Policies to Minimize the Socio-economic Impact of SARS-CoV-2:

An International Comparison

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Abstract

At the end of 2019, a novel coronavirus (later called SARS-CoV-2) emerged in Wuhan, China. Two years after, communities are still fighting this virus that put the world in pandemic state: people had to be lockdown, companies and industries sites had to close doors, kids had to make a break in their education, and for several months cities looked inhabited, a similar scenario to an apocalyptic movie. Countries' governments and health organizations had to join forces and work together to find the best measures to keep people's health safe and the nationals healthcare systems without pressure. Maybe this can be a mere chance event or a warning call from nature to raise awareness for changes in some bad habits and behaviours, but the truth is that the pandemic and subsequent measures have several impacts. If for one hand, COVID-19 brought negative impacts, mostly socially and economically, on the other hand it brought positive impacts for environments and biodiversity. Studying the measures taken and the consequents impacts, it is possible to understand what should be changed for a better and sustainable world. In this research it was used a type of Data Envelopment Analysis, the Benefit-of-Doubt (BoD-DEA) to create a capable and useful "tool" to evaluate countries relative efficiencies during COVID-19 pandemic. This work permits to decision makers understand which areas countries performed better and worse since it was used not only data from the measures that were globally adopted to fight the virus but also other dimensions such as countries' economy, governance and healthcare resources. This way, they can refine their knowledge about their country performance and compare to other efficient countries and change behaviours in that direction. It was perceived that countries efficiency to fight the pandemic is associated with their income: middle- and high-income countries have shown much better results than poorer and less developed countries. Nevertheless, 89%, 86% and 60% of countries from cluster 1, 2 and 3, respectively, achieved an overall efficiency at a rate of 80%.

Keywords: COVID-19 pandemic; Anti-covid policies; Socio-economic analysis; Benchmarking; Benefit-of-Doubt;

Resumo

No final de 2019, um novo coronavírus (mais tarde nomeado SARS-CoV-2) surgiu em Wuhan, China. Dois anos depois, as comunidades ainda lutam contra este vírus que colocou o mundo num estado de pandemia: as pessoas tiveram que entrar em confinamento, empresas e indústrias tiveram que fechar portas, crianças tiveram que fazer uma pausa na sua educação e por vários meses as cidades pareciam desabitadas, um cenário semelhante a um filme apocalíptico. O governo dos países e as organizações de saúde tiveram que unir forças e trabalhar juntos para definir as melhores medidas para manter segura a saúde da população e os sistemas de saúde sem pressão. Talvez isto possa ser um mero evento casual ou um alerta da natureza para sensibilizar para a mudança de alguns hábitos e comportamentos incorretos, mas a verdade é que a pandemia e as medidas subsequentes trouxeram vários impactos. Se por um lado o COVID-19 trouxe impactos negativos, principalmente sociais e econômicos, por outro, verificou-se impactos positivos no ambiente e na biodiversidade. Estudando as medidas adotadas e os consequentes impactos, é possível entender o que deve ser mudado para um mundo melhor e sustentável. Neste estudo foi utilizado um tipo de *Data Envelopment Analysis*, o *Benefit-of-Doubt* (BoD-DEA) para criar uma “ferramenta” capaz e útil para avaliar a eficiência relativa dos países durante a pandemia de COVID-19. Este trabalho permite aos responsáveis pela tomada de decisão entenderem as áreas em que os países tiveram melhor e pior desempenho, pois foram usados não só dados das medidas adotadas para combater o vírus, mas também outras dimensões como economia, governação e recursos disponíveis na saúde. Desta forma, eles podem afunilar o seu conhecimento sobre o desempenho do seu país e comparar com outros países eficientes e mudar comportamentos nessa direção. Percebeu-se que a eficiência dos países no combate à pandemia está muito associada ao seu rendimento: países de rendimento médio e alto apresentaram resultados muito melhores do que os países mais pobres e menos desenvolvidos. No entanto, 89%, 86% e 60% dos países dos *clusters* 1, 2 e 3, respetivamente, alcançaram uma eficiência geral superior a 80%.

Palavras-chave: Pandemia COVID-19; Políticas anti-Covid; Análise Socioeconómica; Benchmarking; *Benefit-of-Doubt*;

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List of Acronyms

AIP:	*Associação Industrial Portuguesa*
ANN:	Artificial Neural Network
ASM:	American Society for Microbiology
BoD:	Benefit-of-Doubt
CA:	Cluster Analysis
CCR:	Charnes, Cooper, and Rhodes
CDC:	Center for Disease Control and Prevention
CFCs:	Chlorofluorocarbons
CI:	Composite Indicator
CO_2:	Carbon Dioxide
COVID-19:	Corona Virus Disease 2019
CRS:	Constant Return to Scale
CRSTE:	Constant Returns to Scale Technical Efficiency
CSSE:	Center for System Science and Engineering
DEA:	Data Envelopment Analysis
DMU:	Decision-Making Unit
ESA:	European Space Agency
GDP:	Gross Domestic Product
GNI:	Gross National Income
HIV/AIDS:	Human Immunodeficiency Virus/ Acquired Immunodeficiency Syndrome
ILO:	International Labour Organization
MICE:	Multivariate Imputation by Chained Equation
NASA:	National Aeronautics and Space Administration
nCoV:	Novel Coronavirus
NO_2:	Nitrogen Dioxide
NO_x:	Nitrogen Oxides
ODS:	Ozone Depleting Substances
OECD:	Organization for Economic Co-operation and Development
OxCGRT:	Oxford COVID-19 Government Response Tracker
PC:	Pragmatic Constructivism
PCA:	Principal Components Analysis
PPE:	Personal Protective Equipment
SARS:	Severe Acute Respiratory Syndrome
SARS-COV-2:	Severe Acute Respiratory Syndrome Coronavirus 2
SBM:	Slacks-Based Measure

SE:	Scale Efficiency
SFA:	Stochastic Frontier Analysis
UK:	United Kingdom
UNICEF:	United Nations International Children's Emergency Fund
USA:	United States of America
VRS:	Variable Return to Scale
VRSTE:	Variable Returns to Scale Technical Efficiency
WHO:	World Health Organization
WSIDEA:	Weighted Stochastic Imprecise Data Envelopment Analysis

1. Introduction

1.1. Problem Description

The world is facing constantly challenges that affects several sectors and entities: some that are a more complex problem while others are more simple and less impactful. A pandemic is certainly in the group of a complex problem that a single country or discipline can't control by itself. Having this in mind and having in account that a pandemic affects the entire world, or a big part of it, it is mandatory that countries, international organizations and other bodies join forces and work as a whole to reach the same goal – minimize the socio-economic and healthcare security impacts and put an end to the spread of the disease. The global public health has been threatened several times since the beginning of humankind. In accordance with the numbers that Rosenwald presented for *The Washington Post* article pandemics affects people from antiquity time till the present day, the modern era (Rosenwald, 2021). The first one to be registered is the Antonine Plague (165-180 A.D.) with 5 million deaths caused by measles and smallpox that leaded to the fall of the Roman empire during the reign of Marcus Aurelius. Other remarkable pandemic is the Black Death (1347-1352) that killed between 75 to 200 million people, that Benedictow (2005) considers to be "the greatest catastrophe ever". Considering the extreme possibility, 200 million deaths would correspond almost to the death of Portugal, Spain, France, and Germany today's population. The Black Death was caused by the bacterium *Yersinia pestis* transmission from rats to humans by the bite of infected fleas (Britannica, 2021). In a more recent time, in 1918, arrived the 1918 Flu or Spanish Flu (1918-1929) caused by the virus H1N1 with genes of avian origin (CDC, 2019). Besides the mentioned pandemics many others have occurred over time: Italian Plague (1629-1631), Yellow Fever (late 1800s), Human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS) (1981-current), Swine flu (2009-2010), and Ebola (2014-2016) (Rosenwald, 2021).

In the present moment, 2022, the world is facing a new pandemic caused by a new type of coronavirus, earlier found associated to the severe acute respiratory syndrome (SARS) outbreak in 2002. The history about past pandemics in the world shows that future disease outbreaks will happen inevitably and for that reason understanding the root cause or causes of their origin and finding ways to prevent it; recognize what they have in common and perceive how to control and act under a pandemic condition is very important. The source of these contagious diseases is highly associated with animals (mainly mammals, such as, rats and bats; and insects), bacteria and viruses. Stopping this type of origin is very difficult since new types of viruses and bacteria are surging around the world in a quite high rate, more than two new human virus species is discovered per year (Woolhouse et al., 2008). Pathogens – viruses, bacteria, fungus and parasites – can be found anywhere including the air, surfaces and food and do not stop evolving. Since it is extremely difficult to preclude a new pandemic to happen, the best conduct is to know how to minimize the effects and how to keep it controlled. In fact, using the past pandemics as reference, it is possible to identify that even the earlier pandemics had measures to fight the disease similar to the ones that are being used to combat Corona Virus Disease 2019 (COVID-19): keeping people isolated, quarantines, use of disinfectants, good personal hygiene and limitations of public gatherings, according with Center for Disease Control and Prevention (CDC) website about 1918 pandemic (CDC, 2019).

It is evident that pandemics are dangerous to global health and economy, therefore, the importance of understanding the efficacy of anti-pandemic policies to take lessons and use the good ones for further better and faster decisions in pandemic environment. Consequently, this dissertation will focus mainly in understanding the used policies to minimize the impact of COVID-19 pandemic in people's health and lives, in countries economy (socio-economic approach) and other factors such as governance and healthcare resources available to measure relative efficiencies between countries. Gathering data for an international comparison is aimed to identify the most used and effective policies and realize socio-economic factors that can influence the results. This study can bring the knowledge that hamper an outbreak to expand into a pandemic.

1.2. Dissertation Motivation

Having accounted the problems stated in last section, it is clear that research in a deep level should be done to be more prepared for future possible disease outbreaks: mitigate the negative impacts and make advance of the positive impacts of it. Since COVID-19 is a global disaster, it affects around 7,9 billion people, thus, it is a case of world interest to understand the consequences of this phenomenon and learn from it. If for one hand the spread of COVID-19 disease makes nefarious consequences on world economy and healthcare systems, on the other hand it brings positive environmental effects – both negative and positive consequences will be more analysed further (see section 2.3). As stated by El Zowalaty et al. (2020), these positive environmental effects are important to understand since it is beneficial to the only planet we have, composed by the symbiosis of animals, planet nature elements (air, water, earth) and humans. These effects are likely mostly temporary but may serve as an illustration of how changes in our lifestyle can have good consequences on the environment.

"*Public health policymakers such as the [World Health Organization] (WHO) may also emphasise the silver linings of the COVID-19 pandemic and seek to promote greater use of some of the public health measures in order to prevent, or at least lessen the impact of, the next global health concern*" (Hoo et al., 2021). This statement illustrates well the importance of analysing the consequences of COVID-19 and understand the efficacy of anti-covid policies used to minimize the socio-economic impact for better control of COVID-19 pandemic and future possible outbreaks.

1.3. Dissertation Objectives

This master thesis is aimed to evaluate the relative efficiency of countries (international approach) in the fight of COVID-19 pandemic, analysing used anti-pandemic policies and other factors that influence countries performance to fight a pandemic. It is expected to give countries the possibility to extract from this work insights about the fields that need more attention and improvement and the areas that achieved better evaluation in order to control the pandemic more efficiently and preparedness for the future. To obtain this main objective, it was outlined the following secondary objectives:

- Present an introductory approach to the subject starting by presenting the origin of the problem, fundamental concepts that will be covered by the project and the study's importance for society to serve as a contextualization. It is expected to find information about positive and negative impacts about COVID-19 pandemic and where they were more felt: the good and bad influence for companies, hospitals, people, and environment and, furthermore, understand the measures taken to face the identified negative impacts. This work will be achieved by assessing scientific reports, reliable journals websites or recognized agencies about pandemics and COVID-19.
- Develop a literature review on the main questions of research, organize main topics and ideas, and finally identify the best methodology to answer the problem, i.e., evaluate countries performance assessing the relative efficiency and find factors that influence the spread of COVID-19 virus and fatality rates. Perceive the benchmarking indicators that are usually used to measure anti-pandemic policies efficacy, how data can be retrieved, what is lacking more study and how the data analysis can be processed in order to identify the best technique for this dissertation purpose.
- Find and understand important concepts that are fundamental to proceed with the study: benchmarking, data treatment methods, data analysis techniques.
- It is aimed to do an international revision and comparison to use a wider sample and obtain greater reliability in the data and hence a better global perception and conclusions since COVID-19 pandemic is a problem of international concern.
- Find and use reliable and relevant data and variables to evaluate countries performance to not fall in the problem of "*garbage in, garbage out"*, knowing that data will always be constrained to its availability (geographical-coverage, time-coverage).
- Use the right methods and procedures to correctly assess the efficiencies, in order to extract reliable conclusions and offer suggestions for future possible pandemics.

1.4. Dissertation Structure

This master thesis has fundamentally seven main chapters. The first chapter is the project's introduction where besides stating the study's goal and relevance for society, is made the initial approach to the subject: a comparison to past pandemics is made giving also important numbers to understand that this subject is a matter of global interest. It is highlighted some similarities of COVID-19 with other pandemics, some general measures taken and that this global diseases outbreaks can have some positive impacts besides the negative ones and the importance of changing some behaviours.

In the second chapter, COVID-19: a pandemic to make a change, is presented a contextualization of the subject, where it is stated the origin of the most recent pandemic and a timeline showing the main milestones. Still in this chapter, it is explained some important terms to clarify some notions: endemic vs outbreak vs epidemic vs pandemic – infectious diseases lifecycle –, and a deep analysis on the impacts of COVID-19 and the measures to face these impacts;

The review literature starts on chapter three, where concepts and methodologies go more on depth to address the problem in a proper way. Information from other certified investigations is organized and integrated in a table to summarize the information, extract the best conclusions, and add additional outputs. Understand the best and most used benchmarking indicators with the same finality of this study, how data can be obtained, what is already most studied and what is lacking more studying. A discussion of the literature is made and taken some decisions about the methodology to use.

In chapter four is shown the techniques that will be used and chosen the best data analysis technique for this study. Research about benchmarking, data envelopment analysis and benefit-of-doubt methods is made.

In chapter five is described the practical work done using the methodology that seemed more adequate for this study (the benefit-of-doubt). The sample, variables or indicators used, the whole process of data treatment and efficiency measure using well-defined composite indicators is explained here. It can also be highlighted some important concepts that are explored in this chapter: principal components, cluster analysis, statistical analysis, imputation of missing data, normalization, and weighting and aggregation methods.

In chapter six is presented the main results and they are discussed in separate and analogously for each cluster of countries.

Finally, in chapter seven is given the main conclusions, limitations found and possible future work that could be made.

2. COVID-19: A pandemic to make a change

2.1. Contextualization

At the fourth quarter of 2019, the world was not prepared for what was about to come. An unexpected news began to make a buzz in the media – newspapers, tv news, internet – and in a short time what started as a mere background noise, a closed murmur inside China's borders, ended up becoming a squabble which is now part of the whole world. Governmental organizations, political bodies, healthcare systems, companies and people had to adjust routines, behaviours, priorities and adapt to the new environment that the world was facing by. Maybe a natural phenomenon that occurred to promote fundamental changes, such as rethinking about world priorities and environmental problems while the globe was halted, but which inevitably resulted in devastating social and economic repercussions and fatalities. The big event that came to make a big change was the outbreak of a new virus that represented a public health emergency of international concern – later called as COVID-19.

Early December 2019, patients with a new type of pneumonia started being reported in Wuhan, the capital and biggest city in Hubei province, in China. To get a better scale perception, compared to Portugal, Wuhan has approximately a population of 11 million in a total area of around 8.500 km^2. On the other hand, Portugal has approximately 10 million people in a total area of around 92.200 km^2. Wuhan, that is a city, has a population density 10 times greater than Portugal, that is a whole country. It is clear that Wuhan can be a dangerous place to be the epicentre of an outbreak and start the spread of a virus. After some epidemiological studies, in later December 2019, the pneumonia of unknown cause cases started being linked to a live wildlife animal market in Wuhan – Huanan Seafood Wholesale Market – that experts describe as a perfect incubator for novel pathogens (Myers, 2020). Kevin J. Olival, biologist and vice president of research with *EcoHealth Alliance*, told the *New York Times* about this type of markets: *"This is where you get new and emerging diseases that the human population has never seen before"* (Myers, 2020). While the exact path of the pathogen has not yet been established, government officials and scientists said the new contagion had ominous similarities with the outbreak of SARS in late 2002, which killed nearly 800 people and sickened thousands more around the world (Myers, 2020).

The most likely origin of this new type of coronavirus is that it comes from bats, that seemed to be unaffected by the virus. Unlike humans, bats have developed specific mechanisms that reduce viral replication and also dampen the immune response to a virus. The result is a beneficial balance: their immune systems control viruses but at the same time do not mount a strong inflammatory response (Valich, 2020). Gorbunova, from the department of Biology and Medicine, University of Rochester, said *"Humans have two possible strategies if we want to prevent inflammation, live longer, and avoid the deadly effects of diseases like COVID-19. One would be to not be exposed to any viruses, but that's not practical. The second would be to regulate our immune system more like a bat"* (Valich, 2020). Coronavirus would have been "jumped" from bats to another mammal, possibly an Asian palm civet – a wildlife animal from Asia – and then to humans that are involved in the trading of this type of wild animals in the markets. On January 1st, 2020, the Huanan Market is closed for being the most likely source of the outbreak: the sale of wild animals was banned throughout the province, but it is not clear what happened to the animals that were already in sale there.

Right after, on January 7th, Chinese CDC, identified the cause for the pneumonia cases, a novel coronavirus (nCoV) – 2019-nCoV. El Zowalaty & Järhult (2020) present the emergence and a generalised route of transmission for this virus. In a matter of days, the virus was crossing borders and, in order of appearance of first confirmed cases, Thailand, Japan and Korea reported the first cases for 2019-nCoV. During this month (January 2020), the first cases of COVID-19 appeared around the world, such as on 21 January 2020 the first confirmed case in United States of America (USA), Washington D.C; and on 24 January 2020 the first case in Europe, France (Spiteri et al., 2020). From that moment the number of reported confirmed cases of COVID-19 contagions significantly increased all over the world and the WHO declared the outbreak to be "*a public health emergency of international concern.*" (Santacroce et al., 2020). According with WHO (n.d.), on February 2020, the virus 2019-nCoV gains a new official designation as *SARS-CoV-2*, that stands for severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2); and the disease is named for the first time has COVID-19. The virus does not stop spreading, the cases multiply, and on 11 March 2020, WHO declares COVID-19 as a pandemic with more than 100.000 cases and 4.000 deaths in 114 countries. Still on March, Europe becomes the epicentre of pandemic and USA declares state of emergency.

More severe population behaviour and hygiene measures had to be taken and in mid/late-March countries seal borders, schools, entertainment/cultural amenities, and non-fundamental shops close doors, employees go home, people start using masks and practicing social distancing and only leave home for supermarkets, pharmacies or hospitals – the world was completely shut down and almost everyone afraid to leave their homes, close to an apocalyptic movie scenario. As stated in American Society for Microbiology (ASM), April starts with a frightful number, on April 2nd, the world reaches 1 million positive confirmed cases (ASM, n.d.). The race for a coronavirus vaccine was ongoing and what would usually need around 10, 15 years of research and development had to be reduced to months. A vaccine is crucial to stop the fatalities number keep growing and put an end to a pandemic. Academic research, create an effective vaccine, trials, vaccines' approval bureaucracy, building/finding factories and resources to produce them, manufacturing, distribution, administration to people and, finally, treat properly the residues is a basic concept of the vaccination process. Plan and control all management and logistic to make this work happen successfully is not an easy task in such small period of time (Thompson, 2020). Nonetheless, having account what was reported by ASM, the vaccines start surging on August 11th with Sputnik V receiving approval to be used in Russia (ASM, n.d.), and considering Moore (2021) on November Pfizer/BioNTech vaccine passed the trials with more than 90% effectiveness. Also in November, Moderna vaccine and AstraZeneca vaccine, made in partnership with Oxford University, shown to be effective. The start of the vaccination process in the beginning of 2021 made flatten epidemic curves. Cases and deaths initially begin to fall which led governments to lift up most of the severest measures imposed. Although, when it all seemed that we have reached the light at the end of the tunnel the virus has encountered new ways of development.

The virus has changed, several mutations were found, and it spread again, rapidly, over communities. According with WHO, variants such as Alpha, Delta, Lambda and Omnicron (presented in order of first discovered documented samples) came to show that the virus was evolving, therefore, symptoms and disease outcomes were changing and that effectiveness of vaccines might be compromised (WHO, 2022) This may be explained due to a non-consistent level of vaccination worldwide and the ability of the virus to change being greater than the vaccination process' pace. The ASM determined that on 11 March 2021, one year after WHO declaring COVID-19 as a pandemic, the world had some "cruel" numbers: 118 million confirmed cases, 2.6 million deaths; but also, some "encouraging" numbers: 66.7 million recovered cases and 70,5 million fully vaccinated individuals (ASM, 2020). Having account what stated by Moore (2021), on 27 April 2021, 1 billion COVID-19 vaccine doses have been administered and the action against the pandemic is still running after two years of complete change.

The pandemic enforced people to show emotional intelligence, comprehension, flexibility, and resilience to keep their psychological health and keep fighting against COVID-19, but also, made people perceive that union among communities and countries and the respect for animals, nature and ecosystems is vital to keep the world running in a better way for everyone. Table 1 summarizes COVID-19 milestones during the first two years of pandemic state based on the stated references throughout this section and on Sifuentes-Rodríguez (2020).

Table 1 - COVID-19 timeline (Source: The author)

Date	**Event**
8 December 2019	Patients with pneumonia of unknown cause started being reported in Wuhan, China.
29 December 2019	Pneumonia cases started being linked to a live wildlife animal market in Wuhan – Huanan Seafood Wholesale Market.
1 January 2020	Huanan Market is closed for being the most likely source of the outbreak and the sale of wild animals was banned throughout the province.
7 January 2020	China CDC identified the cause and named it as 2019-nCoV
13 January 2020	Thailand confirms the first (imported) positive case
15 January 2020	Japan confirms the first (imported) positive case
20 January 2020	Korea confirms the first (imported) positive case
21 January 2020	USA confirms the first positive case, in Washington D.C.
24 January 2020	Europe confirms the first (imported) positive case, France
30 January 2020	WHO declares the outbreak to be a public health emergency of international concern
11 February 2020	International Committee on Taxonomy of Viruses renamed 2019-nCoV virus to SARS-CoV-2; WHO announced "*COVID-19*" as the name of the disease caused by SARS-CoV-2.
11 March 2020	WHO declares COVID-19 as a pandemic with more than 100 000 cases and 4 000 deaths in 114 countries
2 April 2020	World reaches 1 million (positive) confirmed cases
11 August 2020	Sputnik V vaccine receives approval to be used in Russia
September 2020	Alpha variant first discovered
28 September 2020	World reaches 1 million deaths
October 2020	Delta variant first discovered
November 2020	Pfizer/BioNTech vaccine shown to be effective

November 2020	Moderna vaccine shown to be effective
November 2020	Oxford/AstraZeneca vaccine shown to be effective
2 December 2020	United Kingdom (UK) becomes the first country to approve the Pfizer/BioNTech
December 2020	Lambda variant first discovered
27 April 2021	1 billion COVID-19 vaccine doses administered
5 August 2021	Confirmed cases of COVID-19 reaches 200 million
24 November 2021	Omnicron variant first discovered in South Africa
11 January 2022	WHO announces that Omicron is the dominant COVID-19 variant outpacing Delta
8 February 2022	Global COVID-19 cases surpass 400 million
March 2022	Several countries start easing COVID-19 restrictions with caution due to reduction of cases

2.2. Infectious disease lifecycle

The infectious diseases surge usually associated with a new type of virus, and so, in the beginning these diseases have strange or unknown cause on a small number of patients in a specific place. This was the start of COVID-19 that quickly moved from an outbreak to a pandemic state. People are wondering when and how the COVID-19 pandemic will end, and according with Herrero and Madzokere virologists from Griffith University, people will need to learn to live with this novel coronavirus since the most probable to happen is the shifting from pandemic to endemic, with some sporadic outbreaks in some "random" locations (Herrero & Madzokere, 2021). The transition from pandemic to endemic is expected to be different in the several locations around the world: depending on location demography, people willingness to comply health and hygiene measures and mainly the vaccine access, where developed and richer countries are ahead. Ingrid Torjesen writes that herd immunity by vaccination or infection will play a key role in ensuring that the pandemic turns into endemic (Torjesen, 2021); and at this time some scientists predicts that COVID-19 will be more prevalent in unvaccinated young people and those without prior exposure to SARS-CoV-2 (Li et al., 2021). Christopher Dye, an epidemiologist at the University of Oxford, UK, told *Nature* journal: *"I guess COVID will be eliminated from some countries, but with a continuing (and maybe seasonal) risk of reintroduction from places where vaccine coverage and public-health measures have not been good enough"* (Torjesen, 2021), which highlights the key role of obtaining herd immunity and importance of non-pharmaceutical measures.

Pandemic was not a very consensual term until the last years. Even in 2009, NYT published an article *"Is This a Pandemic? Define 'Pandemic'"* (Altman, 2009), asking for a more concrete definition since, for example, for some an explosive transmissibility was enough to be considered a pandemic, for others the severity of infection should also be considered. If for one side some terms were very vague, such as, *"extensively epidemic"* (Stedman, 2006); or *"epidemic … over a very wide area and usually affecting a large proportion of the population"* (Last, 1988); or *"distributed or occurring widely throughout a region, country, continent or globally"* (University of Maryland, 2009); others were extremely restrictive to eliminate ambiguities, such the one used by influenza virologists several decades ago: *"introduction and global spread of novel hemagglutinin subtypes"* (Morens et al., 2009). In avian influenza risk assessment (Taubenberger & Morens, 2009), the cases associated with this virus led to a 60% fatality, and at this time, in 2003, WHO defined that a pandemic agent must be infectious, new, spread easily, and cause serious illness (Morens et al., 2009), what seems to be a balanced and fairly definition. In Morens et al. (2009) article, they present eight epidemiologic features to serve as basic aspects to compare and describe pandemic diseases: *wide geographic extension*, *disease movement*, *high attack rates and explosiveness*, *minimal population immunity*, *novelty*, *infectiousness*, *contagiousness*, and *severity*, that are presented in Figure 1 and described below giving a parallelism to COVID-19 pandemic.

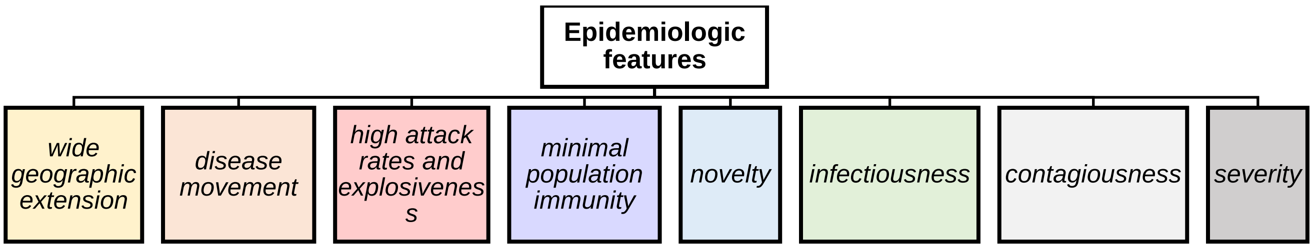

Figure 1 - Epidemiologic features to describe pandemics (Source: The author, according with Morens et al., 2009)

- ***Wide geographic extension:*** Almost all references to pandemics are to diseases that spread across wide geographic regions, such as, black death, 1918 flu and HIV/AIDS. According with Taubenberger and Morens (2009), pandemics could be categorized in transregional (≥2 adjacent regions of the world), interregional (≥2 nonadjacent regions), and global. COVID-19 affected at the present moment 222 Countries and Territories around the world (Worldometer, 2021), thus it is categorized as global.
- ***Disease movement:*** Many references to pandemics refer to disease migration or spread by transmission that can be tracked from one location to another. Examples of disease movement include from person-to-person spread (e.g., influenza, SARS); or by other organisms to people (e.g., dengue mosquitoes, *Aedes albopictus;* or enteric organisms, *Vibrio cholerae*, for example). COVID-19 is the case of person-to-person transmission by the spread of SARS-CoV-2.
- ***High attack rates and explosiveness:*** Pandemics are usually associated with active rates of transmission and high rates of symptomatic disease. For example, in 1999, West Nile virus infection moved from the Middle East to Russia and the Western Hemisphere. Nonetheless, this disease's expansion hasn't been labelled as a pandemic, possibly because attack rates were mild and symptomatic patients were few (Morens et al., 2009), so, presented indolent rates of transmission and low rates of symptomatic disease. In the case of COVID-19, high attack rates (active rates of transmission) and explosiveness (“explosive” spread, i.e., multiple cases appearing within a short time) are presented and for this reason can be considered as a pandemic.
- ***Minimal population immunity:*** If for one hand this may not be an obvious characteristic to measure since immunity does not exactly mean full protection from an infection (Krause et al.,1997), on the other hand it is obvious that a certain level of immunity may be one of the most (if not the most) powerful weapon to fight pandemics. Other pandemics show that immunity is sensitive to the appearance of new variants or different factors, such as people’s gender or age (Taubenberger & Morens, 2009). To fight COVID-19, countries aim to achieve herd immunity that is obtain either by vaccination or by people being infected. Taking Sweden as an example against most European countries, they opted for an anti-

lockdown policy, that shown to be not a good model to follow since death rate is up to 10 times higher than its neighbours' countries (Bendix, 2021). In fact, WHO corroborates this idea defending that *"achieving 'herd immunity' [should be] through vaccination, not by allowing a disease to spread through any segment of the population, as this would result in unnecessary cases and deaths"* (WHO, 2020).

- ***Novelty:*** Pandemics have been used to describe illnesses that are either new or related with novel variants of existing pathogens. For example, in the past 200 years have been 7 cholera pandemics, presumably all caused by variants of the same organism (Morens et al., 2009). COVID-19 was caused by a novel coronavirus, SARS-CoV-2 – a new variant of SARS-CoV identified earlier in SARS outbreak from 2002.
- ***Infectiousness:*** Pandemics are usually used to describe infectious diseases although it was already used several times, for example, for obesity (Meldrum et al., 2017), and cigarette smoking (Shafey et al., 2003), that are non-infectious but geographically extensive diseases. Using the term "Pandemic" in cases like this is more to communicate and educate for the importance of this health problems for the whole world rather than for a scientific purpose. COVID-19 is an infectious disease generally transmitted from people-to-people caused by a respiratory virus, so this epidemiologic feature is applied undoubtedly.
- ***Contagiousness:*** Pandemics are usually associated to a transmission mechanism. For example, plague is contagious from fleas and cholera is contagious from water. Usually, most infectious diseases considered to be pandemic are contagious from person to person, such as influenza and COVID-19.
- ***Severity*:** Most uses of the term pandemic imply severe or fatal diseases (e.g., black death, Spanish flu, and HIV/AIDS) although it was already used to describe diseases of low or moderate severity, such as acute hemorrhagic conjunctivitis in 1981 that had an "explosive" spread or scabies that affected a vast geographical area.

Morens et al. (2009) suggestion seems to be the most reasonable and the one that can complement WHO's definition presented above – defining pandemic as a large epidemic associated with infectious diseases that share many of the same epidemiologic features discussed above.

With this study it is possible to understand the meaning of a pandemic and the importance of shifting a pandemic to an endemic condition as mentioned in the first paragraph of this section. But what does that really mean? To answer this question and for a better understanding of the different concepts, that are many times misunderstood, it is possible to find the lifecycle of infectious diseases in Figure 2. Moving upwards on the arrow is what usually happens naturally and the undesirable scenario, associated with the origin of pandemics. Moving downwards on the arrow is the desirable scenario associated with the end of pandemics with the lessen of deaths, illness, need for social isolation and other health measures as the population acquires some immunity through exposure or vaccination. It is explained below the meaning of *Endemic, Outbreak, Epidemic and Pandemic* having in consideration the work made by Grennan (2019).

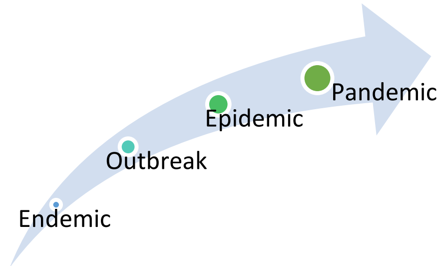

Figure 2 - Infectious disease lifecycle (Source: The author, according with Grennan, 2019)

- ***Endemic:*** When the virus is circulating in a specified location in a stable and predictable rate it is considered an endemic condition/virus. As stated by Grennan (2019), it is when *"the observed number of cases are approximately the same as the number expected"* and can be outlined for a smaller group of people, like the inhabitants from a city, or for larger groups like the inhabitants from a whole continent(s). Examples of endemic virus could be the malaria in Africa, dengue in tropical and subtropical regions and hepatitis B worldwide.
- ***Outbreak:*** If the virus is already known and exists a baseline (endemic level), an outbreak is when the number of cases gets suddenly higher than the expected number of cases. If it is a novel virus, the detection of a single case can be considered an outbreak. Outbreaks happen in small areas, e.g., a town, a park, or a market, and usually, associated to shorter periods of time. Examples of outbreaks could be COVID-19 outbreak in Huanan Seafood market, in Wuhan; or measles outbreak among unvaccinated children in a theme park in 2015, in USA.
- ***Epidemic:*** Epidemics is when an outbreak gets bigger proportions affecting larger geographical areas. An example could be the Ebola virus outbreak in Africa that spread into several West African countries, from 2014 till 2016, that covered an area large enough to be considered epidemic; or the Zika virus that spread in 2014 from Brazil to most Latin America and the Caribbean. Doing a parallelism to the current COVID-19 disease, if it affected only China and some Asian countries would be considered an epidemic instead of a pandemic.
- ***Pandemic:*** A pandemic is an epidemic that spreads globally. Usually associated with infectious diseases from a novel virus or variants that spread easily through a transmission mechanism and cause serious/severe illness and deaths.

When scientist say that people will need to learn to live with the virus is because the end of the pandemic means turning the virus endemic, which means, detecting a new stable level of SARS-CoV-2 transmission that will serve as baseline of COVID. In Phillips (2021), it is possible to see a survey made to 113 immunologists and virologists about this topic. After achieving the endemic state, it is probable that some resurgences occur in some location, as with flu, and for that reason keep tracking population immunity and possible variants because if *"immunity wanes quickly and there are no booster shots available, COVID could go from endemic back to epidemic"* very easily, as stated by Herrero & Madzokere (2021).

2.3. Impacts of COVID-19

2.3.1. COVID-19 and Biodiversity

Human tend to look himself with an anthropocentrism point of view, i.e., putting himself in the center of the universe/world. Moved sometimes by egoism and money forgets that over exploration of natural resources leads to global warming and natural threats like COVID-19 that reminds people to rethink their visions and actions and the importance of environmental ethics. Having in consideration the research made by Verma & Prakash (2020) the lockdowns provided an opportunity to shift our ideology of human centric worldview to eco-centric worldview since it brought an increase of bird (e.g., vultures) and insect pollinators appearance on plants. Other animals also started to appear in the localities, such as, hedgehogs, deers, badgers and foxes that are usually intimidated or ran over by cars and trucks. Coyotes have been spotted on the Golden Gate Bridge in San Francisco, deer in Washington, wild boar in Barcelona and Bergamo, and peacocks in Wales, for example (Watts, 2020). Verma & Prakash also observed that due to decreased deposition of home and industrial effluents, the water of Rapti, Saryu, Ganga and Yamuna rivers became cleaner and more translucent. The same should have happened for the other rivers around the world. Marine life and organisms are taking the lead now with less water pollution and noise pollution, caused mainly by cruisers and powerful seismic air gun tests, used to locate the deposits of gas and oil in the deep oceans. Seems that many species are returning to their natural habitats and reproduction activity (Khan et al., 2020). In addition, lockdowns also brought pollution level down (e.g., less garbage and plastics disposal) in touristic points such as forests, sea beaches and hills (Verma & Prakash, 2020), which provided a perfect environment for olive ridley turtles in the beaches (Khan et al., 2020). These are good indicators of ecological balance and biodiversity and that organisms are flourishing better due to reductions in pollution level.

2.3.2. COVID-19 and Society

Social distancing and lockdown made people perceive that activities that seemed necessary and important before, now it is not that essential. People reduced the over consumption and lived with the essential resources, and this didn't make them live worse, in fact, according with Verma & Prakash (2020) people are feeling healthy without any major clinical problems. Purchases focused on essential goods in supermarkets, which led families to save money. Families were forced to stay at home which enabled them to talk, play and eat together every day, which sometimes were not possible for some families. Working from home made people sleep better, which enhances immunity and the stress free of travelling for work means more efficiency and productivity. However, the social "reclusion", financial insecurity, fear and uncertainty increased domestic violence according with have been reported in many countries. Being lockdown can bring some psychological stress that can be soften with new technologies: mobile phones, internet and keeping busy with online classes or work.

It is important to note that COVID-19 attacks everyone without judgements or discrimination, however the ones living in poverty are more exposed to the disease since sometimes do not have shelter or means for a good hygiene.

2.3.3. COVID-19 and Education

The COVID-19 affected the educational system, and according with United Nations International Children's Emergency Fund (UNICEF), monitoring 188 countries, says that more than one billion of children (about 73,5% of the world's student population) got affected due to school closures (UNICEF, 2020). Schools, teachers and families from more than 90% of the countries used remote learning programmes and educational platforms to reach students, according with UNICEF. UNICEF data shows also that 31% of schoolchildren worldwide (463 million) cannot be reached by distant learning policies in many low- and middle-income nations where the access to these technologies is limited and in families that live in rural areas and/or in vulnerable finance. Television was the best communication channel for e-learning reaching 62% of the students globally, as Portugal did with "*#EstudoEmCasa*" tv show transmitted in the public channel, for example.

2.3.4. COVID-19 and Global Supply Chain and Economy

The International Labour Organization (ILO) report shows that 85% workers worldwide have been affected by full or partial workplaces closures due to COVID-19 crisis that resulted in the loss of around 8,8% of working hours in 2020, which is equivalent to 255 million full-time equivalent jobs, comparing with the fourth quarter of 2019 (ILO, 2021). In 2020, the global unemployment rate moved from 5,4% to 6.5% (raise of 1,1%), which means that 33 million people got unemployed; while 81 million people shifted to inactivity. This numbers illustrates how the pandemic disrupted industries and manufacturing operations, and therefore, the global supply chain. This means that a system of organizations and operations collaborate to create, produce, and deliver a product or service to a market have to work as a whole, and when one part is fully stopped or working partially the whole chain gets affected, which pulls the economy years back (Verma & Prakash, 2020). The sectors that felt more COVID-19 pandemics were accommodation and food service activities, works in arts, entertainment and recreation, retail, and construction sectors but positive job growth evident in a number of higher skilled services sectors, such as information and communication, and financial and insurance activities. Even though the pandemic affected globally, some regions were substantial more affected than others in terms of working-hour losses in 2020. Latin America and the Caribbean, Southern Europe and Southern Asia were the more interrupted whereas Eastern Asia and Central, Western and Eastern Africa working-hour losses were lower, reflecting less strict lockdown measures in these subregions.

Taking Portugal as an example of the pressure that companies felt because of COVID-19 pandemic, in accordance with *Associação Industrial Portuguesa* (AIP) numbers about business in Portugal, only 26% of companies didn't felt the pandemic effect since they kept or increased the business volume in 2020, however, about 35% saw the business volume go down in more than 40%, and some of these (17,3%) had a break greater than 70% when compared to 2019 activity. This breaks in companies' turnover usually result in sacking, and in fact, 27% of the companies analyzed sacked workers or pretend to do it. Some pressured companies appeal to financing to react and try to survive during pandemic times, and in fact the sectors mentioned before that were more affected by COVID-19 are the ones that tried to obtain finance – restaurant and hospitality sectors (57%) and industry (40%). Transportation and warehousing, and commerce also show big numbers, about 36% each. The medium and exporting companies are the ones appealing more for financing. The companies struggling more to survive sometimes come out defeated. 6% of the companies proceeded with the insolvency procedure in 2020, and again, the transport and warehouse (15,9%), and restaurant and hospitality sectors (10,3%) are the ones contributing more for the 6%. However, some hopeful numbers is the one regarding about the return to economic activity measures in 2020, where 61% of the companies find it enough to go back (AIP, 2020).

2.3.5. COVID-19 and Environment

Humans began to harm nature through anthropogenic activities with little regard for long-term sustainable growth (Verma, 2019). Therefore environmental pollution has been a global concern, nowadays, that obviously brings more propensity for bacterial and viral diseases (Verma & Prakash, 2020). COVID-19 pandemic brought worldwide “destruction” on human civilisation but created a very positive and inspiring impact on the world environment.

When compared with 2019 values, the emissions during coronavirus lockdown were minor and very polluting areas, such as Eastern and Central China showed a reduction of approx. 25% in nitrogen dioxide (NO2) levels (El Zowalaty et al., 2020), that can cause inflammation in respiratory track and asthma in just two weeks of lockdown (Kulshrestha, 2020), about 18% carbon emissions went down between early February 2020 till mid-March 2020 (Watts, 2020), and the quality of air improved up to 11.4%, in 337 Chinese cities, that saved 50 thousand lives that could have died because of polluted air (Khan et al., 2020), according with WHO. Main cities of USA (Los Angeles, Seattle, New York, Chicago, and Atlanta) showed a reduction in air pollution (Plumer & Popovich, 2020), since the major source of CO2, the traffic, has fallen almost 40%; for Europe was forecasted a cut of around 390 million metric tonnes of carbon. A type of particulate matter, PM2.5, a pollutant that cause 4 million deaths of heart diseases, strokes, lung cancer, chronic lung diseases and respiratory infections (WHO, 2019), has decreased drastically, e.g., 60% in Delhi, India; 44% in China; 31% in Los Angeles, USA; and 32% in São Paulo, Brazil (Khan et al., 2020).

Due to COVID-19 measures to restrict travelling globe’s, motorways, and streets with almost no cars brought better air quality and almost zero emission of green-house gases and ozone depleting substances (ODS), such as Chlorofluorocarbons (CFCs), CO2 and NOX, to the environment (Verma & Prakash, 2020). National Aeronautics and Space Administration (NASA) experts say that ozone layer is healing (NASA, 2021). TomTom Traffic Index (2020) about mobility reports confirm that urban traffic decreased massively in 2020. Considering 416 main countries around the globe, the average congestion was decreased in 387 cities (93%), 16 cities had no change (4%) and only 13 cities (3%) verified an increase in congestion. Also aviation emissions, that counts for 2,4% of global CO2 emissions in 2018, dropped significantly (Ritchie, 2020) since global air traffic reduced by 60% during lockdown period (Khan et al., 2020). According NASA (2020) and Verma & Prakash (2020) research, during lockdown period that led to less land and air congestion and closure of industrial sites, the emissions of CO2, that is responsible for climate change, reduced in a way never seen since World War-II around the globe. Less 48% of CO2 emissions in UK, 27% in Italy, 7,5% in USA, 18% in China and 17% in Pakistan, for example. But experts say that it not may be enough to reach the Paris Agreement goals to keep global warming from rising above 1,5 ºC (Verma & Prakash, 2020). This transportation restriction led to a much lesser fuel consumption that according with U.S. Energy Information Administration, the oil, gas and diesel demand decreased 9% over 2020 when compared to 2019, that represents the largest decline since 1980 (Baron, 2021; El Zowalaty et al., 2020). In the late 2021, a consequence for lifting the measures was the abrupt change on demand for fuels that went back to almost pre-covid levels in 2019 which resulted in reduced inventories and higher prices for crude oil and petroleum products.

Due to closure of factories or minimal activity from industries, the air and water quality was improved since industrial waste, use of fossil fuels and other energy sources decreased extensively. The combination of lockdown, and the cease of several factories and industrial sites activity, made NASA and European Space Agency (ESA) perceive a massive decrease in NO2 concentration in China, that moved later for the rest of the world: ESA used Sentinel-5P satellite to obtain images from world troposphere and it is possible to confirm that NO2 emissions in China reduced up to 40%, and in Europe reduced up to 45-50%, when compared to pre and post lockdown periods (ESA, 2020); Cities like Los Angeles, San Francisco, San Diego, Phoenix and Las Vegas saw a reduction of 31%, 22%, 25%, 16% and 10%, respectively, in NO2 emissions when compared to 2019 numbers (Khan et al., 2020).

In conclusion for this section – impacts of COVID-19 – seems that the pandemic brought both negative and positive effects in several areas. Since COVID-19 triggered the largest falls in CO2, NO2 and other gases/chemicals emissions, ecosystems are recovering, many inhabitants from big cities are experiencing clearer skies and river waters and animals are living better in these healthier conditions. If the policies to fight the pandemic are good for the environment and bad for the world economy and both should not be compromised, the suggestion and better approach should be to find the balance using eco-friendly technologies and clean energy-based systems when the pandemic ends. Humanity can learn some lessons and understand that some changes in behaviour are important and can make big differences.

2.4. Measures to face COVID-19

COVID-19 pandemic can be seen as a mere chance event or as a warning call from nature to raise awareness for changes in some bad habits and behaviours. Nevertheless, one thing is certain, this pandemic was a revolution on the modern days and the world had to stop the normal course, give some steps behind and re-think. Governments and non-governmental organizations needed to work together in a regional, national, and international scale to address the pandemic in support of the public good. The biggest challenge on the fight of COVID-19 pandemic is to find the best measures in a very fast and responsive way to not only protect people from being “caught” by the virus, but to also treat the ones that are already infected without compromising harshly the country’s economy. Under an environment where health systems are cracking, companies suffering financially, and people reluctant for the change (and sometimes fighting against it), it is hard to take decisions and create the policies when there are no clear answers.

According with Kissler et al. (2020), prolonged or intermittent social distancing is necessary to keep the care capacities not overwhelmed. However, one-time and intermittent interventions are not sufficient to keep COVID-19 controlled and care capacity bellow “break point”. Seasonal variation in transmission is good since in summer the number of cases decreases but an intense resurgence in autumn can disrupt the epidemic control and for that reason other permanent interventions are crucial. It is expected to have peaks on autumn/ winter seasons, due to the increasing of indoor crowding in winter, the start of school term and work comeback in autumn, and climate factors for example (Lipsitch & Viboud, 2009). Measures like intensive testing to identify the cases and contact tracing, and lockdown/quarantines to isolate the cases, have been shown to be effective strategies to control the spread of infectious diseases, including the COVID-19 pandemic, in some places like Singapore and Hong Kong (Aleta et al., 2020; Madubueze et al., 2020; Wells et al., 2020). Lockdown is a very strong measure to stop the confirmed positive cases to keep getting higher but that reflects also in less mobility in the cities and in schools, companies and industrial sites closure which holds serious economic consequences. Teleworking and long-distance learning policies were also measures created when the economic and educational systems started to feel vulnerable. To ensure that patients receive adequate care and to reduce the pandemic duration, increase the critical care capacity is also very important (Kissler et al., 2020). According with WHO, hygiene measures are also very important: mask-wearing mainly in poorly ventilated places and when the physical distance of at least 1 metre is not possible, hand sanitizing with alcohol-based disinfectants or soap and water, cover mouth and nose while coughing or sneezing with a tissue or bent elbow, clean and disinfect surfaces frequently touched are the guidelines more recurrent (WHO, 2021). This health measures should serve as a (very important) complement to the other non-pharmaceutical measures and were crucial while there was no vaccine for SARS-CoV-2 virus. Mass vaccination and herd immunity is the most powerful weapon to fight the virus and it has shown its efficiency in a Brazil town that had an COVID-19 outbreak and a vaccine with relatively low efficacy could control the situation: *"Population may have reached herd immunity after 75% got two shots of a low-efficacy Chinese COVID-19 vaccine"* is possible to read on *Science* journal website (Moutinho, 2021). By the end of December 2021, there were nine vaccines approved for full use, nineteen authorized but in limited use, thirty-four vaccines in Phase III testing, eighteen in phase II testing and thirty in phase II, according with the NYT coronavirus vaccine tracker (Zimmer et al., 2021). Vaccines accumulate immunity in the population and reduces the duration and intensity of some control measures referred before, such as lockdowns (Kissler et al., 2020). If it was not the surging of new variants, herd immunity could have been reached by now in many countries since, according with *Our World in Data* website, USA (99%), Cuba (92%), Portugal (90%), Chile (90%), Singapore (88%), China (87%), Canada (83%) and Italy (80%) have more than 80% of the people fully or partly vaccinated by 1st January 2022 (Ritchie et al., 2021). The pandemic situation is always evolving, many resurgences have already happened, and people are still facing COVID-19 in 2022, thus, communities and organizations should keep on track the situation and update COVID-19 prevention strategies based on community spread, health system capacity, vaccination coverage, early detection of COVID-19 increases and population at risk, according with CDC website (Christie et al., 2021).

Table 2 summarizes the main measures consensually adopted globally to fight COVID-19 pandemic and respective positive and negative impacts in social, economic and environmental terms based on the stated references throughout this section and on Moores (2020).

Table 2 - COVID-19 Pandemic: sum up of main measures and some respective positive/negative impacts (NOTE: RED CELLS: Negative impacts / GREEN CELLS: Positive impacts / RED LETTERS: Negative economic impacts) (Source: The author)

COVID-19 PANDEMIC

MEASURES		IMPACTS		
	Traveling restriction	Reduce CO_2 and other pollutant gases emission	Reduce fossil fuel consumption	Animals' freedom/ecosystems recovery
		Global warming lessens	Psychological pressure on people	Less pollution in touristic spots
	Lockdown/ quarantines	Companies labour get affected severely	Families' have more time to be together	Difficult education access; remote learning less effective
		Increase in demand for communication technology companies	Psychological stress / Financial insecurity or fear	Reduce over-consumption – families save money; less waste disposal
	Companies/ industrial closure	Reduce noise pollution	Less NO_2 and other pollutant gases emission	Lower income for people that are fired or work less hours – some families can fall below poverty line
		Companies have zero income	Less waste disposal/Less water pollution	Ozone hole heals
	Use of PPE[1]	High income for PPE producers	Soil and water pollution	Plastic waste
	Massive testing	Enables routines and companies' comeback quicker and easily	Logistic and resources to create testing centres, workforce and results treatment and delivery	Healthcare workers highly exposed to the virus and, therefore, a strong transmission source
		High costs for country	Pressure on national healthcare system and increase on medical waste	Community feels safer since transmission is being tracked
	Vaccination	Global economy pressured to develop vaccines quickly	Global chain pressured economically and logistically to develop, produce, deliver, and administer the vaccines to society	More knowledge for future diseases/ infections
		Concern for vaccination material proper disposal	High income for pharmaceutical industry and companies	Countries' economic resources pressured to buy vaccines

[1] PPE: Personal Protective Equipment (e.g., face mask, face shield, disinfectants, gloves)

3. Literature review

The literature review is presented in the form of table for a clearer understanding of how the studies usually are processed, and for a better comparison between what has already been considered and what has not been assessed until now. Table 3 presents the literature review collected listed in alphabetical order. Seems important to extract for each study the analysis' goals, the methodology, models and/or programming languages used, the dataset collected and that the analysis will focus on, how the data was obtained (dashboards, websites, reports, etc.), and the time-period considered for data collection. Seems also important to know about the variables used (in many methods inputs and outputs), and the main conclusions and highlights of the study. In this section, the goal was to collect reliable scientific articles that would focus on the measure of efficiencies and/or assessed a statistical analysis regarding factors that could influence the COVID-19 disease.

In the beginning, while the literature was being collected it was perceived that many studies focused in measuring the relative efficiency using Data Envelopment Analysis (DEA) models. For example, to compare efficiency of different hospital units. For this reason, and since the work is on the subject of COVID-19, the scope of the paper must be about COVID-19 to integrate the literature review. Furthermore, many studies of performance measure focused on explaining the effects of pre and post COVID-19 outbreak on company's financial and performance fields, such as Kusche & Tooker (2020); Aguinis & Burgi-Tian (2020); Sousa et al. (2020); and Tziner & Rabenu (2021); or focused on giving strategies and guidelines to measure company's efficiency during the COVID-19 pandemic, example of Smyth (2020) and Williams (2021). These studies were also not integrated in the literature review since it was focused more on a business analysis rather than on a statistical analysis.

Despite existing already a considerable number of articles about COVID-19, this reduced considerably the available literature since COVID-19 is a relatively recent topic but very important subject of study. This studies when done in the beginning of a pandemic can give important highlights that can lead to the cease of it or at least alleviate the measures that are being imposed. Additionally, these studies contribute to understand infectious disease more, know what to expect and how to better react to it and so, prevent future possible pandemics.

Table 3 - Literature review (Source: The Author)

LITERATURE REVIEW					
REFERENCE	**OBJECTIVES**	**MODEL USED**	**DATA SET / SOURCE / PERIOD**	**INPUTS/OUTPUTS VARIABLES**	**MAIN CONCLUSIONS**
Aydin & Yurdakul, 2020	Analyse via a new three staged framework the performances of 142 countries against the COVID- 19 outbreak	**1ST STAGE:** machine learning algorithm (clustering analyses: using k-means and hierarchic clustering) **2ND STAGE:** DEA model (WSIDEA[2]) **3RD STAGE:** machine learning (decision tree and random forest algorithm)	142 countries separated in three clusters / Kaggle website / 21 January 2020 - 28 July 2020	**INPUTS: (1)** sum of total deaths; **(2)** stringency index; **(3)** extreme poverty; **(4)** death rate due to heart attack; **(5)** diabetes prevalence; **(6)** female smokers; **(7)** male smokers **OUTPUTS: (1)** population; **(2)** gross domestic product (GDP); **(3)** Hospital beds; **(4)** total recovered; **(5)** total test **FLEXIBLE: (1)** sum of total cases; **(2)** active cases	Only 20 of 142 countries were fully effective, 36% of them were found to be effective at a rate of 90%; The rate of CVD death, GDP and smoking rates variables do not affect the effectiveness level of the countries; Stringency index, diabetes prevalence and number of hospital beds have a remarkable effect
Dogan et al., 2021	Study the responses of 21 OECD[3] countries to the Covid-19 outbreak	Three models of DEA: (1) CCR[4] model; (2) Super-efficiency model (3) Cross-efficiency model	21 countries from OECD / OECD, WHO and Actopharma websites / 09 April 2020–20 August 2020	**INPUTS: (1)** population density (%); **(2)** 65+ aged (%); **(3)** hospital beds per 1,000; **(4)** chronic diseases (%) **OUTPUTS: (1)** recovered; **(2)** confirmed cases; **(3)** deaths	11 of the 21 nations studied were effective for certain weeks
Imtyaz et al., 2020	Analyse different governments' responses to the pandemic to understand the best way to fight the coronavirus	Machine learning algorithm: clustering analyses using k-means; bivariate analysis	30 most-affected countries / John Hopkins University CSSE[5], WHO, European CDC, United States CDC / 20 January 2020 – 1 June 2020	**VARIABLES: (1)** number of cases; **(3)** mortality rate (%); **(2)** elderly population (%);	Lockdowns and higher number of tests are effective in reducing the spread of the virus, better control, and lower mortality rates; The mortality rate fatality rate is directly proportional to the percentage of elderly (65+); Countries like Germany, Portugal, and Singapore seem to have implemented reasonable measures against the virus, as their mortality rates are lower than in other countries with similar age demographics; Countries like Mexico and Brazil need to increase their testing rate;

[2] WSIDEA - weighted stochastic imprecise data envelopment analysis
[3] OECD - Organization for Economic Co-operation and Development
[4] CCR – Charnes, Cooper and Rhodes
[5] CSSE - Center for System Science and Engineering

LITERATURE REVIEW

REFERENCE	OBJECTIVES	MODEL USED	DATA SET / SOURCE / PERIOD	INPUTS/OUTPUTS VARIABLES	MAIN CONCLUSIONS
Kamel & Mousa, 2020	Measure and evaluate the operational efficiency of 26 isolation hospitals in Egypt during COVID-19, as well as identifying the most important inputs affecting their efficiency	**1ST PART:** DEA using CCR and BCC model; **2ND PART:** Sensitivity analysis; Super- and Cross-efficiency analysis; **3RD PART:** Tobit regression	26 isolation hospitals / CMIC[6] at the MOHP[7], and the CAPMAS[8] / 14 February 2020 – 30 August 2020	**INPUTS: (1)** number of physicians; **(2)** number of nurses; **(3)** number of beds **OUTPUTS: (1)** number of Infections; **(2)** number of recoveries; **(3)** number of deaths	From 26 isolation hospitals, 4 were efficient with CCR model and 12 were efficient with BCC model; Tobit regression results confirmed that the number of nurses and beds are common factors impacted the operational efficiency of isolation hospitals, while the number of physicians had no significant effect on efficiency.
Khan et al., 2020	Analyse the effect of the COVID-19 pandemic on different countries through COVID-19 cases, deaths and recoveries	Statistical analysis using R language	13 most-affected COVID-19 countries / Kaggle, CoronaTracker and WHO websites / 23 January 2020 – 31 May 2020	**VARIABLES: (1)** infectious rate (%); **(2)** death rate (%); **(3)** recovery rate (%)	The number of cases in a country is dependent of two main factors: number of tests and preventive measures; Countries with older populations will show a higher number of deaths; Countries with high positive cases do not necessarily have a high death rate, as death rates are determined by people's immunity and healthcare services
Malik et al., 2021	Find the convincing demographic factors associated with COVID-19 in SAARC[9] countries and report the status of SARS CoV-2 situation in these countries.	Mathematical and statistical methods: exponential growth (EG) method; time dependent (TD) method	8 SAARC countries / Johns Hopkins University and Medicine dashboard / April 2020 – December 2020	**VARIABLES: (1)** population density; **(2)** Literacy (%); **(3)** poverty (%); **(4)** adult population (%); **(5)** BCG vaccination; **(6)** health care expenditure (% GDP)	Lockdown, limited gathering and maintaining social distancing contribute for a lower death rate and improvement on the control of the pandemic considering the overall decline in the Rt value; There was a significant positive correlation between COVID-19 deaths and health expenditure (% GDP); The other factors such as population density, literacy (%), adult population (%), and poverty (%) are not significantly correlated with COVID-19 cases and deaths;
Malki et al., 2020	Identify the weather and demographic factors that play more on the spreading rate of COVID-19	Machine learning: linear regression, decision tree, random forest, SVM (support vector machine) and many other machine learning algorithms.	Several states around the world aggregated by country / Kaggle, GitHub, and the Johns Hopkins CSSE websites	**VARIABLES: (1)** country; **(2)** longitude; **(3)** latitude; **(4)** date; **(5)** confirmed cases; **(6)** number of deaths; **(7)** number of recoveries; **(8)** active cases; **(9)** minimum daily temperature; **(10)** maximum daily temperature; **(11)** humidity; **(12)** precipitation **(13)** snowfall; **(14)** moon	The weather variables (temperature and humidity) are more relevant in predicting COVID-19 mortality rate when compared to demographic factors (population, age, and urbanization); The higher the value of temperature the lower number of infection cases;

[6] CMIC - Clinical Medicine Information Center
[7] MOHP - Ministry of Health and Population
[8] CAPMAS - Central Agency for Public Mobilization and Statistics
[9] SAARC - South Asian Association for Regional Cooperation

LITERATURE REVIEW					
REFERENCE	**OBJECTIVES**	**MODEL USED**	**DATA SET / SOURCE / PERIOD**	**INPUTS/OUTPUTS VARIABLES**	**MAIN CONCLUSIONS**
			/ 12 December 2019 – 22 April 2020	illumination; **(15)** sunlight hours; **(16)** ultraviolet index; **(17)** cloud cover; **(18)** wind speed; **(19)** wind direction; **(20)** wind pressure; **(21)** population density; **(22)** fertility rate; **(23)** median age; **(24)** intensive care unit (ICU) beds per 1000 People; **(25)** infection ratio	
Min et al., 2021	To identify sources of the success and failure of various combinations of COVID-19 control measures among OECD countries and identify which cultural factors critically influence the efficiency of these measures	**1st PART:** DEA with two-stage network SBM[10] models with VRS[11] and CRS, respectively **2ND PART:** Tobit regression	34 OECD countries / Johns Hopkins University and Medicine, Coronavirus Resource Center, World Bank website, Hofstede Insights website / (?)	**INPUTS: (1)** population size; **(2)** gross national income per capita; **LINK VARIABLES: (1)** number of hospital beds; **(2)** number of confirmed cases; **FINAL OUTPUTS: (1)** number of recovered cases; **(2)** number of deaths	2 out of 34 OECD countries were fully efficient in both stages; Greece is efficient at stage 1 (has a sufficient health care capacity) but not efficient on stage 2 (handles COVID-19 poorly); The two cultural factors playing more are the uncertainty avoidance (the higher the better) and the individualism (lower the better);
Mitchell et al., 2021	Evaluate the quality performance management of three countries to fight the first wave of COVID-19 outbreak	Pragmatic constructivism (PC)	3 countries (Germany, Italy, UK / governments and health institutions, national and international institutions websites / During first wave of COVID-19 pandemic (March - May)	**4 DIMENSIONS: (1) VALUES:** health, economy; **(2) FACTS:** health care system, surveillance system; **(3) POSSIBILITIES:** treatment illness, produce knowledge; **(4) COMMUNICATION:** coordination **PERFORMANCE INDICATOR:** mortality rate	Germany is the country that shown better results (even statistically the death rate is significantly lower in Germany) because they have a strong integration of the four PC dimensions; Germany was the first to recognise the severity of COVID-19, to organise mass testing and tracking and to establish isolation procedures; Germany has a very strong communication network involving scientists, politicians and the public which is an crucial factor to make the difference.
Mohanta et al., 2021	Measure the performance of 32 states and union territories (UTs) in India against COVID-19 using the undesirable output	DEA using the undesirable output model with CRS	32 states and UTs / Census, the Ministry of health & family welfare,	**INPUTS: (1)** public health expenditure; **(2)** number of hospitals; **(3)** number of hospital beds; **(4)** number of health workers (%); **(5)** population density; **(6)** number of infected	16 (50%) of 32 Indian states & UTs were efficient; Chandigarh is the most efficient unit and Meghalaya is the most inefficient; Undesirable output model provides better results than the CCR and BBC model

[10] SBM – slacks-based measure
[11] VRS – variable return to scale

LITERATURE REVIEW

REFERENCE	OBJECTIVES	MODEL USED	DATA SET / SOURCE / PERIOD	INPUTS/OUTPUTS VARIABLES	MAIN CONCLUSIONS
	model with CRS[12] and compare to CCR and BBC model		Government of India websites / Start of COVID-19 – 22 October 2021	**OUTPUTS: (1)** number of recovered; **(2)** number of deaths	
Pereira et al., 2022	Estimate the efficiencies of 55 countries in the fight of COVID-19 considering a social and a financial perspective	Network DEA	55 countries / WHO, World Bank, Eurostat, Our World in Data, Worldometer and other governmental and health institututions websites / 2019 - 2020	**INPUTS: (1)** health expenditure; **(2)** costs with instruments used in COVID-19 diagnostic testing; **(3)** costs with disinfection and sterilisation products; **(4)** costs with oxygen therapy equipment; **DESIRABLE INTERMEDIATE PRODUCT: (1)** population that uses PPE; **UNDESIRABLE INTERMEDIATE PRODUCT: (1)** population that does not use PP; **(2)** infected population; **(3)** infected population that needs hospitalisation; **(4)** hospitalised population that needs treatment in the ICU; **DESIRABLE OUTPUT: (1)** non-infected population; **(2)** home recoveries; **(3)** hospitalization recoveries; **(4)** ICU recoveries; **UNDESIRABLE OUTPUTS: (1)** hospitalization deaths; **(2)** ICU deaths;	Estonia, Iceland, Latvia, Luxembourg, the Netherlands, and New Zealand are the countries showing better efficiencies; Island nations (Australia, Iceland, Japan, and New Zealand) seem to have higher efficiencies. Countries with larger population showed worse performance which may be explained with more complex national COVID-19 strategies; There is no apparent relation between efficiency scores and level of development; GDP per capita, human development index, and percentage of population that uses PPE shown to be significant variables to account for the measure of nations' efficiency in the fight against COVID-19;
Revuelta et al., 2021	Create a predictive model (DEA-ANN) of the clinical course of the kidney transplant recipients admitted due to a SARS-CoV-2 infection while identifying patients at risk of progressing towards severe disease	DEA-ANN (artificial neural network)	38 recipients / Hospital admission data / 3 March 2020 – 25 April 2020	**INPUTS: (1)** age at COVID-19 diagnosis; **(2)** diabetes mellitus; **(3)** hypertension; **(4)** ACEI/ARB; **(5)** dialysis vintage; **(6)** previous solid organ transplant; **(7)** pneumonia; **(8)** cough; **(9)** days starting symptoms to hospital admission; **(10)** white blood count cells at admission; **(11)** lymphocytes at admission; **(12)** LDH at hospital admission; **(13)** CRP at hospital admission; **(14)** SCr at hospital admission; **(15)** acute kidney injury; **(16)** eGFR at hospital admission; **(17)** current SOT vintage **OUTPUTS: (1)** ICU needs; **(2)** Tocilizumab; **(3)** pulse of steroids use	Prediction accuracy is higher when the output categorization process is determined by DEA, and for that reason DEA-ANN prediction accuracy is 96.3%, while just using ANN based on the values of the output variables achieves a maximum of 69%; DEA-ANN is great to use for cases with small data sets; The model offers a complete profile of the patients allowing a direct evaluation of their relative performances and the probable behaviour of the output variables

[12] CRS – constant return to scale

3.1. Literature review discussion

The goal is to take positive insights from several articles that can be used on this study, do not use the negative aspects from these articles and perceive the areas that have been already more extensively studied. This way, it is possible to identify the aspects that lack more research and where this study can focus on. This will be the originality and the add-value of the present study. After completing the fill of Table 3, eleven articles were revised to compose the literature review of this project. Since they are all under COVID-19 subject, they are recent studies made between 2020 and 2021 so it was always used apart from reliable information, up-to date information.

The studies that had more resemblance with this project are the Pereira et al. (2022); Dogan et al. (2021); Mohanta et al. (2021); Min et al. (2021); Aydin & Yurdakul (2020); Imtyaz et al. (2020); and Mitchell et al. (2021) since they had the same study objective. All of them measured the efficiency on the performance of the policies taken by the governments in several countries. The first five used DEA models, the fifth used machine learning algorithms and the last one used PC. Since DEA was the most used for measure the countries' performance efficiency and these five articles were very complete and found analytically the countries that were more efficient seems a good approach to use in this study. Besides this, DEA is not only but very used to measure efficiency in medical/hospital/health fields (Ozcan & McCue, 1996), which this study is inserted partly. Some of the studies use other methods to complement the DEA: Aydin & Yurdakul (2020) used also machine learning algorithms (clustering analysis, decision tree and random forest algorithm) and Min et al. (2021) used also Tobit regression. Mitchell et al. (2021) has the same goal of this work but uses a very different approach. They use the PC that is a much more qualitative and empirical study since uses the observation of factual evidence that happened in the three countries analysed and not in theories or scientific/mathematical methods. In the referred analysis, it is used a matrix that indicates on the horizontal axis when the performance management differences occurred and how they occurred on the vertical axis. The 60 cells from the matrix locates the strengths and weaknesses of each country's performance management and so make the linkage between factual/empirics and the theory. A limitation of it is that the matrix does not explain why they occurred (Mitchell et al., 2021). This study seemed vague, the conclusions obtained looked imprecise and to have lack of more data processing techniques to be more analytical. To use the PC method would be needed to work with a small data set (they used only three countries to compare) and for these reasons, the PC method is discharged.

On the other hand, other articles were found relevant to be included in the literature review since they evaluated the influence of some factors in COVID-19 pandemic effect. They are the Malik et al. (2021) that studies the influence of demographic factors using mathematical and statistical methods, the Malki et al. (2020) studied the influence of weather and demographic factors using machine learning algorithms such as, linear regression, decision tree, and random forest and Min et al. (2021) analysed cultural factors effects.

Regarding the variables used in the literature, it is noticed that the inputs are more related with the resources available (e.g., number of hospitals; number of hospital beds; number of health workers (%)), with demographic factors (e.g., population density (%); public health expenditure; population density; gross national income (GNI) per capita), and with number of infected/confirmed cases. On the other hand, outputs are more related with the pandemic outcomes (e.g., number of recovered; number of deaths) that are directly related with the healthcare system performance. It is expected that the difference between recovered and deaths to be wider if the performance is better. For our study, inputs and outputs will follow this logic although some studies show different ways of thinking for input and outputs. It can be concluded that the choose of the variables will always vary the results obtained, which is a drawback of the data analysis.

Finally, some conclusions taken from the literature give some insights for our study. Mohanta et al. (2021), concludes that the undesirable output model provides better results than the CCR and BBC model; Revuelta et al. (2021) says that DEA-ANN is great to use for cases with small data sets (and for that reason will not be used on the study); and many researchers after performing the DEA analysis used Tobit regression or machine learning algorithms for examining the causal relationship between factors and the control measures (Min et al., 2021) or between the variables used and the results on the countries' performance measure (Kamel & Mousa, 2020; Aydin & Yurdakul, 2020). Some variables used in the literature shown to be relevant such as the number of beds (Kamel & Mousa, 2020; Aydin & Yurdakul, 2020), the number of nurses (Kamel & Mousa, 2020), the percentage of elderly (Imtyaz et al., 2020; Khan et al., 2020) and health expenses(%GDP) (Malik et al., 2021). On the other hand, variables like number of physicians (Kamel & Mousa, 2020), positive cases (Khan et al., 2020), population density, literacy (%), adult population (%), and poverty (%) (Malik et al., 2021), GDP (Aydin & Yurdakul, 2020) shown to not be relevant. This can serve as insights for the variables choose. Some studies also take conclusions about some factors and measures relevance, for example, in Imtyaz et al. (2020) lockdowns and higher number of tests are effective in reducing the spread of the virus and lower mortality rates; in Min et al. (2021) the two cultural factors playing more are the uncertainty avoidance (the higher the better) and the individualism (lower the better); and in Malki et al. (2020) the weather variables (temperature and humidity) are more relevant in predicting COVID-19 mortality rate when compared to demographic factors (population, age, and urbanization).

To conclude, based on the previous paragraphs, DEA seams a good approach to evaluate the countries performance since it uses a *best-practice frontier* to compare (relative) efficiencies. This way, it is obtained analytical results based on real data retrieved from reliable sources about countries in study. However, the variables used seems very limiting since COVID-19 does not only depend in the number of beds, deaths and recovers, for example. The literature seems to study the pandemic with very restrict boundaries, i.e., does not evaluate the pandemic using different dimensions that affects countries efficiencies to fight COVID-19 disease. To counter these problems, the Benefit-of-Doubt (BoD) will be used since this approach accommodates key performance indicators that can evaluate several dimensions at the same time. The technical part will be explained in detailed in section 4.3 and over the thesis will be clarified several notions about this type of DEA.

4. Methodology

4.1. Benchmarking

Benchmarking is a technique usually known to very used on business sector so companies can do comparison of their efficiency against the competitors present in the market. This way companies can find best procedures and achieve superior performance. Nevertheless, this tool can be used in a much broader context rather than business. Benchmarking can be seen simply as an efficiency analysis to evaluate performance level to not only estimate the current level, but also to provide (benchmarking) information on how to remove inefficiency. Sherman, 1988, defines efficiency as *“the ability to produce outputs or services with a minimum resource level required”*. Only this way resources are neither lacking neither wasting the available ones.

In benchmarking literature, best practice or frontier analysis methods are developing rapidly which includes mainly two types: data envelopment analysis and Stochastic Frontier Analysis (SFA) (Bogetoft & Otto, 2011; Coelli et al., 2005). The main difference is that one is a parametric and stochastic approach (SFA) while the other is non-parametric and deterministic approach (DEA). The main difference of non-parametric approach from DEA to the parametric approach from SFA is that the last one uses a fixed and finite number of parameters that needs to be defined a priori to build the (parametric) model. For another set of parameters, it lies in the observed values to model the non-observed ones relying on statistical distribution in the data, for example, normal distribution or Weibull distribution. This is a drawback because this assumption might not be true. Regarding the stochastic from SFA and the deterministic approach from DEA the relevant distinction is that in the last one the random noise that can occur and affect the observations is suppressed while the stochastic models try to identify the underlying mean structure (Bogetoft & Otto, 2011).

Benchmarking have been used in many investigations for different sectors and even though both DEA and SFA methodologies accommodate multiple inputs and outputs to measure a relative efficient performance (Rosko et al., 2016), i.e., both uses an efficient frontier and compare it with each DMUs actual performance. However, DEA creates this efficient practice frontier based on the best practices found among the DMUs used while SFA uses an estimated or theoretical efficient frontier. For this reason, DEA will give always some 100% efficient DMUs while SFA can have no 100% efficient DMUs (Rosko & Mutter, 2010). The choose between these two models is usually not clear since according with Coelli et al. (2005) the selection should be based on the available data and study’s goals, so, it depends on the context. In addition, Rosko & Mutter (2010) defends that the most probable is that a consensus will never occur regarding the best choice between DEA and SFA. However, a good sign is that when using SFA or DEA models the concordance between both gets higher with the use of better-quality data (Schmidt, 2008).

4.2. Data Envelopment Analysis

Data envelopment analysis is a very powerful benchmarking tool that have been used in very different sectors: DEA have been assessing the efficiency performance of public organizations such as healthcare systems, educational institutions, and governmental entities but also private organizations such as banks and private service providers (Ahn et al., 2017), and even for regions such as towns and countries efficiency (Huguenin, 2012). Additionally, Zhou et al. (2018) also identified the most usual application areas of DEA between 1996 and 2016: agriculture, utilities, manufacturing, energy, transportation, and logistics sectors were the most popular. In this research, the DEA model will be used to measure the performance of anti-covid policies taken by several countries.

DEA was first presented by Charnes, Cooper and Rhodes (Charnes et al., 1959) to measure the efficiency levels of similar decision-making units (DMUs). DMUs are the term used in DEA to call firms, companies, institutions, organizations, etc., i.e., the entities that are in the evaluation. The first DEA model introduced was then the CCR that corresponded to the authors initials (Charnes, Cooper and Rhodes). After the DEA-CCR, it was introduced the BCC model by Banker et al. (1984). These two models are very used in the literature and in many studies, they use both to compare the results (e.g., Kamel & Mousa (2020)) but especially in the last decade many other DEA models have been surging due to some handicaps that DEA models have (Liua et al., 2016). According with Aydin & Yurdakul (2021), these issues can be, for example, when the analysis result is equal to 1 for some DMUs, they are considered as fully efficient, but it can be considered as fully efficient even if the score is less than 1, i.e., 0.9. in some cases. Another problem is that sometimes it is not clear if some data should be considered as input or output and for that reason Cook & Zhu 2007 proposed the imprecise DEA model to deal with this uncertainty. Besides this deterministic DEA models already presented (that requires complete and precise data set) many other authors already tried to introduce probabilistic data with predictions about the future that are called as *"chance constraint DEA model"*. An example of this DEA type of model is the one proposed by Sueyoshi (2000), that named it as the *"future DEA model of Sueyoshi"*. Another clear problem when compared with the traditional DEA models, is that the expert's opinion and insights can't be included. To face this limitation, Aydin & Yurdakul (2021) proposed the Weighted Stochastic Imprecise Data Envelopment Analysis (WSIDEA) that besides being a stochastic model that have in consideration both current and future prediction of the DMUs state, in WSIDEA all variables are considered, i.e., none of them can be zero and so the effects of all variables are considered in the analysis. Thirdly, with WSIDEA experts can attribute importance to different data. Thus, WSIDEA is a very powerful method. Besides the mentioned ones, there are many others DEA models in the literature such as two-stage DEA (Chen et al., 2009; Min et al., 2021), fuzzy DEA (Guo & Tanaka, 2001) and other models with integrated applications (e.g., DEA-ANN in Revuelta et al. (2021)). Several mathematical formulations (CCR model; imprecise DEA model; future DEA model of Sueyoshi; WSIDEA model) presented before can be seen in Aydin & Yurdakul (2021).

Even though there are so many different DEA models that differ mainly in the way that they define the performance standard (called as technology in the literature) and in the way that they evaluate the achievements against the established standard (i.e., the concept used to estimate the efficiency) (Bogetoft & Otto, 2011), DEA have some basic fundaments and concepts, that will now be explained. According with the literature, a general and simple but complete definition for DEA could be that DEA is a non-parametric technique that provides a mathematical programming method based on linear programming that aims to create the best practice production frontier and measure with that the relative performance of different DMUs. Relative performance because DEA is basically using the concept that some DMU is more efficient if can produce more with the same or less resources than another, i.e., for each DMU efficiency is made linear combinations to compare with the other DMUs efficiency. The DEA needs inputs and outputs to process and has the capability to evaluate several inputs and outputs at the same time. Although the choice of which variables are input and which are output is left to the user, there are some experts that tried to define rules to choose better the numbers of inputs, outputs and DMUs. Golany & Roll, 1989, defined that the number of DMUs should be at least twice the number of inputs and outputs considered (see equation 1), Bowlin 1998 mentions the need to have three times more DMUs as there are input and output variables (see equation 2), and, finally, Dyson et al. (2001) recommend that should be used a total of two times more DMUs than the product of the number of input and output variables (see equation 3).

$$DMUs = 2 \times (i + o), i = number\ of\ inputs;\ o = number\ of\ outputs \quad (1)$$

$$DMUs = 3 \times (i + o), i = number\ of\ inputs;\ o = number\ of\ outputs \quad (2)$$

$$DMUs = 2 \times (i \times o), i = number\ of\ inputs;\ o = number\ of\ outputs \quad (3)$$

Having said this, it is important to clarify the importance of applying one of these rules for a balanced number of variables (inputs and outputs) used and the size of the sample because choosing to many variables for few DMUs can lead to bigger (not real) efficiency levels (Harrison e Sexton, 2006). Taking an example of 3 inputs and 5 outputs, we would obtain 16 DMUs, 24 DMUs and 30 DMUs, respectively. In fact, using as many DMUs as possible is good since it is possible to obtain more high-performance units that will constitute the efficient frontier and improve the discriminatory power (Sarkis, 2002), which can be deduced that the results obtain are dependent of the DMUs chosen. DEA models have usually two basic important concepts that should be decided as the most adequate for the respective process production (Ferreira et al., 2013). These two concepts are the type of orientation and the type of return to scale. Regarding the orientation, DEA models can be input, or output oriented according with Huguenin (2012) or non-oriented according with Ozcan (2008):

- ***Input oriented model:*** Input orientation is used when there is more control of the inputs than the outputs. The inputs are managed to get lower while the outputs are kept constant to obtain the same outcomes. The basic concept underneath is the reduction of inputs/(resources) waste.
- ***Output oriented model:*** in an output orientation the outputs are changed while the inputs are kept constant. This is used on the cases when it is considered to be possible to manage the outputs, for example, give better customer service or better marketing actions. Therefore, used when it is possible to obtain more efficiency with the available inputs/(resources)
- ***Non-oriented model:*** This model considers that is possible to change both inputs and outputs at the same time: lower the inputs and increase the outputs. Thus, it is possible to manage inputs and outputs to make the DMU more efficient.

According with Huguenin (2012) the *best-practice frontier* will not be affected by the orientation chosen, i.e., DMUs located on the efficient frontier in an input orientation will also be on the frontier in an output orientation or non-oriented model. However, this is not what happens with the return of scale question. There are two types of return to scale, the Constant Return to Scale (CRS) and the Variable Return to Scale (VRS), that both influence the DEA models *best-practice frontier*. Follows an explanation based on Huguenin (2012) and Ferreira et al. (2013) to distinguish these two types of return to scale:

- ***CRS technology:*** first proposed by Charnes et al. (1978) when DMUs are operating at their optimal scale, i.e., the entries of inputs and the exit of outputs is made at constant rate. This technology focus on the technological efficiency and enables that inputs and outputs to be dimensioned linearly without having increase or decrease on efficiency.
- ***VRS technology:*** later proposed by Banker et al. (1984) when it is believed that the DMU is not operating at the optimal scale, i.e., when the production scale changes, and the efficiency does not change proportionally. VRS allows the breakdown of efficiency into technical and scale efficiencies in DEA.

The CRS model computes an efficiency score called Constant Returns to Scale Technical Efficiency (CRSTE), while VRS model computes an efficiency score called Variable Returns to Scale Technical Efficiency (VRSTE) and the quotient between the efficiencies determines another efficiency measure, the scale efficiency (SE):

$$SE = \frac{\theta_{VRS}}{\theta_{CRS}} \tag{4}$$

4.3. Benefit-of-Doubt

Benefit-of-Doubt is a quite used DEA approach proposed by Melyn & Moesen (1991) in the context of macroeconomic performance evolution and revised by Cherchye et al. (2007). This work has the purpose to evaluate the performance efficiency of countries fighting COVID-19 pandemic, which is one of the reasons for applying the BoD in this study, i.e., since it is a macro-assessment of countries' performance to fight a pandemic. BoD models have been used in several applications, for example, in a more international approach Rentizelas et al. (2019) used BoD associated to the Slack-Based Measure (SBM) to study international alternatives for biomass transport and Färe et al. (2019) used BoD to construct a composite index of public health for 180 countries. In turn, BoD can be used also in more closed comparisons – country assessment –, Castro-Pardo et al. (2020) used BoD to create a sustainable rural development composite indicator considering an environmental dimension to rank regions in Spain, and Karagiannis & Karagiannis 2018 constructed a composite indicator for evaluating the financial performance of hospitals in Greece.

According with Cherchye et al. (2007) it is possible to say about BoD the following:

This DEA approach uses indicators instead of the usual inputs and outputs variables from other DEA models. These indicators are called as composite indicator (CIs) that aggregate several weighted performance sub-indicators in order to compare a country relative to the other countries in the set and/or to some external benchmark. In the case of this study, countries' performance will be compared between each other.

As stated, BoD is simply another approach of DEA, in fact, literature explains that BoD is equivalent to the traditional (input-oriented) DEA method presented by Charnes et al. (1978) but that in this case it is used CIs to consider the products (or outputs) and used unitary dummy variables with value equal to one for each

DMU. It is simple to understand then, that the main difference between the usual DEA approaches and the BoD is that the CIs used by this model looks only for the outcomes and do not "bother" itself with the required inputs to achieve the goals.

BoD perceives, or at least assumes, for each country that the dimensions represented by the sub-indicators that achieve better relative performance, are the policies dimensions that the country considers more important. Therefore, the model gives higher weights to the sub-indicators that have better performance and less weight to the sub-indicators that have lower performance. Thus, this results in the BoD model optimizing the CIs (Shwartz et al., 2010). This statement is seen by some as a limitation of the model since different DMUs are being weighted differently.

There are three main ideas that can be seen as strengths of this approach: one of them is that BoD uses endogenous and flexible weights, i.e., weights can adapt to the choice of measurement units, which means that the step of having to normalize indicators can be skipped. This unit invariance is in fact a great feature of BoD-DEA since that means that composite indicators values are not dependent of the units of measurement of the sub-indicators. The second one is that even with such flexible weighting a country can be outperformed by some other country in the sample – benchmark idea is present. The third one, is that having information about the weights, that information can be accommodated by the model.

The mathematical formulation of this model and the construction of CIs is the following one:

$$I_c = \max_{w_{c.i}} \frac{\sum_{i=1}^{m} w_{c,i} \cdot y_{c,i}}{\max\limits_{y_{j,i} \in \{studied\ countries\}} \sum_{i=1}^{m} w_{c,i} \cdot y_{j,i}} \tag{5}$$

s.t.

$$\sum_{i=1}^{m} w_{c,i} \cdot y_{j,i} \leq 1 \text{ , n constraints, one for each country j} \tag{5.1}$$

$$w_{c,i} \geq 0 \text{ , m constraints, one for each indicator i} \tag{5.2}$$

With the presented formulation, it is possible to retrieve that the model has a benchmarking basis: the value results on the comparison between the actual overall performance (numerator of equation 5, that corresponds to the weighted sum of its sub-indicators) and the benchmark overall performance (denominator of equation 5, that reflects the best performances retrieved from the observed sample). If no a priori information is given to the weights, that some experts could have and give if wanted, the "$\max\limits_{w_{c.i}}$" term makes the method to choose the weights that maximise the composite indicator for each country, i.e, any other weighting attribution would put the country less quoted/evaluated. This way, any country could not argue that a poor relative performance is because of the weighting attribution. Regarding the constraints, equation 5.1 represents a normalization constraint which imposes that the CI can't be higher than 1 if the same weighting scheme is being used for another country in the set. Equation 5.2 represents a non-negativity constraint that imposes that the weights used must be positive in order to reflect that CI is a non-decreasing function of the sub-indicators, (Karagiannis & Karagiannis, 2018). This makes also that the CI to have values only between 0 and 1. Thus, it is easy to understand that if CI is equal to one, that means the best performance (the same performance that is benchmarked) and closer to zero means weaker performance.

5. Model Implementation (Case Study)

5.1. Sample, data selection and data treatment

The pandemic affected countries for a quite long time, so, a period of time to gather data was needed to be defined. It was thought that focus on COVID-19 data from March 2020 till December 2021 would be a good time span since it is pertinent and long enough. For the construction of the sample to be used in this analysis, it was required also to have a wide and representative sample since the goal is to make an international revision and comparison of the countries around the world affected by COVID-19 pandemic. Despite having very information and updated data for the OECD countries, using only this 38 countries, as several studies presented in the literature review did, would be very restrictive for this study. The biggest and most-known countries would be considered but countries from south America, Africa and Asia (except Japan) would not be covered. For this reason, it was planned to use in the analysis the same countries that Nuclear Threat Initiative, the Johns Hopkins CSSE and the Economist Impact used to construct the Global Health Security index. This indicator is used to assess and benchmark health security in case of outbreaks using 6 categories, 37 indicators and 96 sub-indicators for 195 countries. Since the work that is intended with this thesis is comparable to the work done to construct the GHS index it was thought that would be easy to find similar reliable and updated data for these countries. However, the study was not carried out with this 195 countries since several of them had very missing data for the variables used. Thereby, from the initial 195 countries, 39 were excluded due to different reasons[13]:

- **7 countries** because had missing data superior to 30%, i.e., the available data is not higher than 70% in the variables used to perform the Cluster Analysis (CA).
- **16 countries** because data about covid-19 was important for this study, thus, countries that have no data for containment and health index variable used in the CA (which is highly probable that have no other COVID-19 data as well) were removed to not hamper the reliability of the results obtained in our data analysis.
- **16 countries** because had missing data superior to 65% for the variables used to perform the BoD in the majority of months of the analysis.

In Table 4 it is shown the 156 countries conducted in this study divided by the three clusters obtained with the CA. This is a sample big enough to represent the whole population and to not verify the dimensionality problem of DEA.

[13] Find in the cloud the excel files with the calculation of missing data and the countries removed: 3) Missing Values

Table 4 – List of countries obtained in each cluster using k-means method (Source: The author)

Countries per Cluster					
Cluster 1	**Cluster 2**		**Cluster 3**		
Bahrain	Argentina	Luxembourg	Afghanistan	Ghana	Nigeria
Bangladesh	Australia	Malta	Albania	Guatemala	Oman
Belize	Austria	Netherlands	Algeria	Guinea	Paraguay
Bhutan	Barbados	New Zealand	Angola	Haiti	Romania
Brunei	Belgium	Norway	Azerbaijan	Honduras	Russia
China	Brazil	Panama	Belarus	Hungary	Rwanda
Egypt	Canada	Peru	Benin	Iran	Senegal
Fiji	Chile	Poland	Bolivia	Iraq	Serbia
Guyana	Colombia	Portugal	Bosnia and Herzegovina	Jordan	Sierra Leone
India	Costa Rica	Singapore	Botswana	Kazakhstan	Somalia
Indonesia	Cuba	Slovakia	Bulgaria	Kenya	South Africa
Jamaica	Cyprus	Slovenia	Burkina Faso	Kyrgyzstan	Syria
Laos	Czechia	South Korea	Burundi	Latvia	Tajikistan
Malaysia	Denmark	Spain	Cambodia	Lebanon	Tanzania
Mauritius	Ecuador	Suriname	Cameroon	Liberia	Thailand
Mexico	Estonia	Sweden	Cape Verde	Libya	Timor
Myanmar	Finland	Switzerland	Congo	Madagascar	Togo
Nepal	France	Trinidad and Tobago	Cote d'Ivoire	Malawi	Tunisia
Pakistan	Germany	United Kingdom	Croatia	Mali	Turkey
Papua New Guinea	Greece	United States	Democratic Republic of Congo	Mauritania	Uganda
Philippines	Iceland	Uruguay	Dominican Republic	Moldova	Ukraine
Qatar	Ireland		El Salvador	Mongolia	Uzbekistan
Saudi Arabia	Israel		eSwatini	Morocco	Venezuela
Seychelles	Italy		Ethiopia	Mozambique	Vietnam
Sri Lanka	Japan		Gabon	Namibia	Yemen
Sudan	Kuwait		Gambia	Nicaragua	Zambia
United Arab Emirates	Lithuania		Georgia	Niger	Zimbabwe
Total of countries in cluster 1**: 27**	Total of countries in cluster 2: **48**		Total of countries in cluster 3: **81**		
Total of countries: 156					

In CA, it is made natural groups (or clusters) from multivariate data objects based on similarities or dissimilarities (distances) among them (Härdle, 2015; Johnson & Wichern, 2007). This separation was done based on eight variable that reflects the countries characteristics and demographic similarities/disparities, stated in Table 5. In Imtyaz et al. (2020) it was shown that COVID-19 deaths were associated with population age (older population being more affected) and Malik et al. (2021) shown a significant positive correlation between COVID-19 deaths and health expenditure as a share of GDP. The usage of containment and health index was to represent in a more direct way the stringency of the measures taken to fight the pandemic at the time of grouping the countries. The other variables are commonly associated to factors or diseases that the risk of dying from COVID-19 is higher for these patients.

Table 5 - Variables used to perform the Cluster Analysis (Source: The author)

a.	GDP per capita	**b.**	citizens over 65 years of age
c.	population density	**d.**	healthcare expenditure as a share of GDP
e.	diabetes prevalence	**f.**	cardiovascular disease death rate
g.	respiratory disease death rate	**h.**	containment and health index

Since the data had some missing values, the imputation process is applied to the blank data with some of the most used and basic methods before performing the cluster analysis. For this dataset, it was only used “*listwise deletion*” (omission of some observations) as mentioned before, and “*mean imputation*” (the value of the variable’s mean is imputed for the missing observations) which does not affect the mean of that variable (Ferreira et al., 2021). These imputation methods are easy to implement and justified, making it very used and well-known.

While, for example, the variable GDP per capita has monetary values, the population density refers to number of people per square kilometer, and the containment and health index includes values with a range between 0% and 100%, each value in the dataset had to be scaled/normalized. With this finality, using r software, it was used the function “*scale*” that for each observation simply subtracts by their respective variable’s mean and divides by their respective variable’s standard deviation. This is a good practice also because this way the variables turn more homogeneous (all of them have the same weight in the construction of the clusters) and the results aren’t compromised for having very big values in some variables which make these variables more important erroneously. As stated by Shalabi et al. (2006), for classification techniques that involve neural networks or distance measures, such as closest neighbor classification and clustering, normalization is very helpful and should be applied since it also removes redundant data and improve the efficiency of clustering algorithms, and so, the quality of the clusters obtained. This is important since the Euclidean distance used in the clustering algorithm is very sensitive to changes in the size of the different variables (Patel & Mehta, 2011). After this step, the dataset was ready to be submitted to the CA, however, the results obtained were not consistent.

For this reason, to reduce some noise that could have among the dataset, it was performed a Principal Component Analysis (PCA). PCA is a very useful method to reduce the number of variables through linear combinations without losing the main information based on loadings and correlation between the PCs and the original variables (Bro & Smilde, 2014), making it easier to explore, visualize and take conclusions. The ideal number of principal components to retain can be employing recognized techniques like the 80%-90% rule, the Keiser’s rule and the scree plot (Rodrigues, 2020). According with the Keiser’s rule, 3 PCs should be kept (the ones with eigenvalue greater than or equal to 1); according with the 80%-90% rule should be kept 5 PCs (cumulative proportion of variance between 0,80 and 0,90 and it is only achieved for 5 PCs with 0,82) and to the visualization of the scree plot 3 PCs should be retained (the biggest elbow can be seen for dimension 3), represented at Figure a1. Thus, it was taken the decision to trade a little accuracy for more simplicity by reducing the original 8 variables to just 3 non-correlated principal components that can still explain the most variance of the original variables. Therefore, the data carried for the cluster analysis was using only this 3 PCs instead.

Next, it must be determined the ideal number of clusters that should be used and for that it was applied the hierarchical Ward method with Euclidean distance. The result obtained can be seen in Figure a2. With the plot it is possible to verify that the highest cluster distance is obtained at the vertical lines that are crossed by the horizontal red line at the height around 40 units. This red line crosses three perpendicular lines from the dendrogram, which means that 3 clusters are the ideal number to group the several 172 countries (marked with the three red squares in Figure a2). To validate this result it was also applied other methods using fviz_nbclust function in r: the *"silhouette"* method (for average silhouette width) obtained 3 clusters as the optimum number, the *"wss"* method (for total within sum of square) 3 or

4 clusters as the ideal number, and *"gap_stat"* method (for gap statistics) reveals that 3 are the best number of clusters to use (see the three different results/plots at Figure a3). Finally, after knowing the ideal number to group the countries, the k-means was applied, having in mind that k-means method reduces intra-cluster variance and maximizes inter-cluster variance (Imtyaz et al., 2020). The result can be seen in Figure a4 and in Table 4 (here with the excluded countries mentioned previously), using k-means method with Euclidean distance, based on the Hartigan and Wong algorithm (Hartigan & Wong, 1979), that seems to stratify the data in the most convenient and explanatory manner.

Analyzing the result obtained in Figure a4, the isolated points of Monaco and Singapore could be possible outliers that must be identified. For that reason, to evaluate the presence of outliers it was used two methods with that purpose in excel[14]. In method 1, it is computed a lower bound and an upper bound using the mean and the standard deviation for each of the eight variables. Next, for the values observed in Monaco and Singapore for each variable, it is verified if it is between the respective upper and lower bound values. The values were between the admissible range for almost all variables which permitted to conclude that these two countries were not outliers. Method 2 has similarities to method 1, however the upper and lower bounds are computed using the first and third quartiles, as well as the inner quartile range, which resulted in the same conclusion. Additionally, method 2 was also applied to all other countries as an afterthought and the results were the expected: any country was an outlier. Therefore, at this point, any modification was made to the cluster's elements. In Figure a5, it is possible to see the countries' geographic location for each cluster. The Figures a6 and a7 sourced from *The World Bank* classify the world by regions and income and are used to have a better notion of how each cluster is composed (The World Bank, 2021).

To measure the countries relative efficiencies against the pandemic, it was also vital to understand which dimensions are important to study in this analysis and which indicators can be used to measure these dimensions. The explanation of each dimension and indicators used will be later described in section 5.2. After establishing the variables, it was also needed to do some data treatment before performing the BoD analysis. It could be explained in this section, but it was decided to make it in dedicated sections (section 5.3, 5.4 and 5.5) since it is very closely linked to BoD and to the good practices to create composite indicators, that are the inputs required to perform de BoD analysis. In short, it was used mainly the proposed methodology to create the CIs by Nardo et al. (2008) from OECD organization that suggest some key-steps, such as, the theoretical framework, data selection, imputation of missing data, multivariate analysis, normalization, weighting and aggregation and visualization of the results.

After performing this initial but very time-consuming step of gathering and treating data, the efficiency analysis can be done with the BoD. The BoD analysis will be then carried out for the three clusters separately analogously. For this reason, the results and conclusions taken will be always made for each cluster independently since they aren't comparable.

5.2. Dimensions and variables

Having in mind the goal of this study, measure and understand the efficiency among countries to fight the COVID-19 pandemic considering socio-economics aspects, it was defined the dimensions and

[14] Find in the cloud the excel file to determine the presence of outliers: [Finding outliers.xlsx]

Table 6 - List of the 41 indicators used by group and dimension, and the respective time of measurement and the polarity it should take (NOTE: indicator 3.2.2 was removed from the analysis) (Source: The author)

Dimension (CI)	**Group (Partial CI)**	**Variables/KPIs/Indicators**	**Time-Period**		**Polarity[15]**
			Yearly[16]	**Monthly[17]**	
1. COVID-19	1.1 Tests and vaccination response	1.1.1 Total Tests Per Thousand		X	⊕
		1.1.2 Positive Rate		X	⊖
		1.1.3 Total Vaccinations Per Hundred		X	⊕
		1.1.4 People Vaccinated Per Hundred		X	⊕
		1.1.5 People Fully Vaccinated Per Hundred		X	⊕
		1.1.6 Total Boosters Per Hundred		X	⊕
	1.2 Policy and strategy response	1.2.1 School Closures		X	⊕
		1.2.2 Workplace closing		X	⊕
		1.2.3 Cancel Public Events		X	⊕
		1.2.4 Restrictions on gatherings		X	⊕
		1.2.5 Public Transportation		X	⊕
		1.2.6 Stay at Home Order		X	⊕
		1.2.7 Restrictions on Internal Movement		X	⊕
		1.2.8 International Travel Controls		X	⊕
		1.2.9 Public Information Campaigns		X	⊕
		1.2.10 Testing Policy		X	⊕
		1.2.11 Contact tracing		X	⊕
		1.2.12 Facial coverings		X	⊕
		1.2.13 Vaccination policy		X	⊕
		1.2.14 Protection of elderly people		X	⊕
	1.3 COVID-19 outputs/outcomes	1.3.1 Fatality Ratio		X	⊖
		1.3.2 Excess Mortality Cumulative Per Million		X	⊖
		1.3.3 Reproduction Rate		X	⊖
2. Access and Quality of Health	2.1 Social sanitation and Hygiene, and Development	2.1.1 Share of Population with Access to Basic Handwashing Facilities	X (2020)		⊕
		2.1.2 Human Development Index	X (2021)		⊕
	2.2 Healthcare resources	2.2.1 Hospital beds per 1 000	X (2021)		⊕
		2.2.2 Medical Doctors per 10 000 population	X (2020)		⊕
		2.2.3 Nursing and midwifery personnel per 10 000 population	X (2020)		⊕
		2.2.4 Healthcare Access and Quality Index	X (2015)		⊕
3. Security and Compliance in Governance	3.1 Accountability	3.1.1 Transparency Accountability Index	X (2010)		⊕
		3.1.2 Corruption Perception Index	X (2018)		⊖
	3.2 Political stability	3.2.1 Public trust in politicians	X (2018)		⊕
		~~3.2.2 State legitimacy~~	~~X (2021)~~		~~⊕~~
		3.2.3 Score of adoption and implementation of national disaster risk reduction (DRR) strategies in line with the Sendai Framework	X (2020)		⊕
		3.2.4 Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies (%)	X (2020)		⊕
4. Fragility in Economy and Finance	4.1 Expenditures on Healthcare	4.1.1 Total health expenditure as percentage of GDP (%)	X (2019)		⊕
		4.1.2 Population covered by health insurance (%)	X (2011)		⊕
	4.2 Economic stability	4.2.1 Economic decline indicator	X (2021)		⊖
		4.2.2 Economic globalization index	X (2019)		⊕
		4.2.3 Direct economic loss attributed to disasters	X (2020)		⊖
	4.3 Economic support	4.3.1 Income Support		X	⊕
		4.3.2 Debt/contract relief for households		X	⊕

[15] The polarity shows the relationship between the indicator and the phenomenon to be measured. ⊕ higher the better (positive polarity); ⊖ lower the better (negative polarity)

[16] For some indicators and entities, the data has the latest available point instead of the year that is shown (cross-sectional data)

[17] Indicators marked as monthly means that it was used for the analysis data from March 2020 till December 2021 aggregated by month (time series data)

variables presented in Table 6[18]. Since this is one of the first works till this date with such aim and using composite indicators, finding the best way to evaluate the several aspects and how to arrange the several variables into the several groups and dimensions to create meaningful CIs was quite demanding. In this regard, it was used the proposal of George et al. (2020) that answered their research question *"How can we benchmarking COVID-19 performance data across countries?"* as a starter point, and some important aspects learned from the literature review done in section 3. Both had a strong influence in the construction of dimension 1 and 2 presented in Table 6. Even though George et al. (2020) didn't consider cultural aspects, the literature review showed that this aspect has effects in COVID-19 outcomes (Min et al., 2021; Mitchell et al., 2021), which resulted in the construction of dimension 3 presented in Table 6. Despite both literature review and the proposal of George et al. (2020) lacked the evaluation of economic aspects, it was a necessary aspect to consider in this study and for that reason it was made a more autonomous and extensive search for possible good indicators, and it was chosen the ones presented in Table 6 in dimension 4. Finding the indicators to use was also limited to the ones available (and for free) on internet, its time-period, and its geographic coverage. For example, it was found several indicators that could be used in this study but had information only about OECD countries, which is very limited, and for that reason these had to be discarded. In dimension 2, it was pretended to use some variables to reflect healthcare needs (COVID-19 ICU patients per million and the COVID-19 hospital patients per million variables) but these variables were only available for around 14% of the countries in study and for that reason couldn't be used.

The final dimensions and indicators used is shown in Table 6 and will be described below by dimension and group.[19] At the end of each dimension it is made a statistical analysis to understand the data in hands (descriptive statistics) and evaluate the correlation between variables to understand if some of them should be removed to not introduce redundancy/noise to the study[20].

1. COVID-19 dimension

This dimension reflects the data that is related directly with COVID-19. It is intended to measure the ability of countries in the direct fight of the pandemic by means of testing and vaccination (group 1.1), and policies taken to contain the virus and reduce its spread among population (group 1.2). It is also accounted the negative impacts of the disease (group 1.3).

1.1. Tests and vaccination response

1.1.1. ***Total Tests Per Thousand:*** total COVID-19 tests made per 1000 people. Testing is a very powerful strategy to handle the pandemic since tracing the disease it is possible to prevent its spread by isolation of positive cases.

1.1.2. ***Positive Rate:*** the share of total tests that has positive result. Higher value is problematic since it means that more people are infected, and the virus is spreading easily.

[18] Find in the cloud the PDF file with the discrimination of the (reliable) sources and respective websites for each of the 41 indicators used: Source of the indicators used.pdf

[19] Find in the cloud the excel file with the data for each indicator (one sheet per indicator): INDICADORES_BOD.xlsx

[20] Find in the cloud the files (.R / .txt) with the code used to perform the statistical analysis: 3) Statistical Analysis

1.1.3. ***Total Vaccinations Per Hundred:*** total COVID-19 vaccines administrated per 100 people in the total population of the country. Vaccination is an important process since it helps to create herd immunity that has a key role in ensuring that the pandemic turns into endemic.

1.1.4. ***People Vaccinated Per Hundred:*** total number of people vaccinated per 100 people in the total population of the country. This indicator is different from 1.1.3 as far as this one considers only if the people have taken at least one dose and 1.1.3 considers the total number of vaccine doses administrated, including boosters, counted individually. For this reason, if someone takes the second dose, the indicator 1.1.4 will remain with the same value but to indicator 1.1.3 will be added 1 more unit (before taking the division).

1.1.5. ***People Fully Vaccinated Per Hundred:*** total number of people who received all doses prescribed by the initial vaccination protocol per 100 people in the total population of the country. If a person receives the first dose this indicator does not change but if they receive the second dose, the indicator goes up by 1 (before taking the division).

1.1.6. ***Total Boosters Per Hundred:*** total number of booster doses administered per 100 people in the total population of the country. Booster doses are the ones administered additionally to the ones prescribed by the initial vaccination protocol.

1.2. Policy and strategy response

The 14 indicators included in this group are used to evaluate the stringency of the policies taken as government response to the pandemic. They construct the *"Containment and Health index"* from Oxford COVID-19 Government Response Tracker (OxCGRT) and each indicator has an ordinal scale. This means that the scale of severity or intensity of the policies taken are measured by categories. For example, for indicator 1.2.3 (Cancel public events), 0 means *"no measures"*, 1 means *"recommend cancelling"* and 2 means *"require cancelling"*. For simplicity's sake and with the concern of saving space, was decided to not include a description for each indicator since they are very self-explanatory and would result in a very dense text that would not bring any add-value[21]. This metric is solely intended for comparison and shouldn't be taken as a judgment on the suitability or efficacy of a country's response (Hale et al., 2020), which suits the present study.

1.3. COVID-19 outputs/outcomes

1.3.1. ***Fatality Ratio:*** share of people that died among the infected ones. This indicator was computed using other two variables: it is the quotient between total COVID-19 deaths and total confirmed COVID-19 cases. Fatality rates are useful to understand the severity of a disease and identify at-risk populations.

1.3.2. ***Excess Mortality Cumulative Per Million:*** Cumulative difference between the reported number of deaths and the projected number of deaths for the same period based on previous years, per million people. For this variable, it was needed to perform data translation to remove the negative values that can't be used as input for the BoD. The shift to positive values didn't change the meaning of the variable since the proportion between data are kept

[21] Find the description of each indicator and respective ordinal scale at the most updated OxCGRT data and documentation available via the project GitHub repository: https://github.com/OxCGRT/covid-policy-tracker.

(Zhu & Cook, 2007; Zanella et al., 2013). Therefore, the same conclusions can be taken from this variable although the values are different.[22]

1.3.3. ***Reproduction Rate:*** Estimates the effective reproduction number of COVID-19 infectious disease, which is helpful to assess the effectiveness of non-pharmaceutical interventions (Arroyo-Marioli et al., 2021). The computation of this data was made using the work of Arroyo-Marioli et al. (2021) that used Kalman filter to obtain this values.

It is a good practice in statistics to evaluate the data in hands and find a way to summarize and describe the data. A summary of the descriptive statistics (minimum, maximum, mean and standard deviation) for all variables from dimension 1 can be found in Table b1. It is also a good practice to study the relation between variables to find some redundancy that might exist. It was made an assessment to evaluate the correlation between variables using the *Pearson's* correlation coefficient and *Spearman's* correlation coefficient that is more suitable for time series data. Using *Pearson's* (*Pearson's* correlation: *-0,309 ≤corr(xi,xj)i≠j ≤ 0.976*) exists high significative correlation between variables 1.1.3 (total vaccinations per hundred), 1.1.4 (people vaccinated per hundred), and 1.1.5 (people fully vaccinated per hundred). Using *Spearman's* (*Spearman's* correlation: -0,346 ≤corr(xi,xj)i≠j ≤ 0.992, see Table b2) exists also high significative correlation between variables 1.1.3, 1.1.4, 1.1.5, and 1.2.13 (vaccination policy). These results make sense since they are obviously related, but it was considered that they offer complementary analysis about countries performance regarding vaccination policy to fight the pandemic and the omission of some of them could be very reductive for this study. It is not only important to know the number of doses administrated but also if people received all prescribed doses (fully protected) or if received just one dose, because it clearly has different impacts in COVID-19 outcomes.

2. Access and Quality of Health dimension

This dimension measures the ability of countries for delivering a good healthcare system and an easy and equal access to medical care. As known, the SARS-COV-2 spreads easily among people and sanitation and hygiene is an important barrier to protect the population (group 2.1). The capacity to provide the services and the availability of resources to treat the infected patients should be also considered (group 2.2).

2.1. Social sanitation and Hygiene, and Development

2.1.1. ***Share of Population with Access to Basic Handwashing Facilities:*** Share of population that has safe managed sanitation services and uses handwashing facilities with soap and water. Targets rural and urban populations. This indicator is used to reflect the availability countries to provide water, safe social sanitation, and hygienic facilities to the population that are considered core socio-economic and health indicators according with United Nations[23].

2.1.2. ***Human Development Index:*** A very well-know composite indicator used to measure a long and healthy life, knowledge, and a decent standard of living. This indicator is useful to

[22] Find in the cloud the excel file with the explanation of the data translation made for this variable: INDICADORES_BOD.xlsx (sheet: "Excess Mortality Cumulative")

[23] More information about this indicator can be found online at the website of "United Nations": https://unstats.un.org/sdgs/metadata/files/Metadata-06-02-01a.pdf

evaluate COVID-19 and the policies taken asking how countries with the same level of GNI per capita can end up with different human development outcomes (United Nations, 2021).

2.2. Healthcare resources

2.2.1. ***Hospital beds per 1 000:*** Reflects the availability of healthcare resources to treat the infected patients.

2.2.2. ***Medical Doctors per 10 000 population:*** Reflects the availability of healthcare skilled labor resources to treat the infected patients.

2.2.3. ***Nursing and midwifery personnel per 10 000 population:*** Reflects the availability of healthcare skilled labor resources to treat the infected patients.

2.2.4. ***Healthcare Access and Quality Index:*** This composite indicator is used to measure personal healthcare access and quality in countries evaluating the mortality rates from causes that shouldn't be fatal in the presence of effective medical care (Barber et al., 2017). Therefore, it is possible to reflect in a general and reliable way the healthcare resources available (through its access and quality) for the several countries in study.

A summary of the descriptive statistics (minimum, maximum, mean and standard deviation) for dimension 2 variables can be found in Table b3. The correlation between variables was also determined using the *Pearson's* correlation coefficients and in Table b4 it is possible to see that $-0{,}486 \leq corr(xi,xj)_{i \neq j} \leq 0{,}922$. The significative high correlation is between variables 2.1.1 (share of population with access to basic handwashing facilities) and 2.1.2 (human development index), and between 2.1.2 and 2.2.4 (healthcare access and quality index). It makes some sense that variable 2.1.2 is correlated with variable 2.1.1 and 2.2.4 since they are all connected with the *"long and healthy life"* component that is measured by human development index. However, the three indicators deliver complementary information and for that reason they were considered necessary. In addition, the removal of indicator 2.1.2 would result in group 2.1 having just one element, and it is not possible to compute the partial CI 2.1 (social sanitation and hygiene, and development) with just one sub-indicator. Hence, any variable was removed from the analysis.

3. Security and Compliance in Governance dimension

This dimension measures the transparency and the accountability of governments when taking decisions that affects, naturally, all the country population. As shown previously in section 3 the success of the measures taken is associated with the availability of people to comply with the rules imposed and with their confidence in the government. People's trust is achieved with good levels of accountability and transparency, low corruption, and building good disaster risk reduction strategies for pandemics that can make people rely on and feel secure (group 3.1 and 3.2). For simplicity's sake and with the concern of saving space, was decided to not include a description for each indicator since they are very self-explanatory and would result in a very dense text that would not bring much add-value. Therefore, for indicators 3.1.1, 3.1.2 and 3.2.1 it is important to highlight that having lower perceived corruption, higher transparency and accountability and higher public trust in politicians brings on people more trust and willingness to help, and so, the results of the policies defined by countries are better. With these indicators it is possible to reflect how countries turn governmental aspects into public information, the quality and reliability of these information, the importance of having a free media to expose illegal or improper decisions and the government's response towards accountability of these non-supposed acts (Williams, 2014).

Regarding indicators 3.2.3[24] and 3.2.4 are intended to measure the capacity of countries to prevent new and control in a better way the existing disaster risk. Therefore, the global targets of the Sendai framework make countries to strengthen their people's and governments' resilience in the face of disasters hence the importance of following it. Although these disaster risk reduction strategies are created for a better preparedness for several natural hazards, pandemics is one of the elements of the list, and for that reason its usability in this study.

The descriptive statistics (minimum, maximum, mean, and standard deviation) for dimension 3 variables can be found in Table b5. The correlation between these variables was evaluated and was found a significative high correlation between variables 3.1.1 (transparency accountability index) and 3.2.2 (state legitimacy) and between 3.1.2 (corruption perception index) and 3.2.2 (see Table b6, where it is possible to perceive that *Pearson's* correlation varies between $-0.844 \leq corr(xi,xj)i \neq j \leq 0,740$). The high correlation makes sense in a way that countries can have a more legitime state delivering transparency and avoiding corruption to population. This permits to conclude that variable 3.2.2 brings redundancy to the analysis and should be excluded from the analysis.

4. Fragility in Economy and Finance dimension

This dimension accounts for the economic capacity of countries. Pandemics affects negatively in large scale the countries' economy since more monetary resources are needed to curtail the spread of the virus (i.e., flattening the curve by testing, vaccination, and other policies) and to treat COVID-19 positive patients. Group 4.1 reflects the importance that countries give to the health, group 4.2 shows the stability of countries' economy and possible shifts (in economy) that can occur because of COVID-19 pandemic, and group 4.3 reflects the economic support that countries gave to merchants and households to handle more properly the negative consequences of the disease.

4.1. Expenditures on Healthcare

4.1.1. ***Total health expenditure as percentage of GDP (%):*** Reflects the importance that countries give to the healthcare system. This indicator captures the spendings of governments funding health care systems and social health insurance. Regarding the COVID-19 pandemic is expected that countries that financed healthcare in a bigger proportion of GDP had better results than others.

4.1.2. ***Population covered by health insurance (%):*** Proportion of people that has health insurance (members of health insurance or free access to healthcare services provided by the state). This metric is also a clear measure of spendings on healthcare in the way that more people being covered by an easy and free access to healthcare reflects in more costs to countries. Regarding COVID-19, governments not only had to fund tests, vaccines and treatment to infected people but also offered economic support to companies and families.

4.2. Economic stability

[24] More information about this indicator and the Sendai Framework can be found online at the website of "United Nations": https://www.unisdr.org/files/50438_implementingthesendaiframeworktoach.pdf

4.2.1. ***Economic decline indicator:*** This indicator reflects the economic decline within a country by per capita income. It uses factors, such as, gross national product, unemployment rates, inflation, productivity, debt, poverty levels, and business failures to understand patterns of gradual economic decline of the society. It also considers any collapse or depreciation of the national currency, as well as unexpected declines in commodity prices, trade revenue, or foreign investment. All this factors were affected by the pandemic which resulted in a more fragile economy and is expected to be measured with the help of this indicator.

4.2.2. ***Economic globalization index:*** This indicator is composed of trade globalization and financial globalization indicators that accounts for actual economic flows and restrictions to trade and capital that were, certainly, affected by COVID-19 pandemic. The first one accounts for data on trade, foreign direct investment (FDI), and portfolio investment and second one for hidden import barriers, mean tariff rates, taxes on international trade, and an index of capital controls.

4.2.3.***Direct economic loss attributed to disasters:*** This indicator measures the ratio of direct economic loss attributed to disasters in relation to GDP. Related with indicators 3.2.3 and 3.2.4 but with an economic basis as an attempt to measure the impacts of disasters in economy. The pitfall of this indicator is that it does not only counts for pandemics but has a more generic usage for several natural disasters.

4.3. Economic support

4.3.1. ***Income Support:*** This indicator records for the economic support given to households that lost their jobs or cannot work because of COVID-19. Therefore, if government is providing payments to people that are missing for their salary it is reflected in this indicator with ordinal scale: “0” if no income support is given, “1” if government is paying less than 50% of lost salary and “2” if more than 50% is paid.

4.3.2. ***Debt/contract relief for households:*** This indicator records also for economic support given to households but now by means of relieving financial obligations that people might have. For example, if government freezes the obligation for repayment of loans, prevents essential services from stopping, or banns evictions it is accounted in this indicator. Bigger values of this indicator (and 4.3.1) are considered good because it shows concern and availability of economic resources of countries to alleviate their people and companies.

In Table b7 it is possible to see the descriptive statistics (minimum, maximum, mean and standard deviation) for variables from dimension 4. For the cross-sectional data was used the *Pearson’s* correlation (-0.669≤ corr(xi,xj)i≠j ≤ 0,618, see Table b8) and for the time series data was used the *Spearman’s* correlation coefficients (corr(xi,xj)i≠j = 0,376, see Table b9), which permitted to conclude that all these variables have no significative correlation between them and for that reason should be kept for the analysis.

5.3. Imputation of missing data[25]

This step refers to the need of dealing with observations that has no values (missing data) in order to provide a complete dataset, which is a requirement to perform the BoD. Therefore, BOD needs a perfect

[25] Find in the cloud the excel files with the missing data and the respective imputed data: 3) Missing Values

knowledge of data. Several methods are very well-known and scientifically recognized and can be divided into three types: case deletion, single imputation and multiple imputation (Ferreira et al., 2021; Tamboli, 2021). The three types were used and in Table b10 it is possible to see a summary of the imputed methods used for the several 41 variables. Using multiple imputation the missing data is filled multiple times and then pooled to reflect uncertainty about the values to impute which does not happen in single imputation (Nardo et al., 2008), thus, can be viewed as a better approach.

The imputation of missing data[26] will be divided in two groups in this work: one corresponds to the variables that had a monthly time measurement, i.e., the data points change from month to month (time series data), and the other one corresponds to cross sectional data, i.e., the data points are always the same for the whole period of study (March 2020 – December 2021).

5.3.1. Time series data

In the present study, it refers to the data captured by variables from group 1.1, 1.2, 1.3, and 4.3 that were updated daily to reflect the changes and progression of COVID-19 pandemic over time. Since the values changed daily, in excel, the values from 1 March 2020 till 31 December 2021 were grouped by month (using mean or the maximum values depending of the variable) for each country.

It was used the software r to perform the imputation using the package "*ImputeTS*", that includes a collection of algorithms and tools tailored to impute values in time series data with a very user-friendly approach. Any algorithm can be pointed out as the best one to use, but while *"na_kalman"* and *"na_seasplit"/"na_seadec"* have better results for time series with a strong trend or seasonality, *"na_interpolation"* will deliver the best results for most time series in general (Moritz & Bartz-Beielstein, 2017)[27]. Even though COVID-19 disease can be associated to some seasonality, any study reviewed in literature confirmed that, and, in fact, according with Lipsitch (n.d) the transmission goes more efficiently in winter and the severity of the disease can be decreased as the warmer weather approaches but never enough to stop transmission by its own since the size of the changes is expected to be modest. Therefore *"na_kalman"* and *"na_seasplit"/"na_seadec"* does not seem a good option to use since the imputed values could be more biased using this algorithm to reflect some seasonality that might not be supposed to. It was also available the function "*na_locf*" which the imputed values are replaced by the last/before value in the time series (*Last Observation Carried Forward*) or the next/following value that is ahead of him (*Next Observation Carried Backward*). This could make sense in some cases but not for all of them and could be a too much simple and not very precise approach (even though approved by literature). For these reasons, it was used the function "*na_interpolation"* with the option *"linear"* that fits the best values for the missing points using linear relation within the range of data points. In contrast to "*na_locf*" function, now it is looked for both past and future values to estimate the missing value (Koech, 2022).

It is also important to mention that for variables about vaccination (1.1.3, 1.1.4, 1.1.5, 1.1.6) from March 2020 till December 2020 the blank entries were replaced by zero since vaccination process only started in the beginning of 2021, as stated in section 2.1. In reality, this is a common technique used to overcome the problem of missing data because the replacement of blank entries for a large value (big M)

[26] Find in the cloud the files (.R / .txt) with the code used to impute the values for time series data: [2) Missing Data]
[27] See Moritz & Bartz-Beielstein (2017) for additional information about ImputeTS package and the several algorithms available for univariate time series imputation.

or by zero mitigates the influence of DMUs with missing data on the efficiency assessment of other observations (Ferreira et al., 2021; Kuosmanen, 2009).

5.3.2. Cross-sectional data

This refers to the data captured by variables from group 2.1, 2.2, 3.1, 3.2, 4.1 and 4.2. For variables with lower missing data (less than around 10%) it was used single imputation methods (cold-deck, hot-deck and mean imputation). For variables that missing data was higher (around 30%) it was used multiple imputation. The recognized techniques are descried bellow:

- ***Cold-deck imputation:*** Substitution of missing values for another similar value from another dataset/source (Ferreira et al., 2021). It was used values from previous years (always the latest available year), and in some cases from other reliable sources. For example, for variable 2.2.1 (hospital beds per 1 000) it was used values from previous years.
- ***Hot-deck imputation*** (Reilly, 1993)***:*** In contrast to cold-deck imputation, here the imputed values are always conditioned to the ones already present in the dataset in hands. The imputed value is always from another observation that has similar characteristics, based on the idea that similar DMUs exhibit identical consumption and production profiles (Ferreira et al., 2021; Nardo et al., 2008). For example, in variable 3.1.2 (corruption perception index) for Belize it was used the value of Jamaica since according the *Country Similarity Index*[28] it is the most similar country to Belize.
- ***Mean imputation*** (Raaijmakers, 1999)***:*** When it was not possible to use one of the previous techniques and the missing data was very low for the respective variable, the missing value was replaced by the mean of the variable (computed with the known values).
- ***Multivariate Imputation by Chained Equation (MICE):*** The imputed value consists in the average of the several estimations and the resulting standard errors and p-values are adjusted according with the variance of the several corresponding estimations (Nardo et al., 2008). For the variables that missing data was higher it was used "*mice*" package in r software to impute all the blank cells. This package has several methods included to perform the estimations and was decided to use the default one: predictive mean matching ("*pmm*") (Little, 1988). This is a good overall semi-parametric imputation method that can conserve the non-linear relations because the imputed values are restricted to the observed values (van Buuren & Oudshoorn, 2000).

5.4. Normalization

Normalization is a step that make all variables comparable since they usually have different unit measurements. As explained in section 5.1, the eight variables used to perform the cluster analysis was scaled with this finality. To perform the BoD analysis is no different, and for that reason normalization is required prior to any data aggregation to construct the CIs[29]. However, the choose of the best normalization method is not straightforward since it depends on the data and objectives. In literature exists several methods and can be highlighted three methods: *Min-Max*, *Z-score and Ranking*. In r software using the package "*Compind*", the package used to construct the CIs, there is one function "*normalise_ci*" that

[28] It is evaluated demographic (20%), culture (20%), politics (20%), infrastructure (20%) and geographic (20%) characteristics to find the similarity between countries. For more information about the *Country Similarity Index* see: https://objectivelists.com/2020/05/30/country-similarity-index/

[29] Find in the cloud the files (.R / .txt) with the code used normalize values: 4) BoD

permits to normalize the variables prior to the formation of CIs. It was studied the viability of this three methods and *Ranking* method was the best option for the present dataset, delivering more consistent values for all variables and months of the analysis. Furthermore, it is possible to say the following:

- ***Z-score (or Standardization)*:** this method is good when exists outliers in the data; and converts the original measurement unit to a common one that range between -3 and +3 units and all observations are converted to have mean of zero and a standard deviation of 1 (Nardo et al., 2008). As explained before, for variable 1.1.3 it was made a data translation to remove the negative values because the inputs to perform the BoD analysis must be all positive. Hence, since this method can transform the original values into negative ones, this approach was discarded even.
- ***Min-max:*** this normalization method subtracts the minimum value and divides by the range of the indicator values to convert the original measurement unit to a range between 0 and 1. It should be used for datasets that does not have outliers since extreme values can distort the normalization transformation (Nardo et al., 2008). As explained in section 5.1, it was made an assessment to identify the presence of outliers and no one was found, so, this approach could be used. However, when applying this method to normalize the present dataset, r software gave some error messages for indicators 1.1.3, 1.1.4, 1.1.5, 1.1.6 (indicators about vaccination) for the months between March – December 2020. It was easy to understand that since all observations for this period had only zero values (vaccination process only started in the beginning of 2021) the normalized values could not be computed since the minimum and maximum values are the same ones. The same happened for some variables from group 1.2 (indicators about policies and strategy responses).
- ***Ranking:*** this normalization method converts the original measurement unit to a natural number that ranges from 1 till the number of DMUs present in the dataset, i.e., for each indicator it constructs a ranking giving a position for each country according with the polarity of the indicator (to obtain standardized indicators with the same polarity) (Vidoli & Fusco, 2015). Nardo et al. (2008) explains this method is not affected by outliers and since the normalization is made of relative positions it allows to follow the performance of countries over time. It is the simplest technique that works very well in the present dataset. No errors using this normalization method.

5.5. Weighting and Aggregation

This step refers to giving weights (also designated by multipliers) to provide relative importance to the indicators that are used to construct the CIs. Therefore, the weights are simply value judgments given to each indicator that can affect the overall CI and the country rankings (Nardo et al., 2008). In literature exists several methods to choose the weighting scheme but does not exist any "one-size-fits-all" solution (Greco et al., 2019). Many approaches are valid and used in literature: for example, not attributing any weights (e.g., Slottje, 1991); attribute the equal weighting (e.g., Bandura, 2008); and in Hermans et al., 2008) it is asked to a panel of experts to assign the weights, which is not possible in this study due to the absence of expert stakeholders with sufficient knowledge about the causal relationship between indicators. All approaches have advantages and disadvantages and will not be explored here.

In this study, the traditional Benefit-of-Doubt method using a weighting range restriction was used. According with Vidoli & Fusco (2018) this approach is advantageous since weights are endogenously determined by the observed performances and then, the benchmark is not based on theoretical bounds, but it's a linear combination of the observed best performances. To achieve this, in r software, was used the function *"ci_bod_constr"* from the package *"Compind"* to construct the CIs, that permits to impose weight constraints. It was only imposed that the range of weights should be between 5% and 95% to ensure that all indicators are counted for the analysis, i.e., the system is not able to attribute zero weight to some indicator(s). Having in mind this restriction, BoD forms the overall composite indicator making a weighting sum of the indicators in a way that the weighting scheme maximizes the countries performance, therefore, any country cannot claim that the weights attributed are not favouring their country and favouring the other ones (Yang et al., 2017). Hence, since there is no sure about which weights to use, it is looked for the *"*benefit of the doubt*"* weights, in a way that the weights used makes the overall relative performances as high as possible. According with Calabria et al. (2016), this (almost) total flexibility that BoD has to define the multipliers is fundamental to define which DMUs have low performance, even when using the optimal weighting scheme that maximizes their performance. This is a major factor for this approach enormous success (Cherchye et al., 2007; 2008). It is understandable that to achieve this, the weighting scheme needs to be different between countries and according with Lovell et al. (1995) that is not a problem, on the contrary, he defends that weights must vary between countries, over time, and across objectives. The results obtained show that the weights are different between countries and months but that are always between 0.05 and 0.95, which is in accordance with the weight restriction made.

After section 5, it is possible to understand how the composite indicators constructed for this study followed important steps proposed by Nardo et al. (2008) to create meaningful CIs:

- Initially was performed a principal component analysis and a cluster analysis to identify group of countries that are statistically "similar", therefore, comparable;
- CIs were constructed based on a theoretical framework that helped to achieve a clear understanding of the multidimensional phenomenon to be measured, which could be improved with the usage of dimensions to define better what is intended to measure: in sum, dimension 1 to understand how countries were handling directly with COVID-19 pandemic (through tests, vaccination and other policies); dimension 2 to measure the healthcare system and resources available to treat people; dimension 3 to reflect cultural aspects that influence the results obtained in the fight of the pandemic; and dimension 4 to account for the economic aspects;
- Data was selected from reliable sources and entities to have the best data quality possible but always constrained to its availability (country-coverage, time-coverage);
- Different imputation methods were explored and used in attempt to always estimate the best missing values having account the type of data (time series or cross-sectional data) in hands and the degree of missing data;
- *Pearson's* and *Spearman's* correlation coefficients were calculated to remove redundant variables to avoid double counting and overweighting (statistical analysis);
- All indicators were normalized for comparability and different methods (z-score, min-max, ranking) were explored and used the one that fitted better the study's dataset (ranking);
- All indicators were weighted using BoD with the constrain that weights must vary [0,05;0,95] in order to ensure that all indicators are accounted for the analysis;

6. Visualization and Discussion of Results

6.1. General considerations

To obtain the ranking of countries to evaluate their relative performance using the proposed composite indicator with 41 indicators aggregated by 10 groups and 4 dimensions (see Table 6) the BoD method had to be applied several times. This results that from 41 indicators it was possible to obtain 10 partial CIs (one for each group) and from these partial CIs obtain other 4 (one for each dimension). Finally, from these 4 partial CIs was possible to obtain the final CI. In another words, the outcomes (partial CIs) that results from applying the BoD to the simple indicators, turns to be the new observations for the next application of BoD till the moment that the final CI is obtained. In this phase of the process the values do not need to be normalized since all values are between the range of 0 (not-efficient DMUs) and 1 (benchmark DMUs) but all values were weighted constrained (weights between 5% and 95%) to ensure that all partial CIs were accounted for the construction of the final CI (Cherchye et al., 2007). Figure 3 is a diagram created to clarify what has just been explained and despite results' analysis will focus on dimensional and final CIs, all composite indicators can be consulted in the cloud[30][31]. The final CI is useful to have a global perspective of the DMU performance having account the several categories in an integrated way (Morais & Camanho, 2011). Dimensional and groups partial CIs are useful to have a more focused understanding of DMUs performances in the different areas of study, and therefore, for example, understand if the poor performance of some country is due to the healthcare system or to the governance.

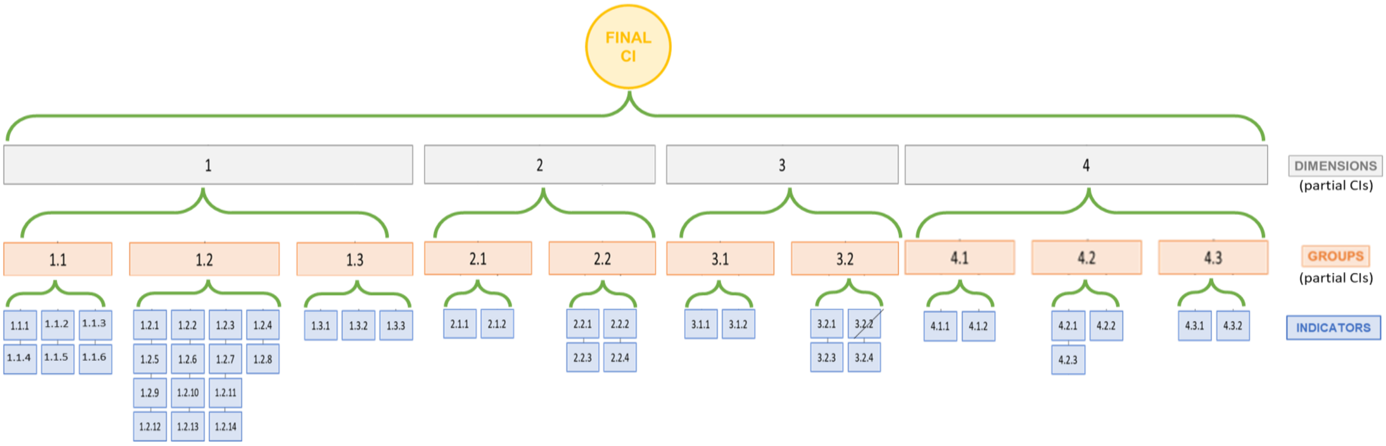

Figure 3 - Diagram of the building of the Final CI. (NOTE: each green arrow represents one execution of the BoD) (Source: The author)

Having in mind Figure 3, it is also important to highlight that all 15 times that BoD is applied (represented by the 15 green arrows) to obtain all CIs, it refers only to one month of the analysis. It is also useful to not only have the performances aggregated by the several categories (final CIs) but also have the several CIs aggregated by the several months to have a perception of the DMUs performances over time. Despotis (2002) proposes obtaining an equal number of distinct composite scores for each DMU and then to take the average value as the unique global score.

To sum up, it is intended to clarify that in this study dimensional and group composite indicators are, in fact, partial composite indicators since they are used to construct the final composite indicator; and that global scores accounts for the composite indicators averaged for the whole months in analysis (March

[30] Find in cloud the excel files with the CIs for each country per month: RESULTS

[31] Find in cloud the files (.R / .txt) with the code used to perform the weight constrained BoD: 4) BoD

2020 – December 2021). Both values (CIs scores and global scores) range between [0,1] as mentioned before, and values closer to 1 means better performances. In the results discussion that follows, sometimes it is also referred to ranks that means that CIs scores are converted into natural numbers [1;n], n represents the number of countries in the respective cluster, to rank countries' performances.

It is possible to find in cloud[32] all results, i.e., all CIs scores and weights and respective graphs and tables in excel files.

6.2. Countries from cluster 1

6.2.1. CI for COVID-19 dimension

The maximum, minimum and mean values obtained for the CI representing COVID-19 dimension during the whole period of analysis can be seen in Figure 4. At least one country was found fully efficient at some month, but some countries had very poor performance in this dimension since at least one of them had only 0,359 score units at some point of time. On the other hand, the average says that, in general, countries handled COVID-19 in a relatively good way since the mean of scores obtained was 0,866. In Figure a8 is represented the scores obtained for each country in each month during the whole period.

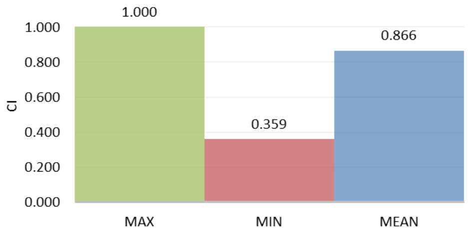

Figure 4 – Maximum, minimum and mean values obtained for COVID-19 dimension considering all values obtained in each month, cluster 1 (Source: The author)

In Figure 5 is represented the number of benchmark countries in each month. The values are not very stable and could be a representation of the difficulty of fighting the pandemic and the constant changes in the pandemic state. It is known that countries in some periods could feel more safe (lower transmissibility rate) and in the next month the positive cases could be much higher again (higher transmissibility rate). In fact, for instance, the lower values are seen for April – May 2021 and for August – September 2021 which correspond to the third and fourth wave.

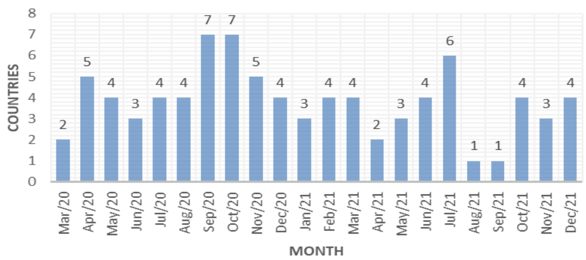

Figure 5 - Number of benchmarking countries for each month in CI 1, cluster 1 (Source: The author)

As explained before, the global scores are an attempt to have a global perception of the country's efficiency for the whole period of analysis, that consists simply in the averaged values of the scores obtained in each month. The maximum, minimum and mean values obtained for the global scores for

[32] Find in cloud (excel files) the results obtained with tables and graphs for each level of CI and clusters: RESULTS

COVID-19 dimension can be seen in Figure 6. It is possible to understand that any country was fully efficient (or benchmark country) in all months since the maximum is not 1. However, Qatar, Seychelles and Malaysia are the three countries showing better efficiencies in this dimension. The mean value could be seen as a target for countries that have a global score closer to the minimum value, and therefore, the DMUs that still need to improve more to achieve a decent efficiency in the fight of pandemic. This is the case of Sudan, Mexico and Egypt that are the three countries with lower global scores. The best country (Qatar) has the possibility to improve 1,6% and the worst country (Sudan) 32,3%, in average. Regarding the whole sample, countries could improve in average 13,4%, which is a considerable margin for improvement. In Figure 7 is demonstrated the global scores for COVID-19 dimension by range of values to have a better understanding of DMU's distribution throughout efficiency ranges. 81% of the countries are considered efficient having just 5 countries showing the worst results.

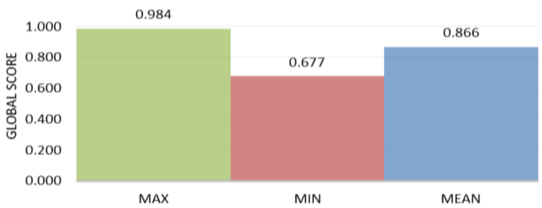

Figure 6 – Global scores maximum, minimum and mean values obtained for COVID-19 dimension, cluster 1 (Source: The author)

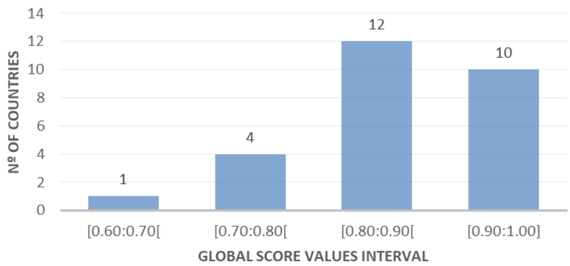

Figure 7 - Global scores distribution for COVID-19 dimension by range of values, cluster 1 (Source: The author)

6.2.2. CI for Access and Quality of Health dimension

The maximum, minimum and mean values obtained for the CI representing the access and quality of health dimension during the whole period of analysis can be seen in Figure 8. It is important to remember that the variables used to compute this CI do not vary over the period of analysis (cross-sectional data), and therefore, the values are always the same in all months. That being said, it is clear that the notion of global scores is not useful here. Considering Figure 8 and 9, two countries are fully effective, thus, benchmarking countries (Saudi Arabia and Brunei), and that at least one country had very poor performance in this dimension. Papua New Guinea is the country revealing the worst performance (score=0,215 units). In contrast to the previous CI, the mean says that, in general, countries from cluster 1 have low access and quality to social sanitation and hygiene, and healthcare since the efficiency values' mean are below 80%. Considering the efficiency score's mean, countries showing weaker performances, has a margin to improve their performance in about 28%, in average. This can be sustained with the fact that cluster 1 is composed mainly with countries from Caribbean, Middle East and North Africa, South Asia, East Asia and Pacific regions that are also considered, in a general way, to have a middle income (see Figures a5, a6 and a7). Health levels depends on several factors, but income is certainly correlated with health since health is affected by money and resources (*Relationship between Income and Health*, 2021).

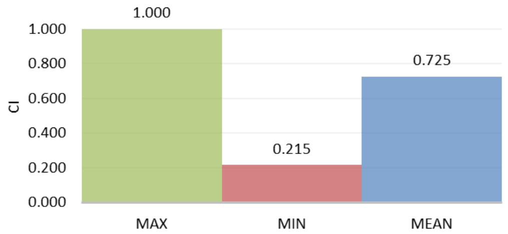

Figure 8 - Maximum, minimum and mean values obtained for Access and Quality of health dimension, cluster 1 (Source: The author)

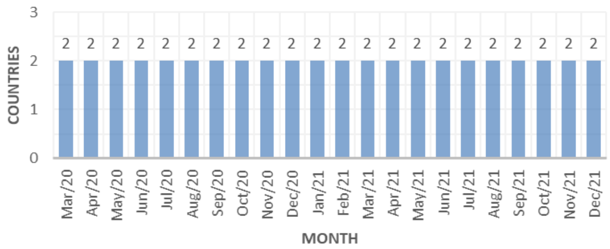

Figure 9 - Number of benchmarking countries for each month in CI 2, cluster 1 (Source: The author)

In Figure a9 is represented the CI efficiencies obtained for each country, and in Figure 10 is presented the number of countries with these efficiencies by range of values to have a better understanding of DMU's efficiency's distribution. It is possible to understand that the values have more dispersion when compared to the previous CI: 7 countries have bad performance (score<0,40), 7 countries have a fair performance (0,50<score<0,80) and 13 countries have very good performance (score>0,80). Around 52% of the countries should change their performance to the standards observed in the efficient entities. Therefore, the DMUs demonstrate a weaker relative performance and some interventions should be carried out to bring them closer to the desired performance levels of access and quality of health.

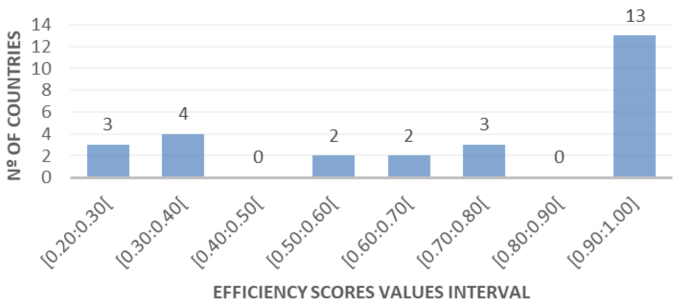

Figure 10 - Efficiency scores distribution for Access and Quality of Health dimension by range of values, cluster 1 (Source: The author)

6.2.3. CI for Security and Compliance in Governance dimension

As verified for CI 2, the simple indicators used to compute CI 3 are also formed of cross-sectional data, and for that reason, the values do not change between months. In Figure 11 is represented the maximum, minimum and mean values obtained for the security and compliance in governance dimension during the whole period of analysis. In this case, the efficiency's mean is better and since it is higher than 80%, it is considered that countries, in average, are relative efficient. However, there are still a quite high margin for countries to improve since they are (in average) close to the lower limit to be considered efficient. In average, countries could improve their performance in around 15% to achieve a better and less corrupt governance. At least one country (Seychelles) has a very poor performance in this dimension reaching the minimum efficiency score (score=0,345). On the other hand, considering Figure 11 and Figure 12, 3 countries reach the maximum relative efficiency achieving the recognition of benchmark countries. Consequently, it seems that Bahrain, Bangladesh and India have a transparent and trustfully government.

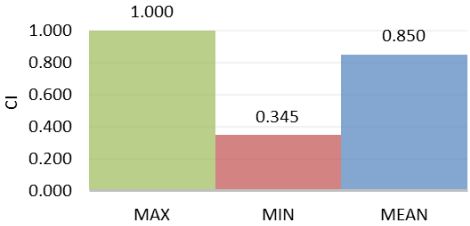

Figure 11 - Maximum, minimum and mean values obtained for Security and Compliance in Governance dimension, cluster 1 (Source: The author)

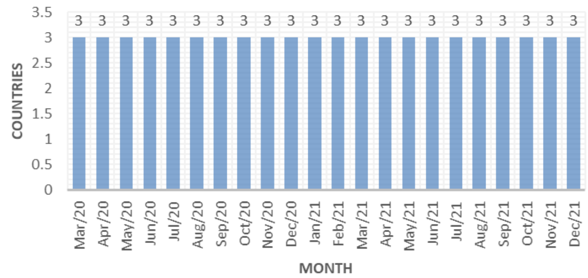

Figure 12 - Number of benchmarking countries for each month in CI 3, cluster 1 (Source: The author)

In Figure 13, it is represented the efficiency scores distribution for security and compliance in governance dimension by range of values and is easy to see that only two countries have a terrible performance in this dimension. They are Seychelles and Fiji. 6 countries have a decent efficiency but most of them (around 70%) are considered efficient. In Figure a10 is possible to see each efficiency score obtained for CI 3 per country during the whole period of analysis. This graph is great to understand how each country performed relatively to each other.

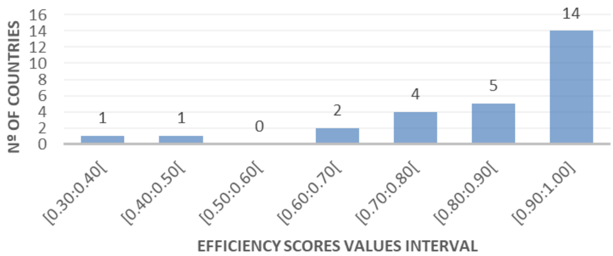

Figure 13 - Efficiency scores distribution for Security and Compliance in Governance dimension by range of values, cluster 1 (Source: The author)

6.2.4. CI for Fragility in Economy and Finance dimension

For fragility in economy and finance CI, the simple indicators used to compute it are now formed of time-series data, and for that reason, the relative efficiencies obtained for each DMU is different from month to month. This is the same case seen for the first CI (COVID-19 dimension), and therefore, the explained notion of global score makes sense to use again. Figure 14 shows the maximum, minimum and mean obtained when it is considered all values obtained in each month. It permits to infer that at least at some month at least one country was considered benchmarking (score=1), and that at some point of time at least one country had a very poor performance in this dimension (score=0,371), showing fragility in their economy. It Is possible to track the relative efficiencies for each country in each month in Figure a11.

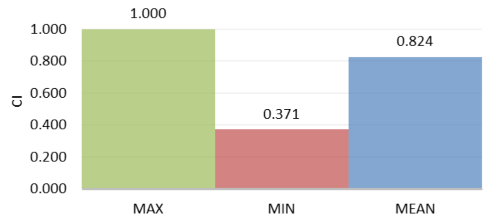

Figure 14 - Maximum, minimum and mean values obtained for Fragility in Economy and Finance dimension considering all values obtained in each month, cluster 1 (Source: The author)

With Figure 15 it is possible to gain the knowledge that in every month existed always benchmarking countries and how many. It is known that for this dimension only 4.3.1 (Income support) and 4.3.2 (Debt/contract relief for households) simple indicators were time series, thus, the variables responsible for the efficiencies scores variation throughout the months. Having this said, Figure 15 permits to presume that from June 2020 till June 2021 it is the period with more countries achieving the "perfect" efficiency due to this two "policies" to support families and companies. These countries show an excellent concern and availability of economic resources to alleviate their people and companies.

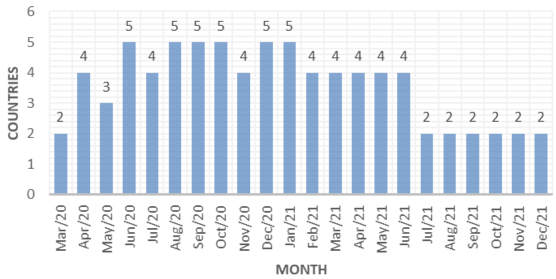

Figure 15 - Number of benchmarking countries for each month in CI 4, cluster 1 (Source: The author)

When the efficiency scores obtained in each month are averaged the global scores are obtained to have a global perception for the whole period of time, as explained before. Considering Figure 16, at least one country (Mauritius) was fully efficient in all months since the maximum global score is equal to 1. Regarding the minimum global score, it permits to see that some country (Sudan) was not efficient as it should be since it had around 46% of inefficiency, considering the whole period. However, the global scores' mean shows that countries were, in average, efficient but it could be better since exists still a margin to improve of about 18%. With Figure 17 it is possible perceive how efficiency scores are distributed. Around 63% of the countries were efficient and the other 10 countries were below what was wished, despite in this CI the relative efficiencies are not that low when compared to CI 2 and CI 3.

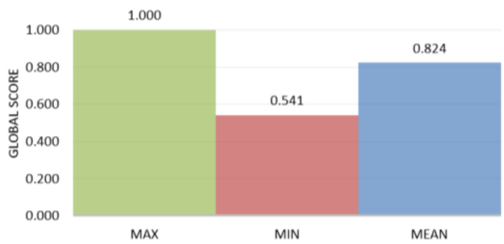

Figure 16 - Global scores maximum, minimum and mean values obtained for Fragility in Economy and Finance dimension, cluster 1 (Source: The author)

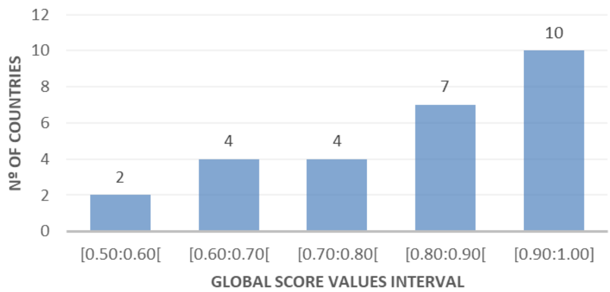

Figure 17 - Global scores distribution for Fragility in Economy and Finance dimension by range of values, cluster 1 (Source: The author)

6.2.5. Comparison between dimensions

It is useful to understand the distance between the maximum and the minimum efficiency found intra-dimension to have a better perception of the differences and discrepancies magnitude found (Calabria et al., 2016). Understanding these magnitudes helps to infer in which dimension country performances went better and worst since lower magnitudes means that range of efficiency values are lower and closer to the maximum. Then, the distance between maximum and minimum global scores for each dimension was computed and the results are in Figure 18 (blue line). Also in this figure, is represented the mean of the global scores obtained in each dimension (red line). It permits to conclude that if in one hand COVID-19, and fragility in economy and finance dimensions are the ones that countries achieved better performances (and thus need less improvements), on the other hand access and quality of health and security and compliance in governance dimensions are the ones that show more discrepancies in the relative efficiencies' values. In contrast, the mean shows that countries' performances were similar in average and all of them quite efficient. Except for access and quality of health dimension that has a mean below efficiency standards (below 80%). This means that the worst results are achieved for this dimension. In general, seems that countries are offering a poor social sanitation and system and lacks healthcare resources (e.g., few doctors, nurses, beds). It is in this sense that improvements must be made with more urgency. The dimension that achieved better results is the COVID-19 dimension that permits to assume that in general the policies taken, and testing and vaccination processes went well.

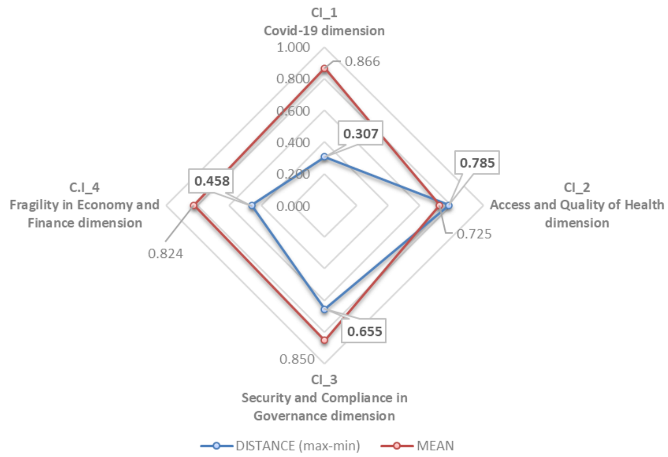

Figure 18 - Radar chart with distance between maximum and minimum global scores values (blue line), and mean global scores (red line) in each CI/dimension, cluster 1 (Source: The author)

To have a more clear, fast and easy understanding about which dimension each country performed better and worst, see Figure a12. For each country it is represented the efficiency scores obtained in each dimension (with different colors) using the global scores, i.e., the average of the efficiencies obtained in each of the 22 months in analysis. It is easy to perceive that ideally countries would have efficiency scores equal to 4, which would be the maximum score possible (1 unit for each dimension). Therefore, with this representation it is easy and fast to see that Qatar, Bahrain and Mauritius are the top three countries and that relative efficiencies were always more than 90%, which permits to say that they were very efficient since they present excellent results in all dimensions. On the other hand, Sudan, Nepal and Papua New Guinea are the three countries "at the end of the table". It is possible to check that these countries had very poor performances in several dimensions. It is also interesting to note that the minimum efficiency scores presented previously in Figures 6, 8 and 16 are from Sudan. For this reason, this is the country presenting the worst results. Also in Figure a12, it is possible to note which dimensions went better and worst. The red bars that represent dimension 2 (access and quality of health), are the smaller ones in general which permits to conclude that this dimension shows the worst results. This is in line with the conclusions drawn earlier with Figure 18. Then, analyzing just the size of the bars, seems that, in general, despite the lack of a good social sanitation and providing good healthcare resources to the population and the fragile economies, these countries have a good trust in their politicians (in this case, due to the countries in hands it can also be associated to some lack of awareness and instruction) and had a good response to the fight of COVID-19.

In Table b11, it is represented countries ranks listed from best to worst performance in average showing the rankings obtained in each dimension and in each time-period to track the evolution over time. To avoid a very dense table with 22 columns (one for each month) that would bring too much "noise", the relative efficiencies were averaged according 4 time-periods. The first three time-periods correspond to semesters, and the last one to a quadrimester. With the averaged efficiencies obtained in each time-period, it was computed the rankings. Not surprisingly, countries with higher efficiencies are ranked first. Better rankings have greenish colors, medium rankings have yellowish colors and worst rankings have reddish colors. With this table, it is clear that Qatar, Bahrain and Mauritius are the ones showing the more stable results in a good way; and Pakistan, Laos, Nepal and Sudan in a bad way.

6.2.6. Final composite indicator

Even though mentioned before, it is important to highlight again for the fact that to compute the final CIs it was used weights constrains to account for all dimensions. Since countries' performances is not due only to one dimension, this way it is possible to get closer to the reality having each dimension (or partial composite indicator) interacting between each other to evaluate their performance as a whole (see Figure 3). In contrast to dimensional CIs, each country has one and only one efficiency score per month using the final CIs.

In Figure 19, it is represented the maximum, minimum and mean values obtained for the final CI representing the countries performances in a global perspective (i.e., considering all dimensions) and contemplating the values obtained in all months. The values obtained are in general higher to the ones obtained with the dimensional partial CIs, which makes sense since CIs are values generated to always give the best performance possible for each DMU, as explained in section 5.5. However, the notion of relative efficiency is always kept which makes possible to infer countries performing better and worst. In general, countries show to be efficient but exists still a margin to improve of 7,6%.

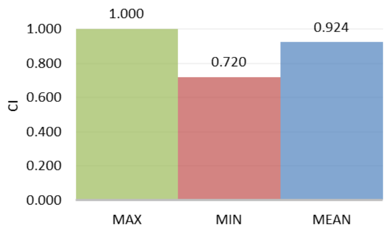

Figure 19 - Maximum, minimum and mean values obtained for Final CI considering all values obtained in each month, cluster 1 (Source: The author)

Regarding the number of benchmarking countries over months, it is possible to note some dispersion of the values but some consistency in consecutive months (see Figure 20). For the final CI the several dimensions are contributing for these results, but this dispersion is mainly caused because of dimension 1 and 4 that accounts for time-series data. The fight of the pandemic had very “ups and downs” that could make some countries being efficient in one month and not efficient in the following month. However, this is not the case for some countries that shown to be efficient in all months (see Figure 21). They were Bahrain and Qatar. This is not surprising since analyzing the dimensions in the previous sections this two countries were the ones providing always high efficiencies in all dimensions and the ones showing more consistency of their good performance over the whole period. On the other hand, Figure 21 permits also to note that some countries are showing lack of efficiency (minimum global score = 0,743). They were Nepal, Papua New Guinea, Sudan. These results are also not surprising since they are in accordance with the analysis done previously but confirms that these three countries are the ones showing the worst overall efficiency performances having account all dimensions and months in analysis.

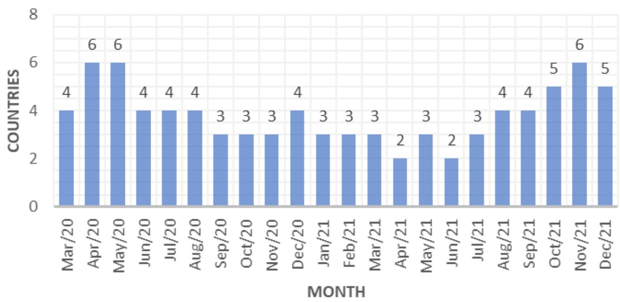

Figure 20 - Number of benchmarking countries for each month in Final CI, cluster 1 (Source: The author)

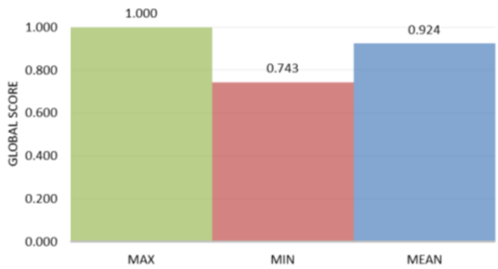

Figure 21 - Global scores maximum, minimum and mean values obtained for Final CI, cluster 1 (Source: The author)

Figure 22 shows the number of countries with the respective global efficiency score range to have a better perception of the countries efficiency’s distribution. The dispersion in not very high and emphasizes the fact that around 89% of the countries are efficient and that only three countries are bellow efficiency. Some interventions should be made with more urgency for these three countries to have no less than the efficiency score of 80% and the countries showing relative efficiencies below the mean value (0,924) should also make efforts to improve their efficiency to at least this value. In Figure a13 is shown the final CI efficiency values obtained for each country.

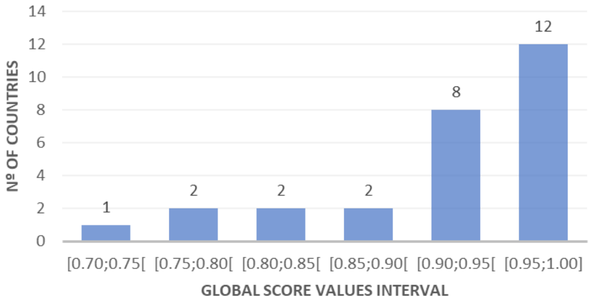

Figure 22 - Global scores distribution for final CI by range of values, cluster 1 (Source: The author)

Table 7 was created with the aim to have the rankings of countries and aggregate several results from the dimensional CIs analysed in sections 6.2.1 – 6.2.5 and the results from the final CI in a single table. Therefore, in columns FC, CI_1, CI_2, CI_3 and CI_4 is identified the countries' rankings obtained in each CI. This table has the countries listed according with the ranking obtained in the final CI since it has the overall measurement of performances obtained in all dimensions.

Table 7 – Countries' rankings in the several CIs and respective comparisons between final CI (FC) and dimensional partial CIs (COVID-19 dimension (CI_1), access and quality of health dimension (CI_2), security and compliance in governance (CI_3) and fragility in economy and finance (CI_4)), cluster 1 (NOTE: rankings obtained using global scores) (Source: The author)

	countries	FC	CI_1	DIF(FC-CI_1)	CI_2	DIF(FC-CI_2)	CI_3	DIF(FC-CI_2)	CI_4	DIF(FC-CI_4)
	Bahrain	1	4	-3	11	-10	1	0	5	-4
	Qatar	1	1	0	5	-4	11	-10	2	-1
TOP 5	Mauritius	3	5	-2	10	-7	6	-3	1	2
	Brunei	4	6	-2	1	3	16	-12	11	-7
	China	4	11	-7	6	-2	5	-1	17	-13
	Malaysia	6	3	3	7	-1	20	-14	4	2
	Saudi Arabia	7	24	-17	1	6	13	-6	10	-3
	United Arab Emirates	8	10	-2	3	5	24	-16	3	5
	Mexico	9	26	-17	4	5	8	1	16	-7
	Jamaica	10	14	-4	20	-10	4	6	18	-8
	Belize	11	19	-8	8	3	22	-11	12	-1
	Egypt	12	25	-13	12	0	10	2	6	6
	Sri Lanka	13	13	0	13	0	23	-10	7	6
	Philippines	14	7	7	15	-1	9	5	25	-11
	Indonesia	15	15	0	19	-4	7	8	21	-6
	Bhutan	16	8	8	14	2	25	-9	9	7
	Guyana	17	17	0	18	-1	12	5	23	-6
	India	17	9	8	22	-5	1	16	20	-3
	Myanmar	19	18	1	17	2	14	5	15	4
	Seychelles	20	2	18	9	11	27	-7	14	6
	Bangladesh	21	22	-1	24	-3	1	20	26	-5
	Fiji	22	21	1	16	6	26	-4	8	14
	Laos	23	12	11	21	2	21	2	22	1
	Pakistan	24	23	1	23	1	17	7	13	11
LAST 5	Nepal	25	16	9	25	0	19	6	24	1
	Papua New Guinea	26	20	6	27	-1	15	11	19	7
	Sudan	27	27	0	26	1	18	9	27	0

It also shows the difference between the rank obtained in the final CI and partial CIs. This is useful to have a better notion of the change in countries rank positions for the different dimensions when compared with the final rank. What is more evident is that countries from the top half of the table showed a better ranking in the final CI and the countries in the bottom half showed better rankings when analysing the dimensions individually[33]. This can be justified with the presence of more negative values than positives in the difference's columns in the top half of the table. However, what seems to happen is that countries that have better positions in (almost) all dimensions have a better ranking in the final CI and countries that

[33] Find in cloud the excel file that validates this statement: FINAL_cluster1_bod_scores_normalization-method-3.xlsx (sheet: GRAPHS)

shows worst performances in (almost) all dimensions have a worst ranking in the final CI, which makes sense.

The rankings should also be seen as a motivational factor as far as the countries in the bottom of the table must change their behavior and make some adjustments to achieve better positions and get closer to the efficient ones. One great advantage of Table 7, is that those countries even know in which dimensions they have more urgency for improvements and make bigger changes. For example, Philippines has a relatively good position in dimensions that regards for covid-19 policies and governance but must improve with more urgency and in a bigger scale their healthcare system, deliver better sanitation for all families, and have a more stable economy. The countries showing worst results are Sudan, Papua New Guinea, Nepal, Pakistan and Laos. These countries should make changes in all dimensions to achieve the positive results of Bahrain, Qatar, Mauritius, Brunei and China, that are the top five countries. These results can also be verified in Table b12, where countries ranks obtained with the final CI in each time-period are shown to track the evolution over time. This table is great to show the performance pattern and it is possible to note that countries show a relatively constant performance over time.

6.3. Countries from cluster 2

The results' discussion for cluster 2 is analogous to the one done in section 6.2 for cluster 1. Therefore, for simplicity's sake, the discussion will be now more synthetic and expositive.

6.3.1. CI for COVID-19 dimension

Considering the mean value of the relative efficiencies obtained in this CI means that countries, in general, handled COVID-19 pandemic in an efficient way since the mean is higher than 0,80, in Figure 23. The maximum tells that at some point of time at least one country was found fully efficient (efficiency=1), and the minimum reveals that a country at some month had a terrible performance in this dimension. This value was obtained for Brazil in April 2020, the first moment that COVID-19 attacked with strength. In turn, Figure 24 shows that existed in every month at least two fully efficient countries. The quite high dispersion of the values can be associated to the volatility of the changes in countries state against COVID-19 due to different waves. During the pandemic were always countries going through a relatively good phase, maybe close to an end, and other countries battling at maximum to resist the virus. Few months later countries could be facing the reverse. For this reason, it is normal that in some months could exist more countries being fully efficient than in other months. In fact, it is comprehensible that few countries could be always fully efficient in all months.

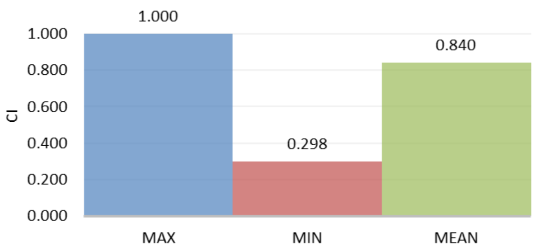

Figure 23 - Maximum, minimum and mean values obtained for COVID-19 dimension considering all values obtained in each month, cluster 2 (Source: The author)

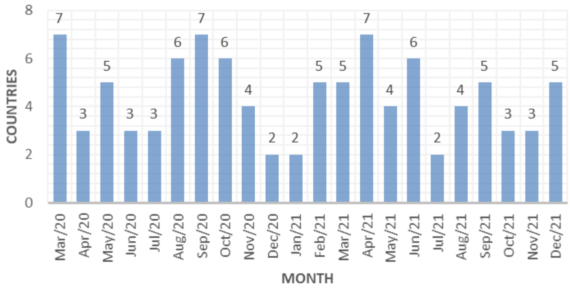

Figure 24 - Number of benchmarking countries for each month in CI 1, cluster 2 (Source: The author)

Figure 25 shows that any country was fully efficient, therefore benchmark, in all months since the maximum value is not 1. The maximum also suggests that even the country that achieved the best performance has still 4,8% of inefficiency, in average. This good result belongs to Singapore. Israel, Chile and Malta achieved similar relative efficiencies, showing also a very good performance. On the other hand, the country that needs to improve more to be considered fully efficient is Ecuador since it is the country that achieved the worst averaged performance. Therefore, Ecuador is the country showing more difficulty to fight the pandemic through tests, vaccination and other policies since had around 38% of inefficiency and should have the primary goal to achieve at least the mean efficiency, i.e., 84% of efficiency. Other countries showing the worst results are Trinidad and Tobago, Sweden and Suriname. Sweden is the country that stands out from the not efficient ones since its several qualities as European country with high income. This reflects the controversial decisions that Sweden took to fight the pandemic that everyone heard about in the news. They only impose very light measures to leave the virus spread among the population to achieve faster herd immunity. However, the price to put behind the pandemic faster was too high with positive cases surging in a very fast and high rate and with the cumulative death rate going up in a short term.[34] Regarding the whole sample, countries could improve in average 16%, which is a considerable margin for improvement. With Figure 26 it is possible to perceive the DMU's distribution throughout efficiency ranges and understand that 73% of the countries are considered efficient (global score>0,80). The thirteen countries below efficiency level should identify good practices from the other ones and direct their behavior accordingly. To account for the scores obtained for each country in each month during the whole period, it is possible to find online a graph similar to Figure a8 for cluster 2.[35] It is not shown here due to its dimension and complexity.

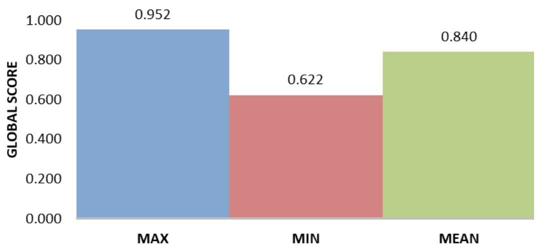

Figure 25 - Global scores maximum, minimum and mean values obtained for COVID-19 dimension, cluster 2 (Source: The author)

[34] Read more about Sweden's decisions to fight COVID-19 and consequences in: https://www.science.org/content/article/it-s-been-so-so-surreal-critics-sweden-s-lax-pandemic-policies-face-fierce-backlash

[35] Excel file for the graph: DIMENSION_cluster2_bod_scores_normalization-method-3.xlsx (sheet: GRAPHS)

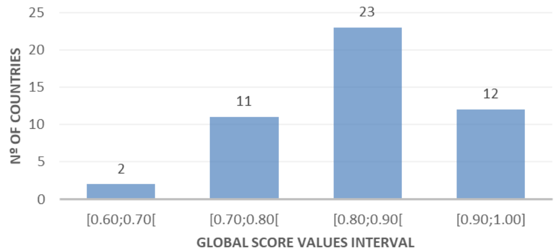

Figure 26 - Global scores distribution for COVID-19 dimension by range of values, cluster 2 (Source: The author)

6.3.2. CI for Access and Quality of Health dimension

The countries seem to show worse results in access and quality of health when compared to the previous dimension. Based on Figure 27, despite at least one country was fully efficient, one country showed a very poor relative efficiency. The country being fully efficient was Norway and considering Figure 28, it is possible to realize that it was the only one country achieving such "perfect" performance.

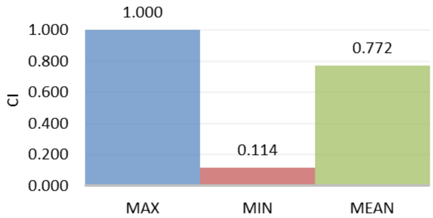

Figure 27 - Maximum, minimum and mean values obtained for Access and Quality of health dimension, cluster 2 (Source: The author)

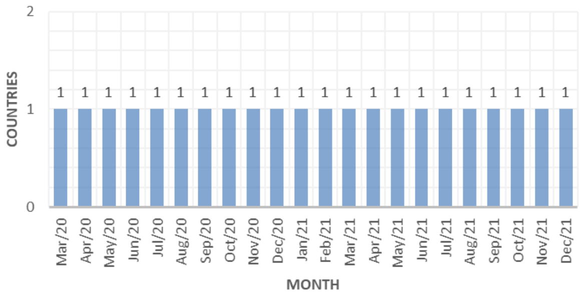

Figure 28 - Number of benchmarking countries for each month in CI 2, cluster 2 (Source: The author)

Despite the BoD didn't attribute a relative efficiency of 100% to any other countries, Switzerland, Germany, Finland, Belgium, Austria, Iceland, Ireland and Sweden achieved also great relative efficiencies, more than 99,0%. The country showing the worst performance was Colombia with a relative efficiency of 11,4%. This means that this country is showing 88,6% of inefficiency. Of course this value is so reduced because BoD measures relative efficiencies, and when compared to European high-income countries such as Norway, Colombia and other states from poorer and less developed countries will have a much more reduced efficiency. This statement is easily validated with Figure 29 since it is mainly Latin American countries that shows relative efficiencies below 50% (Colombia, Suriname, Ecuador, Costa Rica, Kuwait, Brazil, Peru, Panama, Chile and Argentina). Other countries that are still below efficiency but achieved more than 50% are for example, Israel, New Zealand and Cyprus. Finally, countries from Europe and North America, and Australia, Japan and South Korea are considered to be efficient in terms of providing a quality healthcare with a good number of resources (beds, medical personnel) and capable social sanitation and hygiene for their population. It Is possible to see the relative efficiencies for each country during the whole period of analysis in Figure a27.

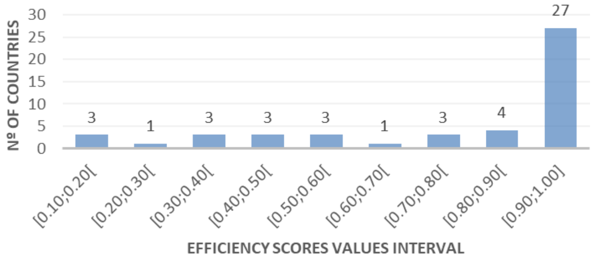

Figure 29 - Efficiency scores distribution for Access and Quality of Health dimension by range of values, cluster 2 (Source: The author)

6.3.3. CI for Security and Compliance in Governance dimension

In contrast to the previous CI, the mean of the relative efficiencies obtained for security and compliance in governance is above efficiency, according with Figure 30. However, countries have still a margin of improvement of 19,6%, in average. According with Figure 30 and 31, four countries were fully efficient in this dimension: Estonia, Finland, New Zealand and United Kingdom seem to trust their governments. On the other hand, Brazil is the country showing more inefficiency (70,7%) which reveals less political trust and transparency from their politicians, and so, a more reluctant population to comply with their decisions and measures. Brazil and countries bellow efficiency should look for good practices verified in efficient countries and implement some interventions to raise their performance in this CI.

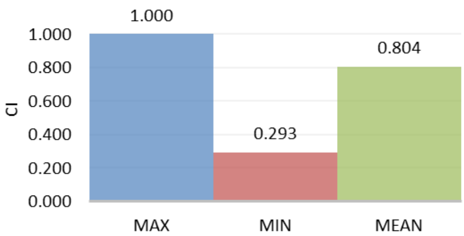

Figure 30 - Maximum, minimum and mean values obtained for Security and Compliance in Governance dimension, cluster 2 (Source: The author)

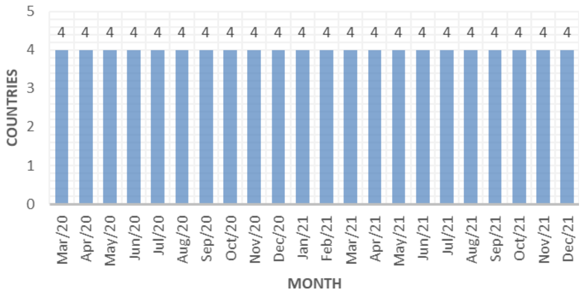

Figure 31 - Number of benchmarking countries for each month in CI 3, cluster 2 (Source: The author)

In Figure 32, the efficiency scores distribution for security and compliance in governance dimension by range of values are presented. Around 60% of countries are efficient and Brazil, Ecuador, Cuba, Israel and Italy are the five countries with worst performances in dimension. In Figure a28 is possible to see each efficiency score obtained for CI 3 per country during the whole period of analysis.

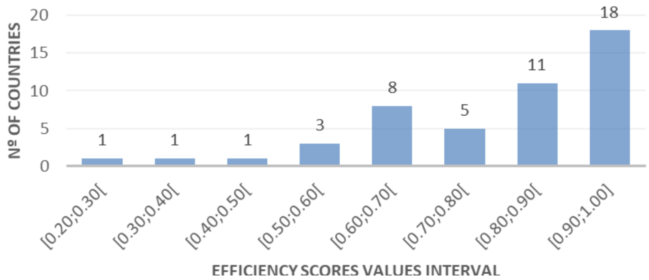

Figure 32 - Efficiency scores distribution for Security and Compliance in Governance dimension by range of values, cluster 2 (Source: The author)

6.3.4. CI for Fragility in Economy and Finance dimension

According with the mean presented in Figure 33, it seems that countries achieved a good level of efficiency in fragility in economy and finance CI, the best one when compared to the other CIs. However, one country (Suriname) had a very low performance at some point of time (relative efficiency=0,346) showing 65,4% of relative inefficiency. Based on Figure 33 and 34, it is possible to understand that were always at least four countries being fully efficient in each month during the pandemic and the results seem relatively stable. The countries considered benchmarks in many months are always countries recognized to have a good economic structure, such as, Austria, Germany, Iceland, Netherlands, Australia and Japan.

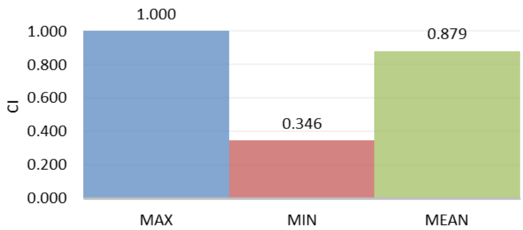

Figure 33 - Maximum, minimum and mean values obtained for Fragility in Economy and Finance dimension considering all values obtained in each month, cluster 2 (Source: The author)

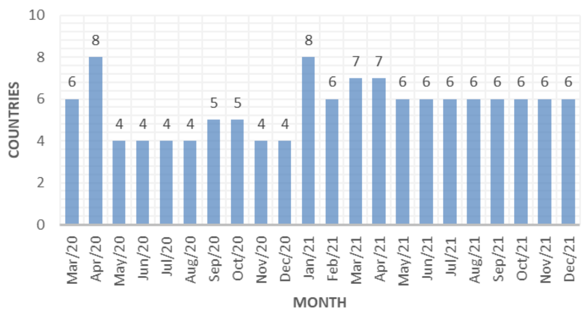

Figure 34 - Number of benchmarking countries for each month in CI 4, cluster 2 (Source: The author)

This contrasts, and this is right and proper, with the fact of Latin American countries achieving the worst performances, which is the case of Suriname, as stated before. Considering the global scores maximum and minimum shown in Figure 35, one country was shown fully efficient in all months and other country achieved an averaged efficiency score of 0,509. The great achievement goes for Austria and the bad one goes for Suriname that had 49,1% of inefficiency, in average. This means that Suriname (and the other countries below efficiency) should try to replicate Austria's actions and measures to have a more stable and supportive economy for their people. In average, countries have still a margin of 12,1% to improve their relative performance in this dimension and should follow the same suggestion. Figure 36 helps to understand that 77% of countries are efficient in what regards to their stability in economy and support for their households during COVID-19. To account for the scores obtained for each country in each month during the whole period, it is possible to find online a graph similar to Figure a11 for cluster 2.[36] It is not shown here due to its dimension and complexity.

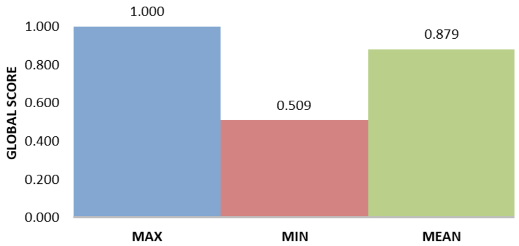

Figure 35 - Global scores maximum, minimum and mean values obtained for Fragility in Economy and Finance dimension, cluster 2 (Source: The author)

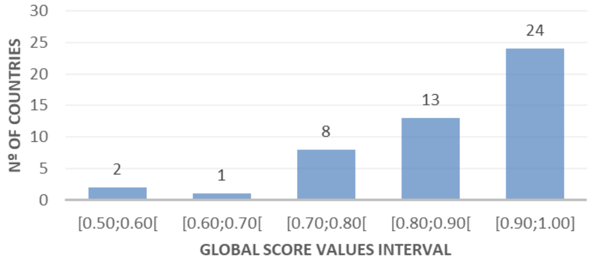

Figure 36 - Global scores distribution for Fragility in Economy and Finance dimension by range of values, cluster 2 (Source: The author)

6.3.5. Comparison between dimensions

In a radar chart (Figure 37) is shown the mean and distance between maximum and minimum global scores to reflect the magnitude of the efficiency ranges. From this chart, stands out immediately that dimension 2 is where countries are showing a poorer performance, in general. Considering the mean (red line), only access and quality of health dimension measured by CI 2 is bellow efficiency. In general, countries are showing less efficiency in terms of managing healthcare resources (beds, medical doctors, nurses) which reflects in the healthcare provided to their population and/or lack of basic social sanitation and hygiene, depending on the country. It is in this way that countries should focus to make improvements with more urgency. It is also for this dimension that the discrepancies in the relative efficiencies are bigger. This is a bad factor but easy to justify in this case when very "strong" countries like European countries, such as Austria or Germany, North American countries (USA and Canada), and East Asia and Pacific countries (Japan, South Korea, Australia) are "competing" with some not that evolved countries like Latin American countries (Colombia, Suriname, Ecuador, etc.). It is obvious that when BoD measures the relative efficiencies with these conditions, the discrepancies will be higher, even though all countries from this cluster are upper middle- and high-income countries. In the other three dimensions, the performances seem to be very close with an averaged efficiency of around 84%. Considering these three dimensions and analysing the blue line seems that some countries need to pay more attention to their stability in economy and support for their households and in creating a more trustfully government to engage people to follow the measures taken, than in the policies taken to fight the pandemic since the distance between maximum and minimum for dimension 1 is lower, and therefore, closer to the maximum efficiency values found.

[36] Excel file for the graph: DIMENSION_cluster2_bod_scores_normalization-method-3.xlsx (sheet: GRAPHS)

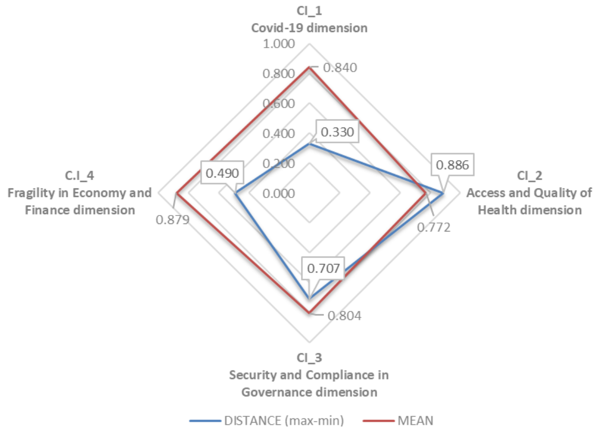

Figure 37 - Radar chart with distance between maximum and minimum global scores values (blue line), and mean global scores (red line) in each CI/dimension, cluster 2 (Source: The author)

In Figure a14, it is represented for each country the efficiency global scores obtained in each dimension in a stacked bar chart that is great to compare efficiencies between countries and between dimensions. Having account the extension of the bars, it is easy to understand which countries performed better and worse in general. Countries performing better are United Kingdom, Norway, Finland, Denmark, and Austria and worse are Ecuador, Suriname, Brazil, Peru and Colombia. This chart is also great to perceive in which dimensions countries are performing better and worse in order to prioritize changes in dimensions with more need of improvement. For example, performance in access and quality of health is much poorer when compared to the performance in the other dimensions for Colombia, Kuwait, and Suriname. It should be in increasing their resources in medical facilities and improve their healthcare and access for basic sanitation that these countries should focus to improve in first place. This does not mean that the other dimensions should be forgotten, it is just a matter of prioritizing what is most urgent to be done. In fact, in many cases they also need to be improved due to their low efficiency. Alternatively, Portugal has very good performance in dimensions 1, 2 and 4 (efficiency superior to 90%) but bellow efficiency, i.e., bellow 80%, for dimension 3. This means that policies to fight the pandemic, testing and vaccination had good results in terms of deaths and containment of the disease, shown an efficient usage of medical resources to provide an efficient healthcare to population, and country's economy shown stable and strong enough to resist the pandemic and supportive to their households under this adverse conditions, but shows lack of trust in their politicians and governance due to the lack of transparency and people's perception for corruption. Thus, Portugal should focus on this dimension to improve with more urgency and look for countries like United Kingdom that had very good results in this dimension.

In Table b13, it is represented countries ranks listed from best to worst performance in average showing the rankings obtained in each dimension and in each time-period to track the evolution over time. It is possible to understand that Austria, Denmark, Germany and Ireland have shown a relatively stable and good performance and that Ecuador, Suriname, Peru and Trinidad and Tobago had always a very poor performance during all period in all dimensions.

6.3.6. Final composite indicator

Final CI is computed to have the dimensional partial CIs interacting between each other to measure the relative efficiencies as a whole, as explained before. With Figure 38, seems that results are better now when compared to the results obtained in the previous section. This makes sense since BoD maximizes the performance for each DMU using the results obtained in the dimensional level to compute the final CI, as explained before. Considering the mean, countries performed very good in general but still exists a margin of improvement of 8,5%. The global score maximum of 1 represents that at least one country was considered fully efficient (100%) in all months. That great achievement was from Finland.

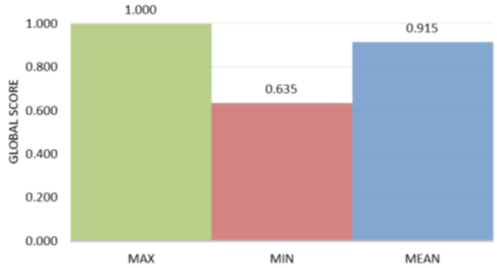

Figure 38 - Global scores maximum, minimum and mean values obtained for Final CI, cluster 2 (Source: The author)

Figure 39 shows that existed always at least three countries being fully efficient (benchmarks) in each month. Due to COVID-19 being an adverse event that brought very instability to countries since in some months things went in a good way and in another one could go terrible, it is reflected in the some dispersion of the values that Figure 39 shows. Besides Finland, other countries that were considered benchmarks in almost all months were United Kingdom, Denmark, Austria and Norway. This is in accordance with analysis done in sections 6.3.1 – 6.3.5.

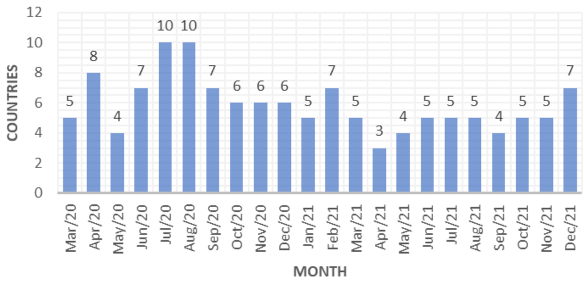

Figure 39 - Number of benchmarking countries for each month in Final CI, cluster 2 (Source: The author)

Regarding the minimum in Figure 38, means that some countries performed bellow efficiency: Suriname, Colombia, Ecuador, Peru, Trinidad and Tobago, Brazil and Argentina are the only countries that had less than 80% of relative efficiency using the final CI, considering the average of all months. This is in accordance with Figure 40. This graph also shows that almost 86% of countries are efficient. Some improvements should be done with greater urgency for these seven countries to achieve an efficiency score of at least 80%, and countries with relative efficiencies below the mean value (0,934) should also make efforts to achieve at least this value. The final CI efficiency values obtained for each nation are displayed in a line graph, similar to Figure a13 but for cluster 2, in excel in cloud.37

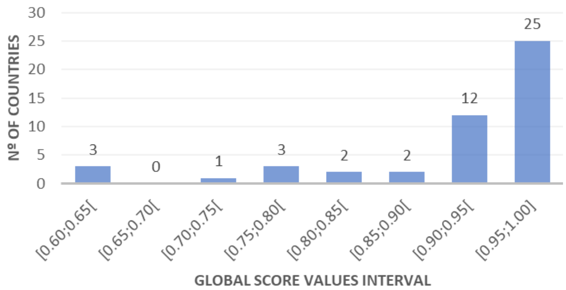

Figure 40 - Global scores distribution for final CI by range of values, cluster 2 (Source: The author)

[37] Excel file: FINAL_cluster2_bod_scores_normalization-method-3.xlsx (sheet: "PERFORMANCE FINAL CI TPs")

The ranks that each country achieved with the final CI that measures the overall performance and with the dimensional CIs that measures the performance in each dimension can be seen in Table 8. It is very clear that European countries are the leading countries in general. North America and East Asia are also fairly good positioned and that Latin American countries appears at the bottom of the table with the worst overall performances. In general, seems that developed countries have more chances to have a better performance fighting a pandemic when compared with countries with less resources, which is natural. Therefore, the importance of preparedness, the existence of resources and capabilities for extreme cases like a pandemic that eventually ends up happening. Considering the difference between final CI and dimensional CIs, seems that countries at the top half of the table have a better ranking when the performance is measured overall and the countries at the bottom half have better performances when the dimensions are analysed individually[38]. This is visible with the presence of more negative values than positives in the difference's columns in the top half of the table. This was also verified in cluster 1.

Countries at the end of the table should feel pressure to improve all dimensions and take top countries like Finland and United Kingdom as their role model. Countries at the middle of table that have a more unbalanced efficiency between dimensions, should look for Table 8 and Figure a14 and identify in which dimensions performed poorly and improve these dimensions in first place to go up on the table.

Table 8 - Countries' rankings in the several CIs and respective comparisons between final CI (FC) and dimensional partial CIs (COVID-19 dimension (CI_1), access and quality of health dimension (CI_2), security and compliance in governance (CI_3) and fragility in economy and finance (CI_4)), cluster 2 (NOTE: rankings obtained using global scores) (Source: The author)

	countries	FC	CI_1	DIF(FC-CI_1)	CI_2	DIF(FC-CI_2)	CI_3	DIF(FC-CI_2)	CI_4	DIF(FC-CI_4)
	Finland	1	29	-28	4	-3	1	0	9	-8
	United Kingdom	2	22	-20	19	-17	1	1	12	-10
TOP 5	Norway	3	19	-16	1	2	11	-8	11	-8
	Austria	4	6	-2	6	-2	24	-20	1	3
	Denmark	5	9	-4	11	-6	7	-2	18	-13
	Germany	6	12	-6	3	3	27	-21	4	2
	Ireland	7	10	-3	8	-1	21	-14	5	2
	Switzerland	8	37	-29	2	6	15	-7	13	-5
	Netherlands	9	30	-21	10	-1	16	-7	2	7
	Iceland	10	5	5	7	3	37	-27	3	7
	Singapore	11	1	10	33	-22	5	6	32	-21
	United States	12	14	-2	12	0	6	6	34	-22
	Estonia	13	23	-10	22	-9	1	12	39	-26
	Belgium	14	20	-6	5	9	33	-19	10	4
	Sweden	15	46	-31	9	6	14	1	7	8
	Czechia	16	35	-19	18	-2	8	8	20	-4
	Australia	17	38	-21	25	-8	20	-3	6	11
	New Zealand	18	36	-18	35	-17	1	17	14	4
	Japan	19	41	-22	29	-10	23	-4	8	11
	Malta	20	4	16	21	-1	39	-19	16	4
	France	21	18	3	15	6	17	4	26	-5
	Slovenia	22	27	-5	14	8	25	-3	21	1
	Portugal	23	8	15	27	-4	34	-11	17	6
	Luxembourg	24	15	9	13	11	26	-2	38	-14
	Canada	25	17	8	17	8	30	-5	23	2
	Cyprus	26	7	19	36	-10	10	16	33	-7
	Spain	27	25	2	16	11	32	-5	22	5
	Israel	28	2	26	32	-4	45	-17	15	13
	Greece	29	16	13	23	6	43	-14	19	10
	Poland	30	39	-9	26	4	12	18	36	-6
	South Korea	31	26	5	30	1	19	12	24	7
	Chile	32	3	29	40	-8	9	23	41	-9
	Lithuania	33	33	0	24	9	22	11	35	-2
	Italy	34	11	23	20	14	44	-10	29	5
	Uruguay	35	13	22	34	1	29	6	31	4
	Barbados	36	21	15	37	-1	13	23	44	-8
	Slovakia	37	32	5	28	9	41	-4	28	9

[38] Find in cloud the excel file that validates this statement: FINAL_cluster2_bod_scores_normalization-method-3.xlsx (sheet: GRAPHS)

	Panama	38	24	14	41	-3	40	-2	27	11
	Cuba	39	28	11	31	8	46	-7	30	9
	Kuwait	40	31	9	44	-4	28	12	43	-3
	Costa Rica	41	40	1	45	-4	18	23	37	4
	Argentina	42	34	8	39	3	42	0	45	-3
	Brazil	43	43	0	43	0	48	-5	25	18
	Trinidad and Tobago	44	47	-3	38	6	35	9	46	-2
	Peru	45	44	1	42	3	38	7	47	-2
LAST 5	Ecuador	46	48	-2	46	0	47	-1	40	6
	Colombia	47	42	5	48	-1	31	16	42	5
	Suriname	48	45	3	47	1	36	12	48	0

6.4. Countries from cluster 3

6.4.1. CI for COVID-19 dimension

Regarding countries behaviour to fight COVID-19, Figure 41 shows that countries were in general efficient (mean>0,800). However, the margin for improvement is 18,5%, which is quite high. The minimum says that one country (Yemen) had a very poor efficiency in the fight of the pandemic. The maximum shows that the country (Dominican Republic) showing the best performance has still 4,4% of inefficiency and that any country was fully efficient in all months. This is natural since COVID-19 disease was very persistent and the pandemic was very volatile for countries with the arrival of different waves and origin of new variants. However, Figure 42 shows that in average existed around four countries being fully efficient monthly. This does not mean that these countries were the most ideal ones in the fight of COVID-19 but that among the countries in this cluster they were the best ones since BoD measures relatives' efficiencies. Nevertheless, the pandemic volatility is reflected in the dispersion of the values of Figure 42.

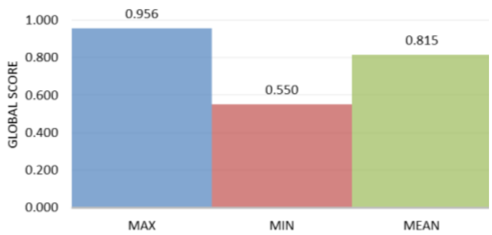

Figure 41 - Global scores maximum, minimum and mean values obtained for COVID-19 dimension, cluster 3 (Source: The author)

With Figure 43 it is possible to perceive countries distribution throughout efficiency ranges and understand that 58% of the countries are considered efficient (global score>0,80). This is not a very exciting information since almost half of the countries are bellow efficiency and therefore in need for improvements. To aggravate the situation, from the 58% efficient countries, most of it are below 90% of efficiency and only thirteen countries are closer to the full efficiency. This permits to conclude that almost all countries have a relatively high margin for improvement in terms of testing, vaccination and policies to fight the pandemic. Due to its dimension and complexity, it is possible to find online a graph similar to Figure a8 for cluster 3, that accounts for the scores obtained for each country in each month.[39]

[39] Excel file: DIMENSION_cluster3_bod_scores_normalization-method-3.xlsx (sheet: GRAPHS)

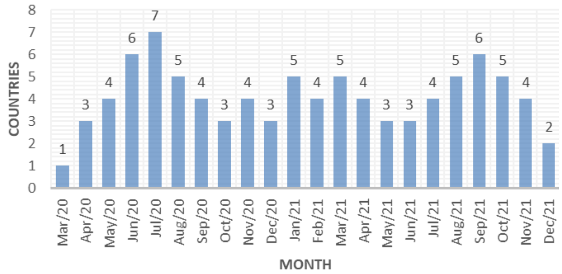

Figure 42 - Number of benchmarking countries for each month in CI 1, cluster 3 (Source: The author)

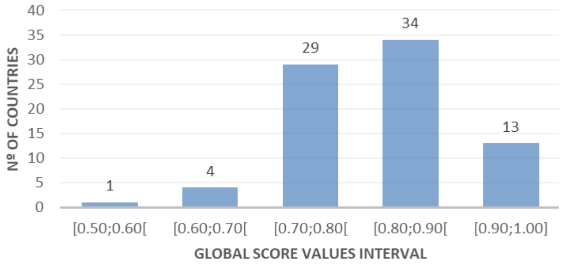

Figure 43 - Global scores distribution for COVID-19 dimension by range of values, cluster 3 (Source: The author)

6.4.2. CI for Access and Quality of Health dimension

Countries performance in terms of access and quality of health was very poor: countries had only an average of 30% relative efficiency which is far below the minimum target of reaching 80% to be considered efficient. Therefore, in average, countries are showing 37% of inefficiency meaning that it is very urgent for countries to improve their access to basic social sanitation and hygiene and to have better resources in medical facilities to assist population with health needs. The country having a very alarming poor efficiency was Niger. No other country obtained a relative efficiency so low in any dimension. However, Niger being the one country in this situation is not very surprising since it is one of the poorest countries in the world. Considering Figure 44 and 45, two countries were fully efficient. They were Hungary and Kazakhstan, even though Croatia, Latvia and Belarus achieved almost the full efficiency with more than 99,0%.

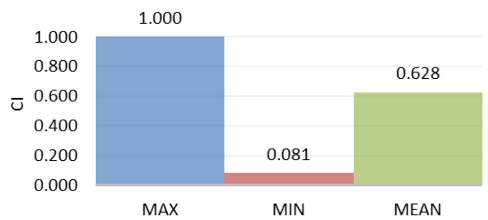

Figure 44 - Maximum, minimum and mean values obtained for Access and Quality of health dimension, cluster 3 (Source: The author)

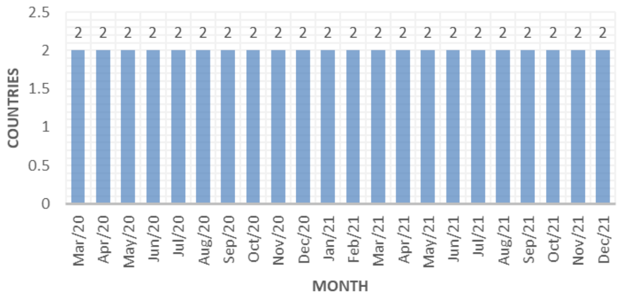

Figure 45 - Number of benchmarking countries for each month in CI 2, cluster 3 (Source: The author)

Taking into account countries' efficiency's distribution in Figure 46, only 32% of them were considered efficient which is very alarming. This way, 68% of countries need intervention and should be carried out to bring them closer to the desired performance levels of access and quality of health. It is interesting to notice that almost all countries that achieved relative efficiencies below 70% are manly from Africa and Latin America and that countries that achieved efficiency were mostly from Europe, and central and south Asia. The correlation between income and health becomes evident again.

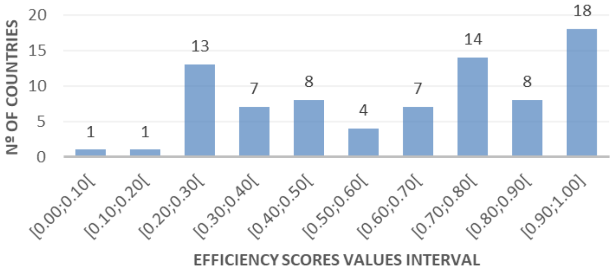

Figure 46 - Efficiency scores distribution for Access and Quality of Health dimension by range of values, cluster 3 (Source: The author)

6.4.3. CI for Security and Compliance in Governance dimension

In comparison to the previous CI, the results in security and compliance in governance dimension are also not positive. Considering the mean in Figure 47, countries are in general not efficient demonstrating almost 33% of inefficiency. In the extreme case, Madagascar has the worst performance in this dimension with about 81% of inefficiency. This country and all countries bellow efficiency level should look for countries that are efficient in this dimension to learn how to improve in this concern. The countries that achieved better results, considered to be fully efficient in Figure 48, were Georgia and Rwanda. Therefore, it is recommended that countries below efficiency take Georgia’s and Rwanda’s transparent and trustfully government as a “role-model”.

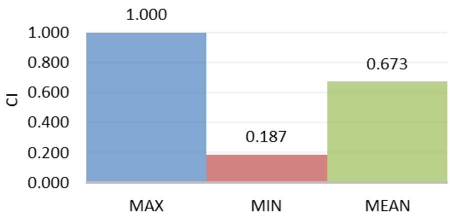

Figure 47 - Maximum, minimum and mean values obtained for Security and Compliance in Governance dimension, cluster 3 (Source: The author)

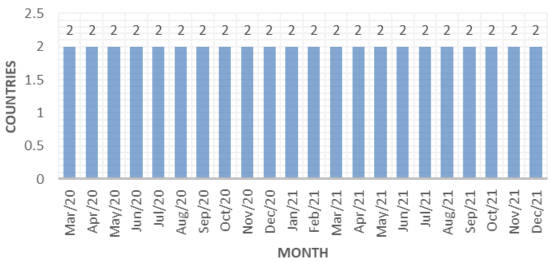

Figure 48 - Number of benchmarking countries for each month in CI 3, cluster 3 (Source: The author)

In this CI, only 30,9% of countries are efficient and exists many countries with very low relative efficiency, which is very alarming (see Figure 49). The countries present in this cluster are mainly African countries, central and south Asia, Latin America and few European countries that are associated to lower level of development. Some countries below efficiency are Madagascar, Croatia, Somalia, Libya and Angola. Some countries that were efficient are Georgia, Rwanda, South Africa, Russia and Hungary. It was not expected to have Croatia in the last positions but analysing the groups CIs seems that this bad performance is more due to political stability dimension and not due to accountability dimension: Croatia should adopt and implement disaster risk reduction strategies because it seems to not have any since in indicators 3.2.3; 3.2.4 the value was zero.

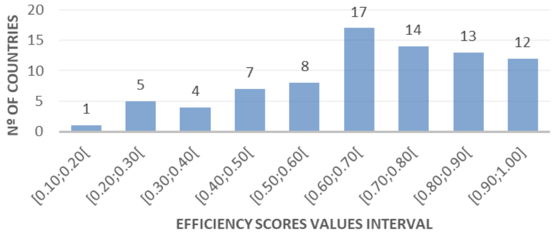

Figure 49 - Efficiency scores distribution for Security and Compliance in Governance dimension by range of values, cluster 3 (Source: The author)

6.4.4. CI for Fragility in Economy and Finance dimension

Even though not so poorly, countries are also below the desired level of efficiency for CI 4, considering the mean value in Figure 50. Considering the maximum, it is perceived that one country has fully efficient in all months, and that great achievement is from Hungary. Nevertheless, Figure 51 shows that in almost all months there were more than one benchmarking country. Bulgaria and South Africa were also benchmark countries in several months. These countries show an excellent concern and availability of economic resources to alleviate their people and companies during the pandemic.

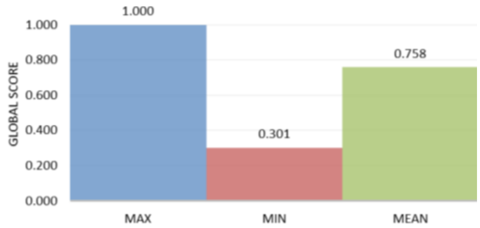

Figure 50 - Maximum, minimum and mean values obtained for Fragility in Economy and Finance dimension considering all values obtained in each month, cluster 3 (Source: The author)

Regarding the worst performances, Angola, Mali, Sierra Leone and Liberia seem to have a more fragile economy and to give not enough economical support for their people. Figure 51 shows a relatively stable result specially in consecutive months. With Figure 52, it is possible to understand that only about 47% of countries were efficient in this dimension revealing a lack of economic structure which can be reflected in the resources for testing, vaccination, and healthcare in general and in the support for their households during the pandemic time.

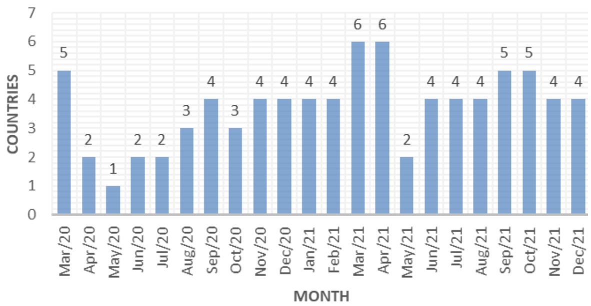

Figure 51 - Number of benchmarking countries for each month in CI 4, cluster 3 (Source: The author)

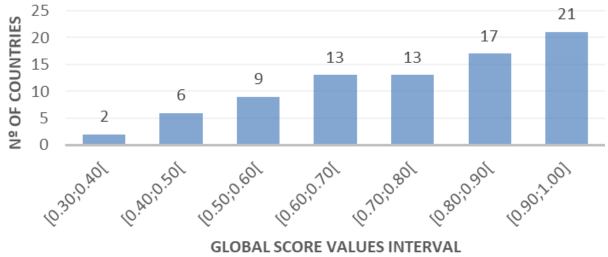

Figure 52 - Global scores distribution for Fragility in Economy and Finance dimension by range of values, cluster 3 (Source: The author)

6.4.5. Comparison between dimensions

The radar chart in Figure 53 permits to take two main conclusions: one is that countries did not achieve the efficiency in almost all dimensions since the mean (red line) is superior to 80% in just only one dimension (COVID-19 dimension) and the second one is that the magnitude of the efficiencies' values dispersion is quite high, mainly for dimensions 2, 3 and 4. This is a bad factor since over and above the low average efficiencies in this three dimensions, there is a greater distance from the desired maximum efficiency found in other countries. In other words, the performance of countries in these dimensions are in general bad and to aggravate the situation some countries have really bad efficiency in them. This permits to conclude that countries found below efficiency in these three dimensions, mainly in access and quality of health and in security and compliance in governance dimensions should look for efficient countries in these dimensions to improve their resources in medical facilities (beds, doctors, nurses), provide a more equal and effective access to a safe, hygienic and basic sanitation to population; a more stable, transparent and trustfully government since it helps to make people feel safe in adverse conditions like a pandemic and to respect and comply to the measures and policies impose; and finally, improve their stability and growth in economy and economic support for people.

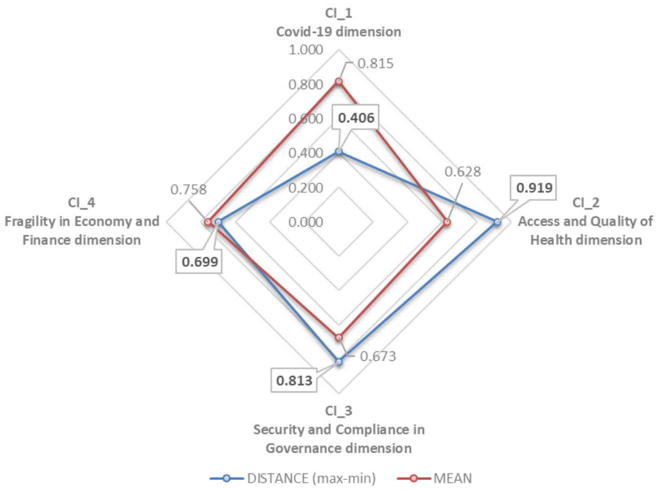

Figure 53 - Radar chart with distance between maximum and minimum global scores values (blue line), and mean global scores (red line) in each CI/dimension, cluster 3 (Source: The author)

In addition, Figure a15 is useful to understand which countries performed better and worse in general according with the extension of the bars. Countries performing better are Hungary, Georgia, Oman, Cape Verde, and South Africa and worse are Somalia, Yemen, Angola, Afghanistan and Niger. With this chart it is also possible for countries to understand in which dimensions efficiency was or not achieved in order to improve with more urgency the dimensions in need. For example, Albania was efficient in dimensions two and four but not in dimensions one and three. Thus, it is in this regard that they should improve with more urgency. Perceive what went bad and try to replicate the good results from efficient entities in these dimensions.

In Table b14, it is represented countries ranks listed from best to worst performance in average showing the rankings obtained in each dimension and in each time-period to track the evolution over time. Georgia, Oman and Cape Verde show a relatively stable and good performance and Somalia, Yemen, Angola, Afghanistan and Niger show always a very poor performance during all period in all dimensions.

6.4.6. Final composite indicator

Comparing with the countries relative efficiencies in each dimension (analysis done before in sections 6.4.1 - 6.4.4), seems that the results are more positive when performance is measured as a whole, when the dimensional CIs interact between each other to compute the final CI. This makes sense since, as previously explained, BoD always enhances the performance for each DMU using the findings in the dimensional level to compute the final CI. In dimensional level, countries only achieved, in average, the efficiency in COVID-19 dimension and when the efficiency is measured with final CI it is obtained for most of the countries, evidenced with the mean value in Figure 54. However, the margin for improvement is still relatively high: 15,5%, in average. Regarding the maximum, global score of one means that at least one country was fully efficient in all months and only Georgia could achieve this. On the contrary, Niger was the country revealing worst performance (global score=53,8%) which is not very surprising since it is one of the three countries with worst human development (United Nations, 2021).

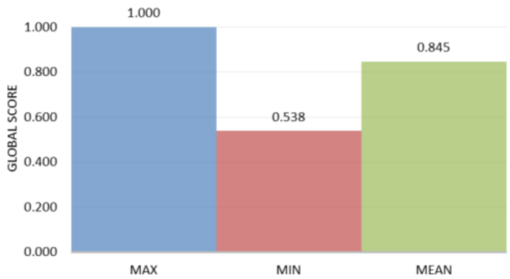

Figure 54 - Global scores maximum, minimum and mean values obtained for Final CI, cluster 3 (Source: The author)

Figure 55 also reveals that in addition to Georgia, existed always another country(ies) being fully efficient in each month. Georgia and Hungary are the countries that revealed more consistency in their relative performance to other countries being fully efficient in almost all months, which is also in line with the dimensional analysis done previously. For the final CI all dimensions are contributing for these results, but the relatively high dispersion of the values is mainly caused because of dimension 1 and 4 that accounts for time-series data, data that changed from month to month according with the evolution of COVID-19 pandemic: the constant changes in countries position regarding the fight of the virus is reflected here. Figure 56 tells that almost 60% of countries were efficient and that 27 countries were below the desired level of efficiency. These countries require more attention and improvement to achieve better results and should use insights from efficient one with that purpose. The final CI efficiency values obtained for each DMU are displayed in a line graph, similar to Figure a13 but for cluster 3, in excel in cloud.[40]

[40] Excel file: FINAL_cluster3_bod_scores_normalization-method-3.xlsx (sheet: "PERFORMANCE FINAL CI TPs")

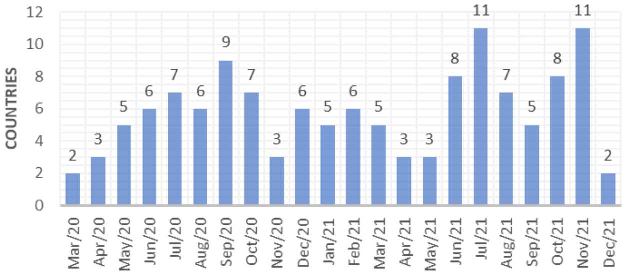

Figure 55 - Number of benchmarking countries for each month in Final CI, cluster 3 (Source: The author)

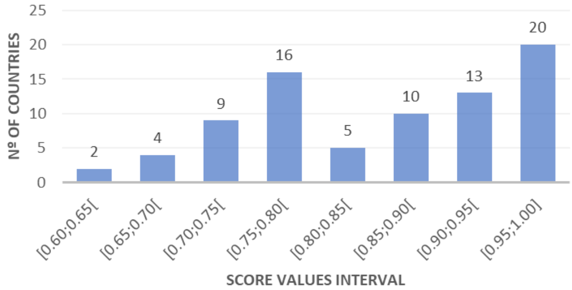

Figure 56 - Global scores distribution for final CI by range of values, cluster 3 (Source: The author)

The ranks that each country achieved with the final CI that measures the overall performance and with the dimensional CIs that measures the performance in each dimension can be seen in Table 9. It is very noticeable that countries from Middle East, South Asia and mainly sub-Saharan Africa are the ones performing with less efficiency and therefore, the more present countries at the bottom of the table: Niger, Yemen, Afghanistan, Somalia and Angola are the five worst countries when the efficiency is measured with the four dimensions at once. On the other hand, at the top of the table there are the countries performing better and Georgia, Hungary, South Africa, Russia and Oman are the top five countries. It is curious that the neighbour countries Oman and Yemen, both from Middle East, are one of the best and one of the worst, respectively. Income turns again to show its influence since Yemen is a low-income least developed country and Oman a high-income developing country, that has more resources and thus, better capabilities to fight a pandemic. Therefore, the importance of preparedness, the existence of resources and capabilities for extreme cases like the origin of a new dangerous virus. Countries at the end of the table should look for important aspects that made top countries like Georgia or Hungary achieving so good results.

As observed before in cluster 1 and 2, the top half countries in Table 9 show better results when their performance is measured with all dimensions interacting between each other (overall performance), and bottom half countries present better in each dimension. This can be noted with the presence of more negative values in the difference's columns from Table 9 in the top half and positive values in the bottom half.[41] Nevertheless, countries that performed relatively good in all dimensions are more efficient and countries that performed bad in all dimensions not efficient, which makes sense.

[41] Find in cloud the excel file that validates this statement: [FINAL_cluster3_bod_scores_normalization-method-3.xlsx] (sheet: GRAPHS)

Table 9 - Countries' rankings in the several CIs and respective comparisons between final CI (FC) and dimensional partial CIs (COVID-19 dimension (CI_1), access and quality of health dimension (CI_2), security and compliance in governance (CI_3) and fragility in economy and finance (CI_4)), cluster 3 (NOTE: rankings obtained using global scores) (Source: The author)

	countries	FC	CI_1	DIF(FC-CI_1)	CI_2	DIF(FC-CI_2)	CI_3	DIF(FC-CI_2)	CI_4	DIF(FC-CI_4)
	Georgia	1	22	-21	13	-12	1	0	13	-12
	Hungary	2	40	-38	1	1	6	-4	1	1
TOP 5	South Africa	3	39	-36	36	-33	4	-1	3	0
	Russia	4	48	-44	8	-4	5	-1	22	-18
	Oman	5	6	-1	16	-11	12	-7	19	-14
	Kazakhstan	6	30	-24	1	5	9	-3	48	-42
	Cape Verde	7	4	3	45	-38	8	-1	2	5
	Jordan	8	34	-26	22	-14	3	5	28	-20
	Serbia	9	21	-12	15	-6	40	-31	4	5
	Bulgaria	10	69	-59	10	0	11	-1	5	5
	Belarus	11	62	-51	5	6	13	-2	30	-19
	Turkey	12	5	7	18	-6	26	-14	27	-15
	Ukraine	13	27	-14	7	6	49	-36	8	5
	Uzbekistan	14	14	0	9	5	43	-29	9	5
	Romania	15	20	-5	6	9	58	-43	6	9
	Morocco	16	3	13	38	-22	24	-8	14	2
	Mongolia	17	2	15	17	0	52	-35	21	-4
	Latvia	18	33	-15	4	14	66	-48	12	6
	Vietnam	19	10	9	40	-21	7	12	33	-14
	Thailand	20	50	-30	27	-7	37	-17	10	10
	Lebanon	21	9	12	14	7	56	-35	17	4
	Rwanda	22	60	-38	55	-33	1	21	15	7
	Moldova	23	38	-15	21	2	10	13	45	-22
	Tunisia	24	29	-5	33	-9	19	5	23	1
	Cambodia	25	8	17	51	-26	23	2	16	9
	Albania	26	67	-41	11	15	33	-7	35	-9
	Gabon	27	18	9	26	1	16	11	39	-12
	Bosnia and Herzegovina	28	63	-35	12	16	64	-36	20	8
	El Salvador	29	16	13	28	1	54	-25	26	3
	Iraq	30	25	5	25	5	14	16	50	-20
	Honduras	31	23	8	42	-11	71	-40	7	24
	Kyrgyzstan	32	51	-19	23	9	45	-13	36	-4
	Timor	33	19	14	31	2	35	-2	32	1
	Guatemala	34	56	-22	48	-14	46	-12	18	16
	Tajikistan	35	37	-2	29	6	21	14	49	-14
	Botswana	36	57	-21	37	-1	27	9	24	12
	Iran	37	35	2	24	13	22	15	51	-14
	Namibia	38	46	-8	43	-5	17	21	37	1
	Azerbaijan	39	7	32	20	19	74	-35	31	8
	Dominican Republic	40	1	39	32	8	75	-35	29	11
	eSwatini	41	11	30	50	-9	50	-9	55	-14
	Croatia	42	15	27	3	39	80	-38	11	31
	Paraguay	43	49	-6	41	2	41	2	34	9
	Algeria	44	44	0	35	9	48	-4	40	4
	Ghana	45	31	14	47	-2	29	16	53	-8
	Venezuela	46	26	20	34	12	73	-27	25	21
	Mozambique	47	42	5	52	-5	25	22	75	-28
	Libya	48	24	24	19	29	78	-30	67	-19
	Bolivia	49	75	-26	46	3	67	-18	38	11
	Mauritania	50	52	-2	61	-11	30	20	64	-14
	Gambia	51	61	-10	64	-13	28	23	46	5
	Guinea	52	13	39	76	-24	36	16	56	-4
	Congo	53	17	36	53	0	76	-23	65	-12
	Syria	54	78	-24	30	24	53	1	57	-3
	Nicaragua	55	74	-19	39	16	68	-13	42	13
	Kenya	56	59	-3	56	0	42	14	47	9
	Senegal	57	79	-22	73	-16	20	37	41	16
	Nigeria	58	47	11	44	14	62	-4	69	-11
	Zambia	59	70	-11	54	5	31	28	68	-9
	Benin	60	41	19	69	-9	47	13	54	6
	Uganda	61	53	8	60	1	55	6	62	-1
	Mali	62	65	-3	67	-5	18	44	80	-18
	Ethiopia	63	45	18	77	-14	15	48	70	-7
	Cameroon	64	32	32	65	-1	57	7	72	-8
	Togo	65	54	11	75	-10	32	33	44	21
	Democratic Republic of Congo	66	66	0	68	-2	51	15	59	7
	Malawi	67	76	-9	72	-5	38	29	43	24
	Liberia	68	28	40	66	2	70	-2	78	-10
	Sierra Leone	69	12	57	80	-11	59	10	79	-10
	Cote d'Ivoire	70	43	27	71	-1	60	10	52	18
	Tanzania	71	77	-6	58	13	39	32	61	10
	Haiti	72	55	17	70	2	63	9	66	6

	Zimbabwe	73	73	0	49	24	72	1	58	15
	Burundi	74	64	10	78	-4	34	40	63	11
	Burkina Faso	75	71	4	74	1	44	31	73	2
	Madagascar	76	36	40	57	19	81	-5	77	-1
LAST 5	Angola	77	58	19	62	15	77	0	81	-4
	Somalia	78	72	6	79	-1	79	-1	71	7
	Afghanistan	79	80	-1	63	16	65	14	76	3
	Yemen	80	81	-1	59	21	69	11	74	6
	Niger	81	68	13	81	0	61	20	60	21

7. Conclusion

7.1. Main findings

The present study has the purpose to understand how COVID-19 pandemic changed the world, analysing the consequences of the origin of SARS-CoV-2, the measures to fight the novel coronavirus, and understand how other country related factors can influence countries' performance to control the pandemic and find a method to assess these performances on a global country level (international comparison).

It was perceived that COVID-19 pandemic has very similarities to other past pandemics that affects countries' economy and people's health, and that probably will not be the last one to happen. Thus, the importance of understating good and bad practices to have a more fast and effective response possible future pandemics. It can also give insights about how to prevent an outbreak to evolve into a pandemic.

The damage is more felt on healthcare systems, that must avoid as many deaths as possible, and on countries' economy, mainly for service-oriented economies. In fact, according with Chen et al. (2021) a key lesson learned from recent pandemics is that the economy should be considered when developing pandemic mitigation policies because the nefarious consequences can take long years of recover. To try to minimize these effects, the governments take non-pharmaceutical measures to difficult the virus spread, and so, reduce the transmission chain. Examples of these are the use of PPE such as disinfectants and face masks, prohibit social gatherings, restrict unnecessary traveling, lockdowns, closure of schools and commerce, etc. Studies shown that vaccination and massive testing for isolation of positive cases are two measures very strong to fight the virus and that enables the alleviation of some measures taken. This is important for economy because people and companies start, slowly and with some minor restrictions, to resume their normal activity. With most people vaccinated and/or recovered from SARS-CoV-2 infection, herd immunity is achieved, and some experts defend it is the key for the end of COVID-19. Besides the negative impacts, it was also possible to learn that the pandemic brought many advantages for environment and biodiversity. Therefore, people should change some "selfish" behaviours towards a sustainable and "green-planet" to protect and take care of planet earth, which helps to prevent the origin of new viruses.

In literature, similar studies use data analysis to access the policies to fight COVID-19 efficiency and the most common ones are DEA and machine learning algorithms. Usually, DEA is preferable since a *best-practice frontier* is constructed considering resources (inputs) and production (outputs) data available, accommodating the needs of the problem in hands, to evaluate DMUs relative efficiencies. However, literature review shown to exist many studies that considered variables that were somehow restrictive to evaluate countries performance because COVID-19 is unlikely resumed to number of deaths, number of recovered and number of beds and medical personnel. It is here that the add-value of the present work enters in play, since it is used a particular model of DEA, the BoD-DEA, that can fit better the analysis of a pandemic since accounts for several performance indicators that can be aggregated in several levels and in a single performance measurement. This is very helpful since not only a *best-practice frontier* is created and countries can be compared directly and ranked, but also find the aspects that conducted to the good or bad results. This way, it is possible to use data of specific anti-covid policies that were used to fight the pandemic (group 1.1 and 1.2), and other performance indicators that influence them directly. In addition, BoD has the great advantages of accommodating both desirable and undesirable indicators (see

Table 6) and attributing weights to the several indicators in a way that makes the overall relative performances as high as possible, so, not favours some countries to the detriment of others.

Sections 2, 3 and 4 were very important to define which indicators to use, and the final composite indicator is constructed with 41 indicators, grouped in 10 groups and 4 dimensions to measure relative efficiencies of 156 countries, arranged in three clusters. Therefore, the final composite indicator constructed with BoD accounts for the policies taken (including testing and vaccination) and negative impacts in dimension 1, for the access and quality of healthcare resources (hospital beds and medical personnel) and the social sanitation and hygiene provided to population in dimension 2, for the availability of people to comply with the rules imposed and with their confidence in the government since it is linked with the success of the measures taken is accounted in dimension 3 and the economic aspects are reflected in dimension 4 (see Table 6). As mentioned before, using the BoD and arranging the simple indicators into groups and dimensions makes possible to construct group and dimensional partial CIs that are used to compute the final CI. This is very helpful to refine the knowledge about the aspects that need more improvement and, this way, understand in which areas performance needs more care and attention.

Table 10 summarizes the main findings to have a more clear and easy perception of the results.

Table 10 - Summary of the results obtained with dimensional CIs and final CI for each cluster (NOTE: efficient DMUs (%) – percentage of countries that achieved, in average, relative efficiency superior to 80%; benchmark DMUs (mean) – average of the number of countries that achieved full efficiency (relative efficiency of 100%) considering all months in analysis (Source: The author)

	Cluster 1	Cluster 2	Cluster 3
CI 1: Best 3 / Worst 3 / Efficiency Average / Efficient DMUs (%) / Benchmark DMUs (mean)	Qatar, Seychelles, Malaysia / Egypt, Mexico, Sudan / 86,6% / 82% / 4	Singapore, Israel, Chile / Sweden, Trinidad and Tobago, Ecuador / 84,0% / 73% / 4	Dominican Republic, Mongolia, Morocco / Senegal, Afghanistan, Yemen / 81,5% / 58% / 4
CI 2: Best 3 / Worst 3 / Efficiency Average / Efficient DMUs (%) / Benchmark DMUs (mean)	Brunei, Saudi Arabia, United Arab Emirates / Nepal, Sudan, Papua New Guinea / 72,5% / 48% / 2	Norway, Switzerland, Germany / Ecuador, Suriname, Colombia / 77,2% / 65% / 1	Hungary, Kazakhstan, Croatia / Somalia, Sierra Leone, Niger / 62,8% / 32% / 2
CI 3: Best 3 / Worst 3 / Efficiency Average / Efficient DMUs (%) / Benchmark DMUs (mean)	Bahrain, Bangladesh, India / Bhutan, Fiji, Seychelles / 85,0% / 70% / 3	Estonia, Finland, United Kingdom, New Zealand / Brazil, Ecuador, Cuba / 80,4% / 60% / 4	Georgia, Rwanda, Jordan / Somalia, Croatia, Madagascar / 67,3% / 31% / 2
CI 4: Best 3 / Worst 3 / Efficiency Average / Efficient DMUs (%) / Benchmark DMUs (mean)	Mauritius, Qatar, United Arab Emirates / Philippines, Bangladesh, Sudan / 82,4% / 63% / 4	Austria, Netherlands, Iceland / Trinidad, and Tobago, Peru, Suriname / 87,9% / 77% / 6	Hungary, Cape Verde, South Africa / Sierra Leone, Mali, Angola / 75,8% / 47% / 4
CF : Best 3 / Worst 3 / Efficiency Average / Efficient DMUs (%) / Benchmark DMUs (mean)	Bahrain, Qatar, Mauritius / Sudan, Papua New Guinea, Nepal / 92,4% / 89% / 4	Finland, United Kingdom, Norway / Suriname, Colombia, Ecuador / 91,5% / 86% / 6	Georgia, Hungary, South Africa / Niger, Yemen, Afghanistan / 84,5% / 60% / 6

It seems that countries, in general, achieved good levels of performance for COVID-19 dimension (CI 1>80%) showing that the anti-pandemic measures were appropriated and useful to control the disease in most of the cases. However, it is important to note that for cluster 3, only 58% of countries achieved the mentioned good results, which means that 34 countries need more attention and need for improvement since were under what is considered efficient.

Countries shown also a relatively good economic structure which can be reflected in resources for testing, vaccination, and healthcare in general and in the support for their households during the pandemic time (CI 4>80% for cluster 1 and 2; CI 4>75% for cluster 3); and a relatively transparent and trustfully government that influence the availability of people to comply with the measures imposed (CI 3>80%) for countries in cluster 1 and 2. Countries from cluster 3 have shown to be some steps behind (CI 3>70%).

The performance of countries is worse in access and quality of health dimension meaning that it is very urgent for countries to improve mainly their resources in medical facilities to assist population with health needs and the access to basic social sanitation and hygiene and to have better (CI 2>70% for cluster 1 and 2; CI 2>60% for cluster 3).

Percentage of efficient DMUs is also important to account for the analysis because it shows the portion of countries that are efficient. For example, any cluster was considered efficient in dimension 2, but 65% of countries from cluster 2 were efficient in this dimension. This means that the discrepancies in the values are higher in this case and, so, that the other 35% had very reduced efficiency. On the other hand, it is easy to perceive that very few countries from cluster 3 were considered efficient in each dimension (~42%, in average). Without hesitation, cluster 3 is the one showing poorer performance in all CIs, which is natural since cluster 3 is most represented by African countries, some central and south Asia and Latin America, and very few European countries. This association between the performance results obtained and the countries regions and income groups more prevalent in each cluster makes sense for all clusters (see Figures a5 and a6). On the contrary, middle-income countries represented mostly in cluster 1 and high-income countries represented mostly in cluster 2 have shown much better results.

The final CI offers an integrated view of the several groups and dimensions which is great since it gives an overall measurement of countries' performance. In accordance with the previous paragraph, cluster 3 is the one showing the worst result even though the efficiency average is superior to 80% for all cluster because only 60% of cluster 3 countries are considered efficient at a rate of 80%, a much more reduced value when compared to cluster 1 and 2.

To conclude, the goal to achieve a clear and comprehensive understanding about countries performance during COVID-19 pandemic is achieved since the created composite indicator permits to aggregate simple individual performance indicators into a performance measurement to evaluate areas, aspects, or dimensions one by one or in an overall or global perspective. This novel CI measures performance at a country level between geographies at a similar development status and statistically similar and is expected to monitor and provide a basis for benchmarking towards a better preparedness and ability to fight a pandemic. The usage of dimensions and groups not only helped for the construction of the final CI but also helps decision makers actors and other important stakeholders to understand which areas need more care and more urgent to be improved, thus, it is possible to refine the knowledge about what went wrong. Therefore, it is recommended to use this CI to identify the more fragile areas that are influencing the results and to compare to other benchmark countries that are efficient in order to extract insights to change behaviours in that direction. This CI has also the advantage of not looking for COVID-19 pandemic in a very limited way, other aspects that also influence the results of the policies taken such as economy, governance and healthcare are accounted. Thereby, the created CI can be used as tool by everyone that wants to understand better countries performance in a pandemic context.

7.2. Limitations

The limitations influence the results and its quality at some point and for that reason are important to be mentioned.

The data and quality of the data retrieved is constrained to its availability on internet for free and from reliable sources. Data is also limited to geographical coverage and time coverage. Since this work is an international comparison, data couldn't be geographical reductive. It was used only indicators that covered at least 70% of countries in study. For example, it was pretended to use some variables to reflect healthcare needs (COVID-19 ICU patients per million and COVID-19 hospital patients per million variables) but these variables were only available for around 14% of the countries in study and for that reason couldn't be used. Regarding time coverage, it was intended to use very recent data and up-to-date data from March 2020 till December 2021 to comprise the months during COVID-19 pandemic in analysis. This was mainly important for COVID-19 data.

Some countries had to be removed of the analysis because had very missing data for the indicators used. It was thought to do the international comparison with 195 countries, but it was reduced to 156 countries (see section 5.1 for more information). The results obtained with BoD are measured in relative efficiencies and therefore, the sample has a strong impact in the results. It is also important to highlight that benchmark countries are considered fully efficient in comparison to the other DMUs from the sample. This means that even these countries should pay attention because it probably has aspects that could be improved.

For the 156 countries some missing data was still present in the dataset and imputation methods were applied to estimate these values. Since they are not the "real and observed" values but just estimations it influences the results obtained that can be a little deviated from the reality, even though it was followed a careful method to impute missing values (see section 5.3 for more information).

The 156 countries in analysis were clustered and resulted three clusters. If the distribution of countries for each cluster had been different, the results would also be different. Nevertheless, the cluster analysis was performed with precaution and properly to minimize misleading results.

The normalization method used has also an influence in the results obtained. If it was opted for another normalization method the results would be different, but it was used the one that shown to be more pertinent having account the dataset in hands (see section 5.4 for more information).

BoD aggregated the indicators attributing weights that were constrained to [0,05;0,95]. This was to ensure that all indicators were accounted to form the CI. However, if the constrain imposed was different the results would also be different. For example, if the interval was [0,10;0,90], or if the weights were attributed with an empirical view to reflect importance to the indicators (see section 5.5 for more information).

BoD does not accommodate negative indicators and for that reason a data translation was performed for indicator 1.3.2, which resulted in an increase in work.

7.3. Future research

Procedures and methodologies could be applied in future research to validate the work done and enhance and add value to this study.

Regarding the first aspect, it could be assessed a robustness and sensitivity analysis to evaluate some uncertainty that always exists when decisions are made, and techniques applied. These analysis could be used to evaluate the usage of different simple indicators and arrangements of them in groups and dimensions; to evaluate the imputation methods used and compare with other ones; to compare with alternative data normalization techniques; to evaluate the usage of different weighting schemes; etc.

Regarding the second aspect, the work done could be proceed with a second-stage DEA method. The usage of second-stage DEA methodologies are always valuable since people can perceive the impact of the variables used on the efficiencies obtained or to analyse how other factors interact and influence the efficiencies. There are several types of second-stage DEA to validate the model. Hoff (2007) compares one of the most used techniques, the Tobit regression, with other two methods (the Papke–Wooldridge approach, and the unit-inflated beta model). Therefore, the second-stage DEA uses the efficiencies obtained with BoD as dependent variable and the non-dependent variable is the factors (exogenous variables) that are not manageable (demographic, socio-economic, environmental factors, for example). Thus, it is possible to understand the causal effect of these external factors with the efficiencies obtained on the first-stage BoD-DEA.

Another suggestion of future work could be to form a panel of experts in benchmarking, key performance indicators, and composite indicators to attribute a different weighting scheme to the indicators used. Choosing this way different weights to the simple indicators, groups and dimensions to construct the final CI could be reflected with strong scientific knowledge a probable better performance measurement in terms of anti-covid measures. For sure dimension 1 (COVID-19 dimension) would be attributed a higher weight/importance. In the present study, was verified that some countries that dealt the pandemic poorly had an overall good score because is very good in all other aspects (for example, Sweden).

These recommendations would validate and enhance the results obtained and bring more knowledge to the scientific field and to countries' governments to be more prepared for possible future outbreaks.

References

Aguinis, H., & Burgi-Tian, J. (2020). Measuring performance during crises and beyond: The Performance Promoter Score. *Business horizons*, *64*(1), 149–160. https://doi.org/10.1016/j.bushor.2020.09.001

Ahn H., Afsharian M., Emrouznejad A., & Banker, R. (2017). Recent developments on the use of DEA in the public sector. *Socio-Economic Planning Sciences*. https://doi.org/10.1016/j.seps.2017.06.001

Aleta, A., Martin-Corral, D., y Piontti, A.P., Ajelli, M., & Litvinova, M., Chinazzi, M., Dean, N.E., Halloran, M.E., Longini Jr., Ira M., Merler, S., Pentland, A., Vespignani, A., Moro, E., & Moreno, Y. (2020). Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19. *Nature Human Behaviour*, 4(9), 964–971

Altman L.K. (2009). *Is this a pandemic? define 'pandemic'*. New York Times. http://www.nytimes.com/2009/06/09/ health/09docs.html.

American Society of Microbiology. (n.d.). *COVID-19 (SARS-CoV-2 Coronavirus).* https://asm.org/Resource-Pages/COVID-19-Resources

Arroyo-Marioli F., Bullano F., Kucinskas S., & Rondón-Moreno, C. (2021). Tracking R of COVID-19: A new real-time estimation using the Kalman filter. *PLoS ONE,* 16(1): e0244474. https://doi.org/10.1371/journal.pone.0244474

Associação Industrial Portuguesa - Câmara de Comércio e Indústria. (2020). *Crise COVID-19: Inquéritos AIP ao Contexto Empresarial.* http://www.aip.pt/pt/financiamento/inqueritos-ao-contexto-empresarial

Aydin, N., & Yurdakul, G. (2020). Assessing countries' performances against COVID-19 via WSIDEA and machine learning algorithms. *Applied Soft Computing*. Vol. 97, Part A, 106792, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2020.106792.

Aydin, N., & Yurdakul, G. (2021). Analyzing the efficiency of bank branches via novel weighted stochastic imprecise data envelopment analysis. *RAIRO - Operations Research*, *55*(3), 1559–1578. https://doi.org/10.1051/ro/2021067

Bandura, R. (2008). A survey of composite indices measuring country performance: 2008 update. *Office of Development Studies, United Nations Development Program*

Banker, R.D, Charnes, A., & Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manege Sci.* 30 1078–1092.

Barber, R.M., Fullman, N., Sorensen, R.J.D., Bollyky, T., McKee, M., Nolte, E., Abajobir, A.A., Abate, K.H., Abbafati, C., Abbas, K.M., Abd-Allah, F., Abdulle, A.M., Abdurahman, A.A., Abera, S.F., Abraham, B., Abreha, G.F., Adane, K., Adelekan, A.L., Adetifa, I.M.O., & Afshin, A. (2017). Healthcare Access and Quality Index based on mortality from causes amenable to personal health care in 195 countries and territories, 1990–2015: a novel analysis from the Global Burden of Disease Study 2015. *The Lancet*, 390(10091), 231–266. https://doi.org/10.1016/s0140-6736(17)30818-8

Baron, J. (2020). *EIA estimates that global petroleum liquids consumption dropped 9% in 2020.* Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=46596

Bendix, A. (2021). *Sweden's anti-lockdown strategy didn't work, led to higher death rate*. Business Insider. https://www.businessinsider.com/sweden-covid-no-lockdown-strategy-failed-higher-death-rate-2021-8

Benedictow, O. (2005). *The Black Death: The Greatest Catastrophe Ever.* History Today. History Today. https://www.historytoday.com/archive/black-death-greatest-catastrophe-ever

Black Death. (2021). *Encyclopedia Britannica*. https://www.britannica.com/event/Black-Death

Bogetoft, P., & Otto, L. (2011). *Benchmarking with DEA, SFA, and R*. Springer.

Bro, R., & Smilde, A.K. (2014). Principal component analysis. *Anal. Methods*, 6(9), 2812–2831. https://doi.org/10.1039/c3ay41907j

Calabria, F.A., Camanho, A.S. e Zanella, A. (2016). The use of composite indicators to evaluate the performance of Brazilian hydropower plants. *International Transactions in Operational Research*, 25(4), 1323-1343

Centers for Disease Control and Prevention. (2019). *1918 Pandemic (H1N1 virus).* https://www.cdc.gov/flu/pandemic-resources/1918-pandemic-h1n1.html

Charnes, A., & Cooper, W.W. (1959). Chance-constrained programming. *Manage. Sci*, 6 73–79.

Chen Y., Cook W. D., Li N. & Zhu J. (2009). Additive efficiency decomposition in two-stage DEA. *European Journal of Operational Research,* 196, 1170–1176

Chen K., Pun, C.S., Wong, H.Y. (2021). Efficient social distancing during the COVID-19 pandemic: Integrating economic and public health considerations. *European Journal of Operational Research*, ISSN 0377-2217. https://doi.org/10.1016/j.ejor.2021.11.012.

Cherchye, L., Moesen, W., Rogge, N., & Puyenbroeck, T.V. (2007). An Introduction to “Benefit of the Doubt” Composite Indicators. *Social Indicators Research*, *82*(1), 111–145. https://doi.org/10.1007/s11205-006-9029-7

Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T., Saisana, M., Saltelli, A., Liska, R., & Tarantola, S. (2008). Creating composite indicators with DEA and robustness analysis: The case of the Technology Achievement Index. *The Journal of the Operational Research Society*, 59(2), 239–251. https://doi.org/10.1057/palgrave.jors.2602445

Cook, W.D., & Zhu, J. (2007). Classifying inputs and outputs in data envelopment analysis. *European Journal of Operational Research,* 692–699.

Christie, A., Brooks, J.T., Hicks, L.A., Sauber-Schatz, E.K., & Yoder, J.S., Honein, M.A. (2021). Guidance for Implementing COVID-19 Prevention Strategies in the Context of Varying Community Transmission Levels and Vaccination Coverage. *Morbidity and Mortality Weekly Report*, 70(30), 1044–1047. https://doi.org/10.15585/mmwr.mm7030e2

Countries where Coronavirus has spread. (2021). *Worldometer*. https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/

Despotis, D.K. (2002). Improving the discriminating power of DEA: focus on globally efficient units. *The Journal of the Operational Research Society*, 53(3), 314-323. http://www.jstor.org/stable/822897

Doğan, M.İ., Özsoy, V.S. & Örkcü, H.H. (2021). Performance management of OECD countries on Covid-19 pandemic: a criticism using data envelopment analysis models. *Journal of Facilities Management*, 19(4), 479-499. https://doi.org/10.1108/JFM-01-2021-0005

El Zowalaty, M.E., & Järhult, J.D. (2020). From SARS to COVID-19: A previously unknown SARS- related coronavirus (SARS-CoV-2) of pandemic potential infecting humans – Call for a One Health approach. *One Health*, 9, 100124. https://doi.org/10.1016/j.onehlt.2020.100124

El Zowalaty, M.E., Young, S.G., & Järhult, J.D. (2020). Environmental impact of the COVID-19 pandemic – a lesson for the future. *Infection Ecology & Epidemiology*, 10(1). https://doi.org/10.1080/20008686.2020.1768023

European Space Agency. (2020). *Air pollution remains low as Europeans stay at home.* https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5P/Air_pollution_remains_low_as_Europeans_stay_at_home

European Space Agency. (2020). *COVID-19: nitrogen dioxide over China*. https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5P/COVID-19_nitrogen_dioxide_over_China

Ferreira, C., Marques, R. C. & Nicola, P. (2013). On evaluating health centers groups in Lisbon and Tagus Valley: efficiency, equity and quality. *BMC Health Services Research*, 13(1), 529.

Ferreira, D.C., Figueira, J.R., Greco, S., & Marques, R. (2021). Data Envelopment Analysis models with imperfect knowledge of input and output values: An application to Portuguese public hospitals. *ArXiv.org*. https://doi.org/10.48550/arXiv.2104.09890

Fried, H., Lovell, C., & Schmidt, S. (2008). Efficiency and productivity. The measurement of productive efficiency and productivity growth. *Oxford University Press*, 3-91

George, B., Verschuere, B., Wayenberg, E., & Zaki, B.L. (2020). A Guide to Benchmarking COVID-19 Performance Data. *PAR: Public Administration Review*. https://doi.org/10.1111/puar.13255

Greco, S., Ishizaka, A., Tasiou, M., & Gianpiero, T. (2019). On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. *Social Indicators Research,* 141, 61–94. https://doi.org/10.1007/s11205-017-1832-9

Grennan, D. (2019). What Is a Pandemic? *JAMA*, 321(9), 910. https://doi.org/10.1001/jama.2019.0700

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, 5, 1–10. https://doi.org/10.1038/s41562-021-01079-8

Härdle W.K., & Simar L. (2015). *Cluster Analysis: Applied Multivariate Statistical Analysis*. Springer Berlin Heidelberg, p. 385-405.

Harrison, J. P., & Sexton, C. (2006). The improving efficiency frontier of religious not-for-profit hospitals. *Hospital Topics*, 84(1), 2-10.

Hartigan, J.A., & Wong, M.A. (1979). A K-Means Clustering Algorithm. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 28: 100-108. https://doi.org/10.2307/2346830

Hermans, E., Van den Bossche, F., & Wets, G. (2008). Combining road safety information in a performance index. *Accident Analysis and Prevention*, 40(4), 1337–1344. https://doi.org/10.1016/j.aap.2008.02.004

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. *European Journal of Operational Research,* 181(1), 425–435. https://doi.org/10.1016/j.ejor.2006.05.019

Hoo, H.E., Loh, H.C., Ch’ng, A.S.H., Hoo F.K., & Looi, I. (2021). Positive Impacts of the COVID-19 Pandemic and Public Health Measures on Healthcare. *PMMB 2021*, 4, 1. https://doi.org/10.36877/pmmb.a0000221

Huguenin, J.-M. (2012). Data Envelopment Analysis (DEA): A pedagogical guide for decision makers in the public sector. *IDHEAP*. ISBN 978-2-940390-54-0. https://serval.unil.ch/resource/serval:BIB_0FC432348A97.P001/REF

Imtyaz, A., Haleem, A., & Javaid, M. (2020). Analyzing governmental response to the COVID-19 pandemic. *Journal of Oral Biology and Craniofacial Research*. 10(4), 504-513, ISSN 2212-4268. https://doi.org/10.1016/j.jobcr.2020.08.005.

International Labor Organization. (2021). *COVID-19 and the world of work*. Seventh edition. https://www.ilo.org/wcmsp5/groups/public/@dgreports/@dcomm/documents/briefingnote/wcms_767028.pdf

Johnson R.A., & Wichern D.W. (2007). *Applied multivariate statistical analysis*. Upper Saddle River, N.J: Pearson Prentice Hall.

Kamel, M.A., & Mousa, M.E.-S. (2021). Measuring operational efficiency of isolation hospitals during COVID-19 pandemic using data envelopment analysis: a case of Egypt", *Benchmarking: An International Journal*, 28(7), 2178-2201. https://doi.org/10.1108/BIJ-09-2020-0481

Karagiannis, R. e Karagiannis, G. (2018). Intra-and inter-group composite indicators using the BoD model. *Socio-Economic Planning Sciences*, 61, 44-51.

Khan, I., Haleem, A., & Javaid, M. (2020). Analyzing COVID-19 pandemic through cases, deaths, and recoveries, *Journal of Oral Biology and Craniofacial Research*. 10(4), 450-469, ISSN 2212-4268. https://doi.org/10.1016/j.jobcr.2020.08.003.

Khan, I., Shah, D. & Shah, S.S. (2020). COVID-19 pandemic and its positive impacts on environment: an updated review. *Int. J. Environ. Sci. Technol*. 18, 521–530. https://doi.org/10.1007/s13762-020-03021-3

Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H., & Lipsitch, M. (2020). Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science*, 368(6493), 860–868. https://doi.org/10.1126/science.abb5793

Krause R.M., Dimmock N.J., & Morens D.M. (1997). Summary of antibody workshop: the role of humoral immunity in the treatment and prevention of emerging and extant infectious diseases. *J Infect Dis*, 176,549–59

Kulshrestha, U.C. (2020). Environmental Changes during COVID-19 Lockdown: Future Implications. *Current World Environment,* 15(1): 01-05

Kuosmanen, T. (2009). Data envelopment analysis with missing data. *Journal of the Operational Research Society*, 60, 1767–1774

Kusche, N., & Tooker, E. (2020). *COVID-19 AND ALTERNATIVE PERFORMANCE MEASURES.* Deloitte. https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/audit/deloitte-covid-19-and-alternative-performance-measures.pdf

Last, J.M. (1988). A dictionary of epidemiology. 2nd ed. *Oxford University Press*

Li, R., Metcalf, C.J. E., Stenseth, N.Chr., & Bjørnstad, O.N. (2021). A general model for the demographic signatures of the transition from pandemic emergence to endemicity. *Science Advances*, 7(33). https://doi.org/10.1126/sciadv.abf9040

Lipsitch, M., & Viboud, C. (2009) Influenza seasonality: lifting the fog. *Proc. Natl. Acad. Sci. U.S.A.,* 106, 3645–3646. https://doi.org/10.1073/pnas.0900933106.

Lipsitch, M. (n.d.) *Seasonality of SARS-CoV-2: Will COVID-19 go away on its own in warmer weather?.* Center for Communicable Disease Dynamics. https://ccdd.hsph.harvard.edu/will-covid-19-go-away-on-its-own-in-warmer-weather/

Little, R.J.A. (1988). Missing Data Adjustments in Large Surveys. *Journal of Business Economics and Statistics*, 6, 287–301

Liua, J.S., Lub, L.Y., & Luc, W.-M. (2016). *Research fronts in data envelopment analysis. Omega*. 58 33–45.

Lovell, C.K., Pastor, J.T., & Turner, J.A. (1995). Measuring macroeconomic performance in the OECD: A comparison of European and non-European countries. *European Journal of Operational Research*, 87(3), 507–518

Madubueze, C.E., Dachollom, S., & Onwubuya, I.O. (2020). Controlling the spread of COVID-19: Optimal control analysis. *Computational and Mathematical methods in Medicine.* https://doi.org/10.1155/2020/6862516

Madzokere, E., & Herrero, L. (2021, September 20). *COVID will likely shift from pandemic to endemic — but what does that mean?*. The Conversation. https://theconversation.com/covid-will-likely-shift-from-pandemic-to-endemic-but-what-does-that-mean-167782

Malik, Y.S., Rajendran, V.O., MA, I., Pande, T., & Ravichandran, K., Jaganathasamy, N., Ganesh, B., Santhakumar, A., Tazerji,S.S, Rahman, M.T., Safdar, M., Dubal, Z.B., Dhama, K. (2021). Responses to COVID-19 in South Asian Association for Regional Cooperation (SAARC) countries in 2020, a data analysis during a world of crises. *Chaos, Solitons & Fractals*. Vol. 152, 111311, ISSN 0960-0779. https://doi.org/10.1016/j.chaos.2021.111311.

Malki, Z., Atlam, E.S., Hassanien, A.E., Dagnew, G., Elhosseini, M.A., & Gad, I. (2020). Association between weather data and COVID-19 pandemic predicting mortality rate: Machine learning approaches. *Chaos, solitons, and fractals*, 138, 110137. https://doi.org/10.1016/j.chaos.2020.110137

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal of Operational Research* 197:792–798. https://doi.org/10.1016/j.ejor.2016.11.008

McNew, D. (2020). *Carbon emissions are falling sharply due to coronavirus. But not for long*. National Geographic. https://www.nationalgeographic.co.uk/environment-and-conservation/2020/04/carbon-emissions-are-falling-sharply-due-coronavirus-not-long

Meldrum D.R., Morris M.A., & Gambone J.C. (2017). Obesity pandemic: causes, consequences, and solutions-but do we have the will?. *Fertility and Sterility*, 107(4),833-839. https://doi.org/10.1016/j.fertnstert.2017.02.104

Min, H., Lee, C.C., & Joo, S.-J. (2021). Assessing the efficiency of the Covid-19 control measures and public health policy in OECD countries from cultural perspectives. *Benchmarking: An International Journal*, ISSN: 1463-5771. https://doi.org/10.1108/BIJ-05-2021-0241

Mitchell, F., Nørreklit, H., Nørreklit, L., Cinquini, L., Koeppe, F., Magnacca, F., Mauro, S.G., Jakobsen, M., Korhonen, T., Laine, T., & Liboriussen, J.M. (2021). Evaluating performance management of COVID-19 reality in three European countries: a pragmatic constructivist study. *Accounting, Auditing and Accountability Journal*, 34(6), 1345-1361. https://doi.org/10.1108/AAAJ-08-2020-4778

Mohanta, K.K., Sharanappa, D.S., & Aggarwal, A. (2021). Efficiency analysis in the management of COVID-19 pandemic in India based on data envelopment analysis. *Current Research in Behavioral Sciences*, Vol. 2, 100063, ISSN 2666-5182. https://doi.org/10.1016/j.crbeha.2021.100063

Moore, S. (2021). *History of COVID-19*. News Medical Life Sciences. https://www.news-medical.net/health/History-of-COVID-19.aspx

Moores, D. (2020). *With COVID-19, the SDGs are even more important.* Development Policy Centre. https://devpolicy.org/with-covid-19-the-sdgs-are-even-more-important-20200616-2/

Morais, P., & Camanho, A.S. (2011). Evaluation of performance of European cities with the aim to promote quality of life improvements. *Omega,* 39(4), 398-409.

Morens, D.M., Folkers, G.K., & Fauci, A.S. (2009). What Is a Pandemic?. *The Journal of Infectious Diseases*, 200(7), 1018-1021. https://doi.org/10.1086/644537

Moritz, S., & Bartz-Beielstein, T. (2017). imputeTS: time series missing value imputation in R. *The R Journal*, *9*(1). ISSN 2073-4859

Moutinho, S. (2021). *Brazilian town experiment shows mass vaccination can wipe out COVID-19*. Science. https://www.science.org/content/article/brazilian-town-experiment-shows-mass-vaccination-can-wipe-out-covid-19

Myers, S.L. (2021). *China's Omnivorous Markets Are in the Eye of a Lethal Outbreak Once Again*. The New York Times. https://www.nytimes.com/2020/01/25/world/asia/china-markets-coronavirus-sars.html

Nardo, M., Saisana, M, Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2008). Handbook on Constructing Composite Indicators and User Guide. *OECD Statistics Working Papers.* https://doi.org/10.1787/533411815016

NASA. (2020). *Data Shows 30 Percent Drop In Air Pollution Over Northeast U.S.* https://www.nasa.gov/feature/goddard/2020/drop-in-air-pollution-over-northeast

NASA. (2020). *NASA Satellite Offers Urban Carbon Dioxide Insights.* https://climate.nasa.gov/news/2957/nasa-satellite-offers-urban-carbon-dioxide-insights/

NASA. (2021). *Local Lockdowns Brought Fast Global Ozone Reductions, NASA Finds*. https://www.nasa.gov/feature/jpl/local-lockdowns-brought-fast-global-ozone-reductions-nasa-finds

Ozcan, Y.A., & McCue, M.J. (1996). Development of a financial performance index for hospitals: DEA approach. *J. Oper. Res. Soc*. 47 (1), 18–26.

Ozcan, Y.A. (2008). *Health Care Benchmarking and Performance Evaluation: An Assessment using Data Envelopment Analysis (DEA).* New York: Springer

Patel, V.R., & Mehta, R.G. (2011). Performance Analysis of MK-means Clustering Algorithm with Normalization Approach. *2011 World Congress on Information and Communication Technologies*, pp. 974-979. https://doi.org/10.1109/WICT.2011.6141380

Pereira, M., Dinis, D., Ferreira, D.C., Figueira, J.R., & MARQUES, R.C. (2022). A network Data Envelopment Analysis to estimate nations' efficiency on the fight against SARS-CoV-2. *Expert Systems with Applications*. Vol. 210, pp. 118-362

Phillips, N. (2021). *The Coronavirus Is Here to Stay - Here's What That Means*. Scientific American. https://www.scientificamerican.com/article/the-coronavirus-is-here-to-stay-heres-what-that-means/

Plumer B., & Popovich N. (2020). *Traffic and Pollution Plummet as U.S. Cities Shut Down for Coronavirus*. New York Times. https://www.nytimes.com/interactive/2020/03/22/climate/coronavirus-usa-traffic.html

Raaijmakers, Q.A.W. (1999). Effectiveness of different missing data treatments in surveys with likert-type data: Introducing the relative mean substitution approach. *Educational and Psychological Measurement*, 59, 725–748

Reilly, M. (1993). Data analysis using hot deck multiple imputation. *Journal of the Royal Statistical Society*, Series D, 42, 307–313

Relationship between income and health. (2021). *The Health Foundation*. https://www.health.org.uk/evidence-hub/money-and-resources/income/relationship-between-income-and-health

Revuelta, I., Santos-Arteaga, F. J., Montagud-Marrahi, E., Ventura-Aguiar, P., Di Caprio, D., Cofan, F., Cucchiari, D., Torregrosa, V., Piñeiro, G. J., Esforzado, N., Bodro, M., Ugalde-Altamirano, J., Moreno, A., Campistol, J. M., Alcaraz, A., Bayès, B., Poch, E., Oppenheimer, F., & Diekmann, F. (2021). A hybrid data envelopment analysis-artificial neural network prediction model for COVID-19 severity in transplant recipients. *Artificial intelligence review*, 54(6), 4653–4684. https://doi.org/10.1007/s10462-021-10008-0

Ritchie, H. (2020). *Short-haul vs. long-haul; rich vs. poor countries: where do global CO2 emissions from aviation come from?*. Our World in Data. https://ourworldindata.org/breakdown-co2-aviation

Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Hasell, J., Macdonald, B., Dattani, S., Beltekian, D., Ortiz-Ospina, E., & Roser, M. (2020). *Coronavirus Pandemic (COVID-19).* Our World in Data. https://ourworldindata.org/covid-vaccinations

Rosenwald, M.S. (2020). *History's deadliest pandemics: Plague, smallpox, flu, covid-19*. The Washington Post. https://www.washingtonpost.com/graphics/2020/local/retropolis/coronavirus-deadliest-pandemics/

Rosko, M.D., & Mutter, R.L. (2010). What Have We Learned From the Application of Stochastic Frontier Analysis to U.S. Hospitals? *Medical Care Research and Review*, 68(1), 75–100. https://doi.org/10.1177/1077558710370686

Rosko, M.D., Wong, H.S., & Mutter, R.L. (2016). Characteristics of High- and Low-Efficiency Hospitals. *Medical Care Research and Review*, 75(4), 454–478. https://doi.org/10.1177/1077558716689197

Santacroce L., Charitos, I.A., & Del Prete, R. (2020). COVID-19 in Italy: An Overview from the First Case to Date. *Electronic Journal of General Medicine*, vol. 17, no. 6, p. em235. https://doi.org/10.29333/ejgm/7926.

Shafey O., Dolwick S., & Guindon G.E. (2003). Tobacco control country profiles. *American Cancer Society*

Shalabi, L.A., Shaaban, Z., & Kasasbeh, B. (2006). Data Mining: A Pre-processing Engine. *Journal of Computer Science*, 2(9), 735-739. https://doi.org/10.3844/jcssp.2006.735.739

Sifuentes-Rodríguez, E., & Palacios-Reyes, D. (2020). COVID-19: The outbreak caused by a new coronavirus. *Boletín médico del Hospital Infantil de México*, *77*(2), 47-53. https://doi.org/10.24875/bmhim.20000039

Simar, L., & Wilson, P. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics,* 136(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009.

Slottje, D.J. (1991). Measuring the quality of life across countries. *Review of Economics and Statistics*, 73(4), 684–693.

Smyth, L. (2020). *Three ways to measure performance in a COVID-19 world*. The CEO Magazine. https://www.theceomagazine.com/business/management-leadership/measure-performance/

Sousa, S., Teixeira, R., & Nunes, E. (2020). Assessing the COVID-19 Performance Indicators Used in the Portuguese Daily Situation Report. *2020 International Conference on Decision Aid Sciences and Application (DASA)*. https://doi.org/10.1109/dasa51403.2020.9317138

Spiteri, G., Fielding, J., Diercke, M., Campese, C., Enouf, V., Gaymard, A., Bella, A., Sognamiglio, P., Sierra Moros, M.J., Riutort, A.N., Demina, Y.V., Mahieu, R., Broas, M., Bengnér, M., Buda, S., Schilling, J., Filleul, L., Lepoutre, A., Saura, C., Mailles, A., … Ciancio, B.C. (2020). First cases of coronavirus disease 2019 (COVID-19) in the WHO European Region, 24 January to 21 February 2020. *Euro surveillance: bulletin Europeen sur les maladies transmissibles = European communicable disease bulletin*, 25(9), 2000178. https://doi.org/10.2807/1560-7917.ES.2020.25.9.2000178

Stedman, T.L. (2006). Stedman's medical dictionary. 28th ed. *Philadelphia: Lippincott, Williams & Wilkins*.

Sueyoshi, T. (2000). Stochastic DEA for restructure strategy: an application to a Japanese petroleum company, *Omega*. 385–398.

Tamboli, N. (2022). *Tackling Missing Value in Dataset*. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2021/10/handling-missing-value/

Taubenberger, J.K., Morens, D.M. (2009). Pandemic influenza: including a risk assessment of H5N1. *Rev Sci Tech*, 28,187–202.

The World Bank. (2021). *The World by Income and Region.* https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html

Thompson, S.A. (2020). *How Long Will a Vaccine Really Take?* The New York Times. https://www.nytimes.com/interactive/2020/04/30/opinion/coronavirus-covid-vaccine.html

Tobin, J. (1958). *Estimation of relationships for limited dependent variables*. Econometrica 26(1):24–36

TomTom Traffic Index. (2020). *TomTom*. https://www.tomtom.com/en_gb/traffic-index/

Torjesen, I. (2021). Covid-19 will become endemic but with decreased potency over time, scientists believe. *BMJ*, 372, n494. https://doi.org/10.1136/bmj.n494

Tziner, A., & Rabenu, E. (2021). The COVID-19 pandemic: A challenge to performance appraisal. *Industrial and Organizational Psychology, 14*(1-2), 173-177. https://doi.org/10.1017/iop.2021.24

UNICEF. (2021). *Education and COVID-19*. https://data.unicef.org/topic/education/covid-19/#status

United Nations. (2021). *Human Development Index*. Human Development Reports. https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

Valich, L. (2020). *Bats offer clues to treating COVID-19*. NewsCenter, University of Rochester. https://www.rochester.edu/newscenter/bats-offer-clues-to-treating-covid-19-443332/

van Buuren, S., & Oudshoorn, K. (2000). Multivariate Imputation by Chained Equations: MICE V1.0 User's Manual. *Netherlands Organization for Applied Scientific Research Prevention and Health*. ISBN-number 90-6743-677-1

Verma, A. (2019). Sustainable Development and Environmental Ethics. *International Journal on Environmental Sciences*, 10(1), 1-5, https://www.researchgate.net/publication/342624965_SUSTAINABLE_DEVELOPMENT_AND_ENVIRONMENTAL_ETHICS

Verma, A.K., & Prakash, S. (2020). Impact of COVID-19 on Environment and Society. *Journal of Global Biosciences*, 9(5), 7352-7363. https://ssrn.com/abstract=3644567

Vidoli, F., & Fusco, E. (2015). Package 'Compind'. *CRAN*

Vidoli, F., & Fusco, E. (2018). Compind: Composite indicators functions based on frontiers in R (Compind package version 2.0). *CRAN*

Walker, P., Whittaker, C., Watson, O. J., Baguelin, M., Winskill, P., Hamlet, A., Djafaara, B.A., Cucunubá, Z., Olivera Mesa, D., Green, W., Thompson, H., Nayagam, S., Ainslie, K., Bhatia, S., Bhatt, S., Boonyasiri, A., Boyd, O., Brazeau, N.F., Cattarino, L., Cuomo-Dannenburg, G., …, & Ghani, A.C. (2020). The impact of COVID-19 and strategies for mitigation and suppression in low- and middle-income countries. *Science*, 369(6502), 413–422. https://doi.org/10.1126/science.abc0035

Watts, J. (2020). *Climate crisis: in coronavirus lockdown, nature bounces back – but for how long?*. The Guardian. https://www.theguardian.com/world/2020/apr/09/climate-crisis-amid-coronavirus-lockdown-nature-bounces-back-but-for-how-long

Wells, C.R., Townsend, J.P., Pandey, A., Moghadas, S.M., Krieger, G., Singer, B., McDonald, R.H., Fitzpatrick, M.C., & Galvani, A.P. (2020). Optimal COVID-19 quarantine and testing strategies. *Nature Communications*, 12(1), 1–9. https://doi.org/10.1038/s41467-020-20742-8

Woolhouse, M.E., Howey, R., Gaunt, E., Reilly, L., Chase-Topping, M., & Savill, N. (2008). Temporal trends in the discovery of human viruses. *Proceedings of the Royal Society B.*, 275(1647), 2111–2115. https://doi.org/10.1098/rspb.2008.0294

World Health Organization. (n.d.). *Naming the coronavirus disease (COVID-19) and the virus that causes it.* https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it

World Health Organization. (2019). *Air pollution*. https://www.who.int/health-topics/air-pollution

World Health Organization. (2021). *Advice for the public on COVID-19*. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public

World Health Organization. (2022). *Tracking SARS-CoV-2 variants*. https://www.who.int/en/activities/tracking-SARS-CoV-2-variants/

Yang, F.C., Kao, R.H., Chen, Y.T., Ho, Y.F., Cho, C.C., & Huang, S.W. (2017). A common weight approach to construct composite indicators: The evaluation of fourteen emerging markets. *Social Indicators Research*, 137, 463–479. https://doi.org/10.1007/s11205-017-1603-7

Zanella, A., Camanho, A.S., & Dias, T.G. (2013). Benchmarking countries' environmental performance. *Journal of the Operational Research Society*, 64(3), 426-438. https://doi.org/10.1057/jors.2012.62

Zhou, H., Yang, Y., Chen, Y., & Zhu J. (2018). Data envelopment analysis application in sustainability: The origins, development and future directions*. European Journal of Operational Research,* 264, 1–16

Zimmer, C., Corum, J., & Wee, S. (2022). *Coronavirus Vaccine Tracker*. The New York Times. https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html

Appendix A

Additional Figures

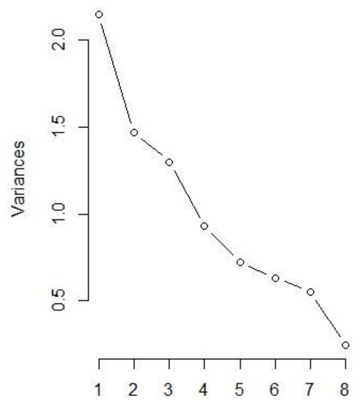

Figure a1– Scree plot to identify the ideal number of PCs to handle using screeplot function in r (Source: The author)

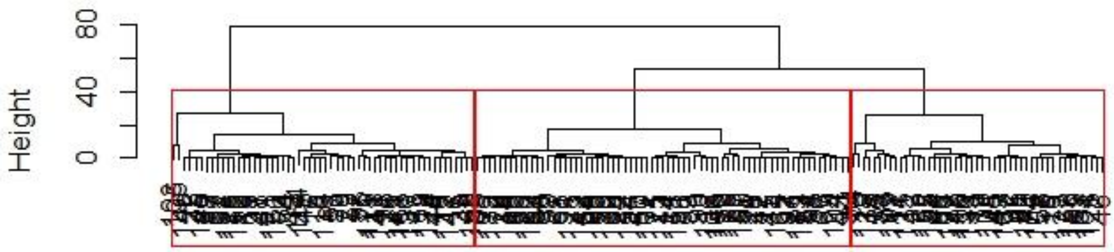

Figure a2 – Cluster Ward Dendrogram for the normalized data and after performing PCA using hclust function in r (Source: The author)

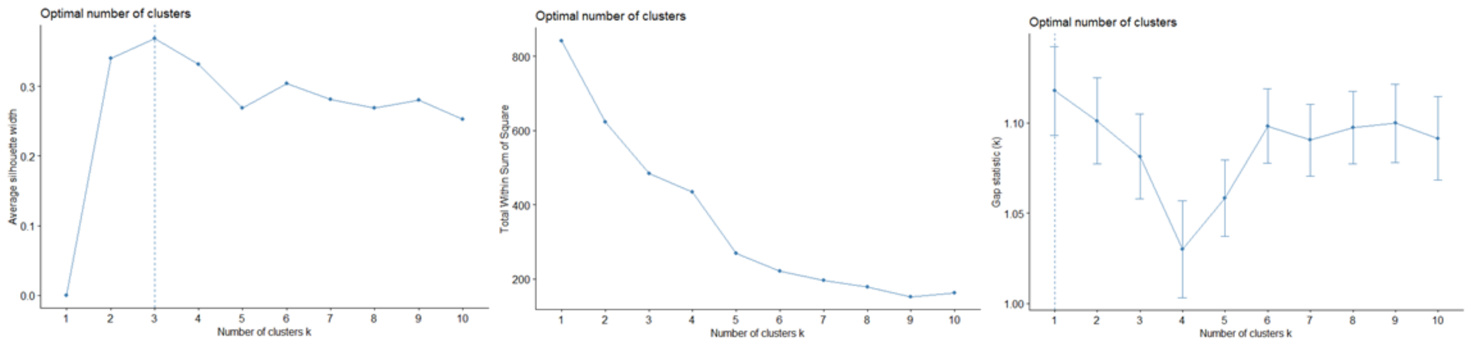

Figure a3 -Optimal number of clusters employing (a) silhouette, (b) wss and (c) gap statistic methods using fviz_nbclust function from r (Source: The author)

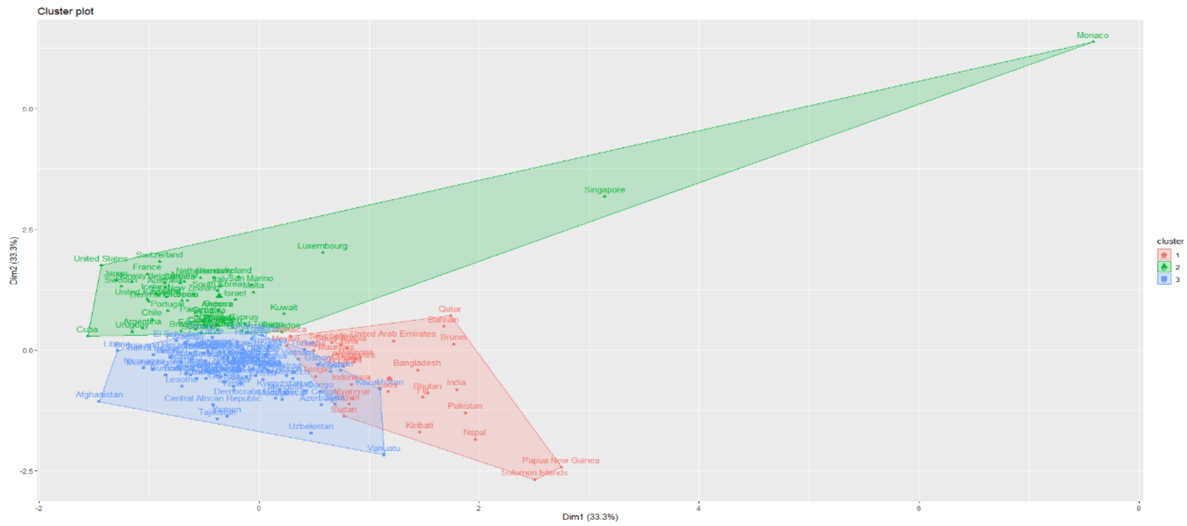

Figure a4 – Cluster plot obtained with k-means in r (Source: The author)

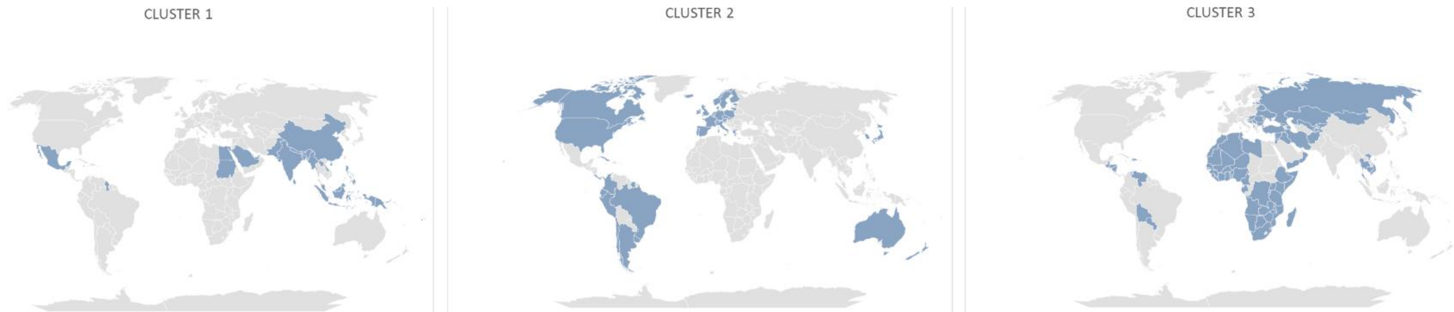

Figure a5 – Countries' geographic location from (a) cluster 1, (b) cluster 2, (c) cluster 3 (Source: The author)

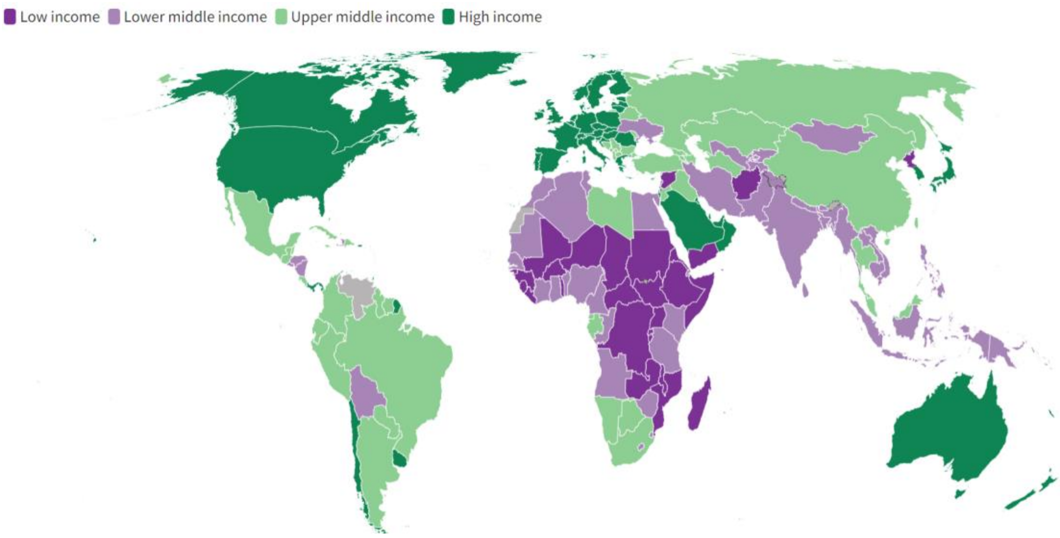

Figure a6 – Countries' geographic location by income groups (Source: The World Bank, 2021)

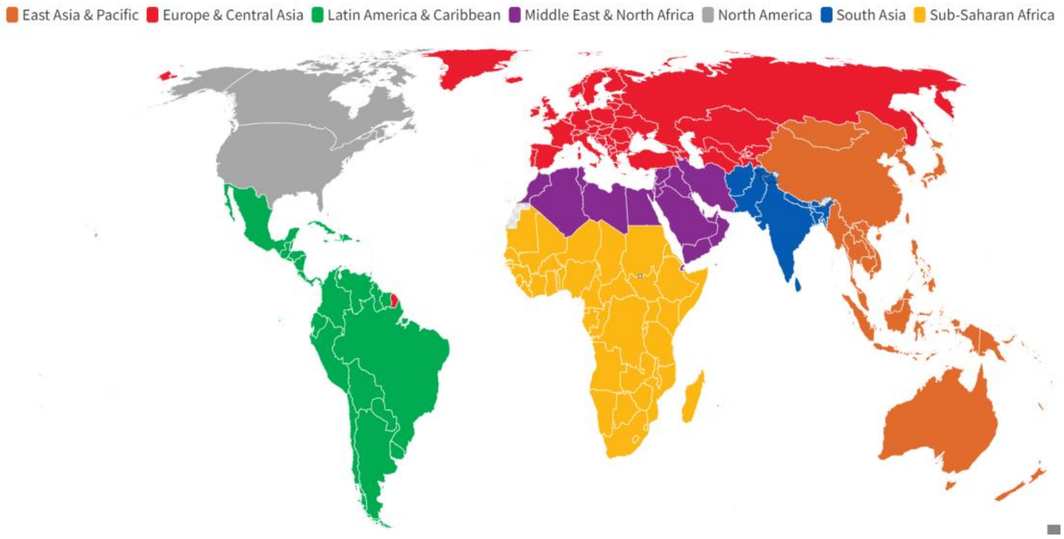

Figure a7 - Countries' geographic location by region groups (Source: The World Bank, 2021)

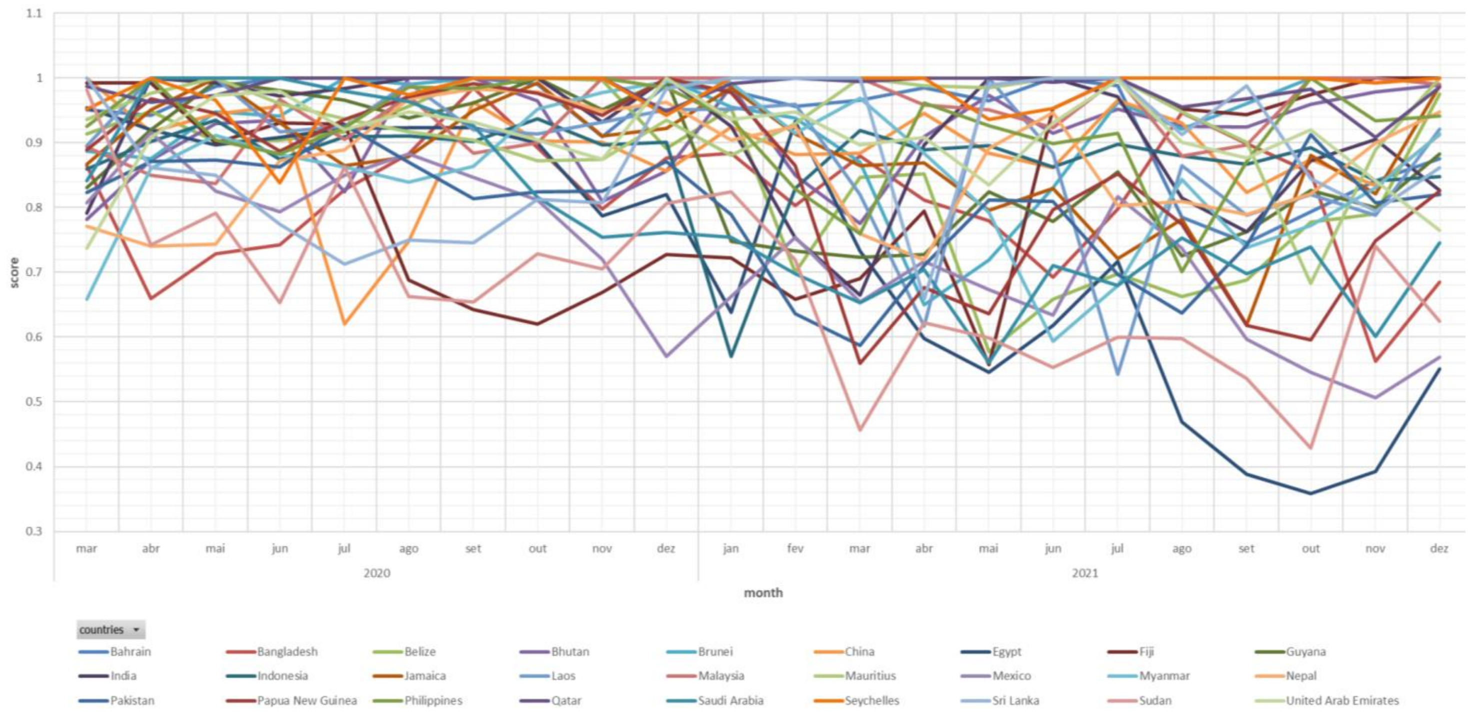

Figure a8 – Efficiency scores obtained for CI 1 in each month per country during the whole period of analysis for cluster 1 (Source: The author)[42]

[42] It is difficult to track countries' efficiency since it is accounted so many DMUs in the same graph. Therefore, it is recommended to see it on excel since it is possible to choose the country (or group of countries) to analyze. The same applies for Figures a11. See excel files in cloud: DIMENSION_cluster1_bod_scores_normalization-method-3.xlsx / FINAL_cluster1_bod_scores_normalization-method-3.xlsx

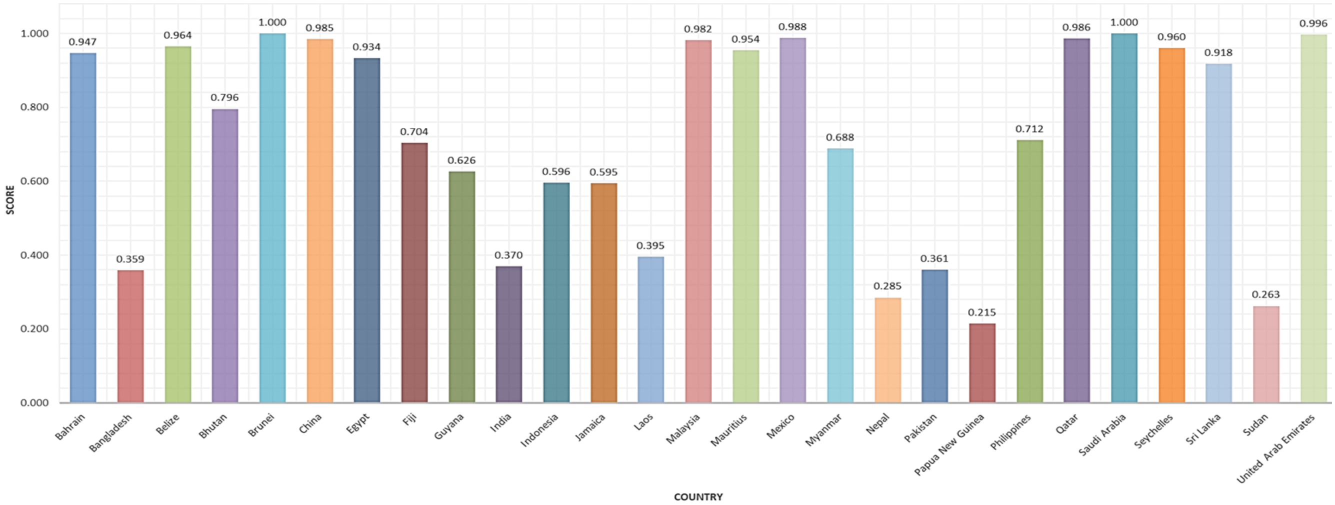

Figure a9 – Efficiency scores obtained for CI 2 per country during the whole period of analysis for cluster 1 (Source: The author)

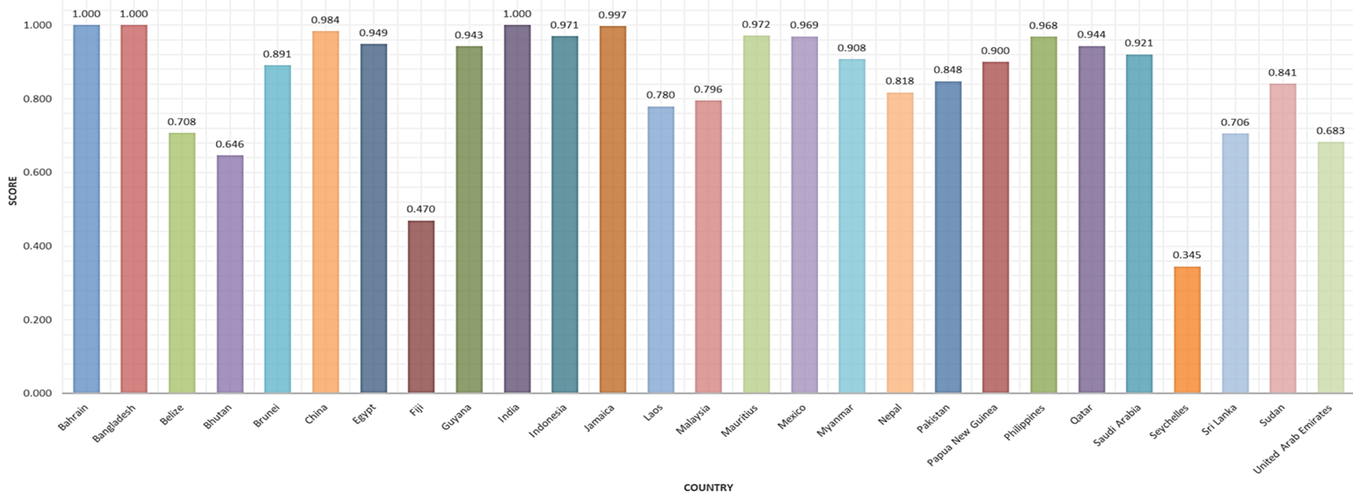

Figure a10 - Efficiency scores obtained for CI 3 per country during the whole period of analysis for cluster 1 (Source: The author)

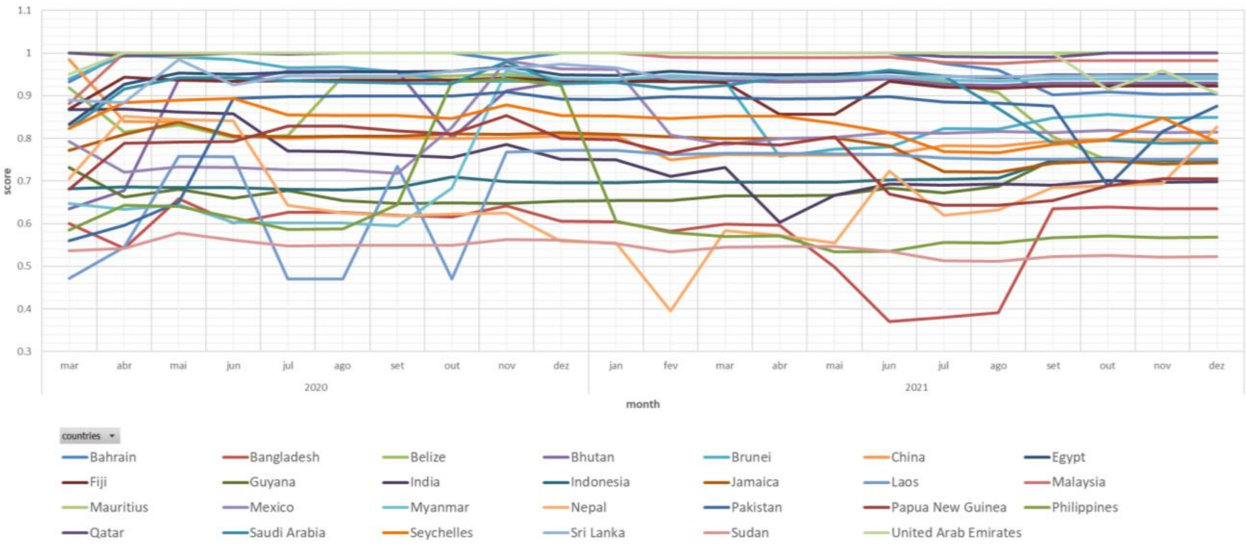

Figure a11 - Efficiency scores obtained for CI 4 in each month per country during the whole period of analysis for cluster 1 (Source: The author

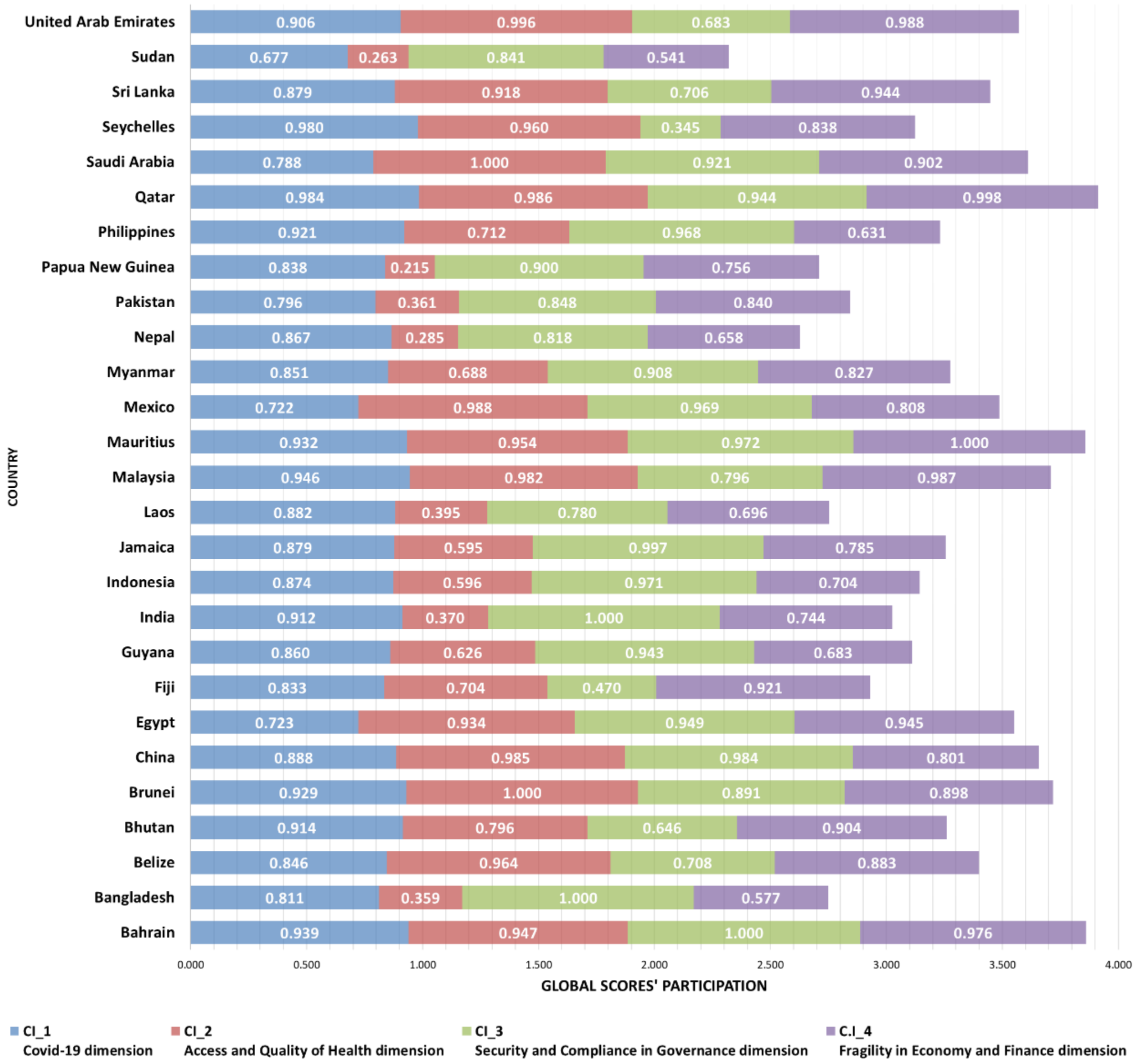

Figure a12 - Composite indicators (using global scores) participation for each country, cluster 1 (Source: The author)

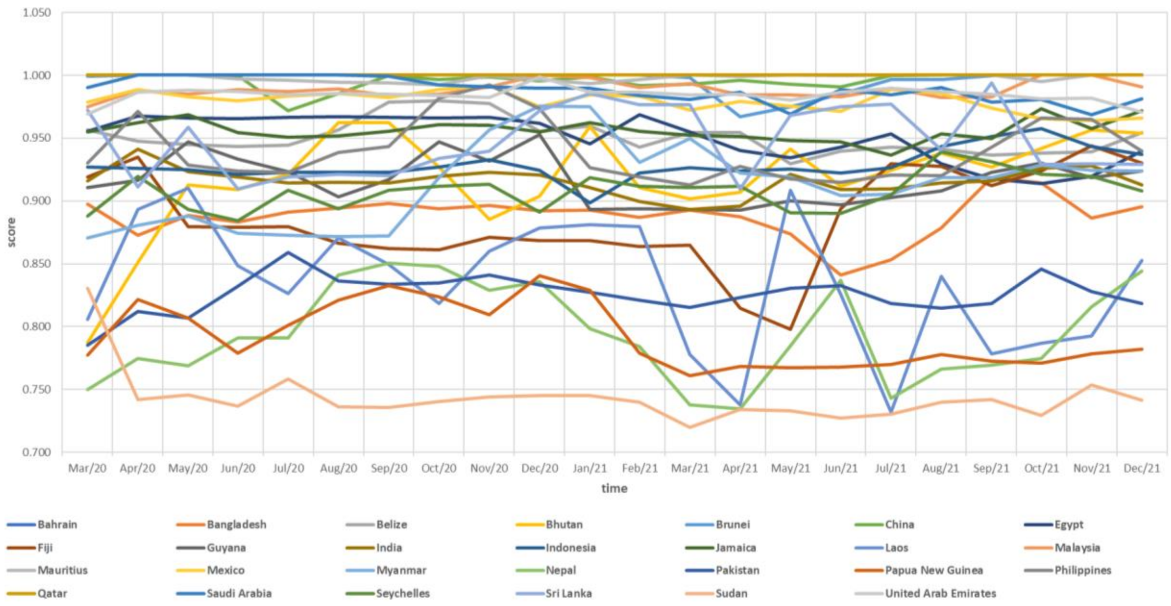

Figure a13 - Efficiency scores obtained for final CI in each month per country during the whole period of analysis for cluster 1 (Source: The author)

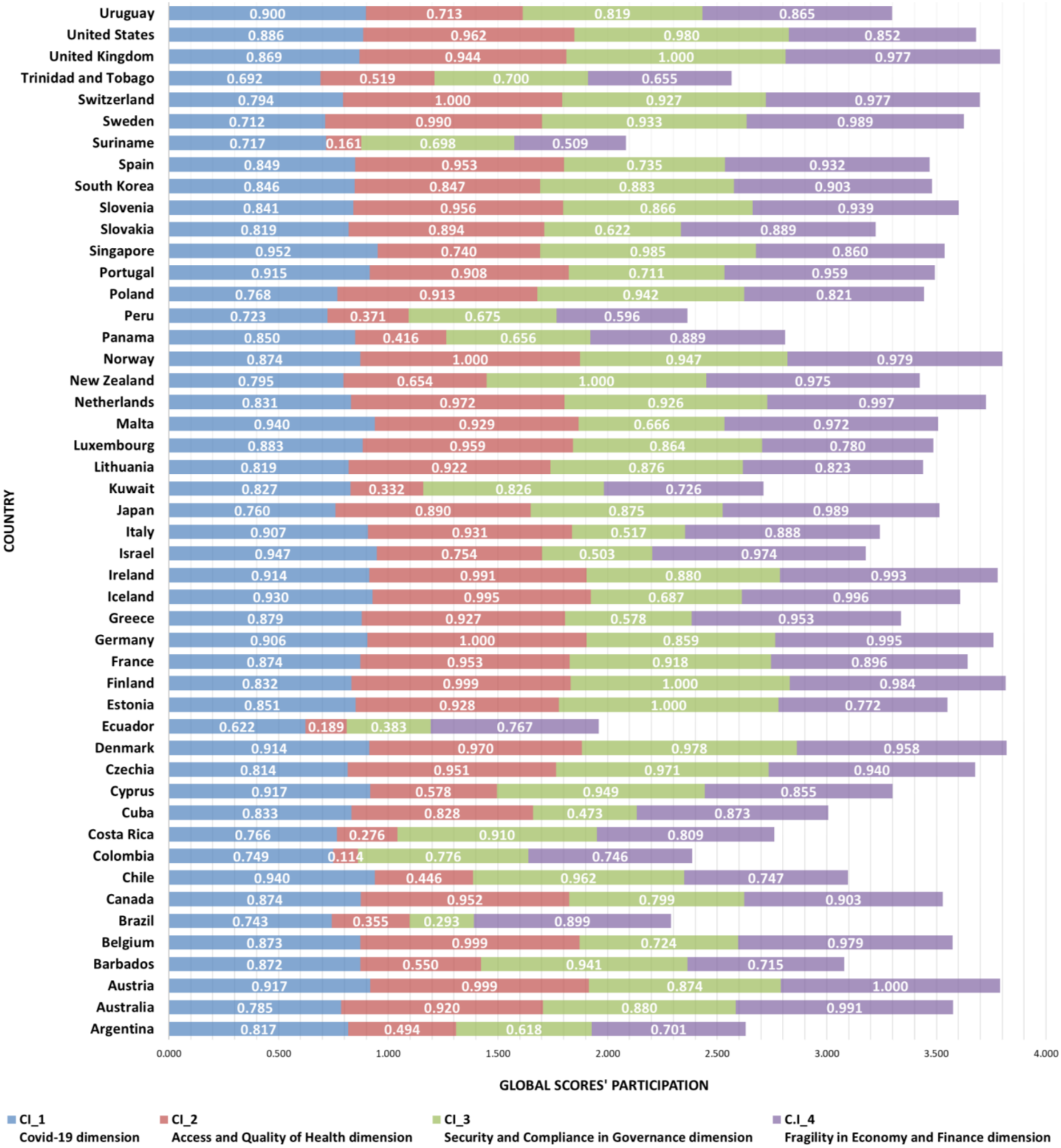

Figure a14 - Composite indicators (using global scores) participation for each country, cluster 2 (Source: The author)

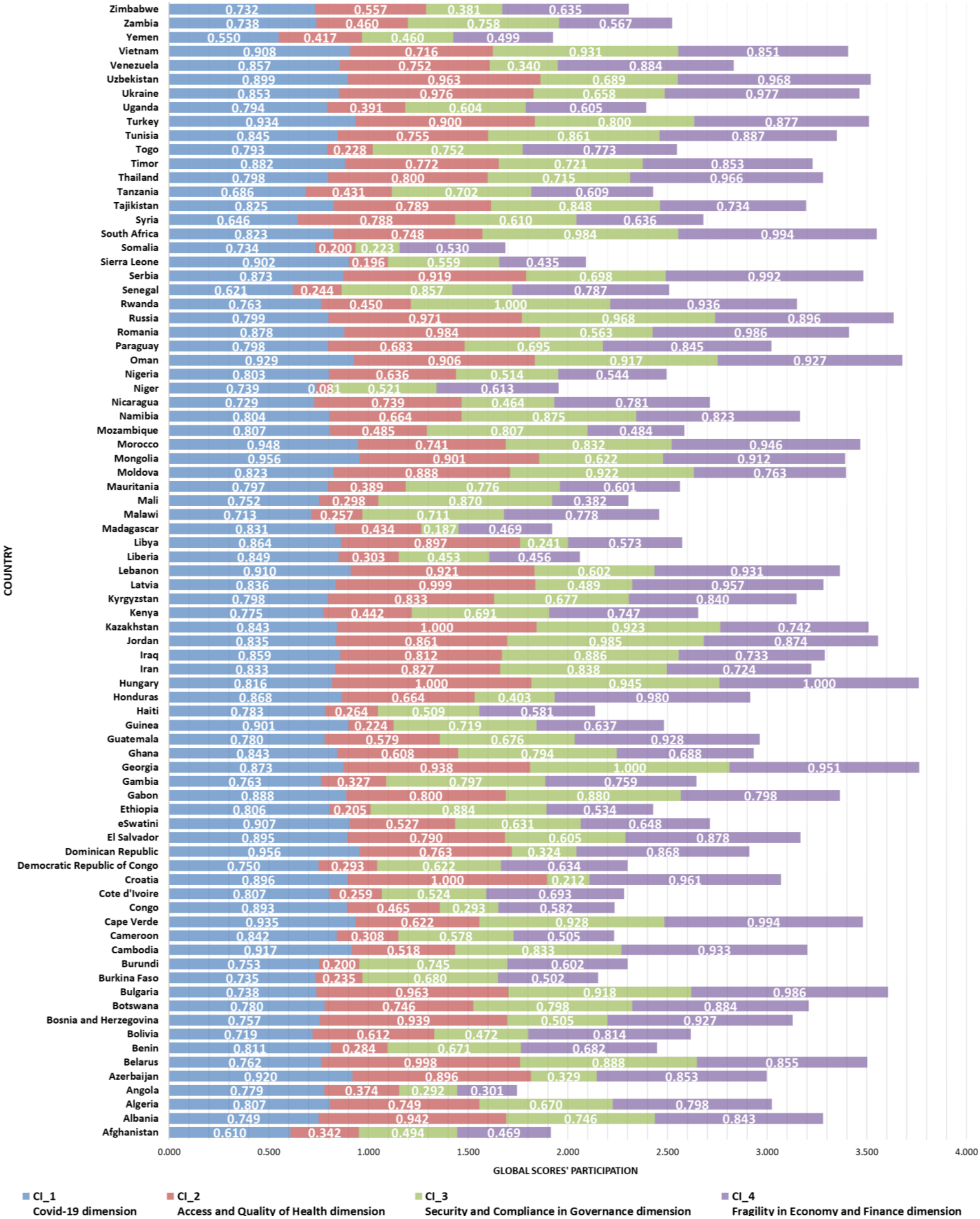

Figure a15 - Composite indicators (using global scores) participation for each country, cluster 3 (Source: The author)

Appendix B

Additional Tables

Table b1 - Descriptive statistics of dimension 1 variables (NOTE: values before normalization) (Source: The author)

Variables		Min	Max	Mean	St. Dev.
1.1.1	total_tests_pt	0.002	21654.089	588.400	1345.000
1.1.2	positive rate	0.000	0.977	0.094	0.100
1.1.3	total vaccinations ph	0.000	272.800	26.260	47.150
1.1.4	people_vaccinated_ph	0.000	98.900	14.500	24.080
1.1.5	people fully vaccinated ph	0.000	90.750	11.280	20.860
1.1.6	total_boosters_ph	0.000	57.450	2.052	6.478
1.2.1	school closures	0.000	3.000	1.736	0.989
1.2.2	workplace_closing	0.000	3.000	1.549	0.825
1.2.3	cancel public events	0.000	3.000	1.507	0.643
1.2.4	restrictions on gatherings	0.000	4.000	2.823	1.258
1.2.5	public_transportation	0.000	2.000	0.597	0.649
1.2.6	stay at home order	0.000	3.000	1.104	0.852
1.2.7	restrictions_on_internal_movement	0.000	2.000	0.911	0.841
1.2.8	international travel controls	0.000	4.000	2.558	1.027
1.2.9	public information campaigns	0.000	2.000	1.912	0.297
1.2.10	testing_policy	0.000	3.000	2.092	0.813
1.2.11	contact tracing	0.000	2.000	1.392	0.686
1.2.12	facial_coverings	0.000	4.000	2.571	1.155
1.2.13	vaccination policy	0.000	5.000	1.776	2.032
1.2.14	protection_of_elderly_people	0.000	3.000	1.367	1.013
1.3.1	fatality ratio	0.000	0.291	0.025	0.029
1.3.2	excess mortality cummulative pm	1.000	9884.775	2649.000	1291.000
1.3.3	reproduction_rate	0.000	3.729	1.036	0.332

Table b2 – Spearman's correlation coefficients of dimension 1 variables (Source: The author)

	1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.1.6	1.2.1	1.2.2	1.2.3	1.2.4	1.2.5	1.2.6	1.2.7	1.2.8	1.2.9	1.2.10	1.2.11	1.2.12	1.2.13	1.2.14	1.3.1	1.3.2	1.3.3
1.1.1 total_tests_pt	1.000	-0.064	0.712	0.716	0.690	0.474	-0.346	-0.025	-0.067	0.113	-0.147	-0.167	-0.193	-0.212	0.093	0.491	0.088	0.186	0.674	0.034	-0.144	0.481	-0.135
1.1.2 positive_rate	-0.064	1.000	0.032	0.034	0.018	0.023	0.110	0.098	0.070	0.097	0.095	0.160	0.086	-0.132	-0.021	-0.058	-0.126	0.201	0.006	-0.009	0.118	0.186	0.038
1.1.3 total_vaccinations_ph	0.712	0.032	1.000	0.992	0.956	0.673	-0.319	-0.029	-0.097	0.031	-0.068	-0.086	-0.160	-0.234	0.059	0.446	0.022	0.232	0.889	-0.010	-0.141	0.548	-0.124
1.1.4 people_vaccinated_ph	0.716	0.034	0.992	1.000	0.956	0.673	-0.313	-0.020	-0.091	0.039	-0.058	-0.076	-0.151	-0.233	0.065	0.452	0.021	0.237	0.894	-0.003	-0.140	0.547	-0.126
1.1.5 people_fully_vaccinated_ph	0.690	0.018	0.956	0.956	1.000	0.685	-0.331	-0.045	-0.111	0.012	-0.065	-0.089	-0.163	-0.237	0.055	0.440	-0.001	0.224	0.898	-0.031	-0.130	0.545	-0.128
1.1.6 total_boosters_ph	0.474	0.023	0.673	0.673	0.685	1.000	-0.317	-0.128	-0.132	-0.110	-0.077	-0.137	-0.141	-0.257	-0.026	0.333	-0.093	0.131	0.717	-0.103	-0.063	0.439	-0.075
1.2.1 school_closures	-0.346	0.110	-0.319	-0.313	-0.331	-0.317	1.000	0.513	0.509	0.366	0.401	0.435	0.479	0.356	0.180	-0.154	0.054	0.060	-0.318	0.263	0.077	-0.207	0.073
1.2.2 workplace_closing	-0.025	0.098	-0.029	-0.020	-0.045	-0.128	0.513	1.000	0.588	0.502	0.415	0.495	0.462	0.260	0.208	0.023	0.126	0.158	-0.044	0.371	0.067	-0.004	0.034
1.2.3 cancel_public_events	-0.067	0.070	-0.097	-0.091	-0.111	-0.132	0.509	0.588	1.000	0.599	0.356	0.444	0.446	0.248	0.200	0.016	0.089	0.184	-0.078	0.281	0.036	-0.009	0.031
1.2.4 restrictions_on_gatherings	0.113	0.097	0.031	0.039	0.012	-0.110	0.366	0.502	0.599	1.000	0.341	0.426	0.338	0.187	0.236	0.108	0.116	0.266	0.027	0.296	0.009	0.082	-0.019
1.2.5 public_transportation	-0.147	0.095	-0.068	-0.058	-0.065	-0.077	0.401	0.415	0.356	0.341	1.000	0.440	0.502	0.234	0.095	-0.029	0.010	0.090	-0.054	0.263	0.054	-0.040	0.031
1.2.6 stay_at_home_order	-0.167	0.160	-0.086	-0.076	-0.089	-0.137	0.435	0.495	0.444	0.426	0.440	1.000	0.550	0.174	0.113	-0.040	0.049	0.239	-0.092	0.404	0.069	0.011	0.013
1.2.7restrictions_on_internal_movement	-0.193	0.086	-0.160	-0.151	-0.163	-0.141	0.479	0.462	0.446	0.338	0.502	0.550	1.000	0.267	0.087	-0.135	-0.008	0.137	-0.161	0.266	0.074	-0.057	0.052
1.2.8 international_travel_controls	-0.212	-0.132	-0.234	-0.233	-0.237	-0.257	0.356	0.260	0.248	0.187	0.234	0.174	0.267	1.000	0.187	-0.085	0.135	-0.125	-0.217	0.193	-0.029	-0.298	0.063
1.2.9 public_information_campaigns	0.093	-0.021	0.059	0.065	0.055	-0.026	0.180	0.208	0.200	0.236	0.095	0.113	0.087	0.187	1.000	0.167	0.272	0.243	0.069	0.182	-0.010	0.039	-0.009
1.2.10 testing_policy	0.491	-0.058	0.446	0.452	0.440	0.333	-0.154	0.023	0.016	0.108	-0.029	-0.040	-0.135	-0.085	0.167	1.000	0.209	0.214	0.466	0.108	-0.122	0.271	-0.062

1.2.11 contact_tracing	0.088	-0.126	0.022	0.021	-0.001	-0.093	0.054	0.126	0.089	0.116	0.010	0.049	-0.008	0.135	0.272	0.209	1.000	0.078	-0.009	0.163	-0.140	-0.039	0.023
1.2.12 Facial_coverings	0.186	0.201	0.232	0.237	0.224	0.131	0.060	0.158	0.184	0.266	0.090	0.239	0.137	-0.125	0.243	0.214	0.078	1.000	0.227	-0.007	-0.033	0.313	-0.129
1.2.13 vaccination_policy	0.674	0.006	0.889	0.894	0.898	0.717	-0.318	-0.044	-0.078	0.027	-0.054	-0.092	-0.161	-0.217	0.069	0.466	-0.009	0.227	1.000	-0.019	-0.114	0.542	-0.120
1.2.14protection_of_elderly_people	0.034	-0.009	-0.010	-0.003	-0.031	-0.103	0.263	0.371	0.281	0.296	0.263	0.404	0.266	0.193	0.182	0.108	0.163	-0.007	-0.019	1.000	0.095	-0.063	0.069
1.3.1 fatality_ratio	-0.144	0.118	-0.141	-0.140	-0.130	-0.063	0.077	0.067	0.036	0.009	0.054	0.069	0.074	-0.029	-0.010	-0.122	-0.140	-0.033	-0.114	0.095	1.000	0.106	-0.047
1.3.2 excess _mortality_cummulative_...	0.481	0.186	0.548	0.547	0.545	0.439	-0.207	-0.004	-0.009	0.082	-0.040	0.011	-0.057	-0.298	0.039	0.271	-0.039	0.313	0.542	-0.063	0.106	1.000	-0.154
1.3.3 reproduction_rate	-0.135	0.038	-0.124	-0.126	-0.128	-0.075	0.073	0.034	0.031	-0.019	0.031	0.013	0.052	0.063	-0.009	-0.062	0.023	-0.129	-0.120	0.069	-0.047	-0.154	1.000

Table b3 - Descriptive statistics of dimension 2 variables (NOTE: values before normalization) (Source: The author)

Variable		Min	Max	Mean	Standard deviation
2.1.1	**access_handwashing_facilities**	1.188	98.999	67.601	31.402
2.1.2	**human_development_index**	0.394	0.957	0.731	0.150
2.2.1	**hospital_beds_pt**	0.100	13.050	2.862	2.398
2.2.2	**medical_doctors_ptt**	0.230	84.199	20.449	17.551
2.2.3	**nursing_midwifery_personnel_ptt**	1.119	229.454	48.389	47.423
2.2.4	**haq_index**	32.500	93.600	64.794	16.402

Table b4 – Pearson's correlation coefficients of dimension 2 variables (Source: The author)

Variables	2.1.1	2.1.2	2.2.1	2.2.2	2.2.3	2.2.4
2.1.1 access_handwashing_facilities	1.000	0.807	0.486	0.714	0.507	0.791
2.1.2 human_development_index	0.807	1.000	0.580	0.799	0.727	0.922
2.2.1 hospital_beds_pt	0.486	0.580	1.000	0.596	0.506	0.550
2.2.2 medical_doctors_ptt	0.714	0.799	0.596	1.000	0.676	0.794
2.2.3 nursing_midwifery_personnel_ptt	0.507	0.727	0.506	0.676	1.000	0.711
2.2.4 haq_index	0.791	0.922	0.550	0.794	0.711	1.000

Table b5 – Descriptive statistics of dimension 3 variables (NOTE: values before normalization; variable 3.2.2 was removed from the analysis – see section 5.2) (Source: The author)

Variables		Min	Max	Mean	Standard deviation
3.1.1	**transp_accountability_index**	21.000	80.000	55.481	13.713
3.1.2	**corruption_perception_index**	10.000	88.000	43.955	19.207
3.2.1	**public_trust_in_politicians**	1.324	6.420	3.131	1.192
~~**3.2.2**~~	~~**state_legitimacy**~~	~~0.500~~	~~10.000~~	~~5.604~~	~~2.826~~
3.2.3	**score_national_DRR_sendai**	0.000	1.000	0.622	0.315
3.2.4	**proport_local_DDR_national_DDR**	0.000	1.000	0.592	0.417

Table b6 – Pearson's correlation coefficients of dimension 3 variables (NOTE: variable 3.2.2 was removed from the analysis due to the high correlation) (Source: The author)

Variables	3.1.1	3.1.2	3.2.1	3.2.2	3.2.3	3.2.4
3.1.1 transp_accountability_index	1.000	0.740	0.204	-0.811	-0.094	0.051
3.1.2 corruption_perception_index	0.740	1.000	0.614	-0.844	-0.017	0.077
3.2.1 public_trust_in_politicians	0.204	0.614	1.000	-0.368	0.086	0.175
3.2.2 state_legitimacy	-0.811	-0.844	-0.368	1.000	0.030	-0.058
3.2.3 score_national_DRR_sendai	-0.094	-0.017	0.086	0.030	1.000	0.214
3.2.4 proport_local_DDR_national_DDR	0.051	0.077	0.175	-0.058	0.214	1.000

Table b7 – Descriptive statistics of dimension 4 variables (NOTE: values before normalization) (Source: The author)

Variables		Min	Max	Mean	St. deviation
4.1.1	**healthexpenditure_GDP**	2.08	16.77	6.387	2.57
4.1.2	**population_covered_by_health_insurance (%)**	0	100	62.077	39.208
4.2.1	**economic_decline_indicator**	1.2	9.8	5.662	2.095
4.2.2	**economic_globalization_index**	28.802	94.28	58.941	16.684
4.2.3	**dir_economic_loss_attributed_to_disasters_in_relation_to_GDP**	0	0.05	0.005	0.008
4.3.1	**income_support**	0	2	0.881	0.746
4.3.2	**debt_contract_relief**	0	2	1.017	0.812

Table b8 – Pearson's correlation coefficients of dimension 4 variables (Source: The author)

Variables	4.1.1	4.1.2	4.2.1	4.2.2	4.2.3
4.1.1 healthexpenditure_GDP	1.000	0.304	-0.250	0.395	-0.017
4.1.2 population_covered_by_health_insurance (%)	0.304	1.000	-0.563	0.618	-0.257
4.2.1 economic_decline_indicator	-0.250	-0.563	1.000	-0.669	0.218
4.2.2 economic_globalization_index	0.395	0.618	-0.669	1.000	-0.202
4.2.3 dir_economic_loss_attributed_to_disasters_in_relation_to_GDP	-0.017	-0.257	0.218	-0.202	1.000

Table b9 – Spearman's correlation coefficients between variables 4.3.1 and 4.3.2 from dimension 4 (NOTE: since these two variables from dimension 4 are time series the correlation had to be done in separate and was used Spearman's instead of Pearson's since it is more adequate for time series data) (Source: The author)

Variables	4.3.1	4.3.2
4.3.1 income_support	1.000	0.376
4.3.2 debt_contract_relief	0.376	1.000

Table b10 - Variables and imputation method used to estimate the missing values (NOTE: Variables with "no missing data" refers to the final 156 countries) (Source: Author)

Variables/KPIs/Indicators	Time Period		Imputation Method				
	Yearly	Monthly	Linear Interpolation / ImputeTS package	Predictive Mean Matching / MICE package	Mean Imputation	Hot-deck Imputation	Cold-deck imputation
1.1.1 Total Tests Per Thousand		X	✓				
1.1.2 Positive Rate		X	✓				
1.1.3 Total Vaccinations Per Hundred		X	✓				
1.1.4 People Vaccinated Per Hundred		X	✓				
1.1.5 People Fully Vaccinated Per Hundred		X	✓				
1.1.6 Total Boosters Per Hundred		X	✓				
1.2.1 School Closures		X	*(No missing data)*				
1.2.2 Workplace closing		X	*(No missing data)*				
1.2.3 Cancel Public Events		X	*(No missing data)*				
1.2.4 Restrictions on gatherings		X	*(No missing data)*				
1.2.5 Public Transportation		X	*(No missing data)*				
1.2.6 Stay at Home Order		X	*(No missing data)*				
1.2.7 Restrictions on Internal Movement		X	*(No missing data)*				
1.2.8 International Travel Controls		X	*(No missing data)*				
1.2.9 Public Information Campaigns		X	*(No missing data)*				
1.2.10 Testing Policy		X	*(No missing data)*				
1.2.11 Contact tracing		X	*(No missing data)*				
1.2.12 Facial coverings		X	*(No missing data)*				
1.2.13 Vaccination policy		X	*(No missing data)*				
1.2.14 Protection of elderly people		X	*(No missing data)*				
1.3.1 Fatality Ratio		X	✓				
1.3.2 Excess Mortality Cumulative Per Million		X	✓				
1.3.3 Reproduction Rate		X	✓				
2.1.1 Share of Population with Access to Basic …	X (2020)					✓	
2.1.2 Human Development Index	X (2021)					✓	
2.2.1 Hospital beds per 1 000	X (2021)						✓
2.2.2 Medical Doctors per 10 000 population	X (2020)		*(No missing data)*				
2.2.3 Nursing and midwifery personnel per 10 000	X (2020)		*(No missing data)*				
2.2.4 Healthcare Access and Quality Index	X (2015)		*(No missing data)*				
3.1.1 Transparency Accountability Index	X (2010)					✓	✓
3.1.2 Corruption Perception Index	X (2018)					✓	
3.2.1 Public trust in politicians	X (2018)					✓	✓
3.2.2 State legitimacy	X (2021)		*(No missing data)*				
3.2.3 Score of adoption and implementation …	X (2020)			✓			✓
3.2.4 Proportion of local governments that adopt…	X (2020)			✓			✓
4.1.1 Total health expenditure as percentage of …	X (2019)						✓
4.1.2 Population covered by health insurance (%)	X (2011)				✓	✓	
4.2.1 Economic decline indicator	X (2021)		*(No missing data)*				
4.2.2 Economic globalization index	X (2019)					✓	
4.2.3 Direct economic loss attributed to disasters	X (2020)			✓			
4.3.1 Income Support		X	*(No missing data)*				
4.3.2 Debt/contract relief for households		X	*(No missing data)*				

Table b11 - Countries ranks in each composite indicator/dimension over time, cluster 1 (NOTE: listed by rankings average) (Source: The author)

	Time-period 1 (Mar-Aug 2020)				Time-period 2 (Set 2020 - Feb 2021)				Time-period 3 (Mar - Aug 2021)				Time-period 4 (Set - Dec 2021)				
countries	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	AVERAGE
Qatar	1	5	11	2	2	5	11	1	1	5	11	3	6	5	11	2	5.125
Bahrain	2	11	1	4	4	11	1	5	5	11	1	4	19	11	1	10	6.313
Mauritius	7	10	6	1	17	10	6	1	2	10	6	1	9	10	6	1	6.438
Brunei	8	1	16	6	3	1	16	9	13	1	16	14	2	1	16	11	8.375
Malaysia	17	7	20	5	5	7	20	4	4	7	20	5	4	7	20	3	9.688
China	21	6	5	14	16	6	5	19	7	6	5	18	12	6	5	15	10.375
United Arab Emirates	15	3	24	3	13	3	24	1	8	3	24	1	13	3	24	6	10.500
Saudi Arabia	3	1	13	10	24	1	13	11	25	1	13	11	24	1	13	16	11.250
Egypt	13	12	10	8	22	12	10	7	26	12	10	6	27	12	10	4	12.563
Mexico	22	4	8	20	26	4	8	14	24	4	8	16	26	4	8	12	13.000
Seychelles	6	9	27	11	1	9	27	15	3	9	27	15	1	9	27	14	13.125
India	4	22	1	15	12	22	1	21	10	22	1	22	14	22	1	23	13.313
Jamaica	14	20	4	16	10	20	4	17	17	20	4	17	16	20	4	21	14.000
Philippines	10	15	9	24	7	15	9	20	12	15	9	25	7	15	9	26	14.188
Sri Lanka	25	13	23	7	19	13	23	6	6	13	23	7	8	13	23	5	14.188
Belize	12	8	22	12	14	8	22	8	21	8	22	9	21	8	22	17	14.625
Bhutan	19	14	25	13	15	14	25	12	9	14	25	10	5	14	25	8	15.438
Myanmar	23	17	14	23	9	17	14	16	18	17	14	8	20	17	14	7	15.500
Indonesia	18	19	7	21	21	19	7	23	11	19	7	21	11	19	7	20	15.625
Fiji	16	16	26	9	27	16	26	10	14	16	26	12	3	16	26	9	16.750
Guyana	9	18	12	22	18	18	12	24	20	18	12	23	18	18	12	18	17.000
Bangladesh	26	24	1	25	20	24	1	25	16	24	1	27	22	24	1	25	17.875
Pakistan	20	23	17	19	23	23	17	13	23	23	17	13	17	23	17	13	18.813
Laos	5	21	21	26	11	21	21	22	19	21	21	19	15	21	21	19	19.000
Papua New Guinea	11	27	15	17	6	27	15	18	22	27	15	20	23	27	15	24	19.313
Nepal	24	25	19	18	8	25	19	26	15	25	19	24	10	25	19	22	20.188
Sudan	27	26	18	27	25	26	18	27	27	26	18	26	25	26	18	27	24.188

Table b12 - Countries ranks in final CI in each time-period, cluster 1 (NOTE: listed by rankings average; TP – time-period) (Source: The author)

countries	RANK_TP1_CF	RANK_TP2_CF	RANK_TP3_CF	RANK_TP4_CF	AVERAGE
Bahrain	1	1	1	1	1
Qatar	1	1	1	1	1
Brunei	3	1	5	4	3.25
China	6	4	4	1	3.75
Mauritius	5	5	3	5	4.5
Malaysia	7	6	6	6	6.25
Saudi Arabia	4	7	8	8	6.75
United Arab Emirates	8	8	7	7	7.5
Mexico	9	9	9	9	9
Jamaica	11	12	11	10	11
Belize	12	10	12	15	12.25
Sri Lanka	14	14	10	13	12.75
Egypt	10	11	13	19	13.25
Philippines	13	13	17	11	13.5
Indonesia	15	18	14	12	14.75
Bhutan	20	16	15	14	16.25
Guyana	16	17	20	17	17.5
Myanmar	22	15	16	18	17.75
India	17	19	19	20	18.75
Seychelles	18	20	18	21	19.25
Fiji	19	22	21	16	19.5
Bangladesh	21	21	22	22	21.5
Laos	23	23	24	24	23.5
Pakistan	24	24	23	23	23.5
Nepal	26	25	26	25	25.5
Papua New Guinea	25	26	25	26	25.5
Sudan	27	27	27	27	27

Table b13 - Countries ranks in each composite indicator/dimension over time, cluster 2 (NOTE: listed by rankings average) (Source: The author)

	Time-period 1 (Mar-Aug 2020)				Time-period 2 (Set 2020 - Feb 2021)				Time-period 3 (Mar - Aug 2021)				Time-period 4 (Set - Dec 2021)				
countries	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	AVERAGE
Finland	37	4	1	16	39	4	1	12	15	4	1	6	27	4	1	5	11.063
Austria	25	6	24	3	2	6	24	1	17	6	24	1	10	6	24	1	11.250
Denmark	16	11	7	4	16	11	7	3	9	11	7	17	13	11	7	35	11.563
Norway	43	1	11	15	22	1	11	13	7	1	11	11	15	1	11	12	11.625
Germany	7	3	27	5	26	3	27	7	18	3	27	1	9	3	27	1	12.125
Ireland	18	8	21	8	15	8	21	6	11	8	21	7	8	8	21	6	12.188
Iceland	13	7	37	6	9	7	37	4	10	7	37	1	4	7	37	1	14.000
United Kingdom	32	19	1	12	24	19	1	10	19	19	1	9	22	19	1	21	14.313
Netherlands	46	10	16	1	28	10	16	5	21	10	16	5	24	10	16	8	15.125
Switzerland	40	2	15	11	32	2	15	20	33	2	15	10	32	2	15	9	15.938
United States	10	12	6	24	3	12	6	37	16	12	6	35	35	12	6	36	16.750
Belgium	21	5	33	9	34	5	33	15	14	5	33	16	18	5	33	13	18.250
Czechia	28	18	8	19	10	18	8	22	37	18	8	25	37	18	8	10	18.250
Sweden	48	9	14	10	41	9	14	2	36	9	14	8	45	9	14	16	18.625
Singapore	8	33	5	38	12	33	5	32	3	33	5	30	2	33	5	28	19.063
New Zealand	31	35	1	13	45	35	1	11	44	35	1	13	1	35	1	18	20.000
France	26	15	17	20	33	15	17	31	13	15	17	31	16	15	17	33	20.688
Slovenia	19	14	25	22	4	14	25	23	30	14	25	20	40	14	25	19	20.813
Malta	2	21	39	17	13	21	39	16	4	21	39	12	20	21	39	11	20.938
Australia	36	25	20	1	38	25	20	8	43	25	20	14	14	25	20	7	21.313
Estonia	20	22	1	35	29	22	1	42	20	22	1	39	30	22	1	43	21.875
Portugal	6	27	34	18	5	27	34	18	23	27	34	19	21	27	34	17	23.188
Cyprus	35	36	10	33	7	36	10	35	2	36	10	33	11	36	10	32	23.250
Canada	15	17	30	21	31	17	30	25	22	17	30	28	17	17	30	31	23.625
Spain	30	16	32	23	17	16	32	21	28	16	32	21	26	16	32	20	23.625
Japan	47	29	23	14	40	29	23	9	39	29	23	1	25	29	23	1	24.000
Luxembourg	11	13	26	29	14	13	26	34	25	13	26	42	28	13	26	46	24.063
Chile	9	40	9	47	11	40	9	24	1	40	9	36	19	40	9	47	24.375
Israel	5	32	45	7	1	32	45	19	12	32	45	18	6	32	45	14	24.375
South Korea	33	30	19	28	37	30	19	30	27	30	19	23	5	30	19	23	25.125
Poland	17	26	12	46	25	26	12	36	40	26	12	29	48	26	12	22	25.938
Greece	39	23	43	27	6	23	43	14	26	23	43	15	12	23	43	15	26.125
Italy	22	20	44	31	20	20	44	28	8	20	44	27	7	20	44	24	26.438
Lithuania	29	24	22	39	19	24	22	39	29	24	22	34	36	24	22	29	27.375
Uruguay	23	34	29	25	18	34	29	17	6	34	29	38	23	34	29	38	27.500
Barbados	12	37	13	45	23	37	13	41	5	37	13	44	38	37	13	41	28.063
Slovakia	14	28	41	30	8	28	41	29	32	28	41	26	47	28	41	25	30.438
Panama	1	41	40	34	21	41	40	26	35	41	40	22	33	41	40	30	32.875
Cuba	45	31	46	32	43	31	46	33	24	31	46	32	3	31	46	27	34.188
Costa Rica	38	45	18	37	42	45	18	38	41	45	18	37	29	45	18	34	34.250
Kuwait	4	44	28	42	27	44	28	45	31	44	28	43	41	44	28	40	35.063
Argentina	24	39	42	36	30	39	42	40	34	39	42	46	31	39	42	44	38.063
Colombia	3	48	31	41	44	48	31	44	45	48	31	41	46	48	31	39	38.688
Trinidad and Tobago	27	38	35	44	35	38	35	47	48	38	35	45	44	38	35	42	39.000
Brazil	42	43	48	26	36	43	48	27	38	43	48	24	43	43	48	26	39.125
Peru	34	42	38	43	47	42	38	48	46	42	38	47	34	42	38	45	41.500
Suriname	41	47	36	48	46	47	36	46	42	47	36	48	39	47	36	48	43.125
Ecuador	44	46	47	40	48	46	47	43	47	46	47	40	42	46	47	37	44.563

Table b14 - Countries ranks in each composite indicator/dimension over time, cluster 3 (NOTE: listed by rankings average) (Source: The author)

	Time-period 1 (Mar-Aug 2020)				Time-period 2 (Set 2020 - Feb 2021)				Time-period 3 (Mar - Aug 2021)				Time-period 4 (Set - Dec 2021)				
countries	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	rank_CI1	rank_CI2	rank_CI3	rank_CI4	AVERAGE
Hungary	67	1	6	1	30	1	6	4	39	1	6	1	33	1	6	1	12.750
Georgia	30	13	1	14	18	13	1	19	43	13	1	13	18	13	1	17	14.250
Oman	2	16	12	18	28	16	12	14	4	16	12	17	16	16	12	30	15.063
Cape Verde	4	45	8	2	7	45	8	1	13	45	8	4	7	45	8	12	16.375
South Africa	14	36	4	4	17	36	4	1	68	36	4	3	53	36	4	1	20.063
Uzbekistan	19	9	43	12	22	9	43	21	17	9	43	5	15	9	43	5	20.250
Russia	35	8	5	24	68	8	5	32	52	8	5	26	44	8	5	10	21.438
Bulgaria	28	10	11	7	67	10	11	7	74	10	11	6	70	10	11	1	21.500
Serbia	36	15	40	8	45	15	40	1	23	15	40	2	10	15	40	1	21.625
Morocco	26	38	24	11	1	38	24	20	7	38	24	21	3	38	24	16	22.063
Turkey	40	18	26	23	15	18	26	18	2	18	26	34	4	18	26	44	22.250
Jordan	74	22	3	32	11	22	3	28	12	22	3	27	49	22	3	26	22.438
Kazakhstan	8	1	9	42	61	1	9	49	38	1	9	50	34	1	9	52	23.375
Ukraine	24	7	49	6	14	7	49	12	57	7	49	10	26	7	49	7	23.750
Mongolia	1	17	52	28	13	17	52	10	3	17	52	22	5	17	52	24	23.875
Romania	37	6	58	5	6	6	58	5	35	6	58	7	23	6	58	11	24.063
Vietnam	12	40	7	37	40	40	7	31	15	40	7	33	1	40	7	29	24.125
Belarus	75	5	13	39	77	5	13	34	18	5	13	30	29	5	13	20	24.625
Gabon	21	26	16	35	8	26	16	24	19	26	16	56	42	26	16	46	26.188
Cambodia	13	51	23	21	5	51	23	15	21	51	23	16	17	51	23	23	26.688
Lebanon	39	14	56	22	2	14	56	23	6	14	56	18	27	14	56	18	27.188
Croatia	25	3	80	3	21	3	80	22	20	3	80	19	11	3	80	6	28.688
Moldova	23	21	10	49	47	21	10	47	42	21	10	44	55	21	10	36	29.188
Tunisia	42	33	19	15	50	33	19	16	11	33	19	36	54	33	19	39	29.438
Iraq	22	25	14	54	49	25	14	51	33	25	14	47	22	25	14	38	29.500
Latvia	29	4	66	9	56	4	66	8	37	4	66	15	32	4	66	19	30.313
Timor	43	31	35	25	23	31	35	42	22	31	35	31	12	31	35	25	30.438
Thailand	73	27	37	17	73	27	37	13	40	27	37	9	2	27	37	9	30.750
El Salvador	5	28	54	27	34	28	54	11	8	28	54	32	30	28	54	40	32.188
Rwanda	47	55	1	13	65	55	1	9	51	55	1	11	72	55	1	35	32.938
Albania	31	11	33	30	51	11	33	33	75	11	33	37	69	11	33	31	33.313
Iran	62	24	22	43	60	24	22	53	14	24	22	53	21	24	22	53	33.938
Tajikistan	79	29	21	50	31	29	21	48	29	29	21	49	8	29	21	51	34.063
Azerbaijan	15	20	74	34	3	20	74	25	24	20	74	35	13	20	74	34	34.938
Kyrgyzstan	9	23	45	47	26	23	45	39	71	23	45	24	63	23	45	14	35.313
Botswana	72	37	27	16	53	37	27	35	50	37	27	28	35	37	27	21	35.375
Dominican Republic	6	32	75	31	9	32	75	27	1	32	75	29	9	32	75	27	35.438
Namibia	71	43	17	36	43	43	17	40	28	43	17	38	47	43	17	32	35.938
Honduras	3	42	71	10	27	42	71	6	53	42	71	8	20	42	71	8	36.688
Bosnia and Herzegovina	20	12	64	20	70	12	64	30	72	12	64	14	65	12	64	13	38.000
Paraguay	51	41	41	19	29	41	41	29	44	41	41	39	71	41	41	45	40.938
Venezuela	44	34	73	33	32	34	73	26	26	34	73	23	24	34	73	22	41.125
Ghana	48	47	29	51	36	47	29	54	31	47	29	55	28	47	29	56	41.438
Guatemala	55	48	46	26	62	48	46	17	60	48	46	20	39	48	46	15	41.875
Algeria	45	35	48	40	42	35	48	36	27	35	48	42	73	35	48	37	42.125
eSwatini	17	50	50	58	10	50	50	56	16	50	50	54	19	50	50	63	43.313
Guinea	11	76	36	41	20	76	36	61	10	76	36	67	31	76	36	67	47.250
Libya	16	19	78	65	4	19	78	67	54	19	78	65	41	19	78	64	47.750
Gambia	53	64	28	52	37	64	28	44	69	64	28	43	67	64	28	42	48.438
Togo	68	75	32	63	58	75	32	37	34	75	32	25	40	75	32	28	48.813
Mozambique	57	52	25	77	44	52	25	75	25	52	25	75	61	52	25	72	49.625
Kenya	54	56	42	44	75	56	42	52	36	56	42	46	56	56	42	47	50.125
Mauritania	66	61	30	55	46	61	30	65	48	61	30	64	36	61	30	66	50.625
Nicaragua	81	39	68	46	74	39	68	43	56	39	68	41	25	39	68	33	51.688
Senegal	59	73	20	29	79	73	20	38	77	73	20	52	80	73	20	48	52.125
Ethiopia	64	77	15	62	33	77	15	66	45	77	15	76	51	77	15	73	52.375
Syria	70	30	53	59	57	30	53	57	81	30	53	58	76	30	53	58	53.000
Bolivia	58	46	67	48	78	46	67	46	65	46	67	12	59	46	67	41	53.688
Zambia	65	54	31	69	72	54	31	69	58	54	31	72	64	54	31	50	53.688
Congo	7	53	76	57	16	53	76	68	9	53	76	69	52	53	76	68	53.875
Benin	61	69	47	61	59	69	47	41	49	69	47	57	14	69	47	57	53.938
Mali	69	67	18	66	38	67	18	80	63	67	18	81	66	67	18	79	55.125
Malawi	76	72	38	38	71	72	38	45	61	72	38	45	62	72	38	49	55.438
Democratic Republic of Congo	10	68	51	45	12	68	51	71	78	68	51	66	78	68	51	55	55.688
Nigeria	63	44	62	68	48	44	62	63	41	44	62	71	46	44	62	69	55.813
Tanzania	80	58	39	67	76	58	39	70	73	58	39	59	45	58	39	43	56.313
Uganda	46	60	55	53	41	60	55	64	59	60	55	70	58	60	55	61	57.000
Cameroon	52	65	57	73	24	65	57	72	30	65	57	74	43	65	57	71	57.938
Cote d'Ivoire	49	71	60	60	55	71	60	50	32	71	60	51	57	71	60	54	58.250
Burundi	60	78	34	64	52	78	34	60	55	78	34	61	74	78	34	59	58.313
Sierra Leone	32	80	59	70	39	80	59	78	5	80	59	79	6	80	59	78	58.938
Zimbabwe	78	49	72	56	69	49	72	55	64	49	72	62	37	49	72	60	60.313
Liberia	27	66	70	80	19	66	70	79	46	66	70	60	48	66	70	76	61.188
Haiti	18	70	63	71	54	70	63	62	67	70	63	63	60	70	63	62	61.813
Burkina Faso	34	74	44	79	64	74	44	77	70	74	44	48	77	74	44	77	62.375
Madagascar	38	57	81	74	35	57	81	59	47	57	81	78	38	57	81	80	62.563
Niger	56	81	61	72	66	81	61	58	66	81	61	40	68	81	61	75	66.813
Afghanistan	33	63	65	78	81	63	65	76	80	63	65	77	79	63	65	74	68.125
Angola	50	62	77	81	63	62	77	81	62	62	77	80	50	62	77	81	69.000
Yemen	77	59	69	76	80	59	69	74	79	59	69	73	81	59	69	70	70.125
Somalia	41	79	79	75	25	79	79	73	76	79	79	68	75	79	79	65	70.625