Targeted Key Indicators for Improving National Innovation Performance

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Abstract

Innovation is becoming more and more a decisive engine of development and economic growth. It impacts the economy on different activity scales: (i) at the micro scale (internal business innovation, business creation), (ii) at the meso scales (development of new activities) and (iii) at the macro scales (employment and growth). Aware of that, policy makers, all over the world, emphasize innovation as a key driver of prosperity and progress in their countries. The purpose of this study is to help identify features that can explain variations in the intensity of innovation between countries. To better understand national innovative capacities, this study proposes identifying distinct groups (or clusters) of countries using their innovation performances. So, available innovation data is used to classify countries with common characteristics into meaningful clusters. Then, these clusters are analyzed and new information that explains the variation of innovation performance between countries is extracted. To this aim, data representing 121 countries and 49 indicators are investigated over a period of 5 years. Unsupervised and supervised data analysis models are applied using the 2015-2019 GII data. This analysis allows the classification of countries and the clustering of those progressing in the same way in terms of innovation. Therefore, 4 major clusters of countries are defined. Another important outcome of this study is the identification of key innovation determinants, or key indicators, with superior effect on innovation outcomes. The analysis emphasizes distinctly the "University/Industry research collaboration" and "Information and Communication Technologies (ICT) use" as the two most important indicators enhancing national innovation performances. Four cases studies are also illustrated in this study representing the four innovation clusters, namely for the USA, Morocco, China, and Brazil. This study's results can assist countries in planning their mid-term innovation strategies by providing: (i) a reduced number of relevant determinants to improve, and (ii) a focused set of prospective countries for potential benchmarking either intra- or inter-cluster.

Keywords
National Innovative Capacity, Innovation determinants, Global Innovation Index, Unsupervised and supervised data analysis models.

1. Introduction
Innovation has been established as a driving force of growth and economic performance of countries. Therefore, many nations facing increased competition have realized the pressing need to innovate (Bhand & Goel, 2017). To improve their nation's innovative capability, governments often set up different strategies and policies (Porter, 1990, Porter and Stern, 1999). In order to monitor and assess the effectiveness of each government's intervention in enhancing a nation innovation climate, various national innovation performance measures and indexes have been developed (Mahroum & Al-Saleh, 2013, Omer et al., 2020).

Measuring innovation at a macro level has evolved through the years. In the 1950s, the focus was on input indicators such as R&D expenditure, capital, and science and technology personnel. In 1970s, emphasis was placed on output indications such as patents, publications, products and quality change. The third generation followed in 1990s with a growth in innovation surveys and benchmarking activities. The fourth generation of innovation measurements turns to the process indicators that can be applied at firm and sectoral levels (Godin, 2006, Gault, 2013, Lizuka and Hollanders, 2017).

Since innovation can be achieved in many ways, measuring innovativeness with a single measure can be challenging. Therefore, many determinants and indexes were introduced to measure innovation capacity. For example, the Global Innovation Index (GII) uses a set of determinants of innovation to annually rank countries according to their ability and success in innovation. The GII uses the global or partial indexes inputs & outputs and seeks to capture the multi-dimensional aspects of innovation in order to provide innovation maps at national and global levels (Cornell et al. 2015, 2019).

This study aims to help identify features that can explain variations in the intensity of innovation between countries. We propose to identify distinct groups (or clusters) of countries using their innovation performances. Therefore, available innovation data is used to classify countries with common characteristics into meaningful clusters. Then, these clusters are analyzed and new information that explains the variation of innovation performance between countries is extracted. Another goal of this study is to extract key indicators for enhancing national innovation performance. Four cases studies are also illustrated in this study representing the four innovation clusters, namely for the USA, Morocco, China, and Brazil.

Given the nature of innovation indicators, which depend on varying laws, education systems, infrastructure, etc., focusing the assessment of national investments in these fields on a single year, may not be very informative. In this study, the analysis covers 5-year data, collected from GII reports from 2015 to 2019. Then, data representing 49 innovation inputs for 121 countries is analyzed.

2. Literature Review

2.1 National Innovation System

According to the Oslo Manual (OECD/Eurostat, 2018), innovation is defined as "a new or improved product or process, or combination thereof, that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)". Also, innovation and technical progress are the product of a complex set of interactions between the actors producing, distributing and applying various kinds of knowledge (NIS, OECD, 1997).

To a large extent, the innovative performance of a country is directly linked to how these actors relate to each other as elements of a collective system, referred to as a National Innovation System (NIS) (Lundvall, 1985; Metcalfe, 1995; Hamidi & Berrado, 2017). In Fact, innovation is not limited to the activities of firms within a naton, but to a system of interaction that combines the efforts of these firms with the actions of other actors such as universities, funding and government agencies (Metcalfe & Ramlogan, 2008; Watkins, Papaioannou, Mugwagwa, & Kale, 2015).

Proposed for the first time by Lundvall (1985 & 1988), the NIS was presented by Metcalfe (1995) as a set of distinct institutions that contribute both jointly and individually to the development and diffusion of new technologies and that provide the framework within which governments form and implement policies to influence the innovation process. Hence, an NIS is a system of interconnected institutions that create, store, and transfer the knowledge, skills, and artifacts that define new technologies.

The heterogeneity of the actors and the nonlinearity of the activities and the interactions make each NIS a complex system. In addition, comparable innovation performances in different countries can be achieved by acting upon different features and enacting different innovation policies (Mahroum & Al-Saleh, 2013).

2.2 Why do Innovation indicators matters?

Aware of the importance of innovation in any development of their countries, policy makers are increasingly interested in tools that measure and manage strategies and policies established to boost innovation activities (Mahroum & Al-Saleh, 2013). These national innovation policies, including various elements such as education, infrastructure, legislations and regulations, can be considered an integrated element of each NIS (Jankowska et al. 2017). Like any government work, national innovation policy requires the adoption and use of measurement tools that assist governments in developing and evaluating the effectiveness of the policy interventions (Gault, 2013).

Therefore, many academic scholars emphasize the importance of creating and using indicators and frameworks to monitor and measure national innovative performances. This become especially relevant knowing that to establishing

an effective innovation policy is tightly linked to the ability to measure the national innovation capabilities (National Endowment for Science, Technology and the Arts (NESTA, 2009).

The most benign use of indicators is the monitoring of the innovation system by comparing the values of a set of indicators over time (Gault, 2013). A few national reports are available, such as the Federal Report on Research and Innovation (BMBF, 2020) which is published every two years in Germany, the indicator report of the Science and technology observatory (OST) in France, and the Science and Engineering Indicators published in the US, every two years (The State of U.S. Science and Engineering, 2020).

Using 25 indicators, the European Innovation Scoreboard (EIS) assesses the strengths and weaknesses of research and innovation systems in the European Union (EU). the Global Innovation Scoreboard extends the assessment of EU countries to high R&D performing countries; and twice a year, the OECD publishes the main Science and Technology Indicators. On the other hand, the Global Innovation Index (GII), recognized as the broadest index in terms of both indicators and countries, gives an annual global ranking of countries according to their ability and success in innovation.

3 Methods and Data Collection

3.1 Data collection

Since this study focuses on national innovation policies and strategies, data covering a period of five years 2015-2019 is collected and used. This was achieved by analyzing data provided by de Global Innovation Index (GII) reports for the chosen period.

The GII report covers around 95% of the global population and about 98% of the world's Gross Domestic Product (GII report, 2019). It adjusts and revises its frameworks on a yearly basis, by accounting for either the revision of a country's indicators, or the availability status of data for a country.
A first step in the preparation of the data was therefore the selection of the sample of countries and indicators that have were consistently covered during the period of the study. As such, the analysis includes 121 countries and 73 indicators divided into 49 inputs and 24 outputs. It should be noted that countries covered by the GII report of varied between 142 countries in 2015, and 129 in 2019.

Only inputs indicators are used in this analysis. this choice is motivated by two main elements: (i) this study focuses on the actions implemented in a national innovation policy (therefore input indicators), and (ii) it has been shown that output indicators used in the GII are indeed correlated with the inputs indicators of the GII (Hamidi & Berrado, 2017; Hamidi & Berrado, 2018). Table 1 presents all used indicators, with normalized score in a 0–100 range.

Table 1. GII innovation inputs used in this analysis

1.Institutions	
X0	Political stability
X1	Government effectiveness
X2	Regulatory quality
X3	Rule of law
X4	Cost of redundancy dismissal
X5	Ease of starting a business
X6	Ease of resolving insolvency
2. Human capital and research	
X7	Expenditure on education
X8	Gov expend on education/ pupil, secondary
X9	School life expectancy
X10	Assessment in reading, mathematics, and science
X11	Pupil-teacher ratio, secondary
X12	Tertiary enrolment
X13	Graduates in science and engineering
X14	Tertiary level inbound mobility
X15	Researchers
X16	Gross expenditure on R&D (GERD)
X17	Global R&D companies
3. Infrastructure	
X18	ICT access
X19	ICT use
X20	Government's online service
X21	Online e-participation
X22	Electricity output
X23	Logistics performance
X24	Gross capital formation
X25	GDP/unit of energy use
X26	Environmental performance
X27	ISO 14001 environmental certificates
4.Market sophistication	
X28	Ease of getting credit
X29	Domestic credit to private sector
X30	Microfinance institutions' gross loan portfolio
X31	Ease of protecting minority investors
X32	Market capitalization
X33	Venture capital deals
X34	Applied tariff rate, weighted mean
X35	Intensity of local competition
5.Business sophistication	
X36	Employment in knowledge-intensive services
X37	Firms offering formal training
X38	GERD performed by business enterprise
X39	GERD financed by business enterprise
X40	Females employed with advanced degrees
X41	University/industry research collaboration
X42	State of cluster development
X43	GERD financed by abroad
X44	Joint venture/strategic alliance deals
X45	Intellectual property payments
X46	High-tech imports
X47	ICT services imports
X48	Foreign direct investment, net inflows

3.2 Methods

In this study, a mixed methodology is applied using unsupervised and supervised data analysis models; namely, K-means cluster analysis and the Random Forest method. The k-means clustering is the most commonly used algorithm to partition the data into a K pre-specified number of clusters (Jain, 2010). It mainly requires three parameters: k the number of clusters, cluster initialization, and distance metric used for computing distance between points and the cluster center (Abdul Nazeer et al., 2009). The basic idea behind k-means clustering consists of defining clusters so that the total intra-cluster variation (known as total within-cluster variation) is minimized.

The Random Forest method, on the other hand, is a non-parametric statistical method consisting on drawing bootstap samples, and building on each sample a Classification and Regression Trees (CART) model and finally aggregating these models. It provides very effective results both for classification and regression problems (Ehrlinger, 2015). This technique also handles well data sets with missing data, and allows classifying input parameters, or determinants, by importance using their effect on explaining the variability within the data (Hastie, et al., 2001).

First the dataset is prepared through imputation of missing values, and data are standardized using a scale function. Then, k-means clustering is applied. The aim is to extract groups of countries (clusters) according to their input indicator scores. The clusters include countries that made approximately similar investments on their national innovation policies during the period 2015-2019. The most important indicators that influence cluster construction are then determined using the Random Forest method.

The last step in the analysis involves scrutinizing one sample country from each cluster to see how the implemented policies changed input innovation indicators; and ultimately affected their output innovation indicators.

4 Results and discussion

4.1 Results of K-means clustering

As described earlier, this analysis concerns data over a period of 5 years covering 121 countries and 49 input innovation indicators. To perform a cluster analysis, any mi,ssing value in the data must be removed or estimated. Once data preparation (estimation of missing values, data standardization ...) is implemented, the optimal number of clusters (K) can be determined. Figure 1 depicts the K choice for the data at hand.

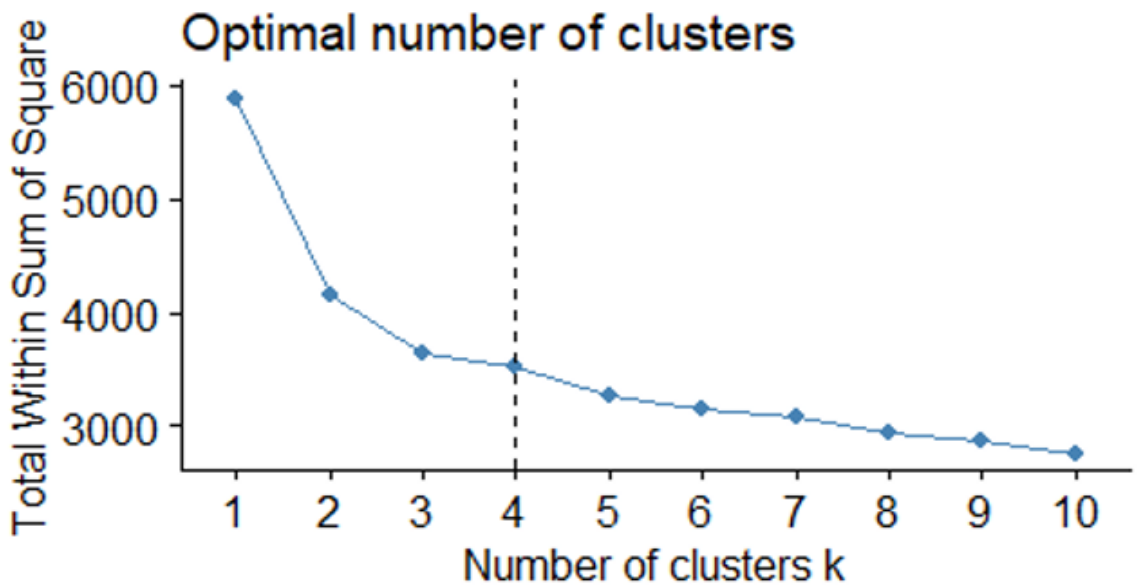

Figure 1. Optimal number of clusters

As shown in Figure 1, the variance within the clusters decreases as the number of clusters, k, increases. However, a bend (or "elbow") is observed at k = 4. This bend indicates that additional clusters beyond the fourth have little added value in the analysis of the data (Tibshirani, et al., 2001). Therefore, analysis yields 4 clusters of countries. These clusters have the following sizes: 21, 30, 42, 28 with distinct non-overlapping boundaries, which argument a good clustering algorithm result.

Using the k-means clustering algorithm, the Figure 2 shows that the analysis classifies countries in multiple groups (i.e., clusters), such that countries within the same cluster are as similar as possible (i.e., high intra-class similarity), whereas countries from different clusters are as dissimilar as possible (i.e., low inter-class similarity).

The distribution of countries clusters obtained, as shown in table 2, is fairly homogeneous with that of the GII annually reports (distribution made according to the annual final score), namely: Innovation leaders (in our case group 3), Innovation achievers (group 1), Performing at expectations for level of development (group 0), and performing below expectations for level of development (group 2).

The countries grouped together in each cluster are countries which have evolved in the same way in terms of input indicators during 2015-2019 period. Major directions of their national innovation policies converge. This classification of countries, progressing in the same way in terms of innovation, allows a better visibility for potential benchmarking either intra-or inter-cluster.

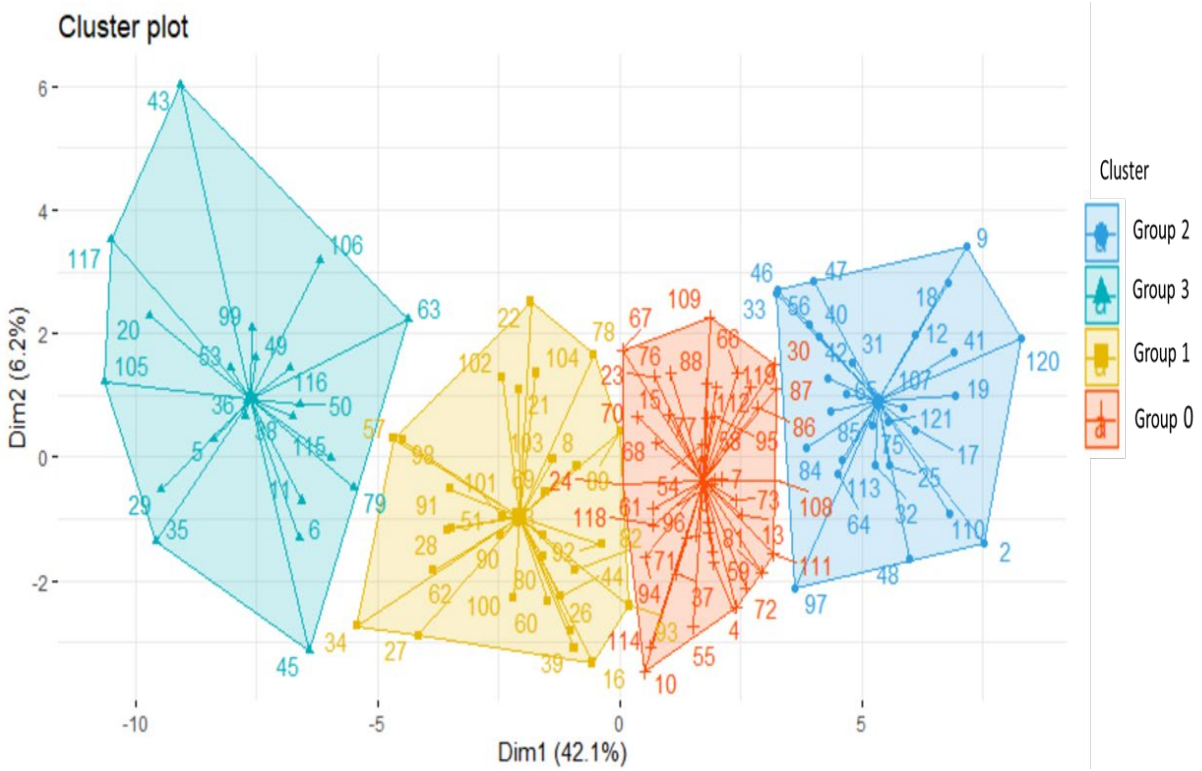

Figure 2. Clusters Plot.

Table 2. Members of clusters obtained

Cluster	Countries
Group 0	Albania, Argentina, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Botswana, Brazil, Colombia, Costa Rica, Dominican Republic, Georgia, Jamaica, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Lebanon, Malawi, Malaysia, Mali, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Mozambique, Namibia, Niger, Panama, Paraguay, Peru, Russian Federation, Rwanda, Saudi Arabia, Tanzania, Thailand, Tunisia, Turkey, Ukraine, Uruguay, Viet Nam
Group 1	Bahrain, Bulgaria, Chile, China, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Italy, Korea, Latvia, Lithuania, Malta, Nepal, New Zealand, Nigeria, Norway, Philippines, Poland, Portugal, Qatar, Romania, Serbia, Slovakia, Slovenia, South Africa, Spain, Sri Lanka
Group 2	Algeria, Bangladesh, Bolivia, Burkina Faso, Cambodia, Cameroon, Cote d'Ivoire, Ecuador, Egypt, El Salvador, Guatemala, Guinea, Honduras, India, Indonesia, Iran, Kenya, Macedonia, Madagascar, Morocco, Oman, Pakistan, Senegal, Tajikistan, Togo, Uganda, Yemen, Zambia
Group 3	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong (China), Iceland, Ireland, Israel, Japan, Luxembourg, Netherlands, Singapore, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States of America

Figure 3 presents a description of the clustering algorithm resulting from our analysis. It allows to better visualize the efforts made by the countries belonging to each group, over a period of five years, to strengthen their innovation activities.

In fact, group 2 includes countries which have a maximum score of X43 and X30 as well as a fairly large score of X24, while group 3 includes countries which have a minimum score of X43 and X24 and all other indicators are almost at their maximum. Group 1 includes countries which have average scores for all variables except for X30 and X48 where it is minimum and X13, X27 and X37 where it is maximum. Group 0 includes countries with a X24, X8 and X37 scores in their maximum.

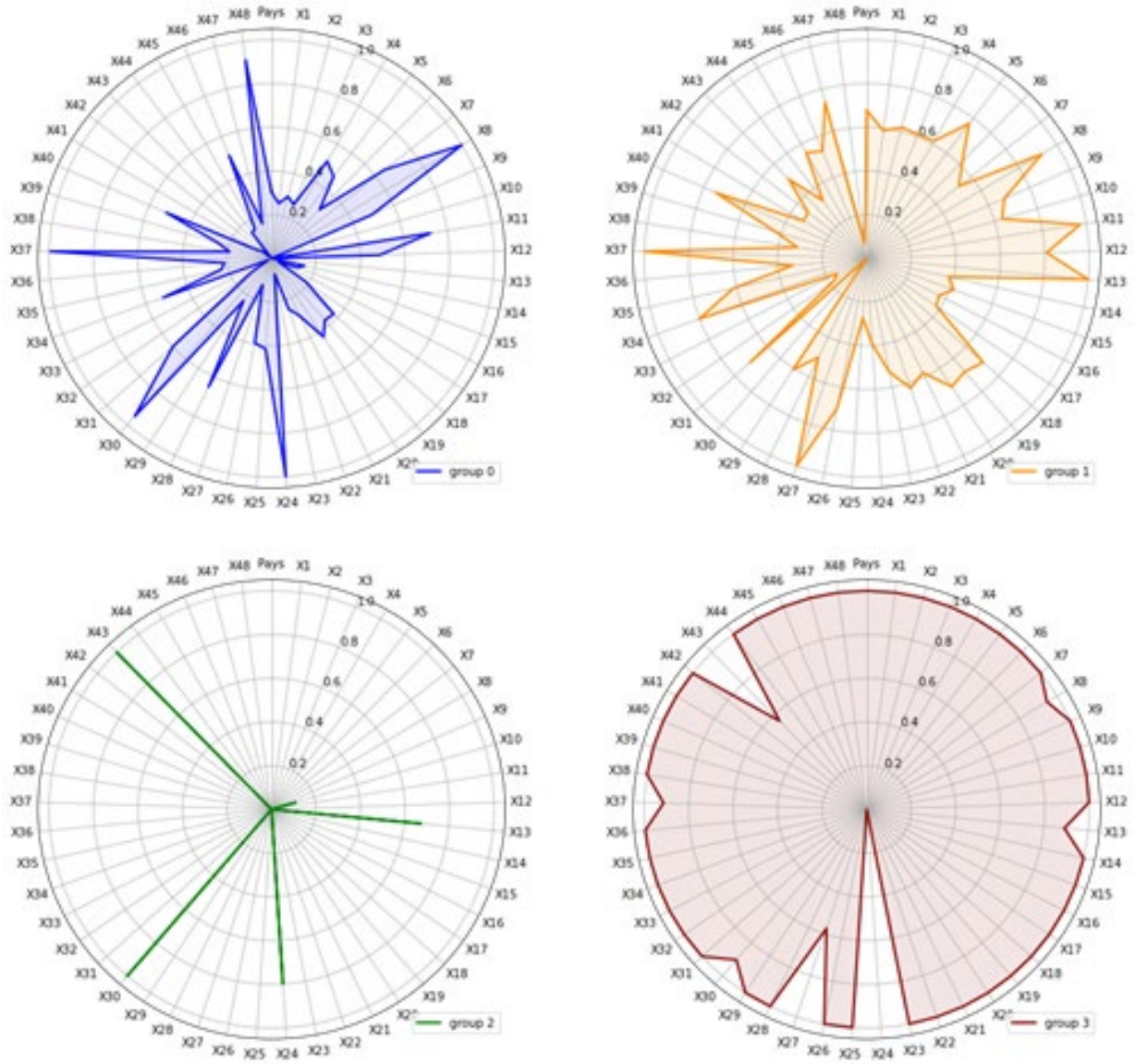

Figure 3. Repartition of the clusters obtained

4.2 Selection of important input indicators

In this step of the analysis, the most relevant input indicators that highly impact national innovation policies are extracted using the Random Forest algorithm, as shown in Figure 4. The Information and Communication Technologies (ICT) use (X19) and the University/industry research collaboration (X41) are by far the major indicators that influence any innovation policy. Followed by the Government effectiveness (X1), the Rule of law (X3), the Logistics performance (X23), and Gross Expenditure on R&D (GERD) performed by business enterprise (X38).

Investment on these features can make an important difference on the outcome of strategies and policies which aim the enhancement of national innovation activities. The list of important variables proposed by the current analysis, offers the possibility to subset the data to only include the most impacting ones.

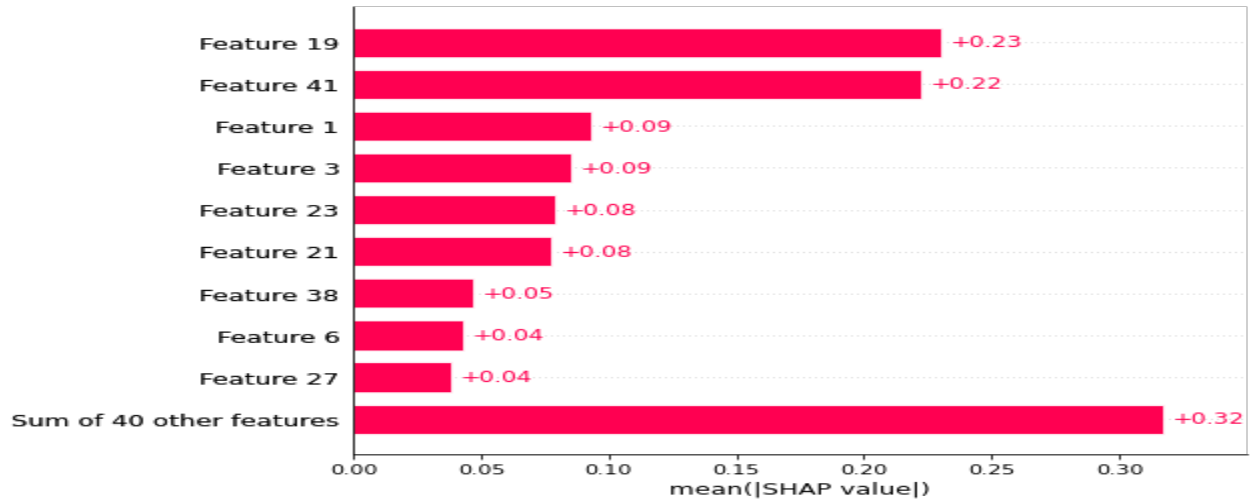

Figure 4. Key input indicators for innovation

4.3 Case Studies

In this section, 4 examples of countries from each cluster are examined. For each proposed country, the analysis identifies the pillars of their policy and to how the choice of investment on the indicators used, has influenced it membership in a given group. The features that positively or negatively impact the outcome of the efforts made by the country are highlighted. These results are performed using random forest algorithm (variables important function).

The cases of United Stat of America (USA) for group 3, Morocco for group 2, China for group 1 and Brazil for group 0, are examined.

4.3.1 The case of the USA (group 3)

As Figure 5 shows, the four most important variables for our algorithm for the USA case are X41 which positively impacts by 46 points, followed by X1, X23 and X19. The innovation policy in the USA relies mainly on the University/industry research collaboration. The strength of this indicator as well as the Government effectiveness, the Logistics performance and the ICT use, allows the USA to be among the Innovation Leaders.

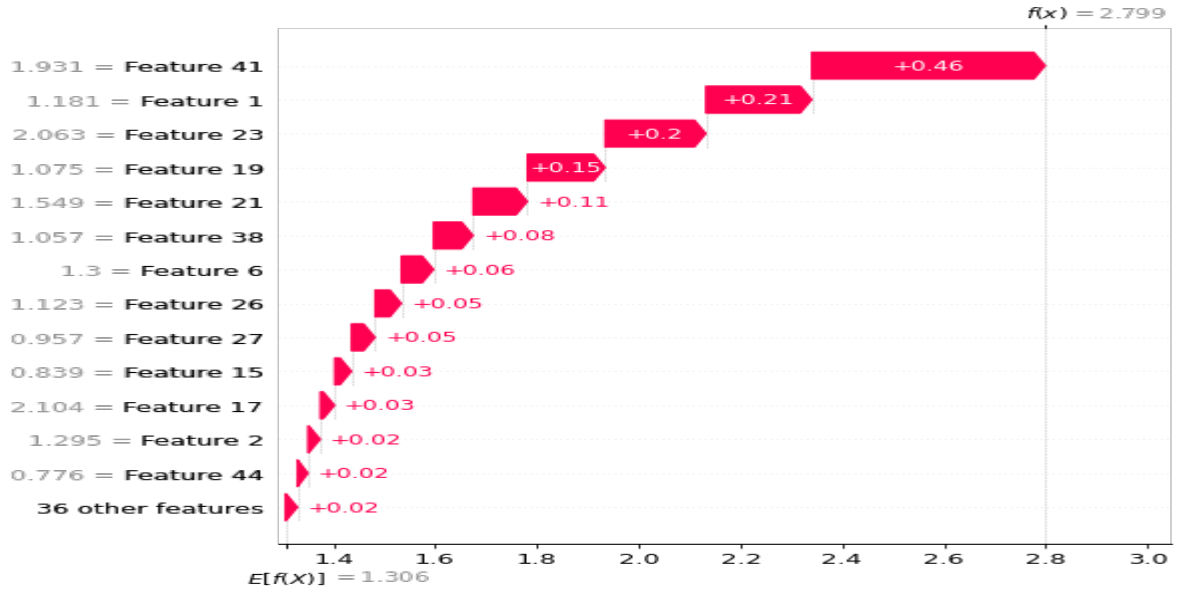

Figure 5. The weight of the innovation indicators in the USA

4.3.2 The case of Morocco (group 2)

For Morocco, the most important variable in its policy is the 19 (the ICT use), which positively impacts the result with 47 points. The weakness of Moroccan policy in terms of University/industry research collaboration, affects negatively its position. The figure 6 gives an illustration of the indicators weight and their effects (positive and negative) on the general result of the country's policy in Morocco.

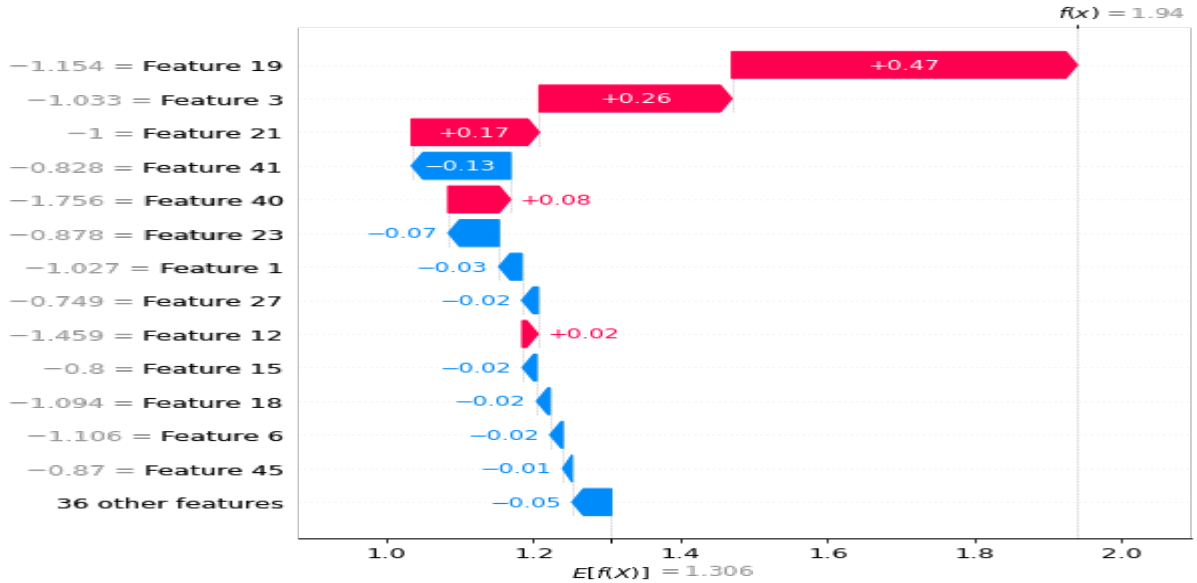

Figure 6. The weight of the innovation indicators in Morocco

4.3.3 The case of China (group 1)

As Figure 7 shows, the 3 most important variables for our algorithm obtained for China are the X41 which has a positive impact followed by the X19 and X1 which has a negative impact. China still has efforts to make in "ICT use" and "government effectiveness" to further improve its position in terms of innovation.

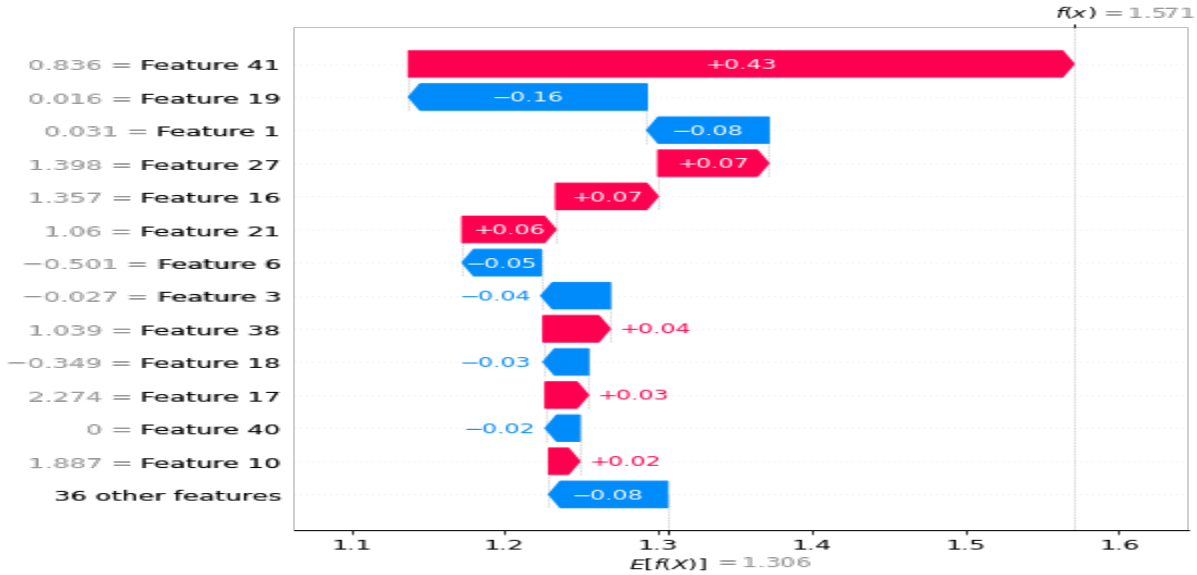

Figure 7. The weight of the innovation indicators in China

4.3.4 The case of Brazil (group 0)

For Brazil, as clearly shown in figure 8, the 3 most important variables are X19, X41 and X3 which all have a negative impact. The nature of Brazil's investment in the most important innovation indicators, as defined by our analysis, does not allow it to achieve objectives.

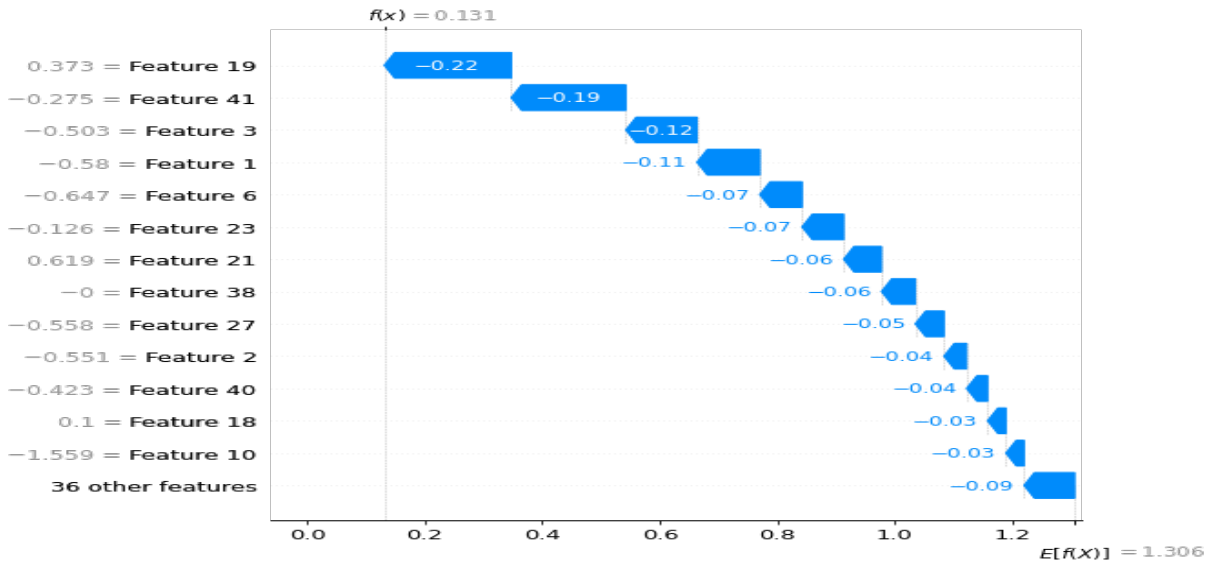

Figure 8. The weight of the innovation indicators in Brazil

5. Conclusions

The innovation system approach has proven useful in explaining the mechanisms behind varying national economic performance. By using GII data over the period 2015-2019, and employing machine learning techniques in the analysis of the innovation performance measures, this study offers an explanation of features clarifying variations in the intensity of innovation between nations. Proceeding by categorizing countries (121 countries used in our analysis) into 4 groups evolving in the same way, we highlight the common characteristics that allow a country to belong to a given group.

Among the 49 innovation input indicators analyzed in this study, a subset of indicators, of which the importance and the impact on the national innovation system are the highest, is proposed. This subset of key indicators enhancing national innovation performance, contains mainly the ICT use, the University/industry research collaboration, the government effectiveness, the Logistics performance and the Gross Expenditure on R&D performed by business enterprise.

To illustrate and better understand the impact of the proposed subset, the cases study of the USA, Morocco, China and Brazil is presented. The analysis allows to understand how the NIS' key elements influence belonging to a given group, and highlight the features that positively or negatively impact the outcome of the efforts made by the country. Further analysis is needed to deeply explain and customize innovation indicators especially for countries performing below expectations for level of development.

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