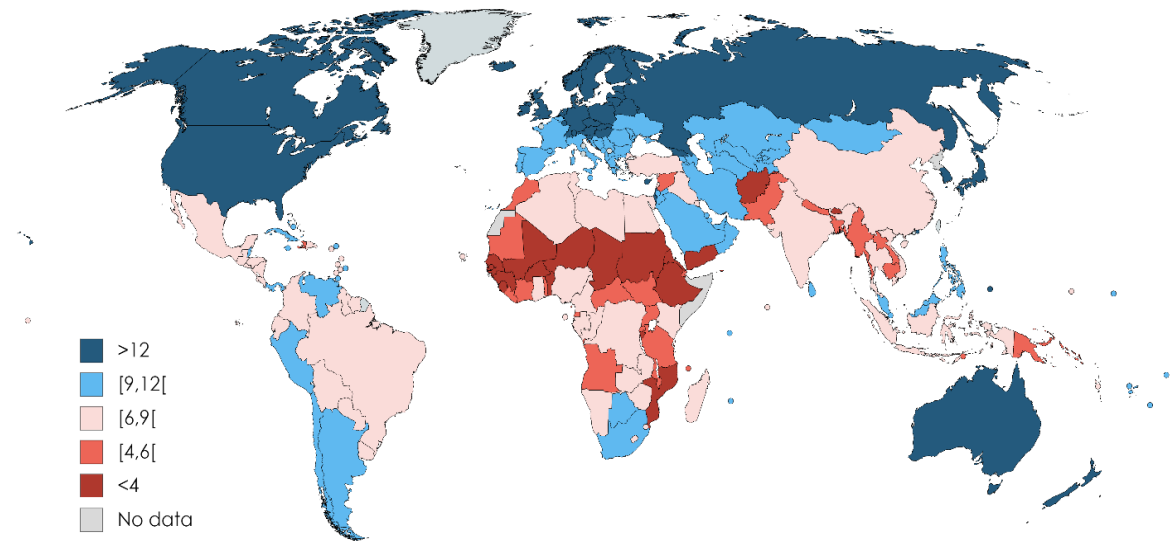


Figure 4.5: Mean years of schooling, 2016

Data source: UNDP [33].

4.3 Countries scores

We calculate a country score as follows:

Country score = Geometric mean (weighted sum of selected indicators, 1 – normalized DALYs)

The complement of DALYs is used here instead of the DALYs for coherence. Higher values for the four selected indicators are preferred, and higher values for the complement of DALYs are preferred as well.

We then rank the countries according to their scores. Interestingly, the weights for the four selected indicators are very close, a thing that encouraged us to examine the possibility of using equal weights as it brings more simplicity to the framework, which is a priority for the decision-makers.

Table 4.2: Countries rank change when moving from original weights (rank1) to equal weights (rank2)

| | Rank change | |
|-----------------------|-------------|------|
| Rank 2 lowest 20% | Min | -1 |
| | Median | 0 |
| | Avg abs | 0.27 |
| | Max | 2 |
| Rank 2 second 20% | Min | -2 |
| | Median | 0 |
| | Avg abs | 0.22 |
| | Max | 1 |
| Rank 2 third 20% | Min | -4 |
| | Median | 0 |
| | Avg abs | 0.89 |
| | Max | 3 |
| Rank 2 fourth 20% | Min | -3 |
| | Median | 0 |
| | Avg abs | 0.89 |
| | Max | 3 |
| Rank 2 highest 20% | Min | -2 |
| | Median | 0 |
| | Avg abs | 0.32 |
| | Max | 2 |

Table 4.2 shows that there are no remarkable changes in ranks when switching to equal weights. Therefore, we decided to use the average of selected indicators. A country's score is eventually calculated this way:

Country score = Geometric mean (average of selected indicators, 1 - normalized DALYs)

The values of indicators, DALYs, and final scores for countries are available in Appendix 2. A comparison in ranks between our framework and GNIpc and HDI are also included.

Figures 4.6 and 4.7 illustrate the correspondence between the countries' ranks resulting from our framework and the ranks that derive from using GNI and HDI. We find a linear relationship in both cases. Also, the points are less scattered for the HDI, which marks the proceeding from an income-based to a development-based evaluation of countries.

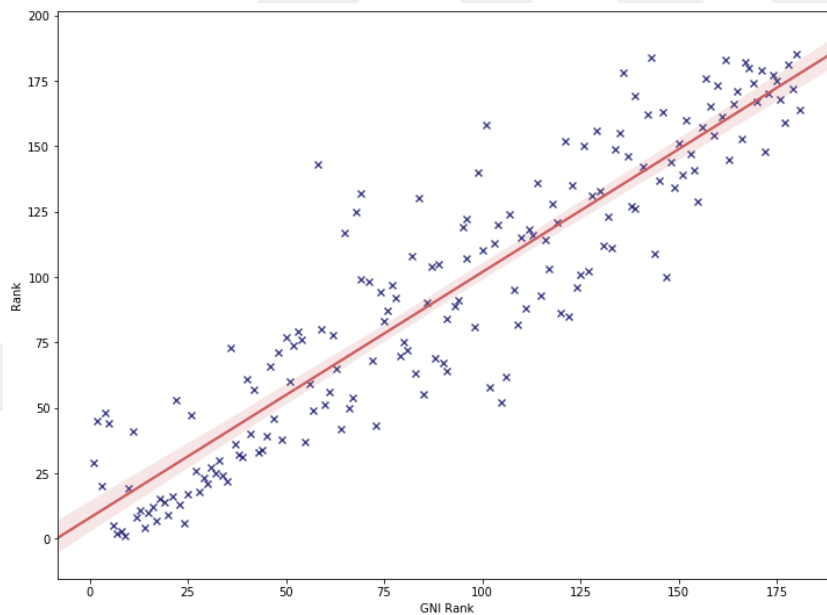


Figure 4.6: Scatter plot describing the relationship between GNI countries' rank and ranks resulting from our framework

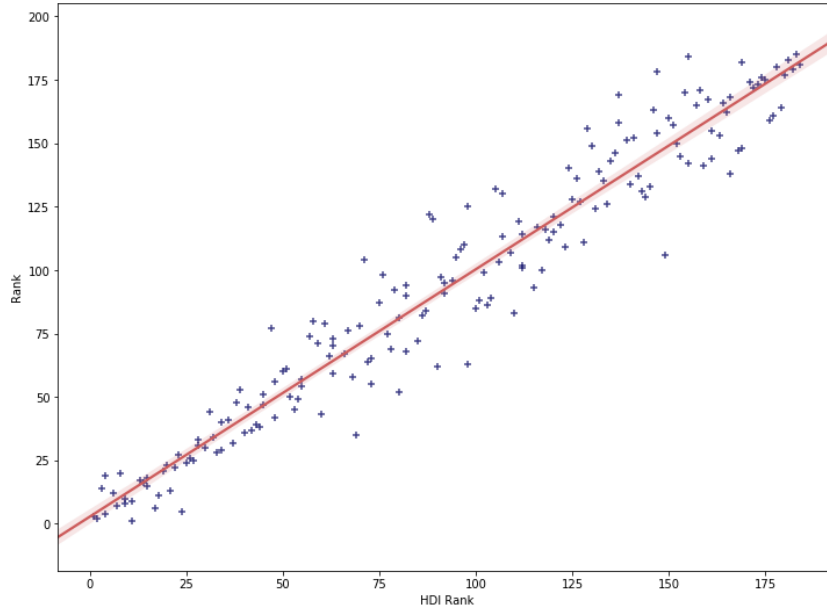


Figure 4.7: Scatter plot describing the relationship between HDI countries' rank and ranks resulting from our framework

4.4 Framework Evaluation

To evaluate our framework, we compare it to the GNIPC and the frameworks proposed by the Equitable Access Initiative teams. We rely on the correlation with three fundamental measures for our comparison: GNIPC, age-standardized DALYs, and Gini index. As a measure of correlation, we choose the Spearman's rank correlation coefficient. A correlation of +1 or -1 indicates a perfect monotonic relationship, while values closer to 0 show a weaker monotonic relationship. We prefer a high correlation with the DALYs, which quantify the disease burden, a high correlation with the Gini index, meaning that countries with high inequalities and preferred. Moreover, we prefer a correlation with GNIPC that is high enough. A low correlation with the GNIPC means many countries have a dramatic change in rank, resulting in some countries losing their eligibility for aid completely while moving to our framework and witnessing a severe shock in their health systems. Still, a marked shift in ranks is needed.

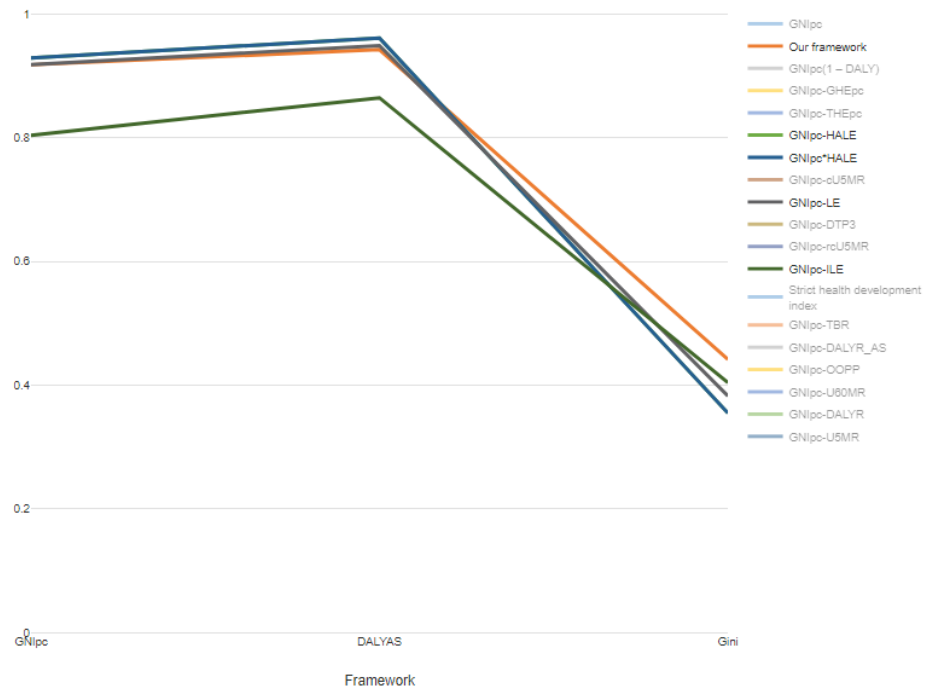


Figure 4.8: Spearman correlation of frameworks with fundamental indicators

Figure 4.8 depicts the comparison of the different frameworks with the non-dominated ones only visible. Our framework correlates highly with the DALYs and is the most highly associated with the Gini index. Its correlation with GNIpc seems too high to serve as an alternative for it. Still, the average and median of absolute change in rank are 16.5 and 13, respectively (note: Pearson's correlation coefficient = 0.67).

The SDGs emphasize the importance of targeting poor people wherever they are [69]. With our framework, populations that their rank improves while moving from GNIpc to our framework are almost four times the ones that their rank deteriorates, with 35 countries positively affected and 14 negatively affected (Figure 4.9).

We repeat the same comparison; this time, we add the non-dominated frameworks in figure 4.8 to compare with GNIpc. Again, with our framework, more countries and people in extreme poverty are positively affected, when fewer countries and people in extreme poverty have their ranks dropped (Table 4.3).

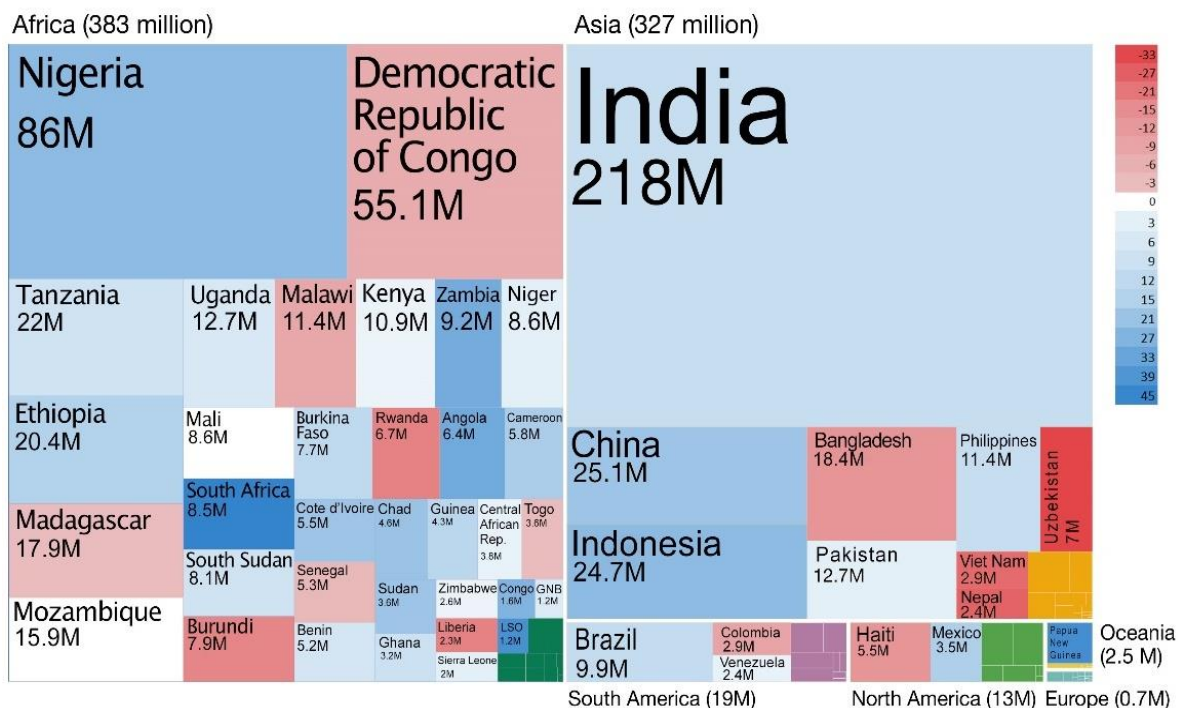


Figure 4.9: Treemap of rank change while moving from GNIPc to our framework for populations in extreme poverty

Sources: Poverty data retrieved from World Bank PovcalNet [70].

Table 4.3: Changes for countries with high populations of people in extreme poverty with performing frameworks when moving from GNIPc

| | Our framework | GNI-HALE | GNI-LE | GNI-ILE |
|---------------------|-----------------------------|----------|--------|---------|
| Negatively affected | Total population (millions) | | | |
| | 149.1 | 273.2 | 286.8 | 300.8 |
| | Average rank change | | | |
| | -14.07 | -16.63 | -15.13 | -14.28 |
| Positively affected | Total population (millions) | | | |
| | 569.5 | 456.2 | 456.3 | 438 |
| | Average rank change | | | |
| | 15.11 | 14.65 | 16.19 | 17.76 |
| Positively affected | Number of countries | | | |
| | 35 | 23 | 27 | 21 |

4.5 The framework at a subnational level

We attempt to apply the framework at a subnational level to learn if it can help target more impoverished, at high-risk people. Finding data for all indicators at a subnational level is quite challenging. The DALYs at the subnational level are available only for several middle-income and high-income countries. We present here the examples of Brazil and Mexico (middle-income countries), and the United States (a high-income country). The United States is not a recipient of development assistance. In fact, it is the largest donor country of foreign aid [71]. Our main purpose of presenting this example here is to show that multicriteria frameworks can help in developing public health policies at the national level.

4.5.1 Brazil

Data on DALYs for Brazil are accessible from [31], government health expenditure per capita are available in [72], mean years of schooling and GNIpc in [34], and data about access to water and sanitation in [73]. All data belong to the year 2017. As a measure of income inequality, data for the Gini index are available for the year 2012 (the most recent year available) in [74].

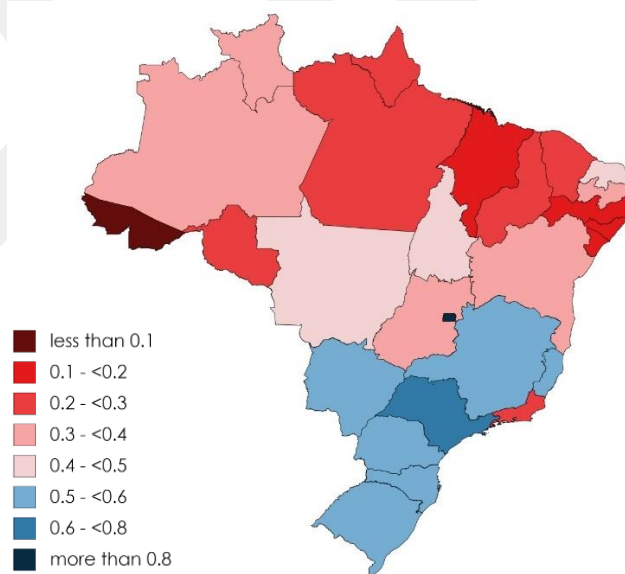


Figure 4.10: Brazilian states scores with our framework

Table 4.4: Spearman correlation of frameworks with key indicators for Brazilian states

| | | Per capita income | Our framework |
|-------|--------------------------|-------------------|---------------|
| DALYs | All states | 0.48 | 0.79 |
| | Income lowest 25% states | 0.64 | 0.61 |
| Gini | All states | 0.47 | 0.44 |
| | Income lowest 25% states | 0.39 | 0.59 |

The scores for the 27 Brazilian states with our framework are displayed in figure 4.10. A North-South divide can be clearly seen, with the most disadvantaged states in the North. A comparison of the framework with the per capita income shows that our framework is more highly correlated with the DALYs when considering all states and outperforms the per capita income in targeting states with the highest inequalities within the lower 25% states in terms of average income. However, the per capita income has a slightly higher correlation with the Gini index for all states and with the DALYs for the lower 25% states with regard to average income (Table 4.4).

4.5.2 Mexico

Data on DALYs for Mexico are accessible from [31], government health expenditure per capita are available in [75], mean years of schooling and GNIpc in [34], data about access to water and sanitation in [76], and data for the Gini index are available in [77]. Data for water and sanitation are for the year 2015. All other data belong to the year 2016.

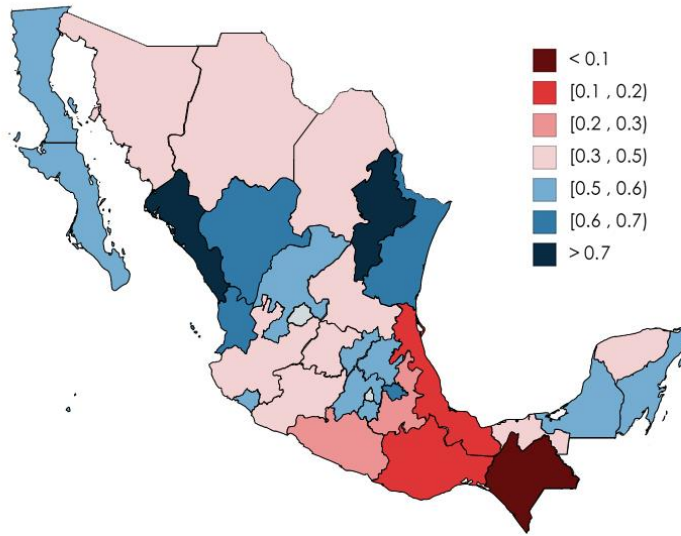


Figure 4.11: Mexican states scores with our framework

Table 4.5: Spearman correlation of frameworks with key indicators for Mexican states

| | | Per capita income | Our framework |
|-------|--------------------------|-------------------|---------------|
| DALYs | All states | -0.09 | 0.80 |
| | Income lowest 25% states | 0.37 | 0.83 |
| Gini | All states | -0.17 | 0.17 |
| | Income lowest 25% states | 0.64 | 0.90 |

The scores for the 32 Mexican states with our framework are given in figure 4.11. The most disadvantaged states are clustered in the southern part of the country and near the United States' borders. Comparing the framework with the per capita income shows that our framework correlates highly with the DALYs, while per capita income has a low or negative correlation. The correlation of the framework with the Gini index is low but still a positive one, which is not the case for income per capita. When considering the lower 25% states in terms of average income, the framework has a very high correlation with the Gini index while income per capita has a moderate one (Table 4.5).

4.5.3 The United States

Data for the DALYs for the United States are accessible from [31]. Government health expenditure data on a state level are not available. Instead, we used Medicaid expenditure for each state [78] divided by the population in each state [79] to obtain Medicaid expenditure per capita. Mean years of schooling and GNIpc are found in [34]. Data about the coverage of basic water and sanitation services are not available, we used the percentage of houses lacking complete plumbing facilities as an alternative indicator [79].

The score for each state is then given as follows: Score = geometric mean (1 – normalized DALYs, average of normalized (mean years of schooling, Medicaid expenditure per capita, percentage of houses having plumbing facilities)).

As a measure of income inequality, data for the Gini index are available in [80]. For all indicators, data represent the year 2017.

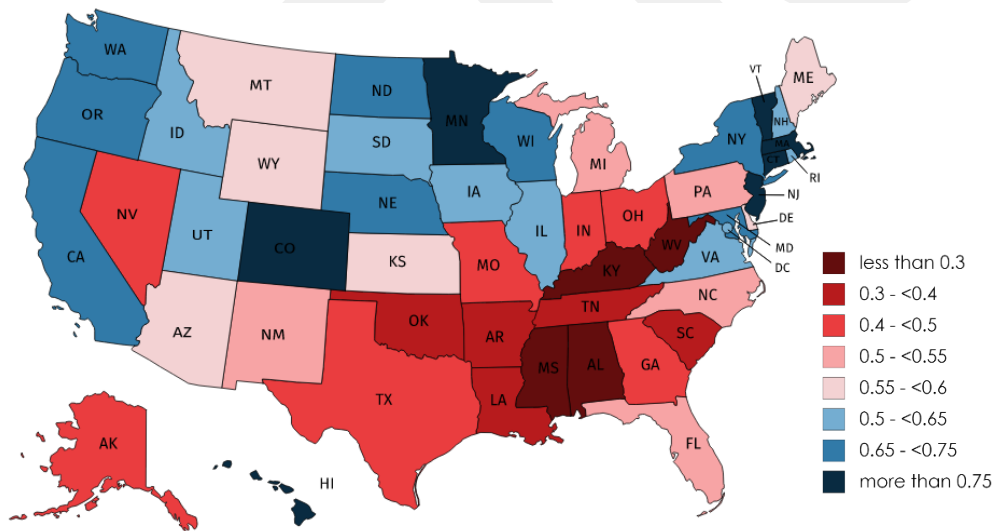


Figure 4.12: Scores of states of the United States with our framework

Table 4.6: Spearman correlation of frameworks with key indicators for states of the United States

| | | Per capita income | Our framework |
|-------|--------------------------|-------------------|---------------|
| DALYs | All states | 0.54 | 0.91 |
| | Income lowest 25% states | 0.04 | 0.93 |
| Gini | All states | 0.10 | 0.27 |
| | Income lowest 25% states | -0.20 | 0.66 |

The scores for the 51 states and territories of the United States with our framework are displayed in figure 4.12. The most disadvantaged states according to our analysis are concentrated in the Southeast region.

Table 4.6 shows that our framework wins the per capita income in directing attention towards states with a higher burden of disease and higher inequalities in income. For the lower 25% states in terms of average income, the per capita income does not correlate with the DALYs and surprisingly has a negative correlation with the Gini index meaning that it gives less priority to the states that have higher income inequalities.

GCPRIS

Chapter 5

Conclusions and Future Prospects

5.1 Conclusions

Development assistance for health is an essential contributor to improving health outcomes in developing countries and supporting them to achieve the Sustainable Development Goals (SDGs). However, increasing funds is never enough if these funds are not directed toward regions of remarkable gaps. The focus of development assistance for health should indeed be on regions with high disease burden and low capacity of response. In this project, we tried to build on previous works in this topic to try to come up with a framework that is reasonably comprehensive of different dimensions of the problem, that is more based on evidence from data than on dispersed propositions of experts, and that avoids pitfalls and limitations of previous works: a framework that guarantees at its end more reliable decision making.

The indicators composing our framework are simple and available for different countries, things that could encourage decision-makers to rely on them. Additionally, while inequality measures lack completeness (which makes them not favorite candidates for feature selection), income share held by the lowest 40% of the population (36.5% of missing data) came in rank right after the four selected indicators. This outcome aligns with the 2019 Human Development Report's theme of moving beyond averages and focusing on inequalities [81]. Nevertheless, while we presented a lack of inequality measures as a critique for the Equitable Access Initiative, our approach still includes these measures implicitly as it integrated them for finding the clustering of countries that guided the selection of indicators.

Our framework outperformed the GNIpc and most other frameworks in prioritizing countries with a higher burden of disease and countries with large populations in extreme poverty. We found supportive results as well while applying the framework at a subnational level.

Our work has some limitations related to (i) relevant problem dimensions: while we started with a broad set of indicators, the studied literature may have ignored other indicators that could be relevant (ii) missing data: data availability for some indicators may affect the quality of our initial clustering. However, for the indicators composing the final formula, data missingness was not an issue (iii) computational complexity in feature selection: we used a search for local optimum to find the best subset for each fold and feature selector. An exhaustive search requires building 5×2^{24} models.

Finally, the framework we proposed may not necessarily serve as an alternative to GNIPC. Our main contribution is to add to the debate about what should direct decisions about aid eligibility and allocation.

5.2 Societal Impact and Contribution to Global Sustainability

Health is represented in the Sustainable Development Goals (SDGs) by Goal 3: Ensure healthy lives and promote well-being for all at all ages. With ten years left to finish the 2030 SDGs agenda, additional efforts are needed from the global community to reach the defined targets. Many countries may miss several health targets, but more financial resources, cooperation, and better policies could make reaching the targets possible. One instrument that could help accelerate the progress is development assistance for health. An increase in development assistance and amelioration of its management will support poor countries in providing health services and sustaining their health reform efforts. Our thesis comes in this context with a new perspective for deciding on eligibility and allocation of development assistance for health. Our data show that the framework we developed gives more priority to countries with larger burden of disease and less capacity to address health challenges. It gives also more consideration to populations in extreme poverty whether they are in poorer or richer countries. The framework proved also its usefulness in guiding national health policies and reducing geographical inequalities. Finally, our methodology can be examined for applicability by the global community to guide vertical health programs and also to shed light on other developmental targets by defining the relevant indicators to start with.

5.3 Future Prospects

We are currently investigating the causes behind the remarkable change in rank for some countries while moving from GNIpc to our framework, and we are also trying to find out if that change is justified.

To further our research, we plan to study the potential positive or negative effects of applying our framework on the health systems of countries with remarkable rank change. Our methodology could also be enhanced by improving the quality of the clustering and feature selection (algorithm choice, parametrization). While a sensitivity analysis could help checking the robustness of our results.

Bibliography

- [1] D. E. Bloom, D. Canning, and D. T. Jamison, “Health, wealth and welfare,” *Financ. Dev.*, pp. 10--15, 2004.
- [2] The United Nations General Assembly, “International Covenant on Economic, Social, and Cultural Rights,” *Treaty Ser.*, vol. 999, p. 171, Dec. 1966.
- [3] K. McCracken and D. R. Phillips, *Global Health: An Introduction to Current and Future Trends*. Routledge, 2017.
- [4] A. Sen, “Why health equity?,” *Health Econ.*, vol. 11, no. 8, pp. 659–666, Dec. 2002.
- [5] S. Dixon, S. McDonald, and J. Roberts, “The impact of HIV and AIDS on Africa’s economic development,” *Br. Med. J.*, vol. 324, no. 7331, pp. 232–234, Jan. 2002.
- [6] G. Lopez-Casasnovas, B. Rivera, and L. Currais, Eds., *Health and Economic Growth: Findings and Policy Implications*, 1st ed., vol. 1. The MIT Press, 2007.
- [7] D. Bundy, *Rethinking School Health: A Key Component of Education for All*. Washington DC: World Bank Group, 2011.
- [8] P. Pridmore, “Impact of health on education access and achievement: a cross-national review of the research evidence,” Falmer, UK, 2007.
- [9] J. W. McArthur and K. Rasmussen, “Change of pace: Accelerations and advances during the Millennium Development Goal era,” *World Dev.*, vol. 105, pp. 132–143, 2018.
- [10] “The Millennium Development Goals Report 2015,” UN, Apr. 2016.
- [11] “Health in 2015: from MDGs, Millennium Development Goals to SDGs, Sustainable Development Goals,” World Health Organization, 2015.
- [12] “SDG Indicators.” [Online]. Available: <https://unstats.un.org/sdgs/indicators/indicators-list/>. [Accessed: 08-Feb-2021].
- [13] *World health statistics 2020: monitoring health for the SDGs, sustainable development goals*. World Health Organization, 2020.
- [14] J. L. Dieleman, A. E. Micah, and C. J. L. Murray, “Global Health Spending and Development Assistance for Health,” *JAMA*, vol. 321, no. 21, p. 2073, Jun. 2019.
- [15] A. Micah, J. Dieleman, and K. O’Rourke, “Financing Global Health 2019: Tracking Health Spending in a Time of Crisis,” Seattle, WA, Aug. 2020.
- [16] Ö. Ergun, P. Keskinocak, and J. Swann, “Introduction to the special issue on humanitarian applications: Doing good with good OR,” *Interfaces*, vol. 41, no. 3. pp. 215–222, May-2011.
- [17] J.-C. Berthélemy, “Aid Allocation: comparing donors’ behaviours,” Sep. 2006.

- [18] D. Dollar and V. Levin, “The Increasing Selectivity of Foreign Aid, 1984-2003,” *World Dev.*, vol. 34, no. 12, pp. 2034–2046, Dec. 2006.
- [19] A. Hoeffler and V. Outram, “Need, Merit, or Self-Interest-What Determines the Allocation of Aid?,” *Rev. Dev. Econ.*, vol. 15, no. 2, pp. 237–250, May 2011.
- [20] T. Ottersen, A. Kamath, S. Moon, and J. A. Røttingen, “Development Assistance for Health: Quantitative Allocation Criteria and Contribution Norms,” 2014.
- [21] A. Sen, F. J. Paul, and J. Stiglitz, *Mismeasuring Our Lives: Why GDP Doesn’t Add Up*. The New Press, 2010.
- [22] A. Sumner, “Where Do The Poor Live?,” *World Dev.*, vol. 40, no. 5, pp. 865–877, 2012.
- [23] B. Zhou *et al.*, “Worldwide trends in diabetes since 1980: a pooled analysis of 751 population-based studies with 4.4 million participants,” *Lancet (London, England)*, vol. 387, no. 10027, pp. 1513–1530, Apr. 2016.
- [24] B. Zhou *et al.*, “Worldwide trends in blood pressure from 1975 to 2015: a pooled analysis of 1479 population-based measurement studies with 19.1 million participants,” *Lancet*, vol. 389, no. 10064, pp. 37–55, Jan. 2017.
- [25] G. Yamey, D. Gonzalez, I. Bharali, K. Flanagan, and R. Hecht, “Transitioning from Foreign Aid: Is the Next Cohort of Graduating Countries Ready?,” *SSRN Electron. J.*, Jul. 2019.
- [26] EAI (Equitable Access Initiative), “The equitable access initiative,” 2016.
- [27] EAI (Equitable Access Initiative), “Equitable Access Initiative - Archive,” *The Global Fund to Fight AIDS, Tuberculosis and Malaria*, 2016. [Online]. Available: <https://www.theglobalfund.org/en/archive/equitable-access-initiative/>. [Accessed: 11-Mar-2020].
- [28] T. Ottersen, K. A. Grépin, K. Henderson, C. B. Pinkstaff, O. F. Norheim, and J. A. Røttingen, “New approaches to ranking countries for the allocation of development assistance for health: Choices, indicators and implications,” *Health Policy Plan.*, vol. 33, pp. i31–i46, 2018.
- [29] M. Roser and H. Ritchie, “Burden of Disease,” *Our World Data*, 2016.
- [30] WHO (World Health Organization), “Metrics: Disability-Adjusted Life Year (DALY),” *WHO*, 2013. [Online]. Available: https://www.who.int/healthinfo/global_burden_disease/metrics_daly/en/. [Accessed: 22-Oct-2020].
- [31] GHDx (Global Health Data Exchange), “Global Burden of Disease Study,” 2017. [Online]. Available: <http://ghdx.healthdata.org/gbd-2017>. [Accessed: 10-Mar-2020].
- [32] World Bank, “World Bank Open Data.” [Online]. Available: <https://data.worldbank.org/>. [Accessed: 10-Mar-2020].
- [33] UNDP (United Nations Development Programme), “Human Development Data

- (1990-2018),” *UNDP*, 2018. [Online]. Available: <http://hdr.undp.org/en/data>. [Accessed: 10-Mar-2020].
- [34] Radboud University, “Subnational Human Development Index,” *Global Data Lab*, 2019. [Online]. Available: <https://globaldatalab.org/>. [Accessed: 10-Mar-2020].
- [35] WHO (World Health Organization), “Global Reference List of 100 Core Health Indicators (plus health-related SDGs),” World Health Organization, Geneva, 2018.
- [36] H. H. Fore and J. Á. Gurría, “Primary Health Care on the Road to Universal Health Coverage,” World Health Organization, 2019.
- [37] X. Wu *et al.*, “Top 10 algorithms in data mining,” *Knowl. Inf. Syst.*, vol. 14, no. 1, pp. 1–37, Jan. 2008.
- [38] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*. Morgan Kaufmann, 2012.
- [39] J. C. Dunn†, “Well-Separated Clusters and Optimal Fuzzy Partitions,” *J. Cybern.*, vol. 4, no. 1, pp. 95–104, 1974.
- [40] P. J. Rousseeuw, “Silhouettes: A graphical aid to the interpretation and validation of cluster analysis,” *J. Comput. Appl. Math.*, vol. 20, no. C, pp. 53–65, Nov. 1987.
- [41] J. Handl and J. Knowles, “Exploiting the trade-off - The benefits of multiple objectives in data clustering,” in *Lecture Notes in Computer Science*, 2005, vol. 3410, pp. 547–560.
- [42] G. H. John, R. Kohavi, and K. Pfleger, “Irrelevant Features and the Subset Selection Problem,” in *Machine Learning Proceedings 1994*, Elsevier, 1994, pp. 121–129.
- [43] M. M. Kabir, M. Shahjahan, and K. Murase, “A new hybrid ant colony optimization algorithm for feature selection,” *Expert Syst. Appl.*, vol. 39, no. 3, pp. 3747–3763, Feb. 2012.
- [44] B. Seijo-Pardo, I. Porto-Díaz, V. Bolón-Canedo, and A. Alonso-Betanzos, “Ensemble feature selection: Homogeneous and heterogeneous approaches,” *Knowledge-Based Syst.*, vol. 118, pp. 124–139, Feb. 2017.
- [45] M. Fernández-Delgado, E. Cernadas, S. Barro, D. Amorim, and A. Fernández-Delgado, “Do we Need Hundreds of Classifiers to Solve Real World Classification Problems?,” 2014.
- [46] B. E. Boser, I. M. Guyon, and V. N. Vapnik, “A training algorithm for optimal margin classifiers,” in *Proceedings of the fifth annual workshop on Computational learning theory - COLT '92*, 1992, pp. 144–152.
- [47] D. E. Rumelhart and J. L. McClelland, “Learning Internal Representations by Error Propagation,” in *Parallel Distributed Processing: Explorations in the Microstructure of Cognition: Foundations*, MITP, 1987, pp. 318–362.
- [48] G. H. John and P. Langley, “Estimating Continuous Distributions in Bayesian Classifiers,” in *Proceedings of the Eleventh Conference on Uncertainty in Artificial*

- Intelligence*, 1995, pp. 338–345.
- [49] L. Breiman, “Random Forests,” *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
 - [50] D. H. Moore, *Classification and regression trees*, by Leo Breiman, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone, vol. 8, no. 5. John Wiley & Sons, Ltd, 1987.
 - [51] S. L. Salzberg, “C4.5: Programs for Machine Learning by J. Ross Quinlan. Morgan Kaufmann Publishers, Inc., 1993,” *Mach. Learn.*, vol. 16, no. 3, pp. 235–240, 1994.
 - [52] D. W. Aha, D. Kibler, and M. K. Albert, “Instance-based learning algorithms,” *Mach. Learn.*, vol. 6, no. 1, pp. 37–66, 1991.
 - [53] R. C. Holte, “Very Simple Classification Rules Perform Well on Most Commonly Used Datasets,” *Mach. Learn.*, vol. 11, no. 1, pp. 63–90, 1993.
 - [54] Y. Freund and R. E. Schapire, “Experiments with a New Boosting Algorithm,” in *Proceedings of the Thirteenth International Conference on International Conference on Machine Learning*, 1996, pp. 148–156.
 - [55] P. Domingos and M. Pazzani, “On the Optimality of the Simple Bayesian Classifier under Zero-One Loss,” *Mach. Learn.*, vol. 29, no. 2–3, pp. 103–130, 1997.
 - [56] N. Williams, S. Zander, and G. Armitage, “Evaluating machine learning methods for online game traffic identification,” Melbourne, VIC, 2006.
 - [57] C. Cortes and V. Vapnik, “Support-vector networks,” *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, Sep. 1995.
 - [58] G. Madzarov, D. Gjorgjevikj, and I. Chorbev, “A Multi-class SVM Classifier Utilizing Binary Decision Tree,” *Inform.*, vol. 33, pp. 225–233, 2009.
 - [59] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, “A review of classification algorithms for EEG-based brain-computer interfaces,” *Journal of Neural Engineering*, vol. 4, no. 2. J Neural Eng, 01-Jun-2007.
 - [60] N. Japkowicz and S. Stephen, “The class imbalance problem: A systematic study,” *Intell. Data Anal.*, pp. 429–449, 2002.
 - [61] S. B. Kotsiantis, “Supervised Machine Learning: A Review of Classification Techniques,” 2007.
 - [62] S. Dimitriadis, D. Liparas, and ADNI, “How random is the random forest? Random forest algorithm on the service of structural imaging biomarkers for Alzheimer’s disease: from Alzheimer’s disease neuroimaging initiative (ADNI) database,” *Neural Regen. Res.*, vol. 13, no. 6, p. 962, Jun. 2018.
 - [63] M. Silver, T. Sakata, H. C. Su, C. Herman, S. B. Dolins, and M. J. O’Shea, “Case study: how to apply data mining techniques in a healthcare data warehouse.,” *J. Healthc. Inf. Manag.*, vol. 15, no. 2, pp. 155–164, 2001.
 - [64] J. J. Hopfield, “Neural networks and physical systems with emergent collective

- computational abilities,” *Proc. Natl. Acad. Sci.*, vol. 79, no. 8, pp. 2554–2558, 1982.
- [65] J. Mahmoudi, M. A. Arjomand, M. Rezaei, and M. H. Mohammadi, “Predicting the Earthquake Magnitude Using the Multilayer Perceptron Neural Network with Two Hidden Layers,” *Civ. Eng. J.*, vol. 2, no. 1, pp. 1–12, Jan. 2016.
- [66] H. Wang, T. M. Khoshgoftaar, and A. Napolitano, “A comparative study of ensemble feature selection techniques for software defect prediction,” in *Proceedings - 9th International Conference on Machine Learning and Applications, ICMLA 2010*, 2010, pp. 135–140.
- [67] A. C. Lorena, L. P. F. Garcia, J. Lehmann, M. C. P. Souto, and T. K. Ho, “How Complex Is Your Classification Problem?,” *ACM Comput. Surv.*, vol. 52, no. 5, pp. 1–34, Sep. 2019.
- [68] V. Bolón-Canedo and A. Alonso-Betanzos, *Recent Advances in Ensembles for Feature Selection*, vol. 147. Cham: Springer International Publishing, 2018.
- [69] UNGA (United Nations General Assembly), “Transforming our world: the 2030 Agenda for Sustainable Development,” 2015.
- [70] World Bank, “PovcalNet: an online analysis tool for global poverty monitoring,” 2016. [Online]. Available: <http://iresearch.worldbank.org/PovcalNet/home.aspx>. [Accessed: 30-Aug-2020].
- [71] A. Micah, J. L. Dieleman, and M. Kahn Case, “Financing Global Health 2018: Countries and Programs in Transition,” 2018.
- [72] CFM (Conselho Federal de Medicina), “Estados reduzem participação no gasto com Saúde,” 2018. [Online]. Available: https://portal.cfm.org.br/index.php?option=com_content&view=article&id=27963:2018-11-12-18-36-26&catid=3. [Accessed: 13-Jul-2020].
- [73] SNIS (Sistema Nacional de Informações sobre Saneamento), “Diagnóstico dos Serviços de Água e Esgotos,” 2019. [Online]. Available: <http://www.snis.gov.br/diagnostico-anual-agua-e-esgotos/diagnostico-ae-2017>. [Accessed: 13-Jul-2020].
- [74] DATASUS (Departamento de Informática do Sistema Único de Saúde), “Indicadores e Dados Básicos - Brasil,” 2013. [Online]. Available: <http://tabnet.datasus.gov.br/cgi/idb2012/matriz.htm#socio>. [Accessed: 28-Aug-2020].
- [75] “Mexico Public Expenditure Review,” Washington, DC., 2016.
- [76] “Gasto en Salud en el Sistema Nacional de Salud,” 2019. [Online]. Available: http://www.dgis.salud.gob.mx/contenidos/sinais/gastoensalud_gobmx.html. [Accessed: 18-Nov-2020].
- [77] “SEMARNAT - Coeficiente de Gini,” 2019. [Online]. Available: [http://dgeiawf.semarnat.gob.mx:8080/ibi_apps/WFServlet?IBIF_ex=D1_POBREZA00_27&IBIC_user=dgeia_mce&IBIC_pass=dgeia_mce&NOMBREENTIDAD=*&](http://dgeiawf.semarnat.gob.mx:8080/ibi_apps/WFServlet?IBIF_ex=D1_POBREZA00_27&IBIC_user=dgeia_mce&IBIC_pass=dgeia_mce&NOMBREENTIDAD=*)

- NOMBREANIO=*. [Accessed: 18-Nov-2020].
- [78] NASBO, “State Expenditure Report,” 2019.
- [79] USCB (U.S. Census Bureau), “United States Census Data.” [Online]. Available: <https://data.census.gov/cedsci/>. [Accessed: 26-Aug-2020].
- [80] PRB (Population Reference Bureau), “United States Indicators,” 2018. [Online]. Available: <https://www.prb.org/usdata/indicator/gini/snapshot/>. [Accessed: 26-Aug-2020].
- [81] UNDP, *Human Development Report 2019: Beyond income , beyond averages , beyond today*. 2019.

Appendix 1: Feature Selection Results

| Attribute * | Naive Bayes | SVM | MLP | RF | Total freqs. | Weight | Top 4 |
|-------------|-------------|-----|-----|----|--------------|--------|-------|
| 1 | 0 | 4 | 1 | 2 | 7 | 0.016 | |
| 2 | 0 | 5 | 2 | 0 | 7 | 0.016 | |
| 3 | 8 | 8 | 7 | 10 | 33 | 0.076 | 0.25 |
| 4 | 4 | 7 | 2 | 6 | 19 | 0.044 | |
| 5 | 5 | 10 | 4 | 1 | 20 | 0.046 | |
| 6 | 2 | 8 | 3 | 4 | 17 | 0.039 | |
| 7 | 3 | 5 | 8 | 6 | 22 | 0.051 | |
| 8 | 1 | 1 | 2 | 4 | 8 | 0.019 | |
| 9 | 1 | 6 | 8 | 7 | 22 | 0.051 | |
| 10 | 1 | 9 | 6 | 6 | 22 | 0.051 | |
| 11 | 4 | 6 | 9 | 5 | 24 | 0.056 | |
| 12 | 4 | 5 | 7 | 0 | 16 | 0.037 | |
| 13 | 2 | 8 | 4 | 6 | 20 | 0.046 | |
| 14 | 6 | 10 | 10 | 9 | 35 | 0.081 | 0.26 |
| 15 | 10 | 8 | 10 | 7 | 35 | 0.081 | 0.26 |
| 16 | 6 | 6 | 3 | 4 | 19 | 0.044 | |
| 17 | 4 | 4 | 2 | 3 | 13 | 0.030 | |
| 18 | 9 | 0 | 8 | 5 | 22 | 0.051 | |
| 19 | 7 | 7 | 3 | 4 | 21 | 0.049 | |
| 20 | 4 | 6 | 4 | 6 | 20 | 0.046 | |
| 21 | 4 | 10 | 8 | 8 | 30 | 0.069 | 0.23 |

432

* The order is the same as Table 3.3.2.1

Appendix 2: Indicators Values and Ranks Comparison

| Countries | Births attended by skilled health staff (% of total) | Current health expenditure per capita, PPP (current international \$) | Domestic general government health expenditure per capita, PPP (current international \$) | GINI index (World Bank estimate) | GNI per capita, PPP (current international \$) | Hospital beds (per 1,000 people) |
|--------------------------|--|---|---|----------------------------------|--|----------------------------------|
| Afghanistan | 53.09 | 162.78 | 8.35 | | 1910 | 0.54 |
| Albania | 99.69 | 759.67 | 314.17 | 28.00 | 12060 | 2.89 |
| Algeria | 96.60 | 998.15 | 675.62 | | 14900 | 1.90 |
| Andorra | | 4978.71 | 2446.03 | | | |
| Angola | 49.60 | 185.82 | 82.02 | | 6410 | |
| Antigua and Barbuda | 100.00 | 976.39 | 591.24 | | 22580 | 4.60 |
| Argentina | 100.00 | 1531.04 | 1139.52 | 42.00 | 19690 | 5.28 |
| Armenia | 99.80 | 876.86 | 144.27 | 32.50 | 9000 | 4.25 |
| Australia | 99.74 | 4529.89 | 3094.25 | 35.81 | 46210 | 3.79 |
| Austria | 98.40 | 5295.18 | 3839.56 | 30.95 | 51600 | 7.60 |
| Azerbaijan | 99.80 | 1193.06 | 238.18 | | 16280 | 1.90 |
| Bahamas | 98.90 | 1435.57 | 715.78 | | 30050 | 2.69 |
| Bahrain | 100.00 | 1866.30 | 1145.24 | | 44120 | 1.51 |
| Bangladesh | 49.80 | 90.60 | 16.27 | 32.40 | 3910 | 0.77 |
| Barbados | 98.73 | 1322.99 | 607.08 | | 17150 | 5.28 |
| Belarus | 99.80 | 1151.41 | 707.50 | 25.30 | 17270 | 11.20 |
| Belgium | | 4667.88 | 3925.96 | 27.68 | 47270 | 6.08 |
| Belize | 96.80 | 541.43 | 359.12 | | 7870 | 1.09 |
| Benin | 78.24 | 83.48 | 17.14 | 48.90 | 2160 | |
| Bhutan | 89.00 | 293.11 | 216.76 | 37.68 | 8850 | 1.30 |
| Bolivia | 89.80 | 496.31 | 326.07 | 44.60 | 7020 | 1.10 |
| Bosnia and Herzegovina | 99.90 | 1123.43 | 795.24 | | 12860 | 3.50 |
| Botswana | 100.00 | 931.30 | 520.90 | 52.10 | 16650 | 1.80 |
| Brazil | 99.24 | 1777.47 | 590.55 | 53.70 | 15010 | 2.15 |
| Brunei Darussalam | 100.00 | 1812.41 | 1720.50 | | 83860 | 2.61 |
| Bulgaria | 99.79 | 1577.94 | 797.86 | 39.00 | 19450 | 6.79 |
| Burkina Faso | 82.58 | 115.60 | 46.35 | 33.50 | 1710 | |
| Burundi | 83.95 | 50.25 | 14.64 | 38.60 | 740 | 0.07 |
| Cabo Verde | 99.93 | 347.64 | 197.40 | | 6470 | 2.10 |
| Cambodia | 86.18 | 228.57 | 49.84 | | 3510 | 0.77 |
| Cameroon | 78.30 | 169.29 | 22.57 | 46.60 | 3490 | |
| Canada | 97.81 | 4718.30 | 3465.30 | 34.40 | 44570 | 2.70 |
| Central African Republic | 78.33 | 29.91 | 4.44 | | 790 | |

| | | | | | | |
|--------------------|--------|---------|---------|-------|-------|------|
| Chad | 20.92 | 94.95 | 17.92 | | 1980 | |
| Chile | 99.73 | 2002.01 | 1170.56 | 46.94 | 22250 | 2.20 |
| China | 100.00 | 761.49 | 441.78 | 37.73 | 15450 | 3.64 |
| Colombia | 99.20 | 829.80 | 526.24 | 50.80 | 14110 | 1.50 |
| Comoros | | 115.85 | 16.86 | 45.30 | 2700 | |
| Congo | 95.03 | 263.29 | 111.31 | | 5410 | |
| Congo (DRC) | 83.05 | 34.49 | 4.23 | | 850 | |
| Costa Rica | 93.78 | 1248.55 | 933.38 | 48.70 | 15570 | 1.13 |
| Cote d'Ivoire | 73.60 | 162.64 | 41.92 | 41.26 | 3650 | |
| Croatia | 99.90 | 1705.21 | 1334.27 | 31.53 | 23740 | 5.91 |
| Cuba | 99.90 | 2457.67 | 2202.08 | | | 4.68 |
| Cyprus | 99.04 | 2270.83 | 958.32 | 32.60 | 33000 | 3.16 |
| Czechia | 99.89 | 2484.63 | 2034.38 | 25.91 | 32950 | 6.28 |
| Denmark | 94.40 | 5092.98 | 4284.34 | 29.23 | 51990 | 2.47 |
| Djibouti | | 122.08 | 55.87 | 42.24 | | 1.40 |
| Dominica | 96.00 | 580.66 | 373.11 | | 10990 | 3.80 |
| Dominican Republic | 99.36 | 936.82 | 428.36 | 45.70 | 14910 | 1.96 |
| Ecuador | 96.70 | 942.89 | 482.68 | 45.00 | 11020 | 1.53 |
| Egypt | 95.70 | 516.34 | 151.29 | 28.49 | 11140 | 0.32 |
| El Salvador | 99.90 | 599.55 | 386.51 | 40.00 | 7290 | 1.34 |
| Equatorial Guinea | | 838.74 | 197.22 | | 20330 | 3.30 |
| Eritrea | | 55.33 | 16.17 | | 2444 | |
| Estonia | 99.40 | 1987.72 | 1499.00 | 33.88 | 30200 | 5.56 |
| Eswatini | 91.45 | 663.25 | 459.66 | | 10210 | |
| Ethiopia | 27.70 | 69.52 | 19.20 | 35.36 | 1740 | 1.95 |
| Fiji | 99.93 | 313.17 | 200.12 | 34.48 | 9270 | 2.64 |
| Finland | 99.80 | 4112.05 | 3181.09 | 26.90 | 44330 | 4.03 |
| France | 97.40 | 4782.29 | 3964.32 | 32.49 | 42840 | 6.04 |
| Gabon | | 555.63 | 358.87 | 38.00 | 16450 | |
| Gambia | 58.30 | 74.31 | 13.80 | 34.36 | 1530 | 1.10 |
| Georgia | 99.96 | 797.18 | 291.38 | 36.60 | 9500 | 2.08 |
| Germany | 98.62 | 5463.33 | 4625.85 | 32.49 | 50910 | 8.30 |
| Ghana | 77.65 | 189.37 | 72.64 | 43.50 | 4060 | 0.90 |
| Greece | | 2261.16 | 1373.51 | 36.71 | 27270 | 4.16 |
| Grenada | 99.30 | 745.10 | 308.04 | | 12580 | 4.34 |
| Guatemala | 68.90 | 462.41 | 172.08 | 48.30 | 7780 | 0.60 |
| Guinea | 62.70 | 107.72 | 13.25 | | 2130 | |
| Guinea-Bissau | 46.00 | 97.97 | 43.35 | | 1690 | |
| Guyana | 82.49 | 332.67 | 196.06 | | 7880 | 1.44 |
| Haiti | 42.73 | 95.44 | 14.64 | | 1800 | 0.70 |
| Honduras | | 400.34 | 183.79 | 50.00 | 4360 | 0.70 |
| Hong Kong | | | | | 60230 | |
| Hungary | 98.86 | 1963.16 | 1293.00 | 33.15 | 26200 | 7.00 |
| Iceland | 97.90 | 4245.11 | 3460.19 | 29.59 | 50320 | 3.20 |
| India | 81.40 | 241.48 | 61.40 | 36.45 | 6560 | |
| Indonesia | 92.59 | 362.72 | 162.25 | 38.60 | 11230 | 1.33 |
| Iran | 100.00 | 1563.75 | 852.64 | 40.00 | 20210 | 1.13 |
| Iraq | | 472.41 | 87.99 | | 17690 | 1.37 |
| Ireland | 99.70 | 5299.65 | 3819.28 | 31.57 | 57920 | 2.80 |

| | | | | | | |
|-------------------------------------|--------|---------|---------|-------|-------|-------|
| Israel | | 2843.04 | 1776.92 | 38.90 | 37170 | 3.21 |
| Italy | 99.90 | 3427.31 | 2552.12 | 35.45 | 39140 | 3.14 |
| Jamaica | 100.00 | 535.66 | 324.40 | | 8340 | 1.70 |
| Japan | 99.90 | 4592.43 | 3838.61 | | 42500 | 13.00 |
| Jordan | 99.70 | 494.75 | 312.81 | 37.00 | 8910 | 1.64 |
| Kazakhstan | 99.82 | 858.77 | 504.87 | 27.20 | 22930 | 6.13 |
| Kenya | 69.00 | 143.54 | 51.93 | 40.80 | 3100 | |
| Kiribati | | 249.84 | 153.62 | | 4300 | 1.91 |
| Korea (Republic of) | 99.99 | 2711.74 | 1604.13 | 30.92 | 37240 | 10.90 |
| Kuwait | 99.33 | 2899.26 | 2432.15 | | 85900 | 2.23 |
| Kyrgyzstan | 98.89 | 240.23 | 93.94 | 26.80 | 3380 | 4.23 |
| Laos | 46.30 | 154.63 | 50.10 | | 6190 | 3.10 |
| Latvia | 99.90 | 1589.69 | 868.49 | 34.01 | 25770 | 4.38 |
| Lebanon | | 1147.37 | 598.15 | | 12490 | 2.90 |
| Lesotho | 84.46 | 242.73 | 154.88 | | 3580 | |
| Liberia | 61.10 | 133.15 | 18.97 | 35.30 | 1160 | 1.40 |
| Libya | 99.90 | 898.97 | 563.26 | | 15390 | 3.70 |
| Liechtenstein | | | | | | |
| Lithuania | 100.00 | 1978.27 | 1297.79 | 38.20 | 29070 | 7.09 |
| Luxembourg | | 6374.20 | 5176.18 | 32.29 | 71350 | 4.70 |
| Madagascar | 44.60 | 90.43 | 43.09 | 43.00 | 1450 | |
| Malawi | 89.80 | 115.16 | 32.30 | 44.70 | 1220 | |
| Malaysia | 99.19 | 1052.55 | 531.24 | 39.96 | 27390 | 1.90 |
| Maldives | 97.43 | 1628.54 | 1181.67 | | 12930 | |
| Mali | 55.72 | 81.18 | 25.65 | | 2070 | 0.10 |
| Malta | 99.80 | 3511.14 | 2215.91 | 28.74 | 35140 | 3.61 |
| Marshall Islands | 100.00 | 934.44 | 491.91 | | 4940 | 2.70 |
| Mauritania | 70.35 | 163.92 | 60.08 | 31.57 | 3890 | |
| Mauritius | 99.80 | 1206.74 | 532.32 | | 22880 | 3.57 |
| Median | 97.97 | 767.77 | 373.11 | 36.70 | 12150 | 2.80 |
| Mexico | 98.03 | 971.82 | 506.79 | 48.30 | 18300 | 1.49 |
| Micronesia (Federated States of) | 100.00 | 431.59 | 120.15 | 40.10 | 3930 | |
| Moldova (Republic) | 99.64 | 480.38 | 234.39 | 26.30 | 6790 | 5.88 |
| Mongolia | 98.32 | 466.69 | 264.50 | 32.30 | 11140 | 8.70 |
| Montenegro | 98.48 | 1333.93 | 1000.71 | 32.54 | 18020 | 4.00 |
| Morocco | 71.10 | 465.70 | 218.21 | 39.50 | 7740 | 0.91 |
| Mozambique | 52.63 | 61.65 | 32.88 | 54.00 | 1230 | |
| Myanmar | 60.20 | 291.09 | 58.48 | 38.10 | 5570 | |
| Namibia | 88.20 | 969.26 | 599.92 | 58.78 | 11000 | |
| Nepal | 58.00 | 155.97 | 28.98 | | 2680 | |
| Netherlands | | 5251.24 | 4252.27 | 27.97 | 50580 | 7.50 |
| New Zealand | 96.38 | 3664.72 | 2882.45 | | 37870 | 3.55 |
| Nicaragua | | 484.53 | 297.26 | 47.12 | 5260 | 0.90 |
| Niger | 43.16 | 61.43 | 14.92 | 34.30 | 960 | 0.30 |
| Nigeria | 40.39 | 213.74 | 27.84 | | 5760 | |
| Norway | 99.10 | 6203.45 | 5281.01 | 28.20 | 60600 | 4.50 |
| Oman | 97.97 | 2826.85 | 2519.90 | | 41690 | 1.50 |
| Pakistan | 62.26 | 144.12 | 40.21 | 31.60 | 5280 | 0.60 |

| | | | | | | |
|----------------------------------|--------|---------|---------|-------|--------|------|
| Palau | 100.00 | 1891.92 | 1130.69 | | 17660 | 4.20 |
| Palestine * | 99.90 | | | 33.70 | 5670 | |
| Panama | 94.60 | 1750.30 | 1148.23 | 50.40 | 20890 | 2.30 |
| Papua New Guinea | | 92.27 | 64.59 | | 4110 | |
| Paraguay | 95.50 | 767.77 | 396.34 | 47.90 | 11790 | 1.30 |
| Peru | 92.40 | 681.00 | 436.34 | 43.60 | 12850 | 1.55 |
| Philippines | 81.75 | 342.29 | 107.97 | 44.47 | 9370 | 1.60 |
| Poland | 99.80 | 1784.40 | 1243.75 | 30.80 | 26640 | 6.50 |
| Portugal | 98.83 | 2778.42 | 1843.59 | 35.90 | 30330 | 3.40 |
| Qatar | 100.00 | 3926.12 | 3204.81 | | 122670 | 1.18 |
| Romania | 96.98 | 1152.18 | 900.86 | 36.01 | 23240 | 5.89 |
| Russian Federation | 99.59 | 1329.29 | 757.03 | 35.60 | 23410 | 7.60 |
| Rwanda | 97.04 | 130.38 | 44.17 | 43.70 | 1930 | |
| Saint Kitts and Nevis | 100.00 | 1479.57 | 638.73 | | 27960 | |
| Saint Lucia | 97.07 | 677.40 | 284.51 | 51.20 | 12030 | 1.22 |
| Saint Vincent and the Grenadines | 99.00 | 409.14 | 314.05 | | 12240 | 3.04 |
| Samoa | 83.18 | 352.80 | 269.47 | 38.82 | 6260 | |
| Sao Tome and Principe | 96.82 | 196.90 | 78.55 | | 3200 | |
| Saudi Arabia | 98.00 | 3117.23 | 2113.53 | | 55480 | 2.49 |
| Senegal | 58.60 | 141.69 | 48.98 | | 3260 | |
| Serbia | 98.53 | 1322.56 | 767.15 | 39.58 | 14760 | 5.92 |
| Seychelles | 99.00 | 1122.56 | 1077.36 | 46.80 | 25560 | 2.85 |
| Sierra Leone | 72.90 | 244.04 | 27.27 | | 1330 | |
| Singapore | 99.60 | 4083.75 | 2226.67 | | 85090 | 1.97 |
| Slovakia | 98.31 | 2172.16 | 1734.24 | 27.50 | 30320 | 5.51 |
| Slovenia | 99.90 | 2772.23 | 2003.98 | 26.98 | 32310 | 4.60 |
| Solomon Islands | 86.20 | 117.76 | 81.52 | 37.10 | 2140 | |
| South Africa | 96.70 | 1071.35 | 575.63 | 63.06 | 12880 | |
| South Sudan * | | | | | 1550 | |
| Spain | | 3259.80 | 2322.22 | 36.51 | 36750 | 3.00 |
| Sri Lanka | 99.95 | 491.49 | 211.80 | 39.80 | 12030 | 3.60 |
| Sudan | 80.05 | 297.86 | 58.04 | | 4260 | 0.89 |
| Suriname | 78.00 | 907.60 | 629.60 | | 13810 | 6.10 |
| Sweden | | 5386.73 | 4498.22 | 29.30 | 49420 | 2.60 |
| Switzerland | | 7867.39 | 4939.04 | 32.33 | 64680 | 6.34 |
| Syrian Arab Republic | | 174.30 | 77.56 | | | 1.50 |
| Tajikistan | 94.73 | 208.51 | 59.63 | 34.53 | 3530 | 4.80 |
| Tanzania | 63.70 | 111.98 | 45.49 | | 2860 | |
| Thailand | 99.10 | 635.02 | 496.18 | 36.90 | 16160 | |
| The FYR of Macedonia | 99.90 | 934.58 | 594.07 | 34.37 | 14220 | 4.40 |
| Timor-Leste | 56.70 | 121.68 | 67.85 | 28.70 | 7390 | 5.90 |
| Togo | 44.95 | 99.90 | 20.03 | 42.37 | 1640 | |
| Tonga | 94.50 | 311.43 | 205.22 | 37.62 | 6130 | 3.20 |
| Trinidad and Tobago | 100.00 | 2180.52 | 1151.15 | | 31150 | 3.00 |
| Tunisia | | 806.34 | 456.68 | 32.20 | 11410 | 2.26 |

| | | | | | | |
|----------------------|--------|---------|---------|-------|-------|------|
| Turkey | 99.71 | 1089.25 | 854.43 | 41.90 | 25870 | 2.70 |
| Turkmenistan | 100.00 | 1116.86 | 207.07 | | 16450 | 7.40 |
| Uganda | 74.20 | 117.11 | 19.39 | 42.80 | 1870 | 1.10 |
| Ukraine | 99.90 | 534.19 | 226.56 | 25.00 | 8210 | 8.81 |
| United Arab Emirates | 99.90 | 2546.19 | 1845.41 | | 72810 | 0.46 |
| United Kingdom | | 4177.82 | 3351.67 | 32.31 | 41900 | 2.80 |
| United States | 98.86 | 9869.74 | 8077.93 | 41.50 | 58960 | 2.90 |
| Uruguay | 99.03 | 1958.90 | 1404.41 | 39.70 | 20750 | 3.48 |
| Uzbekistan | 100.00 | 416.90 | 192.31 | | 6420 | 3.61 |
| Vanuatu | 89.40 | 116.09 | 62.54 | | 2970 | |
| Venezuela | 96.20 | 947.99 | 357.15 | | 18272 | 0.66 |
| Viet Nam | 95.06 | 356.28 | 168.99 | 35.30 | 6100 | 2.30 |
| Yemen | 75.60 | 151.40 | 16.49 | 36.70 | 2820 | 0.70 |
| Zambia | 63.30 | 175.18 | 67.08 | 57.40 | 3910 | 2.30 |
| Zimbabwe | 83.71 | 185.05 | 86.05 | | 2460 | |

* The countries lack values for domestic general government health expenditure per capita, but since they are important aid recipients, we included them in our ranking by using GNI per capita as an alternative for the missing indicator (Spearman's correlation of the two indicators is 0.95)

| Countries | Immuni- zation, DPT (% of children ages 12-23 months) | Incidence of HIV (per 1,000 uninfected population ages 15- 49) | Incidence of malaria (per 1,000 population at risk) | Incidence of tuberculosis (per 100,000 people) | Nurses and midwives (per 1,000 people) | Out-of- pocket expenditure (% of current health expenditure) |
|---------------------|--|--|---|---|---|--|
| Afghanistan | 66 | 0.04 | 23 | 189 | 0.25 | 77.40 |
| Albania | 98 | | 0 | 16 | 3.60 | 57.98 |
| Algeria | 91 | 0.05 | 0 | 70 | 2.24 | 30.88 |
| Andorra | 98 | | 0 | 6 | 4.14 | 41.70 |
| Angola | 55 | 1.7 | 155.66 | 362 | | 35.21 |
| Antigua and Barbuda | 92 | | 0 | 3.4 | 3.12 | 32.19 |
| Argentina | 92 | 0.3 | 0 | 27 | 2.99 | 15.80 |
| Armenia | 94 | 0.1 | 0 | 44 | 5.49 | 80.65 |
| Australia | 94 | 0.08 | 0 | 6.6 | 12.66 | 18.94 |
| Austria | 87 | | 0 | 8.2 | 8.18 | 18.92 |
| Azerbaijan | 97 | | 0 | 66 | 6.96 | 78.92 |
| Bahamas | 94 | 1 | 0 | 26 | 3.70 | 27.72 |
| Bahrain | 99 | | 0 | 12 | 2.51 | 27.99 |
| Bangladesh | 98 | 0.01 | 1.78 | 221 | 0.26 | 71.89 |
| Barbados | 97 | 1.1 | 0 | 1.2 | 5.86 | 45.18 |
| Belarus | 98 | 0.5 | 0 | 42 | 11.28 | 35.80 |
| Belgium | 98 | | 0 | 10 | 11.10 | 15.86 |
| Belize | 95 | 1.4 | 0.02 | 38 | 1.64 | 22.87 |
| Benin | 76 | 0.62 | 368.57 | 59 | 0.61 | 43.48 |
| Bhutan | 98 | 0.2 | 0.03 | 178 | 1.42 | 20.13 |
| Bolivia | 87 | 0.2 | 1.6 | 114 | 0.74 | 28.02 |
| Bosnia and | 78 | 0.01 | 0 | 32 | 6.24 | 28.68 |

| | | | | | | |
|--------------------------|----|------|--------|-----|-------|-------|
| Herzegovina | | | | | | |
| Botswana | 95 | 8.3 | 0.77 | 326 | 3.30 | 5.25 |
| Brazil | 89 | | 3.17 | 42 | 7.39 | 43.56 |
| Brunei Darussalam | 99 | | 0 | 66 | 6.60 | 5.07 |
| Bulgaria | 92 | 0.08 | 0 | 27 | 5.31 | 47.95 |
| Burkina Faso | 91 | 0.2 | 411.62 | 51 | 0.57 | 31.39 |
| Burundi | 94 | 0.2 | 195.1 | 118 | 0.68 | 30.51 |
| Cabo Verde | 96 | 0.3 | 0.34 | 137 | 1.23 | 26.01 |
| Cambodia | 93 | 0.1 | 11.44 | 345 | 0.95 | 58.56 |
| Cameroon | 85 | 2 | 306.16 | 203 | 2.24 | 69.50 |
| Canada | 91 | | 0 | 5.5 | 9.91 | 14.62 |
| Central African Republic | 47 | 2.3 | 387.55 | 407 | 0.22 | 43.08 |
| Chad | 41 | 0.6 | 188.18 | 153 | 0.36 | 61.16 |
| Chile | 95 | 0.5 | 0 | 16 | 0.86 | 34.77 |
| China | 99 | | 0 | 64 | 2.31 | 35.91 |
| Colombia | 91 | 0.2 | 10.69 | 32 | 1.20 | 20.16 |
| Comoros | 91 | 0.01 | 1.44 | 35 | 1.21 | 73.13 |
| Congo | 71 | 1.7 | 201.08 | 378 | | 49.72 |
| Congo (DRC) | 79 | 0.4 | 310.59 | 323 | 0.52 | 37.43 |
| Costa Rica | 97 | 0.3 | 0 | 9.5 | 0.80 | 22.14 |
| Cote d'Ivoire | 85 | 1.3 | 140.1 | 153 | 0.47 | 40.15 |
| Croatia | 93 | 0.04 | 0 | 12 | 8.11 | 15.36 |
| Cuba | 99 | 0.3 | 0 | 6.8 | 8.22 | 10.31 |
| Cyprus | 97 | | 0 | 5.6 | 5.25 | 44.92 |
| Czechia | 96 | 0.07 | 0 | 5.5 | 8.41 | 15.02 |
| Denmark | 94 | 0.05 | 0 | 5.9 | 10.30 | 13.71 |
| Djibouti | 68 | 0.8 | 0.02 | 335 | 0.54 | 25.77 |
| Dominica | 99 | | 0 | 7.8 | 5.90 | 29.15 |
| Dominican Republic | 87 | 0.5 | 0.15 | 50 | 0.49 | 44.62 |
| Ecuador | 83 | 0.3 | 2.49 | 40 | 1.20 | 40.48 |
| Egypt | 95 | 0.05 | 0 | 14 | 1.38 | 61.99 |
| El Salvador | 93 | 0.2 | 0.01 | 60 | 2.28 | 27.16 |
| Equatorial Guinea | 19 | 6.6 | 349.86 | 181 | 0.50 | 72.83 |
| Eritrea | 95 | 0.3 | 17.47 | 74 | | 59.06 |
| Estonia | 93 | 0.5 | 0 | 16 | 6.45 | 22.69 |
| Eswatini | 90 | 19.2 | 0.93 | 332 | 1.48 | 9.90 |
| Ethiopia | 73 | 0.44 | 42.04 | 177 | 0.75 | 37.42 |
| Fiji | 99 | | 0 | 43 | 2.93 | 20.64 |
| Finland | 92 | 0.07 | 0 | 4.7 | 14.72 | 20.35 |
| France | 96 | 0.2 | 0 | 8.7 | 9.69 | 9.76 |
| Gabon | 75 | 1.8 | 169.11 | 533 | 2.58 | 22.51 |
| Gambia | 95 | 1.9 | 124.59 | 174 | 1.63 | 23.59 |
| Georgia | 92 | 0.3 | 0 | 92 | 4.03 | 55.60 |
| Germany | 93 | 0.07 | 0 | 8.1 | 13.20 | 12.41 |
| Ghana | 93 | 1.1 | 271.32 | 156 | 1.55 | 37.82 |
| Greece | 99 | | 0 | 4.2 | 3.37 | 34.34 |
| Grenada | 96 | | 0 | 6.4 | 3.14 | 57.78 |

| | | | | | | |
|--|------|------|--------|------|-------|-------|
| Guatemala | 80 | 0.2 | 0.49 | 24 | 0.93 | 53.34 |
| Guinea | 45 | 0.9 | 338.65 | 176 | 0.38 | 49.76 |
| Guinea-Bissau | 88 | 2.3 | 58.07 | 374 | 1.37 | 35.40 |
| Guyana | 97 | 0.9 | 28.59 | 93 | 1.29 | 35.06 |
| Haiti | 64 | 1.2 | 3.62 | 188 | 0.82 | 41.73 |
| Honduras | 94 | 0.1 | 0.72 | 40 | 1.70 | 45.01 |
| Hong Kong | | | 0 | 69 | | |
| Hungary | 99 | 0.04 | 0 | 8.7 | 6.64 | 29.70 |
| Iceland | 91 | 0.1 | 0 | 2.1 | 15.14 | 16.87 |
| India | 88 | | 10.2 | 211 | 2.10 | 64.58 |
| Indonesia | 79 | 0.3 | 4.95 | 322 | 1.30 | 37.34 |
| Iran | 99 | 0.09 | 0.1 | 14 | 1.64 | 38.79 |
| Iraq | 73 | | 0 | 43 | 1.94 | 78.48 |
| Ireland | 95 | 0.1 | 0 | 7.1 | 14.29 | 12.99 |
| Israel | 94 | 0.11 | 0 | 3.5 | 5.20 | 22.97 |
| Italy | 94 | 0.1 | 0 | 7.3 | 5.96 | 23.11 |
| Jamaica | 99 | 1.4 | 0 | 4.5 | 1.62 | 22.40 |
| Japan | 99 | 0.02 | 0 | 16 | 11.52 | 13.45 |
| Jordan | 98 | 0.01 | 0 | 5.5 | 1.89 | 27.98 |
| Kazakhstan | 82 | 0.2 | 0 | 72 | 8.49 | 35.56 |
| Kenya | 89 | 1.83 | 71.23 | 348 | 1.54 | 27.71 |
| Kiribati | 81 | | 0 | 566 | 4.83 | 0.09 |
| Korea (Republic of) | 98 | | 0.17 | 77 | 6.86 | 33.31 |
| Kuwait | 99 | 0.07 | 0 | 24 | 6.97 | 16.11 |
| Kyrgyzstan | 96 | 0.2 | 0 | 144 | 7.18 | 57.59 |
| Laos | 66 | 0.2 | 8.01 | 175 | 0.98 | 46.44 |
| Latvia | 98 | 0.4 | 0 | 37 | 4.82 | 44.56 |
| Lebanon | 83 | 0.04 | 0 | 12 | 2.48 | 32.14 |
| Lesotho | 93 | 16.6 | 0 | 724 | | 18.89 |
| Liberia | 79 | 0.8 | 194.75 | 308 | 0.11 | 47.26 |
| Libya | 97 | 0.1 | 0 | 40 | 6.68 | 40.35 |
| Liechtenstein | | | 0 | | | |
| Lithuania | 94 | | 0 | 53 | 7.92 | 32.34 |
| Luxembourg | 99 | 0.2 | 0 | 5.8 | 12.24 | 11.23 |
| Madagascar | 77 | 0.3 | 67.97 | 237 | 0.11 | 22.36 |
| Malawi | 84 | 5.1 | 233.45 | 159 | 0.25 | 11.39 |
| Malaysia | 95 | 0.3 | 0.21 | 92 | 4.07 | 37.60 |
| Maldives | 99 | | 0 | 49 | 3.95 | 19.10 |
| Mali | 69 | 1.2 | 383.59 | 56 | 0.38 | 35.28 |
| Malta | 97 | | 0 | 13 | 8.95 | 34.78 |
| Marshall Islands | 71 | | 0 | 422 | 4.74 | 9.00 |
| Mauritania | 74 | 0.06 | 69.4 | 102 | 0.97 | 50.90 |
| Mauritius | 96 | 1.2 | 0 | 12 | 3.43 | 48.16 |
| Median | 93.5 | 0.2 | 0 | 48.5 | 2.92 | 31.17 |
| Mexico | 93 | 0.15 | 0.2 | 22 | 2.90 | 40.38 |
| Micronesia (Federated States of) | 69 | | 0 | 177 | 5.44 | 2.63 |
| Moldova (Republic) | 89 | 0.44 | 0 | 101 | 3.38 | 46.29 |

| | | | | | | |
|----------------------------------|----|-------|--------|-----|-------|-------|
| Mongolia | 99 | 0.02 | 0 | 428 | 3.98 | 35.87 |
| Montenegro | 89 | 0.11 | 0 | 16 | 5.65 | 24.08 |
| Morocco | 99 | 0.05 | 0 | 103 | 0.89 | 48.62 |
| Mozambique | 80 | 11.04 | 338.3 | 551 | 0.40 | 7.67 |
| Myanmar | 90 | 0.4 | 8.34 | 361 | 1.04 | 73.98 |
| Namibia | 85 | 5.7 | 21.14 | 446 | | 7.72 |
| Nepal | 87 | 0.06 | 0.33 | 154 | 2.03 | 55.44 |
| Netherlands | 95 | 0.06 | 0 | 5.9 | 11.10 | 11.45 |
| New Zealand | 92 | 0.07 | 0 | 7.3 | 10.92 | 13.58 |
| Nicaragua | 98 | 0.1 | 2.93 | 48 | 1.38 | 32.22 |
| Niger | 80 | 0.2 | 360.75 | 93 | 0.29 | 58.51 |
| Nigeria | 57 | 1.02 | 281.5 | 219 | 1.47 | 75.21 |
| Norway | 96 | 0.06 | 0 | 6.1 | 17.98 | 14.52 |
| Oman | 99 | 0.1 | 0 | 9 | 4.47 | 5.91 |
| Pakistan | 75 | 0.2 | 6.33 | 268 | 0.54 | 65.23 |
| Palau | 98 | | 0 | 123 | 5.53 | 14.45 |
| Palestine | | | 0 | 1 | | |
| Panama | 86 | 0.6 | 0.21 | 56 | 1.41 | 27.43 |
| Papua New Guinea | 72 | 0.4 | 181.71 | 432 | 0.79 | 7.85 |
| Paraguay | 92 | 0.3 | 0 | 42 | 0.87 | 37.86 |
| Peru | 89 | 0.2 | 5.69 | 117 | 1.35 | 28.29 |
| Philippines | 86 | 0.2 | 0.27 | 554 | 0.24 | 53.94 |
| Poland | 98 | | 0 | 18 | 5.72 | 22.94 |
| Portugal | 98 | 0.2 | 0 | 20 | 6.37 | 27.75 |
| Qatar | 98 | | 0 | 23 | 6.60 | 8.55 |
| Romania | 89 | 0.1 | 0 | 74 | 6.10 | 20.75 |
| Russian Federation | 97 | | 0 | 64 | 8.62 | 40.48 |
| Rwanda | 98 | 0.7 | 554.51 | 61 | 0.71 | 6.38 |
| Saint Kitts and Nevis | 97 | | 0 | 0 | 3.98 | 51.51 |
| Saint Lucia | 95 | | 0 | 1.9 | 1.59 | 48.70 |
| Saint Vincent and the Grenadines | 99 | | 0 | 6.3 | | 20.50 |
| Samoa | 80 | | 0 | 7.7 | 1.74 | 11.88 |
| Sao Tome and Principe | 96 | | 11.2 | 165 | 2.26 | 14.40 |
| Saudi Arabia | 98 | | 0.11 | 10 | 5.70 | 14.34 |
| Senegal | 93 | 0.1 | 54.28 | 122 | 0.31 | 51.77 |
| Serbia | 92 | 0.04 | 0 | 19 | 6.12 | 40.50 |
| Seychelles | 96 | | 0 | 15 | 3.26 | 2.08 |
| Sierra Leone | 84 | 1 | 378.04 | 304 | 0.93 | 41.55 |
| Singapore | 97 | 0.06 | 0 | 50 | 7.21 | 31.17 |
| Slovakia | 96 | 0.04 | 0 | 5.9 | 9.17 | 17.83 |
| Slovenia | 94 | | 0 | 6.5 | 9.68 | 12.00 |
| Solomon Islands | 94 | | 142.31 | 84 | 2.13 | 4.60 |
| South Africa | 76 | 10.6 | 0.77 | 618 | 5.13 | 7.75 |
| South Sudan | 45 | 2.5 | 142.2 | 146 | | |
| Spain | 97 | 0.15 | 0 | 12 | 5.53 | 23.83 |
| Sri Lanka | 99 | 0.01 | 0 | 65 | 2.12 | 50.12 |

| | | | | | | |
|----------------------|----|------|--------|------|-------|-------|
| Sudan | 93 | 0.2 | 37.51 | 82 | 0.97 | 73.89 |
| Suriname | 91 | 1 | 0.92 | 26 | 3.97 | 21.82 |
| Sweden | 98 | | 0 | 8.2 | 11.54 | 15.24 |
| Switzerland | 96 | | 0 | 7.8 | 17.28 | 29.56 |
| Syrian Arab Republic | 42 | 0.01 | 0 | 21 | 1.46 | 54.06 |
| Tajikistan | 96 | 0.2 | 0 | 85 | 5.15 | 66.06 |
| Tanzania | 97 | 2.8 | 113.68 | 287 | 0.33 | 21.89 |
| Thailand | 99 | 0.2 | 1.03 | 160 | 2.78 | 12.11 |
| The FYR of Macedonia | 95 | 0.04 | 0 | 16 | 3.72 | 35.41 |
| Timor-Leste | 79 | | 0.69 | 498 | 1.42 | 8.88 |
| Togo | 89 | 1.28 | 376.39 | 46 | 0.68 | 50.42 |
| Tonga | 78 | | 0 | 8.6 | 3.93 | 10.98 |
| Trinidad and Tobago | 97 | | 0 | 18 | 3.23 | 40.08 |
| Tunisia | 98 | 0.04 | 0 | 38 | 2.64 | 39.90 |
| Turkey | 98 | | 0 | 18 | 2.63 | 16.47 |
| Turkmenistan | 98 | | 0 | 46 | 4.63 | 76.19 |
| Uganda | 93 | 3.3 | 203.09 | 201 | 1.02 | 40.32 |
| Ukraine | 19 | 0.6 | 0 | 87 | 7.91 | 54.34 |
| United Arab Emirates | 99 | | 0 | 0.79 | 5.59 | 18.57 |
| United Kingdom | 94 | | 0 | 9.9 | 8.33 | 15.12 |
| United States | 95 | | 0 | 3.1 | 10.00 | 11.09 |
| Uruguay | 95 | 0.4 | 0 | 29 | 6.28 | 17.37 |
| Uzbekistan | 99 | 0.2 | 0 | 76 | 11.88 | 52.25 |
| Vanuatu | 81 | | 15.47 | 56 | 1.39 | 8.42 |
| Venezuela | 84 | | 28.17 | 32 | | 39.96 |
| Viet Nam | 96 | 0.1 | 0.07 | 133 | 1.43 | 44.57 |
| Yemen | 71 | 0.07 | 37.56 | 48 | 0.74 | 79.37 |
| Zambia | 91 | 6.09 | 204.19 | 376 | 0.89 | 12.12 |
| Zimbabwe | 90 | 5.58 | 58.2 | 233 | 1.20 | 21.24 |

| Countries | Income share held by lowest 20% | Income share held by second 20% | Income share held by lowest 40% ** | People using at least basic drinking water services (% of population) | People using at least basic sanitation services (% of population) | Physicians (per 1,000 people) |
|---------------------|---------------------------------|---------------------------------|------------------------------------|---|---|-------------------------------|
| Afghanistan | | | | 64.29 | 42.05 | 0.28 |
| Albania | 8.90 | 13.30 | 22.20 | 91.02 | 97.70 | 1.20 |
| Algeria | | | | 93.52 | 87.54 | 1.83 |
| Andorra | | | | 100.00 | 100.00 | 3.40 |
| Angola | | | | 55.08 | 48.63 | 0.20 |
| Antigua and Barbuda | | | | 96.74 | 87.50 | 2.76 |

| | | | | | | |
|--------------------------|------|-------|-------|--------|--------|------|
| Argentina | 4.90 | 9.70 | 14.60 | 99.08 | 94.26 | 3.96 |
| Armenia | 7.90 | 12.10 | 20.00 | 99.90 | 93.41 | 2.90 |
| Australia | 6.70 | 12.14 | 18.84 | 99.97 | 99.99 | 3.59 |
| Austria | 7.81 | 13.20 | 21.01 | 100.00 | 99.97 | 5.14 |
| Azerbaijan | | | | 90.71 | 92.48 | 3.45 |
| Bahamas | | | | 98.89 | 94.93 | 1.98 |
| Bahrain | | | | 100.00 | 100.00 | 0.94 |
| Bangladesh | 8.60 | 12.40 | 21.00 | 96.88 | 47.01 | 0.48 |
| Barbados | | | | 98.48 | 96.86 | 2.39 |
| Belarus | 9.90 | 14.40 | 24.30 | 96.47 | 97.78 | 4.07 |
| Belgium | 8.57 | 14.12 | 22.69 | 100.00 | 99.49 | 3.32 |
| Belize | | | | 97.58 | 87.53 | 1.14 |
| Benin | 2.48 | 9.60 | 12.08 | 66.32 | 16.35 | 0.16 |
| Bhutan | 6.70 | 10.80 | 17.50 | 97.21 | 68.28 | 0.37 |
| Bolivia | 3.90 | 9.50 | 13.40 | 92.18 | 58.80 | 1.61 |
| Bosnia and Herzegovina | | | | 96.15 | 95.34 | 2.26 |
| Botswana | 4.08 | 7.22 | 11.30 | 89.40 | 76.02 | 0.37 |
| Brazil | 3.20 | 7.30 | 10.50 | 97.85 | 87.43 | 2.06 |
| Brunei Darussalam | | | | 99.90 | 96.35 | 1.62 |
| Bulgaria | 5.39 | 11.55 | 16.94 | 99.15 | 85.99 | 3.99 |
| Burkina Faso | 8.94 | 12.10 | 21.04 | 48.27 | 19.13 | 0.06 |
| Burundi | 6.90 | 11.00 | 17.90 | 60.20 | 45.85 | 0.05 |
| Cabo Verde | | | | 86.49 | 72.25 | 0.77 |
| Cambodia | | | | 76.95 | 56.60 | 0.24 |
| Cameroon | 4.50 | 8.50 | 13.00 | 60.16 | 38.85 | 0.14 |
| Canada | 6.00 | 12.20 | 18.20 | 99.41 | 99.32 | 2.57 |
| Central African Republic | | | | 46.33 | 25.32 | 0.07 |
| Chad | | | | 38.85 | 8.58 | 0.05 |
| Chile | 5.01 | 9.01 | 14.02 | 99.62 | 100.00 | 1.08 |
| China | 6.61 | 10.84 | 17.45 | 92.30 | 83.24 | 1.79 |
| Colombia | 3.90 | 8.00 | 11.90 | 96.96 | 88.59 | 2.00 |
| Comoros | 4.50 | 9.10 | 13.60 | 80.15 | 35.83 | 0.14 |
| Congo | | | | 72.19 | 19.55 | 0.22 |
| Congo (DRC) | | | | 42.98 | 20.43 | 0.09 |
| Costa Rica | 4.20 | 8.30 | 12.50 | 99.70 | 97.55 | 1.15 |
| Cote d'Ivoire | 5.70 | 10.26 | 15.96 | 72.76 | 31.35 | 0.23 |
| Croatia | 7.24 | 12.84 | 20.08 | 99.59 | 96.51 | 3.00 |
| Cuba | | | | 95.32 | 92.81 | 7.48 |
| Cyprus | 8.20 | 11.82 | 20.02 | 99.61 | 99.20 | 1.95 |
| Czechia | 9.76 | 14.67 | 24.44 | 99.88 | 99.13 | 4.31 |
| Denmark | 9.05 | 13.68 | 22.73 | 100.00 | 99.60 | 4.46 |
| Djibouti | 5.31 | 1.00 | 6.31 | 75.60 | 62.35 | 0.22 |
| Dominica | | | | 96.79 | 77.89 | 1.08 |
| Dominican Republic | 4.90 | 9.00 | 13.90 | 96.58 | 83.54 | 1.57 |
| Ecuador | 4.70 | 9.40 | 14.10 | 93.68 | 87.18 | 2.05 |
| Egypt | 9.34 | 13.88 | 23.22 | 99.03 | 94.08 | 0.81 |
| El Salvador | 5.90 | 10.60 | 16.50 | 97.06 | 87.23 | 1.57 |

| | | | | | | |
|---------------------|-------|-------|-------|--------|--------|------|
| Equatorial Guinea | | | | 64.43 | 66.25 | 0.40 |
| Eritrea | | | | 51.85 | 11.94 | |
| Estonia | 7.29 | 12.29 | 19.58 | 99.71 | 99.14 | 3.47 |
| Eswatini | | | | 68.95 | 58.37 | 0.08 |
| Ethiopia | 7.30 | 12.00 | 19.30 | 40.04 | 7.09 | 0.09 |
| Fiji | 8.04 | 11.60 | 19.64 | 93.74 | 95.07 | 0.84 |
| Finland | 9.40 | 14.06 | 23.46 | 100.00 | 99.45 | 3.81 |
| France | 7.94 | 12.83 | 20.77 | 100.00 | 98.65 | 3.23 |
| Gabon | 6.00 | 10.80 | 16.80 | 85.63 | 47.37 | 0.36 |
| Gambia | 7.74 | 11.96 | 19.70 | 77.83 | 39.12 | 0.10 |
| Georgia | 6.70 | 11.50 | 18.20 | 98.17 | 90.25 | 5.10 |
| Germany | 7.59 | 12.87 | 20.46 | 100.00 | 99.22 | 4.21 |
| Ghana | 4.70 | 9.60 | 14.30 | 80.44 | 17.81 | 0.13 |
| Greece | 5.89 | 11.63 | 17.52 | 100.00 | 98.98 | 4.59 |
| Grenada | | | | 95.63 | 91.49 | 1.45 |
| Guatemala | 4.50 | 8.60 | 13.10 | 93.72 | 65.02 | 0.48 |
| Guinea | | | | 62.11 | 21.89 | 0.08 |
| Guinea-Bissau | | | | 66.51 | 20.42 | 2.20 |
| Guyana | | | | 95.54 | 85.76 | 0.73 |
| Haiti | | | | 65.02 | 33.60 | 0.21 |
| Honduras | 3.20 | 7.80 | 11.00 | 94.29 | 80.24 | 0.61 |
| Hong Kong | | | | 100.00 | 96.46 | |
| Hungary | 7.63 | 12.93 | 20.56 | 99.97 | 97.99 | 3.23 |
| Iceland | 9.66 | 13.14 | 22.81 | 100.00 | 98.78 | 3.89 |
| India | 7.60 | 11.45 | 19.05 | 91.86 | 56.94 | 0.76 |
| Indonesia | 6.90 | 10.60 | 17.50 | 88.66 | 71.25 | 0.28 |
| Iran | 6.10 | 10.50 | 16.60 | 95.20 | 88.36 | 1.41 |
| Iraq | | | | 95.61 | 92.43 | 0.84 |
| Ireland | 8.16 | 12.98 | 21.14 | 97.38 | 91.15 | 2.95 |
| Israel | 5.20 | 10.70 | 15.90 | 100.00 | 100.00 | 3.22 |
| Italy | 5.82 | 12.07 | 17.89 | 99.44 | 98.77 | 4.03 |
| Jamaica | | | | 90.62 | 87.32 | 0.46 |
| Japan | | | | 98.97 | 99.90 | 2.41 |
| Jordan | 7.60 | 11.20 | 18.80 | 98.97 | 97.43 | 1.41 |
| Kazakhstan | 9.80 | 13.60 | 23.40 | 95.04 | 97.81 | 3.29 |
| Kenya | 6.20 | 10.30 | 16.50 | 58.28 | 29.30 | 0.20 |
| Kiribati | | | | 70.35 | 46.59 | 0.28 |
| Korea (Republic of) | 7.42 | 13.20 | 20.62 | 99.68 | 100.00 | 2.31 |
| Kuwait | | | | 100.00 | 100.00 | 2.58 |
| Kyrgyzstan | 10.00 | 13.90 | 23.90 | 87.43 | 96.52 | 1.88 |
| Laos | | | | 79.94 | 71.93 | 0.40 |
| Latvia | 6.93 | 12.43 | 19.36 | 98.57 | 91.78 | 3.19 |
| Lebanon | | | | 92.60 | 96.92 | 2.25 |
| Lesotho | | | | 68.63 | 40.77 | |
| Liberia | 7.20 | 11.60 | 18.80 | 72.45 | 16.83 | 0.04 |
| Libya | | | | 98.53 | 100.00 | 2.09 |
| Liechtenstein | | | | 100.00 | 99.95 | |
| Lithuania | 6.21 | 11.41 | 17.62 | 97.07 | 92.81 | 4.34 |
| Luxembourg | 7.47 | 12.39 | 19.86 | 99.91 | 97.61 | 2.92 |

| | | | | | | |
|-------------------------------------|-------|-------|-------|--------|--------|------|
| Madagascar | 4.90 | 9.60 | 14.50 | 53.18 | 10.12 | 0.15 |
| Malawi | 6.40 | 9.80 | 16.20 | 67.91 | 25.90 | 0.02 |
| Malaysia | 6.07 | 10.41 | 16.48 | 96.72 | 99.56 | 1.48 |
| Maldives | | | | 99.24 | 99.21 | 1.04 |
| Mali | | | | 76.58 | 37.75 | 0.14 |
| Malta | 8.53 | 13.43 | 21.96 | 100.00 | 99.96 | 3.83 |
| Marshall Islands | | | | 87.36 | 83.23 | 0.60 |
| Mauritania | 7.77 | 12.77 | 20.53 | 68.83 | 45.93 | 0.12 |
| Mauritius | | | | 99.87 | 95.51 | 2.02 |
| Median | 6.85 | 11.50 | 18.27 | 95.61 | 88.73 | 1.41 |
| Mexico | 4.90 | 8.80 | 13.70 | 98.88 | 90.30 | 2.25 |
| Micronesia (Federated States of) | 5.50 | 10.70 | 16.20 | 78.57 | 88.31 | |
| Moldova (Republic) | 10.00 | 14.10 | 24.10 | 88.69 | 75.83 | 3.12 |
| Mongolia | 8.00 | 12.40 | 20.40 | 82.80 | 58.46 | 2.89 |
| Montenegro | 8.22 | 12.03 | 20.25 | 97.05 | 97.75 | 2.33 |
| Morocco | 6.70 | 10.70 | 17.40 | 86.64 | 88.42 | 0.63 |
| Mozambique | 4.20 | 7.60 | 11.80 | 53.44 | 28.11 | 0.05 |
| Myanmar | 7.30 | 11.30 | 18.60 | 80.84 | 64.71 | 0.62 |
| Namibia | 2.72 | 5.82 | 8.53 | 82.22 | 34.21 | |
| Nepal | | | | 88.35 | 58.87 | 0.60 |
| Netherlands | 8.86 | 13.89 | 22.75 | 100.00 | 97.72 | 3.51 |
| New Zealand | | | | 100.00 | 100.00 | 3.03 |
| Nicaragua | 5.02 | 9.04 | 14.06 | 81.50 | 74.39 | 0.91 |
| Niger | 7.80 | 11.20 | 19.00 | 49.50 | 13.16 | 0.05 |
| Nigeria | | | | 70.03 | 38.41 | 0.31 |
| Norway | 8.88 | 14.03 | 22.91 | 100.00 | 98.06 | 4.49 |
| Oman | | | | 91.76 | 100.00 | 2.02 |
| Pakistan | 8.80 | 12.18 | 20.98 | 91.14 | 58.26 | 0.84 |
| Palau | | | | 100.00 | 100.00 | 1.09 |
| Palestine | 7.30 | 11.90 | 19.20 | 96.48 | 96.93 | |
| Panama | 3.30 | 8.00 | 11.30 | 95.98 | 82.23 | 1.57 |
| Papua New Guinea | | | | 40.73 | 13.54 | 0.05 |
| Paraguay | 4.50 | 8.60 | 13.10 | 98.57 | 88.73 | 0.94 |
| Peru | 4.60 | 9.70 | 14.30 | 90.59 | 73.85 | 1.27 |
| Philippines | 5.67 | 9.27 | 14.93 | 93.07 | 75.40 | 1.33 |
| Poland | 7.30 | 12.80 | 20.10 | 99.38 | 98.38 | 2.40 |
| Portugal | 6.47 | 12.11 | 18.58 | 99.91 | 99.57 | 3.34 |
| Qatar | | | | 99.63 | 100.00 | 2.78 |
| Romania | 4.83 | 11.53 | 16.36 | 100.00 | 83.56 | 2.26 |
| Russian Federation | 6.88 | 11.53 | 18.42 | 96.96 | 90.06 | 4.01 |
| Rwanda | 6.00 | 9.80 | 15.80 | 56.98 | 65.41 | 0.14 |
| Saint Kitts and Nevis | | | | 99.02 | 91.61 | 2.52 |
| Saint Lucia | 3.10 | 7.90 | 11.00 | 98.16 | 88.36 | |
| Saint Vincent and the Grenadines | | | | 95.15 | 87.18 | |
| Samoa | 7.04 | 11.76 | 18.80 | 97.30 | 98.12 | 0.34 |
| Sao Tome and | | | | 84.20 | 42.83 | 0.32 |

| | | | | | | |
|----------------------|-------|-------|-------|--------|--------|------|
| Principe | | | | | | |
| Saudi Arabia | | | | 99.86 | 99.91 | 2.39 |
| Senegal | | | | 79.46 | 50.78 | 0.07 |
| Serbia | 4.80 | 11.10 | 15.90 | 85.53 | 97.60 | 3.13 |
| Seychelles | 5.40 | 9.80 | 15.20 | 96.25 | 100.00 | 0.95 |
| Sierra Leone | | | | 59.56 | 15.29 | 0.04 |
| Singapore | | | | 100.00 | 100.00 | 2.31 |
| Slovakia | 8.27 | 14.27 | 22.54 | 99.79 | 97.93 | 2.46 |
| Slovenia | 9.73 | 14.40 | 24.13 | 99.53 | 99.11 | 3.00 |
| Solomon Islands | 7.00 | 11.40 | 18.40 | 68.54 | 32.75 | 0.20 |
| South Africa | 2.33 | 4.74 | 7.07 | 92.27 | 74.82 | 0.80 |
| South Sudan | | | | 40.81 | 10.44 | |
| Spain | 5.52 | 11.64 | 17.16 | 99.93 | 99.90 | 4.07 |
| Sri Lanka | 7.00 | 10.70 | 17.70 | 88.84 | 95.11 | 1.06 |
| Sudan | | | | 60.22 | 36.49 | 0.41 |
| Suriname | | | | 94.52 | 84.14 | 1.11 |
| Sweden | 8.24 | 13.83 | 22.07 | 100.00 | 99.30 | 5.40 |
| Switzerland | 7.77 | 12.50 | 20.26 | 100.00 | 99.89 | 4.24 |
| Syrian Arab Republic | | | | 97.06 | 91.40 | 1.22 |
| Tajikistan | 7.23 | 11.88 | 19.12 | 79.63 | 96.58 | 1.76 |
| Tanzania | | | | 54.85 | 28.39 | 0.04 |
| Thailand | 7.30 | 11.10 | 18.40 | 99.37 | 98.40 | 0.45 |
| The FYR of Macedonia | 6.06 | 12.19 | 18.26 | 93.15 | 98.70 | 2.87 |
| Timor-Leste | 9.40 | 13.40 | 22.80 | 76.66 | 52.42 | 0.67 |
| Togo | 5.05 | 9.70 | 14.75 | 64.02 | 15.71 | 0.07 |
| Tonga | 6.82 | 11.47 | 18.28 | 99.91 | 93.45 | 0.50 |
| Trinidad and Tobago | | | | 98.18 | 93.40 | 2.85 |
| Tunisia | 8.02 | 12.44 | 20.46 | 95.99 | 90.88 | 1.27 |
| Turkey | 5.70 | 9.90 | 15.60 | 98.88 | 97.25 | 1.76 |
| Turkmenistan | | | | 98.70 | 98.27 | 2.22 |
| Uganda | 6.10 | 9.80 | 15.90 | 47.67 | 18.45 | 0.08 |
| Ukraine | 10.10 | 14.40 | 24.50 | 93.72 | 96.22 | 3.49 |
| United Arab Emirates | | | | 97.41 | 98.58 | 2.39 |
| United Kingdom | 7.52 | 12.07 | 19.59 | 100.00 | 99.11 | 2.80 |
| United States | 5.00 | 10.20 | 15.20 | 99.26 | 99.97 | 2.59 |
| Uruguay | 5.80 | 10.50 | 16.30 | 99.32 | 96.40 | 3.93 |
| Uzbekistan | | | | 97.68 | 100.00 | 2.37 |
| Vanuatu | | | | 90.66 | 36.09 | 0.17 |
| Venezuela | | | | 95.78 | 93.94 | |
| Viet Nam | 6.90 | 11.90 | 18.80 | 93.99 | 81.86 | 0.82 |
| Yemen | 7.30 | 11.50 | 18.80 | 63.32 | 58.77 | 0.31 |
| Zambia | 2.72 | 5.84 | 8.56 | 59.24 | 26.09 | 0.09 |
| Zimbabwe | | | | 64.51 | 36.89 | 0.08 |

** The values for the indicator are calculated by summing the income share held by the lowest and second 20% of population

| Countries | Poverty gap at \$1.90 a day (2011 PPP) (%) | Poverty headcount ratio at \$1.90 a day (2011 PPP) (% of population) | Tax revenue (% of GDP) | Total debt service (% of GNI) | Mean years of schooling |
|--------------------------|--|--|------------------------|-------------------------------|-------------------------|
| Afghanistan | | | 8.84 | 0.31 | 3.6 |
| Albania | 0.30 | 1.80 | 17.59 | 4.89 | 10 |
| Algeria | | | | 0.22 | 8 |
| Andorra | | | | | 10.2 |
| Angola | | | 9.73 | 10.04 | 5.1 |
| Antigua and Barbuda | | | | | 9.2 |
| Argentina | 0.30 | 0.70 | 12.10 | 4.75 | 9.9 |
| Armenia | 0.30 | 1.80 | 21.28 | 13.67 | 11.7 |
| Australia | 0.56 | 0.76 | 22.25 | | 12.9 |
| Austria | 0.33 | 0.50 | 25.52 | | 12.1 |
| Azerbaijan | | | 14.56 | 4.99 | 10.7 |
| Bahamas | | | 14.16 | | 11.1 |
| Bahrain | | | | | 9.4 |
| Bangladesh | 2.70 | 14.80 | 8.77 | 0.76 | 5.2 |
| Barbados | | | 24.57 | | 10.6 |
| Belarus | 0.00 | 0.00 | 13.79 | 13.66 | 12.3 |
| Belgium | 0.00 | 0.00 | 23.07 | | 11.8 |
| Belize | | | 25.59 | 5.81 | 10.5 |
| Benin | 23.25 | 48.60 | | 1.09 | 3.6 |
| Bhutan | 0.24 | 1.64 | 12.49 | 5.44 | 3.1 |
| Bolivia | 3.00 | 7.10 | | 2.33 | 8.9 |
| Bosnia and Herzegovina | | | 19.95 | 6.35 | 9.7 |
| Botswana | 4.05 | 15.75 | 20.85 | 1.12 | 9.3 |
| Brazil | 1.60 | 4.30 | 12.77 | 6.68 | 7.8 |
| Brunei Darussalam | | | | | 9.1 |
| Bulgaria | 0.50 | 1.12 | 20.04 | 15.30 | 11.8 |
| Burkina Faso | 7.52 | 39.06 | 16.66 | 1.17 | 1.5 |
| Burundi | 30.40 | 71.80 | | 1.13 | 3 |
| Cabo Verde | | | 18.60 | 2.75 | 6.1 |
| Cambodia | | | 14.83 | 3.95 | 4.7 |
| Cameroon | 7.60 | 23.80 | 12.07 | 2.89 | 6.3 |
| Canada | 0.30 | 0.80 | 12.46 | | 13.1 |
| Central African Republic | | | 6.94 | 1.37 | 4.3 |
| Chad | | | | 1.41 | 2.3 |
| Chile | 0.83 | 0.68 | 17.40 | | 10.3 |
| China | 0.20 | 0.70 | 9.20 | 1.49 | 7.8 |
| Colombia | 1.80 | 4.50 | 14.96 | 5.66 | 8.3 |
| Comoros | 6.20 | 17.90 | | 0.38 | 4.8 |
| Congo | | | 15.08 | 1.78 | 6.3 |
| Congo (DRC) | | | | 1.34 | 6.6 |
| Costa Rica | 0.50 | 1.30 | 13.91 | 5.17 | 8.8 |

| | | | | | |
|--------------------|-------|-------|-------|-------|------|
| Cote d'Ivoire | 8.91 | 28.07 | 15.71 | 4.46 | 5.1 |
| Croatia | 0.49 | 0.67 | 21.40 | | 11.3 |
| Cuba | | | | | 11.6 |
| Cyprus | 0.00 | 0.00 | 24.00 | | 12.1 |
| Czechia | 0.00 | 0.00 | 14.68 | | 12.7 |
| Denmark | 0.05 | 0.16 | 33.45 | | 12.6 |
| Djibouti | 6.17 | 18.22 | | 9.92 | 4.1 |
| Dominica | | | | 4.78 | 7.8 |
| Dominican Republic | 0.50 | 1.60 | 13.51 | 5.02 | 7.8 |
| Ecuador | 1.20 | 3.60 | | 5.48 | 8.7 |
| Egypt | 0.20 | 1.30 | 11.56 | 2.02 | 7.2 |
| El Salvador | 0.50 | 2.20 | 17.38 | 6.13 | 6.9 |
| Equatorial Guinea | | | 6.38 | | 5.5 |
| Eritrea | | | | 0.39 | 3.9 |
| Estonia | 0.46 | 0.49 | 21.83 | | 12.6 |
| Eswatini | | | | 1.08 | 6.5 |
| Ethiopia | 8.88 | 30.26 | 8.09 | 1.66 | 2.7 |
| Fiji | 0.00 | 0.14 | 23.50 | 1.25 | 10.8 |
| Finland | 0.00 | 0.00 | 20.95 | | 12.4 |
| France | 0.00 | 0.00 | 23.20 | | 11.5 |
| Gabon | 0.80 | 3.40 | 11.47 | 2.78 | 8.2 |
| Gambia | 1.16 | 7.10 | 18.26 | 2.66 | 3.4 |
| Georgia | 1.00 | 3.90 | 23.47 | 18.79 | 12.8 |
| Germany | 0.00 | 0.00 | 11.18 | | 14.1 |
| Ghana | 4.70 | 13.30 | 15.43 | 2.81 | 7.1 |
| Greece | 0.55 | 1.74 | 26.65 | | 10.8 |
| Grenada | | | | 4.99 | 8.7 |
| Guatemala | 2.50 | 8.70 | 10.39 | 4.60 | 6.5 |
| Guinea | | | | 0.75 | 2.6 |
| Guinea-Bissau | | | 10.32 | 0.57 | 3 |
| Guyana | | | | 2.34 | 8.4 |
| Haiti | | | | 1.13 | 5.2 |
| Honduras | 6.30 | 16.00 | 16.59 | 5.16 | 6.5 |
| Hong Kong | | | | | 12 |
| Hungary | 0.27 | 0.64 | 23.32 | | 11.9 |
| Iceland | 0.00 | 0.00 | 37.75 | | 12.4 |
| India | | | 11.09 | 3.40 | 6.4 |
| Indonesia | 1.00 | 6.50 | 10.34 | 7.81 | 8 |
| Iran | 0.00 | 0.30 | 15.48 | 0.50 | 9.8 |
| Iraq | | | 2.03 | | 6.7 |
| Ireland | 0.28 | 0.43 | 19.05 | | 12.5 |
| Israel | 0.10 | 0.20 | 23.25 | | 13 |
| Italy | 1.21 | 1.96 | 23.52 | | 10.2 |
| Jamaica | | | 26.03 | 14.26 | 9.8 |
| Japan | | | 11.15 | | 12.7 |
| Jordan | | 0.10 | 15.29 | 6.33 | 10.4 |
| Kazakhstan | 0.00 | 0.00 | 9.92 | 16.34 | 11.7 |
| Kenya | 11.60 | 36.80 | 16.18 | 1.65 | 6.4 |
| Kiribati | | | 24.92 | | 7.9 |

| | | | | | |
|-------------------------------------|-------|-------|-------|-------|------|
| Korea (Republic of) | 0.02 | 0.30 | 14.83 | | 12.1 |
| Kuwait | | | 1.05 | | 7.2 |
| Kyrgyzstan | 0.20 | 1.40 | 16.95 | 6.89 | 10.9 |
| Laos | | | | 3.68 | 5.2 |
| Latvia | 0.50 | 0.85 | 23.80 | | 12.8 |
| Lebanon | | | 13.50 | 29.73 | 8.6 |
| Lesotho | | | 26.65 | 2.19 | 6.3 |
| Liberia | 13.00 | 40.90 | | 0.41 | 4.5 |
| Libya | | | | | 7.3 |
| Liechtenstein | | | | | 12.5 |
| Lithuania | 0.57 | 0.35 | 16.95 | | 13 |
| Luxembourg | 0.10 | 0.25 | 25.64 | | 12.1 |
| Madagascar | 40.60 | 75.80 | 11.00 | 1.29 | 6.1 |
| Malawi | 29.40 | 70.30 | 15.49 | 1.40 | 4.5 |
| Malaysia | 0.00 | 0.00 | 13.76 | | 10.2 |
| Maldives | | | 21.00 | 3.41 | 6.3 |
| Mali | | | 15.40 | 0.88 | 2.3 |
| Malta | 0.00 | 0.00 | 25.71 | | 11.3 |
| Marshall Islands | | | 17.79 | | 10.8 |
| Mauritania | 0.97 | 6.00 | | 4.88 | 4.4 |
| Mauritius | | | 18.13 | 13.59 | 9.3 |
| Median | 0.50 | 1.40 | 13.54 | 7.53 | 8.6 |
| Mexico | 0.70 | 2.20 | 6.05 | | 8 |
| Micronesia (Federated States of) | 5.50 | 15.40 | 16.25 | 5.00 | 11.6 |
| Moldova (Republic of) | 0.00 | 0.20 | 11.35 | 14.31 | 10.1 |
| Mongolia | 0.10 | 0.60 | | 28.76 | 11.3 |
| Montenegro | 0.12 | 0.39 | 21.45 | 3.74 | 5.4 |
| Morocco | 0.20 | 1.00 | 22.24 | 5.14 | 3.5 |
| Mozambique | 26.10 | 60.17 | 6.41 | 1.29 | 4.9 |
| Myanmar | 1.50 | 6.20 | 28.59 | | 6.8 |
| Namibia | 4.27 | 11.87 | 18.69 | 1.11 | 4.9 |
| Nepal | | | 21.91 | | 12.1 |
| Netherlands | 0.00 | 0.00 | 27.39 | | 12.5 |
| New Zealand | | | 16.17 | 6.41 | 6.7 |
| Nicaragua | 0.22 | 1.56 | | 1.53 | 1.9 |
| Niger | 13.23 | 44.50 | | 0.63 | 6.2 |
| Nigeria | | | 21.84 | | 12.6 |
| Norway | 0.00 | 0.24 | | | 9.5 |
| Oman | | | | 1.46 | 5.2 |
| Pakistan | 0.50 | 2.78 | 19.59 | | 12.3 |
| Palau | | | 6.10 | | 9.1 |
| Palestine | 0.20 | 1.00 | | | 10 |
| Panama | 0.50 | 2.20 | 12.95 | 16.37 | 4.6 |
| Papua New Guinea | | | 9.57 | 3.95 | 8.4 |
| Paraguay | 0.30 | 1.70 | 13.80 | 4.24 | 9.2 |
| Peru | 0.90 | 3.50 | 13.68 | 2.99 | 9.3 |
| Philippines | 1.17 | 5.97 | 16.37 | | 12.2 |

| | | | | | |
|----------------------------------|-------|-------|-------|-------|------|
| Poland | 0.15 | 0.57 | 22.40 | | 9.2 |
| Portugal | 0.29 | 0.46 | | | 9.8 |
| Qatar | | | 16.75 | 10.26 | 11 |
| Romania | 1.90 | 7.54 | 9.14 | 5.73 | 12 |
| Russian Federation | 0.00 | 0.00 | 14.79 | 2.70 | 4.1 |
| Rwanda | 20.20 | 55.50 | 19.27 | | 8.4 |
| Saint Kitts and Nevis | | | 21.19 | 3.04 | 8.9 |
| Saint Lucia | 2.70 | 4.70 | 25.73 | 3.90 | 8.6 |
| Saint Vincent and the Grenadines | | | 24.64 | 2.99 | 10.3 |
| Samoa | 0.10 | 1.10 | | 0.82 | 6 |
| Sao Tome and Principe | | | 3.39 | | 9.5 |
| Saudi Arabia | | | 15.77 | 2.15 | 2.9 |
| Senegal | | | 16.11 | 15.50 | 11.1 |
| Serbia | 3.24 | 5.23 | 31.67 | | 9.5 |
| Seychelles | 0.40 | 1.10 | | 1.17 | 3.4 |
| Sierra Leone | | | 13.35 | | 11.5 |
| Singapore | | | 17.43 | | 12.5 |
| Slovakia | 0.23 | 0.54 | 18.63 | | 12.3 |
| Slovenia | 0.00 | 0.00 | 26.68 | 1.98 | 5.4 |
| Solomon Islands | 6.80 | 25.10 | 27.11 | 4.83 | 10.1 |
| South Africa | 5.30 | 19.41 | | | 4.8 |
| South Sudan | | | 13.86 | | 9.8 |
| Spain | 0.60 | 1.01 | 12.20 | 4.14 | 10.9 |
| Sri Lanka | 0.10 | 0.80 | 7.96 | 0.34 | 3.6 |
| Sudan | | | | | 8.5 |
| Suriname | | | 27.76 | | 12.4 |
| Sweden | 0.37 | 0.50 | 9.75 | | 13.4 |
| Switzerland | 0.00 | 0.00 | | | 5.1 |
| Syrian Arab Republic | | | | 7.75 | 10.5 |
| Tajikistan | 1.02 | 4.82 | 11.39 | 1.42 | 5.8 |
| Tanzania | | | 15.40 | 3.66 | 7.6 |
| Thailand | 0.00 | 0.00 | 16.95 | 8.49 | 9.6 |
| The FYR of Macedonia | 2.09 | 3.85 | 9.89 | 0.04 | 4.5 |
| Timor-Leste | 6.70 | 30.70 | 19.06 | 1.99 | 4.8 |
| Togo | 19.07 | 47.95 | 20.37 | 1.54 | 11.2 |
| Tonga | 0.18 | 0.98 | 25.44 | | 10.9 |
| Trinidad and Tobago | | | 22.04 | 5.01 | 7.1 |
| Tunisia | 0.00 | 0.30 | 18.32 | 8.90 | 8 |
| Turkey | 0.00 | 0.20 | | 0.12 | 9.8 |
| Turkmenistan | | | 13.46 | 3.57 | 5.7 |
| Uganda | 13.20 | 41.70 | 19.63 | 13.28 | 11.3 |
| Ukraine | 0.00 | 0.10 | 0.04 | | 10.8 |
| United Arab Emirates | | | 25.48 | | 12.9 |
| United Kingdom | 0.10 | 0.20 | 10.98 | | 13.4 |

| | | | | | |
|---------------|-------|-------|-------|------|------|
| United States | 1.00 | 1.20 | 23.71 | | 8.7 |
| Uruguay | 0.00 | 0.10 | 14.15 | 1.66 | 11.4 |
| Uzbekistan | | | 16.65 | 1.12 | 6.8 |
| Vanuatu | | | | 7.73 | 10.1 |
| Venezuela | | | | 3.73 | 8.1 |
| Viet Nam | 0.40 | 2.00 | | 0.45 | 3 |
| Yemen | 4.50 | 18.80 | 13.35 | 3.62 | 7 |
| Zambia | 29.08 | 56.12 | 15.75 | 6.57 | 8.2 |
| Zimbabwe | | | | | |

| Countries | HDI label | Cluster | Normalized DALYs | 1 - DALYs | Weighted sum (original weights) | Average of top 4 | Aggregate |
|------------------------|-----------|---------|------------------|-----------|---------------------------------|------------------|-----------|
| Afghanistan | Low | Lowest | 0.586 | 0.414 | 0.244 | 0.240 | 0.315 |
| Albania | High | High | 0.091 | 0.909 | 0.640 | 0.635 | 0.760 |
| Algeria | High | High | 0.122 | 0.878 | 0.597 | 0.590 | 0.720 |
| Andorra | Very high | Highest | 0.031 | 0.969 | 0.754 | 0.748 | 0.852 |
| Angola | Medium | Lowest | 0.416 | 0.584 | 0.253 | 0.252 | 0.384 |
| Antigua and Barbuda | High | High | 0.105 | 0.895 | 0.630 | 0.624 | 0.747 |
| Argentina | Very high | High | 0.105 | 0.895 | 0.689 | 0.683 | 0.782 |
| Armenia | High | High | 0.117 | 0.883 | 0.692 | 0.689 | 0.780 |
| Australia | Very high | Highest | 0.029 | 0.971 | 0.824 | 0.822 | 0.893 |
| Austria | Very high | Highest | 0.031 | 0.969 | 0.832 | 0.829 | 0.896 |
| Azerbaijan | High | High | 0.207 | 0.793 | 0.635 | 0.632 | 0.708 |
| Bahamas | Very high | High | 0.155 | 0.845 | 0.698 | 0.694 | 0.766 |
| Bahrain | Very high | High | 0.126 | 0.874 | 0.700 | 0.692 | 0.778 |
| Bangladesh | Medium | Middle | 0.213 | 0.787 | 0.426 | 0.418 | 0.574 |
| Barbados | Very high | High | 0.121 | 0.879 | 0.690 | 0.685 | 0.776 |
| Belarus | Very high | Highest | 0.141 | 0.859 | 0.718 | 0.716 | 0.784 |
| Belgium | Very high | Highest | 0.039 | 0.961 | 0.828 | 0.824 | 0.890 |
| Belize | High | High | 0.191 | 0.809 | 0.650 | 0.646 | 0.723 |
| Benin | Low | Lowest | 0.438 | 0.562 | 0.181 | 0.179 | 0.317 |
| Bhutan | Medium | Middle | 0.202 | 0.798 | 0.455 | 0.442 | 0.594 |
| Bolivia | Medium | Middle | 0.183 | 0.817 | 0.516 | 0.514 | 0.648 |
| Bosnia and Herzegovina | High | High | 0.089 | 0.911 | 0.665 | 0.659 | 0.775 |
| Botswana | High | Middle | 0.401 | 0.599 | 0.566 | 0.563 | 0.581 |
| Brazil | High | High | 0.129 | 0.871 | 0.609 | 0.601 | 0.723 |
| Brunei Darussalam | Very high | Highest | 0.094 | 0.906 | 0.701 | 0.694 | 0.793 |
| Bulgaria | Very high | High | 0.128 | 0.872 | 0.690 | 0.688 | 0.775 |
| Burkina Faso | Low | Lowest | 0.556 | 0.444 | 0.075 | 0.072 | 0.179 |
| Burundi | Low | Lowest | 0.543 | 0.457 | 0.227 | 0.222 | 0.318 |
| Cabo Verde | Medium | Middle | 0.170 | 0.830 | 0.475 | 0.467 | 0.623 |
| Cambodia | Medium | Middle | 0.283 | 0.717 | 0.360 | 0.354 | 0.504 |
| Cameroon | Medium | Lowest | 0.570 | 0.430 | 0.268 | 0.268 | 0.340 |
| Canada | Very high | Highest | 0.034 | 0.966 | 0.835 | 0.833 | 0.897 |
| Cent. Afr. Rep. *** | Low | Lowest | 1.000 | 0.000 | 0.134 | 0.135 | 0.065 |

| | | | | | | | |
|--------------------|-----------|---------|-------|-------|-------|-------|-------|
| Chad | Low | Lowest | 0.599 | 0.401 | 0.019 | 0.020 | 0.090 |
| Chile | Very high | High | 0.059 | 0.941 | 0.715 | 0.709 | 0.817 |
| China | High | High | 0.088 | 0.912 | 0.569 | 0.562 | 0.716 |
| Colombia | High | High | 0.061 | 0.939 | 0.615 | 0.608 | 0.755 |
| Comoros | Low | Middle | 0.331 | 0.669 | 0.317 | 0.312 | 0.457 |
| Congo | Medium | Lowest | 0.481 | 0.519 | 0.268 | 0.268 | 0.373 |
| Congo (DRC) | Low | Lowest | 0.536 | 0.464 | 0.148 | 0.154 | 0.267 |
| Costa Rica | High | High | 0.039 | 0.961 | 0.674 | 0.666 | 0.800 |
| Cote d'Ivoire | Low | Middle | 0.581 | 0.419 | 0.279 | 0.277 | 0.340 |
| Croatia | Very high | Highest | 0.080 | 0.920 | 0.729 | 0.725 | 0.817 |
| Cuba | High | Highest | 0.066 | 0.934 | 0.732 | 0.730 | 0.826 |
| Cyprus | Very high | High | 0.039 | 0.961 | 0.739 | 0.736 | 0.841 |
| Czechia | Very high | Highest | 0.055 | 0.945 | 0.784 | 0.782 | 0.860 |
| Denmark | Very high | Highest | 0.051 | 0.949 | 0.854 | 0.852 | 0.899 |
| Djibouti | Low | Middle | 0.355 | 0.645 | 0.360 | 0.352 | 0.476 |
| Dominica | High | High | 0.185 | 0.815 | 0.571 | 0.564 | 0.678 |
| Dominican Republic | High | High | 0.136 | 0.864 | 0.588 | 0.580 | 0.708 |
| Ecuador | High | High | 0.080 | 0.920 | 0.603 | 0.597 | 0.741 |
| Egypt | Medium | High | 0.222 | 0.778 | 0.608 | 0.598 | 0.682 |
| El Salvador | Medium | High | 0.099 | 0.901 | 0.582 | 0.573 | 0.718 |
| Equatorial Guinea | Medium | Lowest | 0.418 | 0.582 | 0.353 | 0.349 | 0.451 |
| Eritrea | Low | Lowest | 0.433 | 0.567 | 0.113 | 0.114 | 0.255 |
| Estonia | Very high | Highest | 0.084 | 0.916 | 0.765 | 0.763 | 0.836 |
| Eswatini | Medium | Middle | 0.669 | 0.331 | 0.377 | 0.374 | 0.352 |
| Ethiopia | Low | Lowest | 0.372 | 0.628 | 0.027 | 0.029 | 0.135 |
| Fiji | High | High | 0.391 | 0.609 | 0.655 | 0.652 | 0.630 |
| Finland | Very high | Highest | 0.033 | 0.967 | 0.816 | 0.813 | 0.887 |
| France | Very high | Highest | 0.023 | 0.977 | 0.821 | 0.817 | 0.894 |
| Gabon | High | Middle | 0.346 | 0.654 | 0.445 | 0.444 | 0.539 |
| Gambia | Low | Middle | 0.361 | 0.639 | 0.290 | 0.284 | 0.426 |
| Georgia | High | High | 0.149 | 0.851 | 0.700 | 0.699 | 0.771 |
| Germany | Very high | Highest | 0.045 | 0.955 | 0.891 | 0.891 | 0.923 |
| Ghana | Medium | Middle | 0.377 | 0.623 | 0.311 | 0.312 | 0.441 |
| Greece | Very high | High | 0.039 | 0.961 | 0.729 | 0.724 | 0.834 |
| Grenada | High | High | 0.210 | 0.790 | 0.618 | 0.612 | 0.695 |
| Guatemala | Medium | Middle | 0.175 | 0.825 | 0.492 | 0.485 | 0.632 |
| Guinea | Low | Lowest | 0.563 | 0.437 | 0.161 | 0.157 | 0.262 |
| Guinea-Bissau | Low | Lowest | 0.621 | 0.379 | 0.183 | 0.180 | 0.261 |
| Guyana | Medium | High | 0.291 | 0.709 | 0.593 | 0.586 | 0.645 |
| Haiti | Low | Lowest | 0.418 | 0.582 | 0.253 | 0.252 | 0.383 |
| Honduras | Medium | Middle | 0.168 | 0.832 | 0.537 | 0.528 | 0.663 |
| Hong Kong | Very high | Highest | | | 0.824 | 0.932 | |
| Hungary | Very high | Highest | 0.115 | 0.885 | 0.744 | 0.741 | 0.810 |
| Iceland | Very high | Highest | 0.023 | 0.977 | 0.823 | 0.820 | 0.895 |
| India | Medium | Middle | 0.304 | 0.696 | 0.456 | 0.450 | 0.559 |
| Indonesia | Medium | Middle | 0.219 | 0.781 | 0.515 | 0.510 | 0.631 |
| Iran | High | High | 0.138 | 0.862 | 0.645 | 0.640 | 0.743 |
| Iraq | Medium | High | 0.285 | 0.715 | 0.578 | 0.567 | 0.637 |

| | | | | | | | |
|----------------------------------|-----------|---------|-------|-------|-------|-------|-------|
| Ireland | Very high | Highest | 0.042 | 0.958 | 0.803 | 0.802 | 0.877 |
| Israel | Very high | Highest | 0.024 | 0.976 | 0.785 | 0.783 | 0.874 |
| Italy | Very high | Highest | 0.020 | 0.980 | 0.752 | 0.746 | 0.855 |
| Jamaica | High | High | 0.151 | 0.849 | 0.606 | 0.602 | 0.715 |
| Japan | Very high | Highest | 0.000 | 1.000 | 0.839 | 0.836 | 0.915 |
| Jordan | High | High | 0.135 | 0.865 | 0.680 | 0.675 | 0.764 |
| Kazakhstan | Very high | Highest | 0.187 | 0.813 | 0.694 | 0.692 | 0.750 |
| Kenya | Medium | Lowest | 0.354 | 0.646 | 0.236 | 0.238 | 0.392 |
| Kiribati | Medium | Middle | 0.516 | 0.484 | 0.366 | 0.367 | 0.421 |
| Korea (Republic of) | Very high | Highest | 0.026 | 0.974 | 0.762 | 0.759 | 0.860 |
| Kuwait | Very high | Highest | 0.077 | 0.923 | 0.699 | 0.688 | 0.797 |
| Kyrgyzstan | Medium | High | 0.219 | 0.781 | 0.631 | 0.629 | 0.701 |
| Laos | Medium | Middle | 0.335 | 0.665 | 0.425 | 0.417 | 0.527 |
| Latvia | Very high | High | 0.121 | 0.879 | 0.724 | 0.723 | 0.797 |
| Lebanon | High | Highest | 0.071 | 0.929 | 0.628 | 0.621 | 0.759 |
| Lesotho | Low | Middle | 0.979 | 0.021 | 0.313 | 0.312 | 0.080 |
| Liberia | Low | Lowest | 0.457 | 0.543 | 0.225 | 0.224 | 0.348 |
| Libya | Medium | High | 0.139 | 0.861 | 0.637 | 0.626 | 0.734 |
| Liechtenstein | Very high | Highest | | | 0.721 | 0.957 | |
| Lithuania | Very high | Highest | 0.113 | 0.887 | 0.737 | 0.737 | 0.809 |
| Luxembourg | Very high | Highest | 0.030 | 0.970 | 0.867 | 0.864 | 0.915 |
| Madagascar | Low | Lowest | 0.485 | 0.515 | 0.155 | 0.159 | 0.286 |
| Malawi | Low | Lowest | 0.575 | 0.425 | 0.232 | 0.230 | 0.312 |
| Malaysia | Very high | High | 0.116 | 0.884 | 0.680 | 0.674 | 0.772 |
| Maldives | High | High | 0.069 | 0.931 | 0.639 | 0.626 | 0.764 |
| Mali | Low | Lowest | 0.540 | 0.460 | 0.261 | 0.253 | 0.341 |
| Malta | Very high | Highest | 0.037 | 0.963 | 0.767 | 0.763 | 0.857 |
| Marshall Islands | High | Middle | 0.411 | 0.589 | 0.604 | 0.603 | 0.596 |
| Mauritania | Low | Middle | 0.283 | 0.717 | 0.291 | 0.286 | 0.453 |
| Mauritius | High | High | 0.160 | 0.840 | 0.666 | 0.658 | 0.744 |
| Mexico | High | High | 0.110 | 0.890 | 0.633 | 0.626 | 0.746 |
| Micronesia (Federated States) | Medium | Middle | 0.377 | 0.623 | 0.518 | 0.513 | 0.566 |
| Moldova (Republic of) | High | High | 0.185 | 0.815 | 0.596 | 0.596 | 0.697 |
| Mongolia | High | High | 0.274 | 0.726 | 0.496 | 0.497 | 0.600 |
| Montenegro | Very high | Highest | 0.087 | 0.913 | 0.711 | 0.707 | 0.803 |
| Morocco | Medium | Middle | 0.172 | 0.828 | 0.509 | 0.498 | 0.642 |
| Mozambique | Low | Lowest | 0.582 | 0.418 | 0.158 | 0.157 | 0.256 |
| Myanmar | Medium | Middle | 0.252 | 0.748 | 0.404 | 0.396 | 0.544 |
| Namibia | Medium | Middle | 0.407 | 0.593 | 0.375 | 0.374 | 0.471 |
| Nepal | Medium | Middle | 0.244 | 0.756 | 0.418 | 0.410 | 0.557 |
| Netherlands | Very high | Highest | 0.038 | 0.962 | 0.839 | 0.836 | 0.897 |
| New Zealand | Very high | Highest | 0.039 | 0.961 | 0.810 | 0.807 | 0.881 |
| Nicaragua | Medium | Middle | 0.081 | 0.919 | 0.474 | 0.468 | 0.656 |
| Niger | Low | Lowest | 0.532 | 0.468 | 0.070 | 0.068 | 0.179 |
| Nigeria | Low | Lowest | 0.455 | 0.545 | 0.307 | 0.306 | 0.408 |
| Norway | Very high | Highest | 0.022 | 0.978 | 0.881 | 0.878 | 0.927 |
| Oman | Very high | Highest | 0.101 | 0.899 | 0.709 | 0.703 | 0.795 |

| | | | | | | | |
|----------------------------------|-----------|---------|-------|-------|-------|-------|-------|
| Pakistan | Medium | Middle | 0.342 | 0.658 | 0.434 | 0.426 | 0.529 |
| Palau | Very high | High | | | 0.752 | 0.749 | |
| Palestine | Medium | High | 0.238 | 0.762 | 0.645 | 0.638 | 0.697 |
| Panama | High | High | 0.071 | 0.929 | 0.644 | 0.640 | 0.771 |
| Papua New Guinea | Low | Lowest | 0.541 | 0.459 | 0.084 | 0.088 | 0.201 |
| Paraguay | High | High | 0.147 | 0.853 | 0.620 | 0.613 | 0.723 |
| Peru | High | High | 0.064 | 0.936 | 0.561 | 0.557 | 0.722 |
| Philippines | Medium | Middle | 0.252 | 0.748 | 0.567 | 0.563 | 0.649 |
| Poland | Very high | Highest | 0.074 | 0.926 | 0.747 | 0.744 | 0.830 |
| Portugal | Very high | Highest | 0.041 | 0.959 | 0.716 | 0.708 | 0.824 |
| Qatar | Very high | Highest | 0.064 | 0.936 | 0.769 | 0.762 | 0.845 |
| Romania | Very high | High | 0.125 | 0.875 | 0.675 | 0.672 | 0.767 |
| Russian Federation | Very high | High | 0.195 | 0.805 | 0.694 | 0.692 | 0.747 |
| Rwanda | Low | Lowest | 0.315 | 0.685 | 0.289 | 0.284 | 0.441 |
| Saint Kitts and Nevis | High | High | | | 0.638 | 0.630 | |
| Saint Lucia | High | High | 0.129 | 0.871 | 0.623 | 0.617 | 0.733 |
| Saint Vincent and the Grenadines | High | High | 0.207 | 0.793 | 0.603 | 0.596 | 0.688 |
| Samoa | High | High | 0.205 | 0.795 | 0.672 | 0.667 | 0.728 |
| Sao Tome and Principe | Medium | Middle | 0.256 | 0.744 | 0.377 | 0.373 | 0.527 |
| Saudi Arabia | Very high | Highest | 0.098 | 0.902 | 0.731 | 0.723 | 0.808 |
| Senegal | Low | Middle | 0.372 | 0.628 | 0.322 | 0.313 | 0.443 |
| Serbia | High | High | 0.111 | 0.889 | 0.651 | 0.648 | 0.759 |
| Seychelles | High | High | 0.155 | 0.845 | 0.683 | 0.677 | 0.756 |
| Sierra Leone | Low | Lowest | 0.617 | 0.383 | 0.146 | 0.145 | 0.236 |
| Singapore | Very high | Highest | 0.001 | 0.999 | 0.771 | 0.767 | 0.875 |
| Slovakia | Very high | Highest | 0.090 | 0.910 | 0.768 | 0.765 | 0.835 |
| Slovenia | Very high | Highest | 0.031 | 0.969 | 0.775 | 0.772 | 0.865 |
| Solomon Islands | Low | Middle | 0.464 | 0.536 | 0.272 | 0.270 | 0.381 |
| South Africa | Medium | Middle | 0.479 | 0.521 | 0.591 | 0.589 | 0.554 |
| South Sudan | Low | Lowest | 0.597 | 0.403 | 0.080 | 0.084 | 0.184 |
| Spain | Very high | Highest | 0.013 | 0.987 | 0.743 | 0.736 | 0.852 |
| Sri Lanka | High | High | 0.082 | 0.918 | 0.637 | 0.634 | 0.763 |
| Sudan | Low | Lowest | 0.329 | 0.671 | 0.213 | 0.210 | 0.375 |
| Suriname | High | High | 0.220 | 0.780 | 0.599 | 0.593 | 0.680 |
| Sweden | Very high | Highest | 0.029 | 0.971 | 0.856 | 0.854 | 0.910 |
| Switzerland | Very high | Highest | 0.019 | 0.981 | 0.890 | 0.889 | 0.934 |
| Syrian Arab Republic | Low | High | 0.130 | 0.870 | 0.551 | 0.539 | 0.684 |
| Tajikistan | Medium | High | 0.215 | 0.785 | 0.590 | 0.588 | 0.679 |
| Tanzania | Low | Lowest | 0.422 | 0.578 | 0.207 | 0.209 | 0.348 |
| Thailand | High | High | 0.083 | 0.917 | 0.639 | 0.629 | 0.760 |
| The FYR of Macedonia | High | High | 0.133 | 0.867 | 0.653 | 0.647 | 0.749 |
| Timor-Leste | Medium | Middle | 0.206 | 0.794 | 0.344 | 0.338 | 0.518 |
| Togo | Low | Lowest | 0.486 | 0.514 | 0.192 | 0.192 | 0.314 |
| Tonga | High | High | 0.251 | 0.749 | 0.685 | 0.681 | 0.714 |
| Trinidad and | High | High | 0.185 | 0.815 | 0.701 | 0.697 | 0.753 |

| | | | | | | | |
|----------------------|-----------|---------|-------|-------|-------|-------|-------|
| Tobago | | | | | | | |
| Tunisia | High | High | 0.109 | 0.891 | 0.594 | 0.584 | 0.722 |
| Turkey | High | High | 0.098 | 0.902 | 0.653 | 0.643 | 0.762 |
| Turkmenistan | High | High | 0.248 | 0.752 | 0.667 | 0.661 | 0.705 |
| Uganda | Low | Lowest | 0.493 | 0.507 | 0.146 | 0.150 | 0.276 |
| Ukraine | High | Highest | 0.183 | 0.817 | 0.669 | 0.666 | 0.737 |
| United Arab Emirates | Very high | Highest | 0.124 | 0.876 | 0.732 | 0.727 | 0.798 |
| United Kingdom | Very high | Highest | 0.053 | 0.947 | 0.829 | 0.827 | 0.885 |
| United States | Very high | Highest | 0.087 | 0.913 | 0.984 | 0.983 | 0.947 |
| Uruguay | Very high | High | 0.085 | 0.915 | 0.682 | 0.674 | 0.785 |
| Uzbekistan | High | High | 0.242 | 0.758 | 0.697 | 0.693 | 0.725 |
| Vanuatu | Medium | Middle | 0.436 | 0.564 | 0.400 | 0.397 | 0.473 |
| Venezuela | High | High | 0.102 | 0.898 | 0.653 | 0.648 | 0.763 |
| Viet Nam | Medium | High | 0.127 | 0.873 | 0.569 | 0.563 | 0.701 |
| Yemen | Low | Middle | 0.327 | 0.673 | 0.276 | 0.269 | 0.426 |
| Zambia | Medium | Lowest | 0.615 | 0.385 | 0.242 | 0.246 | 0.307 |
| Zimbabwe | Low | Middle | 0.592 | 0.408 | 0.317 | 0.321 | 0.362 |

*** The country has a value of 0 for the complement of the normalized DALYs. We set the geometric mean as the anti-log(sum of the (log +1) divided by 2) - 1

| Countries | Rank | HDI Rank **** | HDI - Rank | Abs (HDI - Rank) | GNI Rank **** | GNI - Rank | Abs (GNI - Rank) |
|------------------------|------|------------------|------------|------------------|------------------|------------|------------------|
| Afghanistan | 166 | 164 | -2 | 2 | 164 | -2 | 2 |
| Albania | 67 | 66 | -1 | 1 | 90 | 23 | 23 |
| Algeria | 92 | 79 | -13 | 13 | 78 | -14 | 14 |
| Andorra | 28 | 33 | 5 | 5 | | -28 | |
| Angola | 152 | 141 | -11 | 11 | 121 | -31 | 31 |
| Antigua and Barbuda | 76 | 67 | -9 | 9 | 54 | -22 | 22 |
| Argentina | 51 | 45 | -6 | 6 | 60 | 9 | 9 |
| Armenia | 52 | 80 | 28 | 28 | 105 | 53 | 53 |
| Australia | 14 | 3 | -11 | 11 | 19 | 5 | 5 |
| Austria | 11 | 18 | 7 | 7 | 13 | 2 | 2 |
| Azerbaijan | 98 | 76 | -22 | 22 | 71 | -27 | 27 |
| Bahamas | 61 | 51 | -10 | 10 | 40 | -21 | 21 |
| Bahrain | 53 | 39 | -14 | 14 | 22 | -31 | 31 |
| Bangladesh | 126 | 134 | 8 | 8 | 139 | 13 | 13 |
| Barbados | 54 | 55 | 1 | 1 | 67 | 13 | 13 |
| Belarus | 50 | 52 | 2 | 2 | 66 | 16 | 16 |
| Belgium | 15 | 15 | 0 | 0 | 18 | 3 | 3 |
| Belize | 88 | 101 | 13 | 13 | 111 | 23 | 23 |
| Benin | 165 | 157 | -8 | 8 | 158 | -7 | 7 |
| Bhutan | 124 | 131 | 7 | 7 | 107 | -17 | 17 |
| Bolivia | 114 | 112 | -2 | 2 | 116 | 2 | 2 |
| Bosnia and Herzegovina | 55 | 73 | 18 | 18 | 85 | 30 | 30 |
| Botswana | 125 | 98 | -27 | 27 | 68 | -57 | 57 |

| | | | | | | | |
|--------------------------|-----|-----|-----|----|-----|-----|----|
| Brazil | 87 | 75 | -12 | 12 | 76 | -11 | 11 |
| Brunei Darussalam | 48 | 38 | -10 | 10 | 4 | -44 | 44 |
| Bulgaria | 56 | 48 | -8 | 8 | 61 | 5 | 5 |
| Burkina Faso | 180 | 178 | -2 | 2 | 168 | -12 | 12 |
| Burundi | 164 | 179 | 15 | 15 | 181 | 17 | 17 |
| Cabo Verde | 121 | 120 | -1 | 1 | 119 | -2 | 2 |
| Cambodia | 137 | 142 | 5 | 5 | 145 | 8 | 8 |
| Cameroon | 163 | 146 | -17 | 17 | 146 | -17 | 17 |
| Canada | 9 | 11 | 2 | 2 | 20 | 11 | 11 |
| Central African Republic | 185 | 183 | -2 | 2 | 180 | -5 | 5 |
| Chad | 183 | 181 | -2 | 2 | 162 | -21 | 21 |
| Chile | 37 | 42 | 5 | 5 | 55 | 18 | 18 |
| China | 94 | 82 | -12 | 12 | 74 | -20 | 20 |
| Colombia | 72 | 85 | 13 | 13 | 81 | 9 | 9 |
| Comoros | 141 | 159 | 18 | 18 | 154 | 13 | 13 |
| Congo | 156 | 129 | -27 | 27 | 129 | -27 | 27 |
| Congo (DRC) | 172 | 172 | 0 | 0 | 179 | 7 | 7 |
| Costa Rica | 43 | 60 | 17 | 17 | 73 | 30 | 30 |
| Cote d'Ivoire | 162 | 165 | 3 | 3 | 142 | -20 | 20 |
| Croatia | 38 | 44 | 6 | 6 | 49 | 11 | 11 |
| Cuba | 35 | 69 | 34 | 34 | | -35 | |
| Cyprus | 30 | 30 | 0 | 0 | 33 | 3 | 3 |
| Czechia | 24 | 25 | 1 | 1 | 34 | 10 | 10 |
| Denmark | 8 | 9 | 1 | 1 | 12 | 4 | 4 |
| Djibouti | 138 | 166 | 28 | 28 | | | |
| Dominica | 110 | 97 | -13 | 13 | 100 | -10 | 10 |
| Dominican Republic | 97 | 91 | -6 | 6 | 77 | -20 | 20 |
| Ecuador | 81 | 80 | -1 | 1 | 98 | 17 | 17 |
| Egypt | 107 | 109 | 2 | 2 | 96 | -11 | 11 |
| El Salvador | 93 | 115 | 22 | 22 | 115 | 22 | 22 |
| Equatorial Guinea | 143 | 135 | -8 | 8 | 58 | -85 | 85 |
| Eritrea | 176 | 174 | -2 | 2 | 157 | -19 | 19 |
| Estonia | 31 | 28 | -3 | 3 | 39 | 8 | 8 |
| Eswatini | 158 | 137 | -21 | 21 | 101 | -57 | 57 |
| Ethiopia | 182 | 169 | -13 | 13 | 167 | -15 | 15 |
| Fiji | 120 | 89 | -31 | 31 | 104 | -16 | 16 |
| Finland | 16 | 14 | -2 | 2 | 21 | 5 | 5 |
| France | 13 | 21 | 8 | 8 | 23 | 10 | 10 |
| Gabon | 132 | 105 | -27 | 27 | 69 | -63 | 63 |
| Gambia | 148 | 169 | 21 | 21 | 172 | 24 | 24 |
| Georgia | 58 | 68 | 10 | 10 | 102 | 44 | 44 |
| Germany | 4 | 4 | 0 | 0 | 14 | 10 | 10 |
| Ghana | 146 | 136 | -10 | 10 | 137 | -9 | 9 |
| Greece | 33 | 28 | -5 | 5 | 43 | 10 | 10 |
| Grenada | 104 | 71 | -33 | 33 | 87 | -17 | 17 |
| Guatemala | 118 | 122 | 4 | 4 | 112 | -6 | 6 |
| Guinea | 173 | 173 | 0 | 0 | 160 | -13 | 13 |

| | | | | | | | |
|--|-----|-----|-----|----|-----|-----|----|
| Guinea-Bissau | 174 | 171 | -3 | 3 | 169 | -5 | 5 |
| Guyana | 115 | 120 | 5 | 5 | 110 | -5 | 5 |
| Haiti | 153 | 163 | 10 | 10 | 166 | 13 | 13 |
| Honduras | 111 | 128 | 17 | 17 | 133 | 22 | 22 |
| Hong Kong | | | | | | | |
| Hungary | 39 | 43 | 4 | 4 | 45 | 6 | 6 |
| Iceland | 12 | 6 | -6 | 6 | 16 | 4 | 4 |
| India | 128 | 125 | -3 | 3 | 118 | -10 | 10 |
| Indonesia | 119 | 111 | -8 | 8 | 95 | -24 | 24 |
| Iran | 80 | 58 | -22 | 22 | 59 | -21 | 21 |
| Iraq | 117 | 116 | -1 | 1 | 65 | -52 | 52 |
| Ireland | 19 | 4 | -15 | 15 | 10 | -9 | 9 |
| Israel | 21 | 19 | -2 | 2 | 30 | 9 | 9 |
| Italy | 26 | 26 | 0 | 0 | 27 | 1 | 1 |
| Jamaica | 95 | 92 | -3 | 3 | 108 | 13 | 13 |
| Japan | 6 | 17 | 11 | 11 | 24 | 18 | 18 |
| Jordan | 62 | 90 | 28 | 28 | 106 | 44 | 44 |
| Kazakhstan | 74 | 57 | -17 | 17 | 52 | -22 | 22 |
| Kenya | 151 | 139 | -12 | 12 | 150 | -1 | 1 |
| Kiribati | 149 | 130 | -19 | 19 | 134 | -15 | 15 |
| Korea (Republic of) | 23 | 20 | -3 | 3 | 29 | 6 | 6 |
| Kuwait | 45 | 53 | 8 | 8 | 2 | -43 | 43 |
| Kyrgyzstan | 100 | 117 | 17 | 17 | 147 | 47 | 47 |
| Laos | 135 | 133 | -2 | 2 | 123 | -12 | 12 |
| Latvia | 46 | 41 | -5 | 5 | 47 | 1 | 1 |
| Lebanon | 69 | 78 | 9 | 9 | 88 | 19 | 19 |
| Lesotho | 184 | 155 | -29 | 29 | 143 | -41 | 41 |
| Liberia | 159 | 176 | 17 | 17 | 177 | 18 | 18 |
| Libya | 83 | 110 | 27 | 27 | 75 | -8 | 8 |
| Liechtenstein | | | | | | | |
| Lithuania | 40 | 34 | -6 | 6 | 41 | 1 | 1 |
| Luxembourg | 5 | 24 | 19 | 19 | 6 | 1 | 1 |
| Madagascar | 170 | 154 | -16 | 16 | 173 | 3 | 3 |
| Malawi | 168 | 166 | -2 | 2 | 176 | 8 | 8 |
| Malaysia | 57 | 55 | -2 | 2 | 42 | -15 | 15 |
| Maldives | 63 | 98 | 35 | 35 | 83 | 20 | 20 |
| Mali | 161 | 177 | 16 | 16 | 161 | 0 | 0 |
| Malta | 25 | 27 | 2 | 2 | 32 | 7 | 7 |
| Marshall Islands | 123 | | | | 132 | 9 | 9 |
| Mauritania | 142 | 155 | 13 | 13 | 141 | -1 | 1 |
| Mauritius | 79 | 61 | -18 | 18 | 53 | -26 | 26 |
| Mexico | 78 | 70 | -8 | 8 | 62 | -16 | 16 |
| Micronesia (Federated States of) | 127 | 127 | 0 | 0 | 138 | 11 | 11 |
| Moldova (Republic of) | 103 | 106 | 3 | 3 | 117 | 14 | 14 |
| Mongolia | 122 | 88 | -34 | 34 | 96 | -26 | 26 |
| Montenegro | 42 | 48 | 6 | 6 | 64 | 22 | 22 |

| | | | | | | | |
|----------------------------------|-----|-----|-----|----|-----|-----|----|
| Morocco | 116 | 118 | 2 | 2 | 113 | -3 | 3 |
| Mozambique | 175 | 175 | 0 | 0 | 175 | 0 | 0 |
| Myanmar | 131 | 143 | 12 | 12 | 128 | -3 | 3 |
| Namibia | 140 | 124 | -16 | 16 | 99 | -41 | 41 |
| Nepal | 129 | 144 | 15 | 15 | 155 | 26 | 26 |
| Netherlands | 10 | 9 | -1 | 1 | 15 | 5 | 5 |
| New Zealand | 18 | 15 | -3 | 3 | 28 | 10 | 10 |
| Nicaragua | 112 | 119 | 7 | 7 | 131 | 19 | 19 |
| Niger | 181 | 184 | 3 | 3 | 178 | -3 | 3 |
| Nigeria | 150 | 152 | 2 | 2 | 126 | -24 | 24 |
| Norway | 3 | 1 | -2 | 2 | 8 | 5 | 5 |
| Oman | 47 | 45 | -2 | 2 | 26 | -21 | 21 |
| Pakistan | 133 | 145 | 12 | 12 | 130 | -3 | 3 |
| Palau | | | | | | | |
| Palestine | 102 | 112 | 10 | 10 | 127 | 25 | 25 |
| Panama | 59 | 63 | 4 | 4 | 56 | -3 | 3 |
| Papua New Guinea | 178 | 147 | -31 | 31 | 136 | -42 | 42 |
| Paraguay | 89 | 104 | 15 | 15 | 93 | 4 | 4 |
| Peru | 90 | 82 | -8 | 8 | 86 | -4 | 4 |
| Philippines | 113 | 107 | -6 | 6 | 103 | -10 | 10 |
| Poland | 34 | 32 | -2 | 2 | 44 | 10 | 10 |
| Portugal | 36 | 40 | 4 | 4 | 37 | 1 | 1 |
| Qatar | 29 | 34 | 5 | 5 | 1 | -28 | 28 |
| Romania | 60 | 50 | -10 | 10 | 51 | -9 | 9 |
| Russian Federation | 77 | 47 | -30 | 30 | 50 | -27 | 27 |
| Rwanda | 145 | 153 | 8 | 8 | 163 | 18 | 18 |
| Saint Kitts and Nevis | | | | | | | |
| Saint Lucia | 84 | 87 | 3 | 3 | 91 | 7 | 7 |
| Saint Vincent and the Grenadines | 105 | 95 | -10 | 10 | 89 | -16 | 16 |
| Samoa | 85 | 100 | 15 | 15 | 122 | 37 | 37 |
| Sao Tome and Principe | 134 | 140 | 6 | 6 | 149 | 15 | 15 |
| Saudi Arabia | 41 | 36 | -5 | 5 | 11 | -30 | 30 |
| Senegal | 144 | 161 | 17 | 17 | 148 | 4 | 4 |
| Serbia | 70 | 63 | -7 | 7 | 79 | 9 | 9 |
| Seychelles | 71 | 59 | -12 | 12 | 48 | -23 | 23 |
| Sierra Leone | 177 | 180 | 3 | 3 | 174 | -3 | 3 |
| Singapore | 20 | 8 | -12 | 12 | 3 | -17 | 17 |
| Slovakia | 32 | 37 | 5 | 5 | 38 | 6 | 6 |
| Slovenia | 22 | 22 | 0 | 0 | 35 | 13 | 13 |
| Solomon Islands | 154 | 147 | -7 | 7 | 159 | 5 | 5 |
| South Africa | 130 | 107 | -23 | 23 | 84 | -46 | 46 |
| South Sudan | 179 | 182 | 3 | 3 | 171 | -8 | 8 |
| Spain | 27 | 23 | -4 | 4 | 31 | 4 | 4 |
| Sri Lanka | 64 | 72 | 8 | 8 | 91 | 27 | 27 |
| Sudan | 155 | 161 | 6 | 6 | 135 | -20 | 20 |
| Suriname | 108 | 96 | -12 | 12 | 82 | -26 | 26 |

| | | | | | | | |
|----------------------|-----|-----|-----|----|-----|-----|----|
| Sweden | 7 | 7 | 0 | 0 | 17 | 10 | 10 |
| Switzerland | 2 | 2 | 0 | 0 | 7 | 5 | 5 |
| Syrian Arab Republic | 106 | 149 | 43 | 43 | | | |
| Tajikistan | 109 | 123 | 14 | 14 | 144 | 35 | 35 |
| Tanzania | 160 | 150 | -10 | 10 | 152 | -8 | 8 |
| Thailand | 68 | 82 | 14 | 14 | 72 | 4 | 4 |
| The FYR of Macedonia | 75 | 77 | 2 | 2 | 80 | 5 | 5 |
| Timor-Leste | 136 | 126 | -10 | 10 | 114 | -22 | 22 |
| Togo | 167 | 160 | -7 | 7 | 170 | 3 | 3 |
| Tonga | 96 | 94 | -2 | 2 | 124 | 28 | 28 |
| Trinidad and Tobago | 73 | 63 | -10 | 10 | 36 | -37 | 37 |
| Tunisia | 91 | 92 | 1 | 1 | 94 | 3 | 3 |
| Turkey | 66 | 62 | -4 | 4 | 46 | -20 | 20 |
| Turkmenistan | 99 | 102 | 3 | 3 | 69 | -30 | 30 |
| Uganda | 171 | 158 | -13 | 13 | 165 | -6 | 6 |
| Ukraine | 82 | 86 | 4 | 4 | 109 | 27 | 27 |
| United Arab Emirates | 44 | 31 | -13 | 13 | 5 | -39 | 39 |
| United Kingdom | 17 | 13 | -4 | 4 | 25 | 8 | 8 |
| United States | 1 | 11 | 10 | 10 | 9 | 8 | 8 |
| Uruguay | 49 | 54 | 5 | 5 | 57 | 8 | 8 |
| Uzbekistan | 86 | 103 | 17 | 17 | 120 | 34 | 34 |
| Vanuatu | 139 | 132 | -7 | 7 | 151 | 12 | 12 |
| Venezuela | 65 | 73 | 8 | 8 | 63 | -2 | 2 |
| Viet Nam | 101 | 112 | 11 | 11 | 125 | 24 | 24 |
| Yemen | 147 | 168 | 21 | 21 | 153 | 6 | 6 |
| Zambia | 169 | 137 | -32 | 32 | 139 | -30 | 30 |
| Zimbabwe | 157 | 151 | -6 | 6 | 156 | -1 | 1 |

**** We adjusted the ranks of the GNIpc and HDI so that they rank only countries that have their scores available with our framework

CURRICULUM VITAE

2011 – 2016 “Diplôme d'Ingénieur d'État”, Industrial Engineering,
National School of Applied Sciences, Agadir, MOROCCO

2018 – Present M.Sc., Industrial Engineering, Abdullah Gül University, Kayseri,
TURKEY