THE UNIVERSITY OF NEW HAVEN

Benchmarking OECD Countries' Sustainable Development Performance: A Goal-Specific PCA Approach

A THESIS

submitted in partial fulfillment of the requirements for the degree of Master of science in Industrial Engineering

BY

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May 2019

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my thesis advisor, Dr. Gokhan Egilmez. Dr. Egilmez was always available to help me when I had questions regarding my thesis or research findings. He provided clarity when I reached out for help. He also reached out to me when he felt it was appropriate to ensure I was on the correct path to a successful thesis research. Through Dr. Egilmez's knowledge and experience, I was able to have my questions answered, while still allowing this thesis to reflect my own work.

I would also like to thank Dr. Ridvan Gedik, who reviewed my work and accepted to be a member in my committee. His valuable comments on this thesis were always supportive, directing and most of all improving the content of this research project. I will always be gratefully indebted for the time and effort he invested in my thesis. With his help I was able to be successfully complete my thesis to best of my ability.

I would like to thank Dr. Yong Shin Park for being part of my thesis committee, reviewing and providing feedback on my document. I would like to acknowledge my program coordinator Dr. M. Ali Montazer for his constant feedback and interest in knowing how my thesis was coming along. His support helped guide me to improve my thesis. Besides, I would like to thank all my friends and fellow classmates at UNewHaven for all their support and feedback. They were always willing to give suggestions to help me excel in improving my thesis.

Last but not the least, I am extremely indebted to my parents, Keshab Pr. Lamichhane and Laxmi Lamichhane, and to my brother Radha Kr. Lamichhane, who have been with me in all my hard-hopeless times. Finally, my deepest feelings and gratitude go to my wife Neha, whose support was always with me.

ABSTRACT

In this thesis, the current status of the Organisation for Economic Co-operation and Development (OECD) countries' sustainable development performance towards reaching the recently announced 2030 Agenda (17 UN Sustainable Development Goals (SDGs)) was investigated. Over 90 social, economic and environmental sustainability indicators were considered for the performance assessment of OECD countries towards reaching the targeted SDGs. The current weighted averaging approach used in the recent SDG Index and Dashboards Report was used as the benchmark and its limitations were discussed. To overcome the limitations, a novel Goal-Specific Principal Component Analysis (GS-PCA) approach was proposed to create composite sustainability index scores for OECD countries, which takes into account the variance in the dataset and deals effectively with the deteriorating impacts of multicollinearity. The study period included 2017 and 2018, which covered the most recent available data. A total of 34 PCA models were developed, which yielded country and SDG-focused overall and goal-specific sustainable development index (SDI) scores. Results were compared with recent benchmark reports published in 2017 and 2018; and were statistically validated. Findings indicated that the standard deviation of the scores and ranks were found to be substantially greater with the proposed GS-PCA approach. The 2017 and 2018 performances were compared visually and statistically. Even though there was increasing performance observed in some SDGs and some countries, there was no statistically significant difference found between the 2017 and 2018 years. In addition, substantial differences were observed in the scores and ranks of mediocre and poor performing countries compared to the benchmark report, while both the results were found to be strongly positively correlated. Overall, the UN SDG Dashboard and Index reports findings were found to be quite optimistic compared to the results obtained with the proposed GS-PCA approach.

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1. INTRODUCTION

On September 25th, 2015, 193 United Nations (UN) Sustainable Development Summit was convened as a high-level plenary meeting and member countries agreed up adopting a set of short and long term goals that address all the three pillars of sustainable development as a new comprehensive plan(Gokhan Egilmez, 2019) . The product of the summit was a comprehensive plan, which was structured around 17 Sustainable Development Goals (SDGs) (See Figure 1). Each of the 17 SDGs targets specific measurable outcomes to be achieved over the next 15 years, called as the "Envision 2030" (See Fig. 1). The newly proposed SDGs were built on the successes of the Millennium Development Goals while including new policy focus areas such as gender equality, education, technology innovation, sustainable consumption, peace, and justice, among other priorities; that were covered with 169 targets. The proposed 17 SDGs were aimed to cover social, economic, environmental, and ecological aspects of sustainable development and they are interconnected. Thus, successful policy-making and implementation require a thorough and series of efforts rather than individually focusing on specific SD paradigm e.g. environment, society, or economy. The SDGs work in the spirit of partnership and pragmatism to make the right choices now to improve life, in a sustainable way, for future generations. ("Sustainable Development Goals | UNDP," 2018).

OECD was founded in 1961, currently supports the United Nations in ensuring the success of the 2030 Agenda for Sustainable Development by bringing together its knowledge and databases, world trade network, and organizational influence. OECDs network enables maintaining a strong track record of data collection that is key for quantifying and monitoring development performance ("Sustainable Development Goals | UNDP," 2018). In addition, OECD partnerships are creating synergies among private and public, domestic and international, and donor and developing country resources to provide countries with a strong support mechanism on which to build towards a better future. Successful implementation of the SDGs will require striking a balance between socio-economic progress, sustaining the planet's resources and ecosystems, and combatting climate change (Sachs et al.,2017). OECD works with its members, partnering organizations, and other stakeholders to ensure sound environmental management that supports the sustained achievement of economic development and prosperity while delivering human security and resilience.

Figure 1. Sustainable Development Goals (SDSN, 2018a)

Sustainable Development Solutions Network (SDSN), a lobal initiative for the UN, continuously track the status of sustainable development efforts worldwide, and conducts annual assessment of member countries. In this regard, the methods used to create composite sustainability indicators to have long time been a central topic of discussion in the academic literature and still attracts considerable interest by government, non-profit and for-profit due to various reasons. For instance, composite sustainability scoring is a practical and effective approach for policy making and public communication, especially to provide status of countries and corporate performance in fields such as environment, economic, social, or technological improvement (Singh et al.,2012).

Various sustainability scoring methods have been proposed in the literature with the aim of creating sustainability score/index (score and index words are interchangeably used in the literature and in this thesis) of individual countries and to find out how well they are performing towards achieving preset/ predefined sustainable development goals on time(Parris and Kates, 2003). The type of methods includes equal weighting and aggregation, Principle component analysis, Analytic hierarchy process (AHP), Economic Input-output Life-Cycle Assessment (EIO-LCA) with Principle component analysis, PCA in combination with data envelopment analysis (DEA), etc. The summary of relevant literature is provided in table 2.

Sustainability indexing greatly helps in guiding policy decisions for sustainable development as well as monitoring the sustainable development performance. Besides, sustainability scoring creates a common platform, which promotes consistent monitoring and decision making across the countries and organizations in the world. In this context, the Consultative Group on Sustainable Development Indicators (CGSDI), an international panel of a dozen experts in the field, was established in 1996 "to harmonize international work on indicators and to focus on the challenge of creating a single sustainability index(Parris and Kates, 2003). Among the well-known SD indices, well-being index is constructed as a country specific ranking index which addresses the quality of life and environment. The index consists of 88 indicators, which are aggregated into two sub-indexes, namely: human wellbeing and ecosystem well-being. Similarly, the environmental sustainability index constructed by world economic forum comprises 68 indicators 148 countries in which indicators were aggregated into 5 components which assist the move towards a more analytically rigorous and data-driven approach to environmental decision making and tracks environmental trends(Parris and Kates, 2003).

Among the sustainability indexing methods, Bertelsmann Stiftung and Sustainable Development Solutions Network, one of the main collaborating agencies of the UN Sustainable Development Knowledge Platform developed a method that consists of equal weighting and aggregation to create sustainability index of the member countries (Sachs et al., 2017). 2017 SDG Index and Dashboards report provide critical information about the overall performance of countries towards reaching the 17 SDGs (SDSN, 2018b). The method of sustainability scoring involves data collection, data preparation, weighting, and aggregation, etc. The method follows with the min-max normalization method of the data for each indicator by transforming it linearly to scale from 0 to 100, which also ensures comparability. In terms of weighting, equal weight assumption was kept in terms of the importance of each of the 17 SDGs. 2017 SDG Index and Dashboards report include 83 variables for 157 out of 193 UN member countries and additional 16 variables were included for OECD countries in the global SDG index to create an augmented SDG index for OECD countries. An average of 6 indicators were selected for each SDGs. Arithmetic mean was used to aggregate indicators within each SDG to compute the overall index.

Even though this method has credible advantages of unifying the sustainability performance according to each of the 17 SDGs, there are critical limitations in terms of the approach undertaken.

- All the SDGs were given equal importance, but each SDG consists of a varying sub-set of indicators. This may bring a drawback of the higher numbers of indicators will have a higher influence on the sustainability index (Hudrliková, 2013).

- When using equal weights, high degree of correlation among variables could cause the results to be skewed towards the specific SDGs which have higher multi-dimensionality (higher number of variables). In this context, pair-wise correlation plays a vital role in giving weights to the indicators (Guide, 2008).

The aforementioned factors raise concerns towards using a weighted averaging approach. Therefore, in this thesis, a correlation analysis of 93 indicators used for 2017 report and 104 indicators used for 2018 report is conducted (See Table 1). Results indicated that more than 50 % pair of indicators in both years had a correlation greater than 0.3, which indicates that substantial portion of the pairs of variables were found to have pair-wise correlation, which makes it necessary to propose an alternative approach, which will alleviate the deteriorating impacts of multicollinearity, while maintaining the degree of variance in the dataset. Maintaining the variation in such datasets is quite crucial for sustainability assessment of countries due to the fact that each country may have its own unique socio-economic, and environmental impact characteristics. Even though Lafortune et al. (2018)) claimed that PCA is not satisfactory for this problem; using implicit equal weighting could have worse impacts on the performance assessment of OECD countries towards reaching 17 SDGs. Correlation analysis results clearly indicate that PCA could be applied since more than half of the indicators were correlated with a strength of weak to strong correlation.

Table 1. Results of Correlation Analysis

	2017				2018			
SDG	Number of Variables	Total Number of Pairs	Number of Pairs with R >0.3	% Number of Pairs with R >0.3	Number of Variables	Total Number of Pairs	Number of Pairs with R >0.3	% Number of Pairs with R >0.3
1	3	3	1	33.3%	3	3	3	100.0%
2	4	6	2	33.3%	6	15	3	20.0%
3	14	91	53	58.2%	16	120	46	38.3%
4	5	10	9	90.0%	7	21	14	66.7%
5	5	10	6	60.0%	5	10	4	40.0%
6	4	6	1	16.7%	4	6	1	16.7%
7	4	6	2	33.3%	4	6	2	33.3%
8	6	15	8	53.3%	5	10	6	60.0%
9	9	36	35	97.2%	11	55	55	100.0%
10	3	3	1	33.3%	3	3	3	100.0%
11	3	3	2	66.7%	4	6	2	33.3%
12	6	15	8	53.3%	7	21	13	61.9%
13	6	15	6	40.0%	5	10	1	10.0%
14	5	10	3	30.0%	6	15	3	20.0%
15	3	3	1	33.3%	5	10	3	30.0%
16	9	36	21	58.3%	9	36	24	66.7%
17	4	6	3	50.0%	4	6	2	33.3%

The recent literature that aims to create a composite sustainability index by using a high volume of indicators is reviewed. To the best knowledge of the author, the state of art has not addressed the limitations of the approach used in the SDG Index and Dashboards report, which is the main focus of this study. To overcome potential negative impacts of weighted averaging method, this thesis proposes a novel Goal Specific Principal Component Analysis (GS-PCA) approach. PCA is a robust nonparametric approach, which is typically used to group a set of indicators to form a set of principal components (PCs) (whose number is typically less than the number of the variables in a dataset). PCA retains the majority of variability in the multi-variable dataset with the newly created PCs, while eliminating the potentially deteriorating impacts of multicollinearity among the variables with the newly created PCs (Guide, 2008); (Hudrliková, 2013). The rest of the thesis is organized as follows. Section two provides the recent literature review about the methods of sustainability performance indexing. Section three introduces the proposed methodology. Results are depicted and compared with the SDG Index and Dashboards report in section four. Discussion is provided in section five. Conclusions, future work, and limitations are provided in section six.

2. LITERATURE REVIEW

An index is typically termed "*synthesis of numerous factors into one given factor*"(Sainz, 1989). The use of indices in the field of sustainable development facilitates the understanding and interpretation of indicators of a given phenomenon, particularly for the public and other stakeholders (Tanguay et al.,2010). One of the most prominent sustainability indices, launched in 1999, was created jointly by S&P Dow Jones Sustainability Indices (DJSI). DJSI focuses on the measurement and evaluation of thousands of S&P companies in terms of their operations' economic, environmental and social impacts (Searcy and Elkhawas, 2012). In addition to DJSI, various methods have been proposed in the literature, which aim to create a sustainability index for the evaluation of sustainability performance of entities such as countries, cities, regions, industries, etc.

Sustainability indices can be categorized as follows. 1) Innovation, knowledge and technologies indices which includes Summary Innovation Index(European Commission, 2017), Investment in the knowledge-based economy, Technology Achievement Index, etc. 2) Development indices which include Human Development Index, index of sustainable and economic welfare, etc. 3) Market and economy based indices which include, Internal Market Index, Genuine Savings (GS) index, Business climate index etc. 4) Ecosystem-based Indices which includes Sustainability Performance Index (SPI), Living Planet Index (LPI), Ecological Footprint (EF), Fossil Fuel Sustainability Index (FFSI) etc. Moreover, other indices include Environment Sustainability Index, Environment Quality Index, City Development Index, The Sustainable Cities Index, Environmental Performance Index, Environmental Vulnerability Index, Well-Being Index (Singh et al., 2012).

The state of art consists of an abundant number of methods, which have been proposed to develop a sustainability index. The process of developing an index could be termed as follows. 1) Indicator selection and grouping, 2) data collection, preparation (e.g. imputation of missing data, taking care of outliers, etc.), 3) Implementation of multivariate analysis, weighting, and aggregation, 4) Normalization of results, and calculation of the proposed index (Guide, 2008). In these series of steps, weighting and aggregation substantially effects the results of a sustainability index. Correlation and compensability issues among indicators need to be considered and either be corrected for or treated as features of the phenomenon that need to retain in the analysis (Guide, 2008).

In addition, weights could have a significant effect on the overall composite index and the country rankings when used in a benchmarking framework. In this regard, there are various approaches used in the literature for weight assignment. For instance, assumption of equal weights (the most commonly used approach in the literature), using weights derived from a statistical analysis, using benefit of the doubt, using public or expert opinion through surveys (Guide, 2008). This study holds the equal weight assumption to be consistent with the UN SD report, where each of the 17 SDGs has equal importance on the derivation of the composite sustainability index.

Principal component analysis (PCA) is a commonly used multivariate technique for creating indices, which is very robust in reducing the multi-dimensionality in a dataset without losing relevant information (Park et al.,2015). It is used to obtain coefficients that assign correct weights according to the statistical importance of each included variable in the index and is increasingly used in welfare measurements (Lindman, 2011). It is also suggested by European Commission (EC) and OECD guidelines in developing the composite indicators (Guide, 2008). In a typical PCA study, findings exhibit how different variables change in relation to each other and how they are associated (Mainali and Silveira, 2015). PCA is an appropriate and robust method for problems where the researcher(s) need(s) to deal with the high number of variables, which makes the indexing a challenging task. Often times, datasets that consists of higher number of variables hold high levels of pair-wise correlation and the researcher needs to reduce the dimension of the analysis (number of variables) to a smaller number of non-correlated factors (independent factors) to prevent the results being impacted by multicollinearity (Constantin, 2014). In this regard, it is important to note that the literature is still emerging in the context of reaching to a consensus in terms of the best methods to employ for sustainability performance assessment and indexing (Searcy and Elkhawas, 2012).

In terms of the applications of PCA, it was used to develop an energy-focused sustainability performance of rural communities (Doukas et al.,2012), area-based socio-economic index (Krishnan, 2010), energy technology index for rural electrification (Mainali and Silveira, 2015), sustainability water index (Ali, 2009), construction of composite sustainable indicators(Li et al., 2012), assessment of aggregated indicators of sustainability (Rovira & Rovira, 2009), eco-efficiency analysis (Park et al., 2015), human development index (HDI) (Biswas and Caliendo, 2001). The application of (Krishnan, 2010) resulted in a socio-economic index derived with PCA, which was found to be very effective in differentiating disadvantaged areas from privileged ones. In another work, (Doukas et al., 2012) employed PCA to assess' energy sustainability of rural communities based on the outputs of two European "Intelligent Energy for Europe" projects on the Mountainous and Agricultural Communities and Islands regions. The results of the study they believed to support the monitoring of such communities' progress, which is an especially valuable parameter as concerns the development and main implementation of their Sustainable Energy Action Plans.

Moreover, the sustainability performance of energy technologies applied in rural electrification was evaluated using PCA (Mainali and Silveira, 2015). In this study, the focus of sustainability indexing was on creating energy technology sustainability index (ETSI). The index was then used to assess the sustainability performance of ten energy systems in India. In another work, Hosseini and Kaneko, (2011) applied PCA to develop macro sustainability indicators of selected countries to track sustainability in a dynamic manner. Countries were ranked based on the resulting principal components. In anoter work, Lai, (2012) used weighted PCA to measure and analyze the progress of human development in Chinese provinces since 1990. He also compared his scores with the Human Development Index (HDI) scores and found that the results obtained from the PCA and HDI report of China by UNDP were highly similar. (Jollands et al., 2004) provides a unique analysis using PCA to eco-efficiency indicators in New Zealand and the results from their analysis showed that application of PCA is an effective approach for aggregating eco-efficiency indicators and assisting decision makers by reducing redundancy in an eco-efficiency indicators matrix. (Adler et al.,, 2010a) used PCA was integrated with data envelopment analysis (DEA) to measure the relative performance of developing countries in utilizing domestic and external resources. Park et al., 2015) developed an integrated LCA+PCA to assess the eco-efficiency of U.S. industries.

Table 2 illustrates a list of recent works, where PCA was used to create a composite index. Indeed, PCA is a identified as a robust statistical approach, used to evaluate the sustainability performance of a large number of technological systems when compared to the other methodologies (Mainali and Silveira, 2015). To the best knowledge of authors, application of PCA or similar statistical approach has not been addressed to the OECD countries' sustainable development indexing based on 17 SDGs. The methodology that was used in UN SDG Index and Dashboard's report was based on a linear aggregating approach with normalized data and equal weights, where the deteriorating impacts of multicollinearity and working with over 90 indicators were not addressed sufficiently (SDSN, 2018b).

In this study, the current status of OECD countries' sustainable development performance towards reaching the recently announced 17 UN sustainable development goals (SDGs) is investigated. Total of 93 social, economic and environmental indicators are considered as sub-indicators (variables_ of the SDGs in parallel with the UN's SDG Index and Dashboards report. A novel Goal-Specific Principal Component Analysis (GS-PCA) model is developed to create composite index scores for OECD countries. The proposed GS PCA approach is explained in detail in the following section.

Table 2.Summary of Sustainability Indexing Methods with PCA

Study	**Index**	**Focus**	**Method**
Krishnan, (2010)	Socio-Economic index	Development of a socioeconomic index to compare disadvantaged vs. privileged areas in a multivariate context	PCA
Park et al., (2015)	Eco-efficiency	The relationship between the U.S. manufacturing and transportation industries	EIO-LCA+PCA
Jollands et al., (2004)	Eco-efficiency index	Development of aggregate measures of eco-efficiency for use by policymakers	PCA
Adler et al , (2010b)	Socio-Economic index	Estimation the relative efficiency of developing countries in utilizing both their domestic and external resources to achieve the Millennium Development Goals	PCA+DEA
Mainali and Silveira, (2015)	Sustainability	Evaluation of the sustainability performance of energy technologies applied in rural electrification	PCA

Hosseini and Kaneko, (2011)	Sustainability indicators	Attempt to develop macro sustainability indicators of selected countries to track sustainability in a dynamic manner	PCA
Lai, (2012)	Human development index	Measurement and analysis of the progress of human development in Chinese provinces	PCA
Ali (2009)	Water Sustainability index	A conceptual framework incorporating a variety of physical, socio-economic and environmental elements of water status in the Arab region	PCA
Li et al. (2012)	Sustainability indicators	Development of a comprehensive and effective quantitative method to measure the overall sustainability performance of manufacturing companies.	PCA
Biswas and Caliendo (2001)	Human development index	Measures of human development and comparison of the index with HDI itself	PCA
Dong et al., (2015)	Natural Gas Industry Sustainability Index	Trends in natural gas consumptions	PCA
Zhao (2015)	Sustainability index	Judgment of countries based on sets of sustainability indicators	PCA
Choi et al. (2015)	Air Quality Index	Development of an aggregate air quality index to help prepare decision makers, which could rank a state according to the different levels of multiple air pollutants	PCA
Dong et al. (2016)	Sustainability assessment	Development of the assessment process to help soybean farmers document practices and verifiable advances in community, environmental and economic sustainability	PCA-DEA

Si (2006)	External debt sustainability index	construction of an external debt sustainability index to capture the overall effects of external debt indicators on economic growth	PCA
Hag (2017)	Sustainability index	Assessing and monitoring eight community-based water supply management in four different states in Sudan	PCA
Haberland (2008)	Environmental performance index	establishment of an international composite environment index	PCA and Equal Weighting

To calculate SDG index, it is very important that the constituent components be weighted and aggregated with the right approach because weighing individual goal can have vital implications on countries ranking and their sustainability performance. Different weighting methods has been used, for instance equal weighing, experts' weight, PCA, subjective /flexible weight etc. In this study PCA as a method of giving weights is chosen to constituent variables to derive SDG index. The reason of choosing this method is to avoid multicollinearity in the large number of data set. PCA are commonly used to assign weights to individual variables correlated among each other and measuring a common underlying factor(Lafortune et al., 2018).As per correlation analysis conducted on this research (Table 1) shows higher number of correlation between the variables , therefore this research is motivated to employ PCA as a nonparametric analytical approach for developing sustainability index score.

3. METHODOLOGY

A hierarchical methodology that proposes PCA, as a multivariate data analysis approach is developed to create a composite sustainability index for OECD countries. In this regard, a step by step procedure is carried out which consists of data collection, data cleaning and preparation, normalization, PCA, statistical analysis, and discussion. The approach is defined as GS-PCA, since the PCA is implemented for each SDG to be able to create a composite index for each goal, then creating an overall Sustainable Development Index considering the entire set of 17 SDGs. Thus, 17 PCA models are developed over a series of iterations. Goal-specific sustainability index scores are derived from the principal components and finally, composite sustainability index is calculated by taking the average of the individual index scores of 17 goals, and countries were then ranked according to the overall sustainability index. The proposed approach is compared and validated with the 2017 and 2018 SDG Index and Dashboards report (Geus and Satchs, 2017). The hierarchical methodology is depicted in Figure 2.

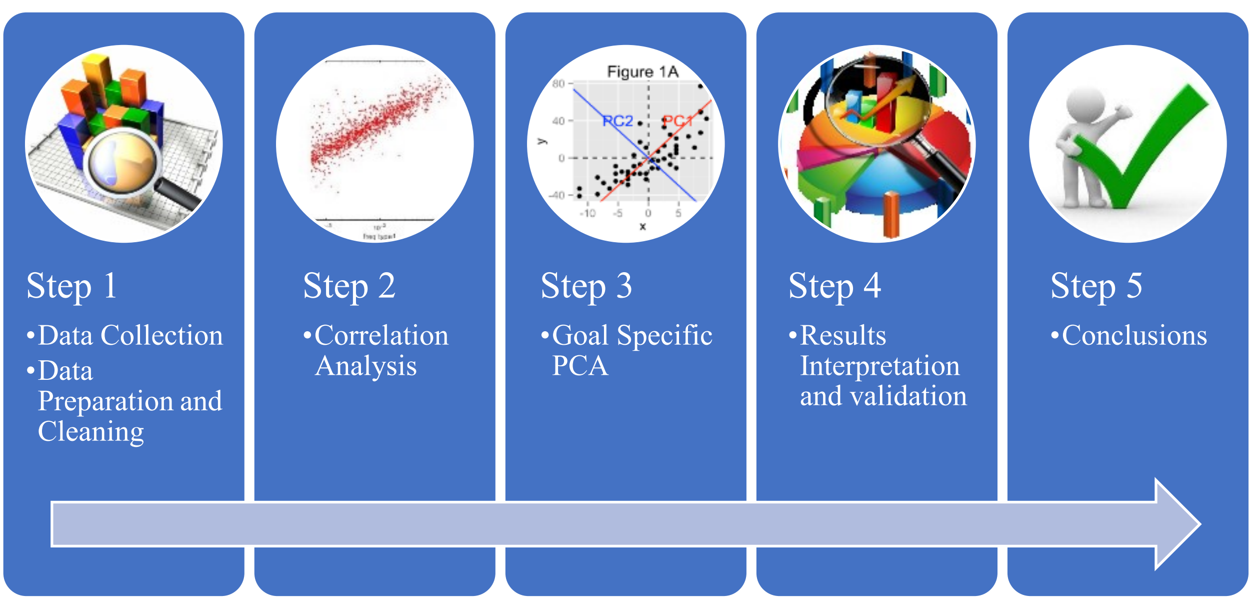

Figure 2. Summary of the Proposed Methodology

3.1. Data Collection

In this study, the main objective is to create a novel sustainability performance index for 35 OECD countries considering recently proposed 17 SDGs. The 2017 and 2018 UN SDG Index and Dashboards Report was used to classify and choose variables for the 17 SDGs (Sachs et al., 2017). The raw dataset consisted of indicators that have a substantial range of data, which necessitates carrying out a normalization procedure. The normalized data consisted of 93 indicators for 2017 and 104 indicators for 2018, where 2-13 indicators were classified under each of the 17 SDGs (Sachs et al., 2017). Then, Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity is conducted to assess the proximity of correlation matrices to the identity matrix for each SDG. Resulting significance (p) values of the test that are less than 0.05, indicate that factor analysis (PCA) could be effectively applied to the set of variables under an SDG (Lolli anddi Girolamo, 2015) (See Table 6).

3.2. Goal Specific Principal Component Analysis (GS-PCA)

PCA (Principal Component Analysis) is a mathematical procedure that uses orthogonal transformation to convert a set of observation of possibly correlated variable into a set of values of linearly uncorrelated variables called principal components. The principal components (PCs) are ordered so that the first component accounts for the largest possible amount of variation in the original variables. The second component is completely uncorrelated with the first component and accounts for the maximum variation that is not accounted in the first. The third accounts for the maximum variation that the first and the second PCs did not account for, and so on (Krishnan, 2010).

The first step carried out to determine the principal components of multiple variables data set is to standardize/normalization of the scale of the data. It is done by transferring data set into scale from 0 to 100. The variables were transferred linearly to a scale between scale 0 and 100 using the following normalized equations (Brijesh Mainali & Silveira, 2015).

$$X' = \frac{X - Min\,(x)}{Max(x) - Min(x)} \tag{1}$$

where x is the raw data value; max/min denote the bounds for best and worst performance, respectively; and x' is the normalized value after rescaling.

After, the correlation matrix of the normalized variable is calculated. Correlation is a measure of how two or more variables related to each other. A correlation has direction and can be either positive or negative i.e. the value ranges from -1 to 1 which means values towards 1 are highly positively correlated and values towards -1 is highly negatively correlated. Zero indicates no relationship between the two variables and r = 1.00 or r = -1.00 indicates a perfect relationship between the variables.

The eigenvalues and eigenvectors of the correlation matrix are calculated. An eigenvalue indicates the extent of variance in the data. The eigenvector with the highest eigenvalue is, therefore, identified as the principal component**.** In this process, the principal components with the largest eigenvalues are retained as they contain the largest portion of the variance in the data. The main intuition behind the calculation of the eigenvalues is the use of the following determinant equation.

$$(R - \lambda I) = 0 \tag{2}$$

where R is the correlation matrix ($n \times n$), λ is the symbol for eigenvalues and I is the unit matrix (Doukas et al., 2012).

Solving for λ, an n^{th} degree polynomial equation is obtained and n eigenvalues, which corresponds to the correlation matrix, thus *R* is calculated. The eigenvalue with the largest rate is the one that holds most of the variation and the eigenvalues with very small rate are usually ignored and the solution of the problem is getting simpler(Doukas et al., 2012). Furthermore, to derive the eigenvectors, the following matrix equation is solved

$$(R - \lambda jI)Fj = 0 \qquad (3)$$

where R is the correlation matrix, λ_j is the corresponding eigenvalue, *I* is the identity matrix, and F_j is the matrix of the eigenvector corresponding to the λ_j eigenvalue (Doukas et al., 2012).

As PCA is sensitive to the difference in the units of measurements of variables, therefore Min-Max normalization method is adopted (Krishnan, 2010). After data is collected, cleaned, and prepared, 17 PCA models were built that will account for all the SDGs. Models were built by using SPSS software v25. After running experiment, factor scores *(f_i)* were obtained and used as the PC weights for composite non-standardized index (NSI) computation. The composite NSI is calculated using the following equation.

$$NSI_k = \frac{\lambda_{1k} * f_{1k} + \lambda_{2k} * f_{2k} + \cdots + \lambda_{nk} * f_{nk}}{\lambda_{1k} + \lambda_{2k} + \cdots + \lambda_{nk}} \qquad (4)$$

where NSI_k is the non-standardized sustainability index of the k^{th} country and λj is the corresponding eigenvalue (Krishnan, 2010). There are *n* PCs It is important to note that the number of variables vary from one SDG to another. The final composite sustainable development index derived from the above equation could be either positive or negative, which creates difficulties in interpretation. Therefore, the NSI scores were standardized by using Eq. 6, which yields the Goal-Specific-PCA Sustainable Development Index (GS-PCA SDI) (Park et al., 2016). This approach was repeated for all 17 SDGs.

$$GS - PCA\ SDI = \frac{NSI_i - Min\ [NSI_k]}{Max\ [NSI_k] - Min\ [NSI_k]} * 100 \tag{5}$$

For instance, the NSI of Australia for SDG 3 is calculated as follows (See Eq. 4) based on the factor scores given in Table 3.

Table 3. Factor Scores for Australia for SDG 3

Country	f_1	f_2	f_3
Australia	-0.0098	-1.1219	0.27

$$NSI = \frac{44.197 * (-0.0098) + 21.306 * 1.1219 + 9.782 * 0.27}{75.286} \quad = \quad 0.346$$

4. RESULTS

This section is organized into seven subsections. In the initial subsection, descriptive statistics of the results are provided. The second and third sub-sections introduce the results of the proposed GS-PCA for 2017 and 2018, respectively. The fourth and fifth sub sections provide the comparison of GS-PCA results in terms of index scores and ranks of the OECD countries with SDG Index and Dashboards report 2017/2018 and PCA SDI scores of 2017 and 2018, respectively. The sixth sub section provides the summary of top 5 best performing and 5 worst performing countries in the consecutive years. Lastly, SDG specific analysis and results are provided in subsection seven.

4.1. Descriptive Statistics of Results

Table 4 depicts the descriptive statistics of the 17 SDGs' SDI scores obtained with the proposed GS-PCA approach for the calendar year 2017. For instance, the mean of the SDG 17 - Partnership for the goal (Revitalize the global partnership for sustainable development goal) and SDG 13 - Climate action (Take urgent action to combat climate change and its impacts) are relatively lower than that of the other SDGs. It can be seen from the table 7 that only Denmark and Netherlands have an impressive score on SDG 13 while all other countries are relatively very low on the same. Being the top ranked country, Sweden has a score of 54.2/100 on climate action. The range of standard deviation is between 18 and 30, while the range of mean SDI scores were between 57 and 80. In Table 4, the Zskewness and ZKurtosis results indicate that majority of the SDGs SDI scores are out of -1.96 and +1.96 range, which is strong indication of non-normality in the results dataset (Taylor et al.,2012). It is also important to note that using PCA as a nonparametric approach could be of importance and a more suitable approach to such problems where normality assumption is not met.

Table 4**.** Descriptive Statistics of the SDI Score in 2017

SDG	N	Min	Max	Mean	Std. Dev.	Skewness[1]	Kurtosis[2]	$Z_{Skewness}$	$Z_{Kurtosis}$
1	35	0.00	100.00	57.39	26.71	-0.232	-0.767	-0.583	-0.986
2	35	0.00	100.00	71.41	18.99	-2.573	7.531	-6.465	9.680
3	35	0.00	100.00	74.85	23.84	-1.733	2.688	-4.354	3.455
4	35	0.00	100.00	71.83	22.11	-1.760	3.241	-4.422	4.166
5	35	0.00	100.00	71.60	20.53	-1.351	2.987	-3.394	3.839
6	35	0.00	100.00	74.90	23.71	-1.670	2.322	-4.196	2.985
7	35	0.00	100.00	58.91	17.20	-0.751	3.946	-1.887	5.072
8	35	0.00	100.00	78.06	24.27	-1.838	3.241	-4.618	4.166
9	35	0.00	100.00	59.37	24.00	-0.607	0.336	-1.525	0.432
10	35	0.00	100.00	66.17	23.29	-1.272	1.892	-3.196	2.432
11	35	0.00	100.00	65.37	25.84	-0.950	0.230	-2.387	0.296
12	35	0.00	100.00	53.94	27.78	-0.018	-0.993	-0.045	-1.276
13	35	0.00	100.00	38.60	21.11	0.637	1.379	1.601	1.772
14	35	0.00	100.00	51.28	21.29	0.074	0.308	0.186	0.396
15	35	0.00	100.00	57.48	25.55	-0.433	-0.577	-1.088	-0.742
16	35	0.00	100.00	56.92	29.43	-0.433	-0.984	-1.088	-1.265
17	35	0.00	100.00	29.93	24.92	1.327	1.712	3.334	2.201

[1] Std. Error=0.398
[2] Std. Error=0.778

Table 5 represents the descriptive statistics of the individual SDI score for the year 2018. SDG 6 i.e. Clean water and sanitation has the highest average SDI score of 85.21 while SDG 9 i.e. Industry, Innovation and Infrastructure has the lowest average SDI score.

Table 5.Descriptive Statistics of the SDI Score in 2018

SDG	N	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis	$Z_{Skewness}$	$Z_{Kurtosis}$
1	35	0	100	75.71	22.1	-1.54	2.81	-0.41	0.01
2	35	0	100	75.26	17.11	-2.73	10.68	-1.49	1.72
3	35	0	100	77	21.63	-1.8	3.89	-0.65	0.25
4	35	0	100	56.06	24.50	-0.322	-0.23	0.03	-0.33
5	35	0	100	65.8	22.76	-1	1.13	0.08	-0.36
6	35	0	100	85.21	7.85	-1.647	2.99	0.59	-0.75
7	35	0	100	76.11	5.86	-1.141	4.24	-1.67	2.40
8	35	0	100	67.28	25.11	-1.32	1.37	-0.21	-0.30
9	35	0	100	48.61	26.09	-0.1	-0.51	0.89	-0.71
10	35	0	100	72.37	23.12	-1.42	2.30	-0.30	-0.10
11	35	0	100	84.64	5.85	-0.173	0.00	-0.35	-0.06
12	35	0	100	56.54	24.63	-0.1	-0.31	0.89	-0.67
13	35	0	100	81.13	12.49	-3.26	13.50	-1.72	1.80
14	35	0	100	51.38	9.66	0.44	2.12	1.26	-0.64
15	35	0	100	47.48	28.19	-0.1	-1.20	0.89	-0.86
16	35	0	100	60.59	25.56	-0.44	-0.71	0.59	-0.75
17	35	0	100	59.67	13.38	0.931	1.27	1.58	-0.64

4.2. Results of the proposed GS-PCA for 2017

The results of KMO tests and p values after arranging variables are provided in Table 6. There are some goals that has KMO value less than 0.5, but their significance value is less than 0.05, which indicates that the proposed PCA model is applicable to the variables and the obtained principal components are statistically reliable. All of the significance values were found to be less than 0.05, which indicates that all PCA models are valid, and the resulting PCs could be used for calculating the composite sustainability index scores for the OECD countries.

In this regard, it is crucial to carry out the KMO and Bartlett's tests in a PCA study. Usually two test KMO and Bartlett's test of sphericity are conducted to check suitability of analysis. The Bartlett's test of sphericity is a test performed on the correlation matrix to verify how close it is to the identity matrix: the closer the correlation matrix is to the identity matrix, the more the variable indicators are uncorrelated. Significance (p) values of the test that are less than 0.05 and KMO greater than 0.5 indicate that PCA could be effectively applied to the studied problem (Lolli & di Girolamo, 2015).

In this study, after implementing PCA to each SDG, it was found that two of the SDGs (SDG #1: No Poverty, and SDG #13: Climate action) unsuitable for carrying out PCA, as their significance level was higher than the acceptable value of 0.05, which was preventing the work to be proceeded to composite sustainability index calculations. The main reason of this problem was attributed to having low number of variables under these SDGs compared to others. To deal with this issue, it was found an SDG that is closely related to the SDG with insignificant sigma value and moved a variable and performed PCA again. For instance, one variable from SDG #2 (No Hunger) was moved to SDG #1 (No Poverty) and two variables were added to SDG #13 (Climate action) from SDG #12 (Responsible consumption). The PCA was performed again, and the results of the two

PCA models built for SDG 1 and SDG 13 were acceptable. Table 6 indicates the KMO and Bartlett's test results (significance), accordingly.

Table 6**.** KMO values and significance 2017

SDG	Number of Variables	KMO Value	Significance
1	3	0.534	0.029
2	4	0.489	0.040
3	14	0.71	0.048
4	5	0.703	0.050
5	5	0.58	0.000
6	4	0.433	0.020
7	4	0.482	0.000
8	6	0.665	0.000
9	9	0.806	0.000
10	3	0.533	0.000
11	3	0.592	0.000
12	6	0.544	0.000
13	6	0.672	0.060
14	5	0.447	0.050
15	3	0.544	0.000
16	9	0.682	0.000
17	4	0.506	0.002

The sustainable development performance index score (SDI score) of OECD countries is shown in Table 7. Each country is ranked according to their average index score of the 17 SDGs. In the table 7, Sweden was ranked as the best performer with the average index score of 83.6, which was followed by Finland, Norway, Denmark and Netherland. In contrast, Mexico was ranked as the worst performer with the average index score of 15.3 over 100. It is important to note that even though the country Sweden was outperformed by countries such as Finland and Norway in SDGs #4, #5, #11, and #14, its overall score was ranked as the highest. The top two countries, Sweden and Finland, scored low on SDG #13,

Table 7**.** OECD countries' SDI scores obtained with the proposed GS-PCA approach 2017

Countries\SDG	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	GS-PCA SDI
Sweden	64.7	80.8	100.0	82.9	94.5	88.7	86.6	99.5	90.5	82.4	95.9	72.7	54.2	63.6	69.6	95.0	100.0	**83.6**
Finland	47.8	80.6	95.7	87.5	95.4	91.8	76.2	87.6	95.3	83.2	97.5	39.9	48.5	100.0	79.2	92.6	67.3	**80.4**
Norway	34.3	76.0	96.8	89.9	100.0	72.4	89.9	99.1	86.9	81.2	100.0	17.8	66.3	86.3	60.6	97.2	83.0	**78.7**
Denmark	78.5	83.0	86.5	83.1	92.8	84.3	65.6	96.4	100.0	78.7	87.8	38.0	85.6	14.7	81.8	76.9	93.8	**78.1**
Netherlands	80.9	82.1	90.2	82.0	82.7	79.3	50.8	98.8	70.4	81.9	85.6	45.7	100.0	24.1	92.0	93.7	39.8	**75.3**
Iceland	67.2	76.5	94.1	77.1	96.2	83.7	100.0	95.4	98.2	79.4	92.3	70.7	30.4	54.9	31.5	77.7	33.2	**74.0**
Belgium	89.9	81.3	82.4	77.6	91.8	48.9	55.0	81.3	64.0	92.8	79.5	81.0	53.2	41.2	100.0	65.4	44.9	**72.4**
Germany	97.4	86.8	87.2	81.5	76.6	83.6	57.9	99.0	58.4	76.8	65.6	62.4	54.1	30.4	80.2	80.1	34.0	**71.3**
Switzerland	73.2	82.8	96.3	81.5	83.9	89.1	71.3	100.0	77.1	74.0	74.9	30.4	53.3	51.3	58.4	100.0	5.6	**70.8**
France	84.1	74.5	83.0	74.9	80.6	90.1	67.4	78.8	57.0	86.3	73.0	50.8	34.2	56.8	60.7	67.8	48.9	**68.8**
Austria	92.2	84.7	84.1	67.5	69.8	91.7	69.6	92.7	64.2	82.7	59.3	37.3	47.9	51.3	56.3	71.3	32.9	**67.9**
UK	91.2	66.7	85.0	91.5	84.9	84.6	54.7	91.8	66.8	56.6	87.3	52.5	49.1	41.4	47.4	84.2	6.2	**67.2**
Czech Republic	77.1	78.1	78.3	66.4	62.7	92.3	57.5	81.2	57.9	100.0	78.9	91.9	25.9	51.3	78.4	36.9	17.6	**66.6**
Slovenia	58.5	72.3	83.1	83.0	85.7	78.9	60.8	83.1	58.5	87.7	39.3	93.8	40.1	29.4	78.9	37.2	37.9	**65.2**
New Zealand	68.1	64.7	76.2	81.3	89.4	87.8	72.2	95.0	71.6	66.4	82.3	24.8	24.3	44.5	26.2	79.5	42.0	**64.5**
Luxembourg	58.1	76.0	84.5	66.6	72.8	54.8	25.7	90.9	78.5	77.8	77.5	23.1	43.6	51.3	96.3	81.1	31.2	**64.1**
Japan	57.1	100.0	93.7	98.0	41.8	87.8	54.8	96.5	67.4	66.5	50.6	70.6	32.6	52.3	44.5	61.2	7.1	**63.7**
Canada	52.2	66.9	86.1	100.0	83.7	55.2	66.0	92.2	57.0	61.1	85.7	9.2	10.0	81.1	49.0	77.9	33.7	**62.8**
Australia	25.4	67.0	89.0	86.6	80.6	100.0	51.3	93.4	74.1	60.4	79.6	12.2	42.2	59.4	36.3	65.9	31.3	**62.0**
Estonia	31.4	76.9	67.0	91.1	65.9	87.3	43.9	90.6	70.7	53.5	63.7	62.5	32.9	65.0	85.5	51.1	4.6	**61.4**
USA	96.5	57.7	62.6	78.1	72.8	85.8	55.6	87.3	56.4	32.8	75.0	25.3	9.5	60.1	30.9	73.5	31.4	**58.3**
Ireland	100.0	71.4	85.5	80.4	70.5	35.0	53.9	79.4	66.8	69.1	41.9	0.0	42.5	29.4	73.0	73.9	15.0	**58.1**
Spain	11.3	74.9	85.6	70.9	83.4	79.0	64.0	66.6	52.3	54.7	89.0	37.1	42.7	30.6	46.1	52.9	29.6	**57.1**
South Korea	46.5	79.4	80.4	87.0	36.6	25.0	55.1	79.1	76.8	69.6	46.7	93.5	33.6	77.8	32.7	31.7	9.3	**56.5**
Portugal	13.5	81.5	77.8	55.0	85.1	93.1	68.3	61.0	45.3	56.5	66.5	44.3	21.4	50.7	60.7	44.4	30.3	**56.2**
Italy	46.6	79.9	85.7	63.3	56.7	75.3	58.2	55.7	36.4	60.1	61.5	53.3	42.7	34.3	67.5	17.9	31.5	**54.5**
Slovak Republic	67.3	71.2	53.8	57.6	59.5	93.9	59.1	67.9	55.2	94.5	0.0	75.9	16.9	51.3	75.6	17.5	1.3	**54.0**
Poland	47.9	72.1	55.9	80.9	60.0	71.2	48.7	70.0	30.8	72.5	39.2	97.9	24.0	0.0	72.6	28.4	12.6	**52.0**
Latvia	28.9	74.9	31.3	72.7	63.8	55.9	59.9	84.1	42.7	52.3	11.5	100.0	60.7	37.2	83.3	25.2	0.0	**52.0**
Greece	28.7	80.5	71.5	53.8	44.6	86.5	56.5	51.6	35.5	57.0	86.4	34.0	41.8	56.8	50.3	15.3	33.4	**52.0**
Hungary	72.5	74.3	42.6	44.5	62.1	98.5	38.4	64.1	29.9	91.9	21.2	71.4	22.3	51.3	61.2	5.7	19.0	**51.2**
Israel	30.9	71.9	92.6	79.4	67.1	22.1	57.6	83.9	63.6	40.9	64.2	35.7	40.0	36.6	12.3	65.9	5.0	**51.2**
Chile	55.6	39.9	43.4	25.3	48.8	91.4	57.7	23.3	11.2	0.0	69.2	74.7	23.9	79.7	17.8	43.0	8.9	**42.0**
Turkey	33.2	12.4	11.7	14.8	0.0	76.4	51.6	0.0	10.6	33.3	45.6	66.9	0.6	86.9	15.0	4.3	10.2	**27.9**
Mexico	0.0	0.0	0.0	0.0	63.3	0.0	0.0	15.0	0.0	1.4	13.6	90.7	0.0	61.8	0.0	0.0	14.8	**15.3**

4.3. Results of the proposed GS-PCA for 2018

The table 8 depicts the values of KMO and Bartlett's test of Sphericity to verify the significance of PCA application in the 2018 data. Except for SDGs 6,11,13,14 and 17, all SDGs were found to be suitable for the implementation of PCA. For those SDGs which are not suitable for PCA, SDI scores from UN SDG Index and Dashboard Report 2018 was kept the same. The SDI scores of OECD countries for the year 2018 is given in table 9. In 2018, the top 5 performing countries remains the same with minor changes in their rank. Mexico and Turkey were still found to be among the worst performing countries. The changes in the score and their ranks are more explained on the comparison section of this report.

Table 8. KMO and values of significance 2018

SDG	Number of Variables	KMO Value	Significance
1	3	0.591	0.000
2	6	0.459	0.000
3	16	0.565	0.000
4	8	0.698	0.000
5	5	0.509	0.000
6	4	0.536	0.092
7	4	0.446	0.000
8	5	0.723	0.000
9	11	0.815	0.000
10	3	0.571	0.000
11	4	0.422	0.324
12	7	0.675	0.000
13	5	0.548	0.071
14	6	0.571	0.110
15	5	0.544	0.000
16	9	0.693	0.000
17	4	0.512	0.089

Table 9. OECD countries' SDI scores obtained with the proposed GS-PCA approach 2018

COUNTRIES/SDG	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	GS- PCA SDI
FINLAND	100	75.0	100	92.7	90.3	93.6	93.7	72.5	79.6	99.2	91.1	48.9	76.6	62.6	74.3	93.8	70	83.2
SWEDEN	79.9	83.0	98	66.7	93.9	92.6	97.7	92.6	90.2	93.8	89.9	46.3	84.9	54.5	61.4	88.2	96.4	82.9
DENMARK	87.7	90.1	85.9	73.5	87	89	88.7	88.7	100	89.5	88.5	41.4	87.4	51.4	81.2	78.9	87.2	82.1
ICELAND	95.7	81.4	99.3	66.9	94.8	85	98.9	100	91.4	100	89.3	60.8	88.9	28	6	77.5	65.2	78.2
NORWAY	87.8	71.4	98.6	83.4	100	84.7	97.4	76.3	78.3	99.3	87.7	20.7	62.2	65.2	27.9	95.6	89.7	78.0
GERMANY	93.5	92.1	84.1	57.3	71.4	86.3	88	89.9	45.7	85.8	91.1	43	88.1	44.3	58.8	80.4	77.2	75.1
IRELAND	94.2	88.0	90.5	61.5	59.6	85	86.7	89.9	58.4	86.6	83.2	52.2	89.7	52.5	79	71.6	32	74.2
NETHERLANDS	92.6	84.4	90.2	64.0	74.5	90.9	85	90.3	58.1	92.2	88.7	29.8	71.3	39.8	60	94.6	49	73.8
SLOVENIA	89.6	80.0	87	64.3	86.9	87.1	90.3	67.4	46.6	84.2	85.5	81.8	91.8	50	55.9	49.2	57.1	73.8
FRANCE	93.7	87.4	81	39.9	90.6	89.5	94.6	59.4	48.9	89.2	89.6	50.2	84.8	61.3	54.6	68.2	71.3	73.8
UNITED KINGDOM	90.8	81.8	81	84.4	78.1	92.6	87.7	82.2	59.6	63.3	91.2	35.5	80.9	53.9	58.6	86	42.1	73.5
NEW ZEALAND	94.2	72.7	70.5	64.2	84.7	88.9	92.7	90	56.7	70	80.7	71.7	87.6	56.7	9.2	82.1	65	72.8
ESTONIA	67.2	71.7	71.6	80.5	54.2	87.3	81.4	73.1	58.5	59	88.5	82	81.5	81.5	89.5	58.1	51.2	72.8
SWITZERLAND	95.7	81.6	96.3	44.1	76.8	93.6	94.2	95.1	62.9	75.4	97.3	8.5	87.4	46.5	11.7	100	51.4	71.7
BELGIUM	86.5	82.9	83.2	44.5	85.1	77	85.9	68.4	46.7	93.5	84.5	46.4	79	47.2	71.5	64.9	58.9	70.9
AUSTRIA	85.7	92.3	85.6	44.4	58.1	94.4	89.1	83.6	55	90.9	83.9	32.3	83.2	46.5	42.9	69.9	66	70.8
CZECH REPUBLIC	90	84.9	80.6	31.1	53.2	87.4	87.2	68.6	47	86.7	86.9	84.7	87.9	46.5	79.4	43.4	49.3	70.3
JAPAN	62.5	83.5	98.2	98.0	15.8	90.7	88.3	82.1	58.8	70	74.1	60.4	85.2	56.4	34.7	72.4	57.3	69.9
CANADA	70.6	71.7	75.1	100.0	75.2	75.4	91.5	77.7	40.8	78.3	81.9	54.4	66.4	54	24.3	79.8	63.4	69.4
POLAND	93.1	73.5	67.7	53.9	64.4	83.1	81.8	55.5	29	71.5	77.2	100	87.5	45.2	80.5	34.5	48.6	67.5
PORTUGAL	58.5	67.7	73.4	53.3	81.8	82.3	90.4	65.5	43.9	63.9	83.6	58.8	89.5	54.4	74.9	47.1	57.3	67.4
KOREA, REP.	67.9	100.0	85.7	83.4	24.1	79.9	88.6	61.7	78.9	62.5	80	70.2	85.4	56	13.2	45.9	49.8	66.7
LUXEMBOURG	96.2	76.6	90.4	22.4	71	86.4	66.7	83.6	33.5	92.5	95.4	0	80.7	46.5	28.6	82.7	50.9	64.9
AUSTRALIA	87.5	64.2	85.9	68.5	71.2	86.7	84	81.6	65.1	63	84.5	43	23.3	55	17	63.5	59	64.9
SPAIN	46.4	68.3	87.4	69.3	73.6	84.6	90.6	49.1	32.9	72	87.9	49.5	88.9	47.5	40.3	52.6	55	64.5
ISRAEL	68.6	68.5	88.9	52.7	72	66.9	89.7	75.9	80.2	51.7	82.2	37.8	88.4	35.8	9.9	68.7	52.4	64.1
LATVIA	56.2	73.2	49.4	66.9	51.6	84.7	86.3	70	15.7	58.1	83.2	75.7	84.2	55.6	100	29	47.6	64.0
UNITED STATES	61.4	82.6	56	54.8	63.7	90.6	87.8	75.5	50.1	40.4	86.8	48.3	65.3	49.7	30.7	73.7	57.1	63.2
SLOVAK REPUBLIC	55.7	72.8	60.6	26.7	56.4	89.6	88.1	52.3	38	82.9	80.9	83.6	76.2	46.5	70.6	29.9	50.4	62.4
HUNGARY	73.7	78.9	52.2	0.0	51	86	85.2	49.5	9.3	82.8	83	86.1	84.1	46.5	73.4	23.3	49.6	59.7
ITALY	40.7	81.4	89.3	56.9	56.5	83.2	87.7	25.2	19.3	73.4	71.9	51.4	82.1	43.3	55.6	30.9	58.5	59.3
GREECE	30.6	76.5	79.4	30.2	54.8	85.8	86.9	15	13.3	62.6	78.3	43.9	78.1	59.4	52.9	24.3	53.8	54.5
CHILE	72.1	49.1	44	7.3	32.4	94.2	87.5	44	0.9	13.5	79.6	85.5	92.4	62.9	28.2	36.6	73.8	53.2
TURKEY	83.4	44.5	28.2	33.8	0	67.7	80.8	0	0	35.4	73.2	95.3	86.8	36.9	0	23.2	63.5	44.3
MEXICO	0	0.0	0	20.6	48.4	59.7	80	2.8	8	0	81.2	98.7	88.1	58.4	5.2	0	61.6	36.0

4.4. Comparison of the GS PCA with the UN SDG Index and Dashboards Reports

The result obtained from the PCA is compared with the SDG Index and Dashboards Report 2017(Sachs et al., 2017) and 2018. The results are shared in Table 10. It was found that except a few top performing countries such as Sweden (ranked and scored as almost the same with the SDG Index and Dashboards report, mediocre or poor performing countries were found to have substantial score differences with the SDG Index and Dashboards report. For instance, Hungary, Luxemburg, and the US were found to have significant differences in their ranks with the SDG Index and Dashboards report. On the other hand, countries like Sweden, France, Portugal, Italy, and Greece were found to have the same ranking but significant score differences.

SDG Index and Dashboards report is using equal weighting approach for the calculation of overall sustainable development index while this study proposes using PCA, a multivariate data analysis technique for the same. It is very crucial to understand the actual relationship between the approach adopted or compare the two or more method of measurements. In this study, the regression analysis for the score and rank difference is conducted to understand the relationship between scores and rank with two different methods The regression line of the rank (Figure 3 and 4) and score difference (Figure 5 and 6) is given below. The R^2 value of the rank difference is 0.75 and 0.875 for the year 2017 and 2018 which suggest that the GS-PCA model explains 75 % and 87.5 % of the variation in the rank of SDG Index and Dashboards report of the year 2017 and 2018 respectively. The GS-PCA model of the year 2018 seems more robust than 2017 model. Also, the high R^2 values validates our proposed GS- PCA model of the score for the year 2017 and 2018.The corresponding R^2 values for the year 2017 and 2018 are 0.78 and 0.874 respectively. The high R^2 values is the strong indication of model validation.

Table 10**.** Comparison of (UN Report vs. GS-PCA SI 2017)

Countries	(1)UN SDG Index	(2)GS-PCA SDI	Absolute [(1)-(2)]	(3) UN-SDG Rank	(4) GS-PCA SDI Rank	Absolute [(3)-(4)]
Sweden	85.6	83.6	2	1	1	0
Denmark	84.2	78.1	6.1	2	4	2
Finland	84.0	80.4	3.6	3	2	1
Norway	83.9	78.7	5.2	4	3	1
Czech Rep.	81.9	66.6	15.3	5	13	8
Germany	81.7	71.3	10.4	6	8	2
Austria	81.4	67.9	13.5	7	11	4
Switzerland	81.2	70.8	10.4	8	9	1
Slovenia	80.5	65.2	15.3	9	14	5
France	80.3	68.8	11.5	10	10	0
Japan	80.2	63.7	16.5	11	17	6
Belgium	80	72.4	7.6	12	7	5
Netherlands	79.9	75.3	4.6	13	5	8
Iceland	79.3	74	5.3	14	6	8
Estonia	78.6	61.4	17.2	15	20	5
UK	78.3	67.2	11.1	16	12	4
Canada	78	62.8	15.2	17	18	1
Hungary	78	51.2	26.8	18	31	13
Ireland	77.9	58.1	19.8	19	22	3
New Zealand	77.6	64.5	13.1	20	15	5
Slovak Rep.	76.9	54	22.9	21	27	6
Spain	76.8	57.1	19.7	22	23	1
Australia	75.9	62	13.9	23	19	4
Poland	75.8	52.0	23.7	24	28	4
Portugal	75.6	56.2	19.4	25	25	0
Italy	75.5	54.5	21	26	26	0
South Korea	75.5	56.5	19	27	24	3
Latvia	75.2	52.0	23.1	28	29	1
Luxembourg	75	64.1	10.9	29	14	15
Greece	72.9	52.0	20.9	30	30	0
USA	72.4	58.3	14.0	31	21	10
Chile	71.6	42.0	29.6	32	33	1
Israel	70.1	51.1	18.9	33	32	1
Mexico	69.1	15.3	53.8	34	35	1
Turkey	68.5	27.9	40.7	35	34	1
Mean	77.7	61.1	16.6	18.0	17.9	3.7
Std. Dev.	4.3	13.9	10.3	10.3	10.3	3.7

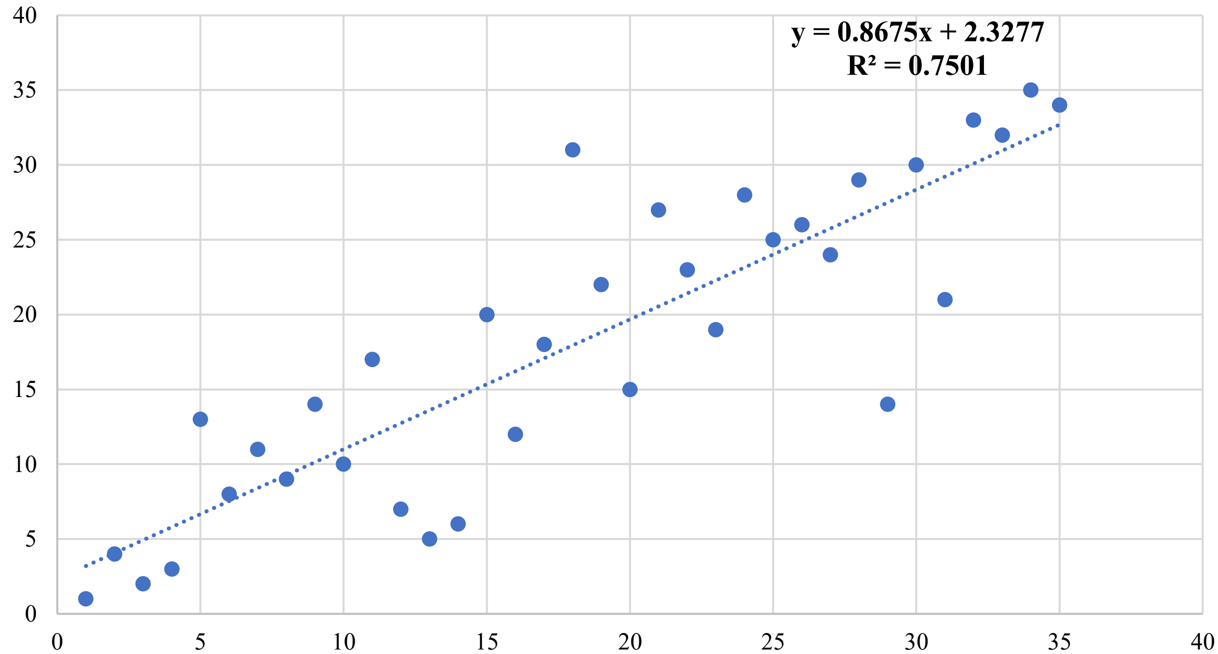

Figure 3. Scatter plot of the Country Ranks Obtained from GS-PCA vs. UN Report 2017

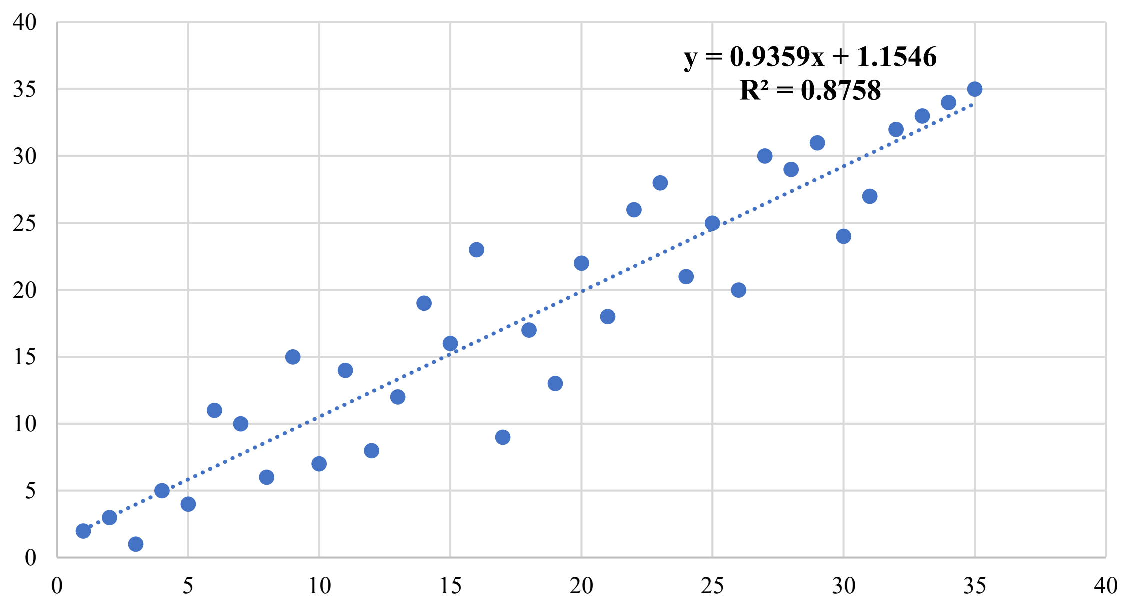

Figure 4. Scatter plot of the Country Ranks Obtained from GS-PCA vs. UN Report 2018

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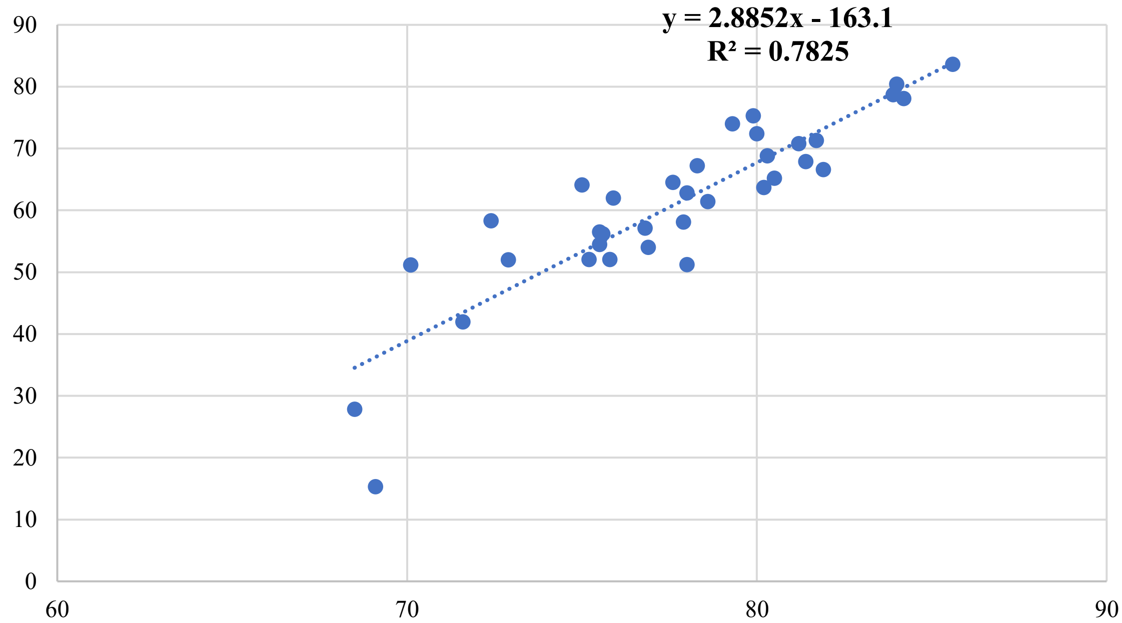


Figure 5. Scatter Plot of the SDI scores Obtained from GS-PCA vs. UN Report 2017

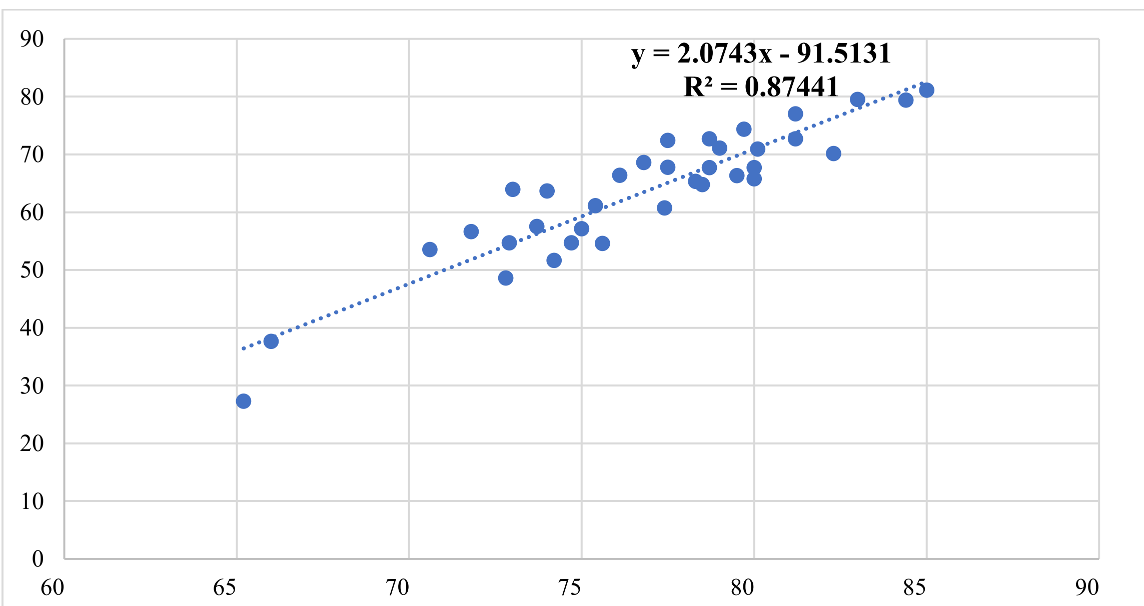


Figure 6. Scatter Plot of the SDI scores Obtained from GS-PCA vs. UN Report 2018

4.5. Comparison of 2017 and 2018 based on the proposed GS-PCA Approach

4.5.1. Graphical Comparison

The following figures depicts the changes in the scores and the ranks of OECD countries between years 2017 and 2018. The difference on the rank and scores is calculated from 2017 minus 2018.

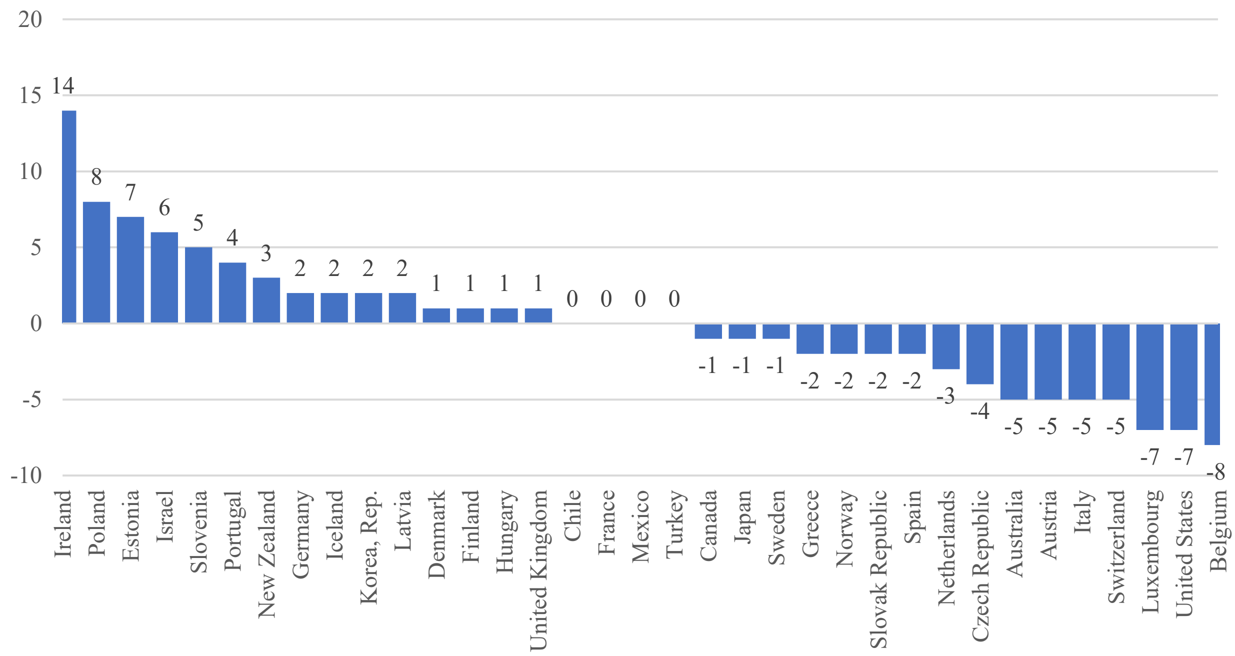


Figure 7. Changes in the SDI Ranks from 2017 to 2018

The figure 7 depicts the rank difference of 2017 and 2018 years. The country Ireland has significantly improved their rank with the improvement of 14 rank followed by countries like Poland, Estonia, Israel and Slovenia with the improvement in their rank by 8,7,6 and 5 respectively. On the other hand, countries like Belgium, United States, Luxembourg has seen significantly lower ranking in 2018 than in 2017.These countries are ranked 15,28 and 21 in the year 2018 while their rank was 7,21 and 14 in 2017 respectively .Some of the top performing countries like Sweden, Finland , New Zealand and low performing countries like Mexico, Turkey Chile ,Latvia experienced no changes in their ranks in two consecutive years even having some improvements in their SDI scores.

The figure 8 shows the score difference of 2017 and 2018. Most of the countries is seen increment in the SDI score in 2018. The countries Mexico, Turkey, Ireland, Poland and Israel has significantly increased in the sustainability score. Netherland, Sweden and Norway, on the other hand, were found to have lower SDI score in 2018 than 2017.The average SDI score in the 2018 is increased by almost 6.7% with the reduced standard deviation of 11.26 in 2018 as compared to 13.70 in 2017.

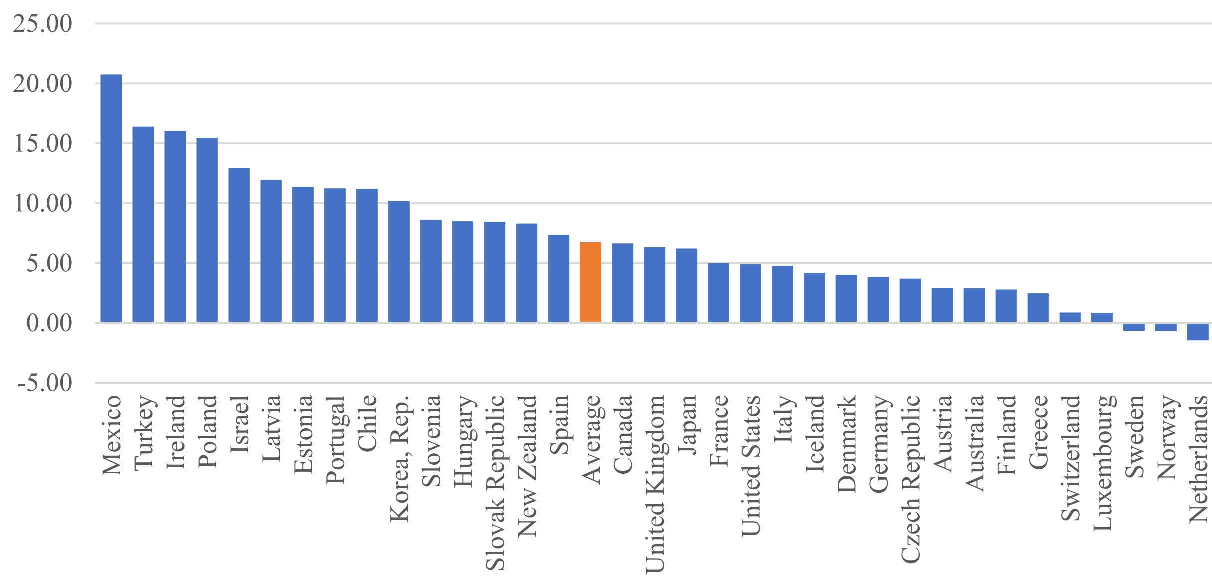


Figure 8. Changes in the SDI Scores from 2017 to 2018

4.5.2. Statistical Comparison

Statistical comparison tests were conducted to compare the SDIs of OECD countries in 2017 and 2018 to see if there was significant difference from 2017 calendar year to the 2018 calendar year in the overall sustainable development performance as well as SDG-specific performance. Normality test is initially conducted to find whether the results data are normal. Depending on the result of normality test, ANOVA or a non-parametric test would be used. Most of them is found to have p value less than 0.05 which indicate the non-normal data set (Table 11). To deal with the non-normal data set, non-parametric test Kruskal Wallis test is performed. The results are provided in Table 12. It was shown in the table that the SDGs 1,4,7,8,11 ,13 and 17 have p-values less than 0.05 meaning there is significant difference in the score between 2017 and 2018. All other goals have p-values that are greater than 0.05, which results in the failure to reject the null hypothesis, thus no significant difference between 2017 and 2018 SDIs. Results indicate that the OECD countries did not experience a statistically significant change from 2017 to 2018 in the majority of the 17 SDGs. But, only 7 SDGs had significant difference from 2017 to 2018. However, the overall p value is less than 0.05 which means we reject null hypothesis and conclude that the average SDI scores for the OECD countries for the year 2018 statistically different than the average SDI scores of 2017 as the P value for overall is less than 0.05.

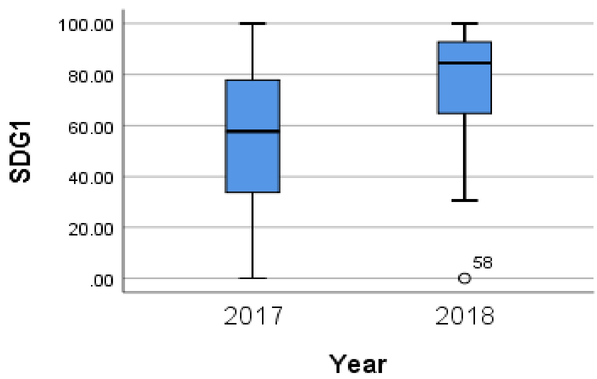
Table 11. Results of the Normality Test

Year/Test		P- Value								
		SDG 1	SDG 2	SDG 3	SDG 4	SDG 5	SDG 6	SDG 7	SDG 8	SDG 9
2017	Kolmogorov-Smirnov	0.200	**0.000**	**0.000**	**0.005**	0.200	**0.000**	**0.006**	**0.000**	**0.034**
2018		**0.006**	**0.000**	**0.003**	0.072	0.200	0.200	**0.000**	**0.013**	0.200
2017	Shapiro-Wilk	0.481	**0.000**	**0.000**	**0.000**	**0.005**	**0.000**	**0.002**	**0.000**	0.155
2018		**0.000**	**0.000**	**0.000**	**0.022**	**0.028**	0.171	**0.000**	**0.001**	0.453
Year/Test		P- Value								
		SDG 10	SDG 11	SDG 12	SDG 13	SDG 14	SDG 15	SDG 16	SDG 17	Overall
2017	Kolmogorov-Smirnov	0.101	0.070	0.200	**0.000**	0.145	0.200	0.061	**0.003**	**0.033**
2018		0.081	**0.001**	0.200	**0.000**	0.077	0.200	0.200	0.200	0.077
2017	Shapiro-Wilk	**0.003**	**0.010**	0.405	0.164	0.601	0.405	0.060	**0.000**	**0.009**
2018		**0.001**	**0.001**	0.397	**0.000**	0.482	0.134	0.171	0.124	**0.023**

Table 12. Results of Kruskal Wallis Test

SDG	P- Value
1-No Poverty	**0.002**
2-Zero Hunger	0.164
3-Good Health and Well Being	0.673
4-Quality Education	**0.002**
5-Gender Equality	0.253
6-Clean Water and Sanitation	0.101
7-Affordable and Clean Energy	**0.000**
8-Decent Work and Economic Growth	**0.010**
9-Industry, Innovation and Infrastructure	0.054
10-Reduced Inequality	0.131
11-Sustainable Cities and Communities	**0.000**
12-Responsible Consumption and Production	0.644
13-Climate Action	**0.000**
14-Life Below Water	0.888
15-Life on Land	0.112
16-Peace and Justice Strong Institutions	0.652
17-Partnerships to Achieve the Goal	**0.000**
Overall	**0.012**

The following Whisker and box plots depicts the variation in the score for the years 2017 and 2018 along with the five number summary .For instance, Minimum, First Quartile ,Median , Third Quartile and Maximum value of the data set .From this, we can visualize the variation in the score between two consecutive years with the amount of variation, outliers , minimum and maximum value in the data set. For example, the SDG 1 in the year 2017, has a first quartile value of around 38 which means approximately 25% of the countries (i.e. 4) has a score less than 38 with median score of approx. 59 and maximum of 100. Where in 2018 the size of the box reduces and the first quartile range increase from 38 to approx. 62. In 2018, 25 % of the countries has score greater than 90, the value for the same in the 2017 was slightly less than 80.


SDG1
100.00
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40.00
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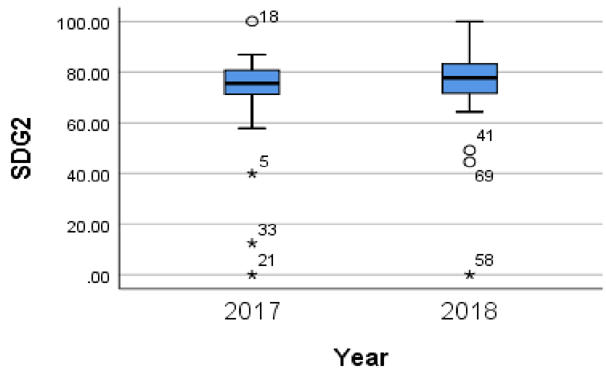
58
2017
2018
Year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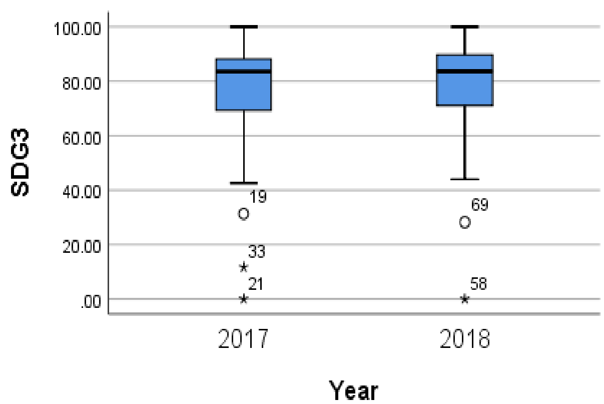
2017
2018
Year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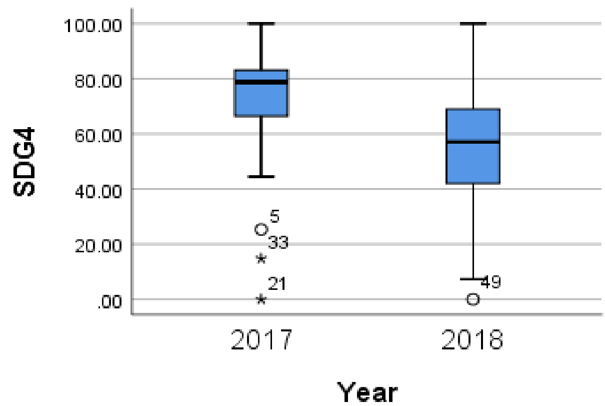
69
58
2017
2018
Year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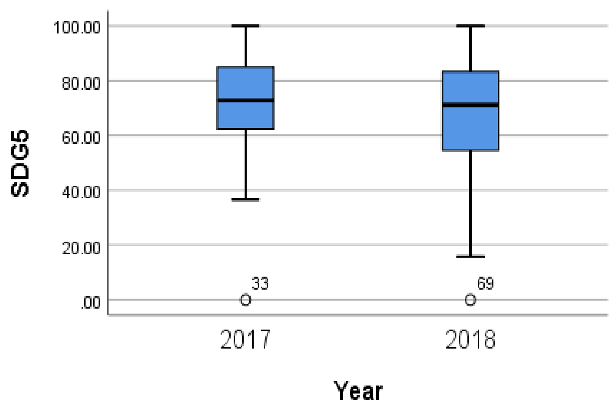
49
2017
2018
Year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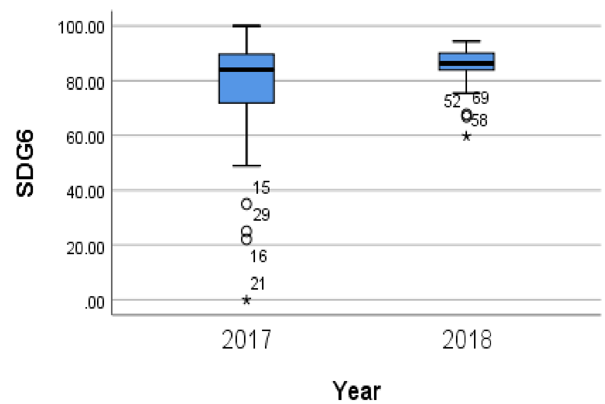
2017
2018
Year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16
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69
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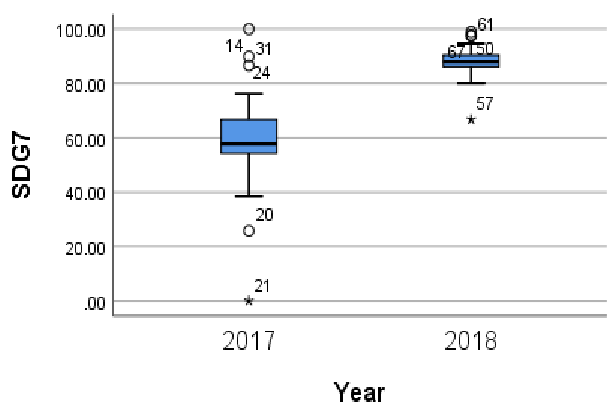
2017
2018
Year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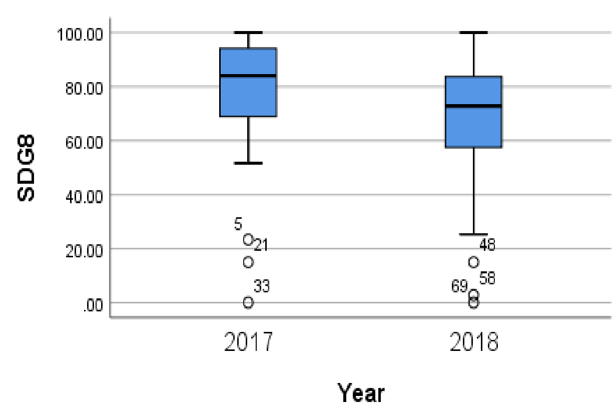
50
57
2017
2018
Year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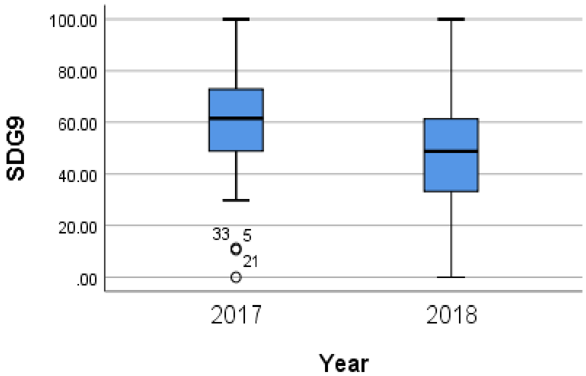
2017
2018
Year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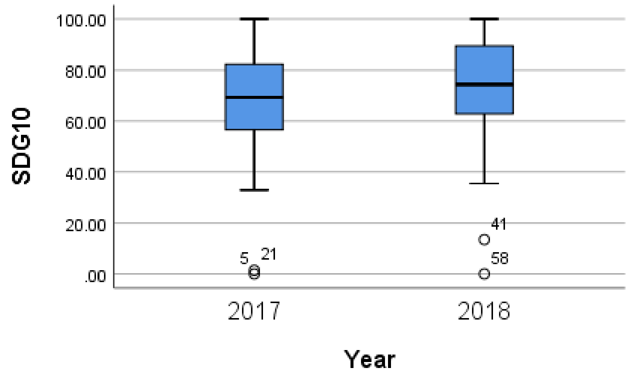
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2018
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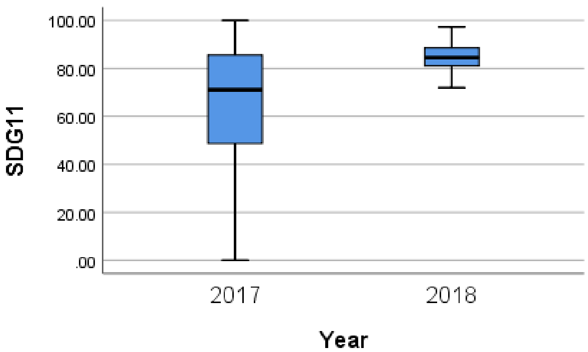
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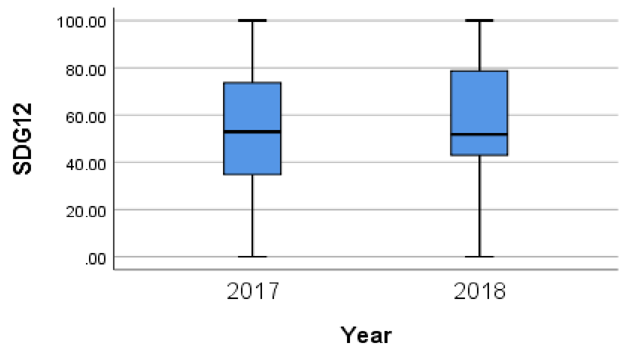
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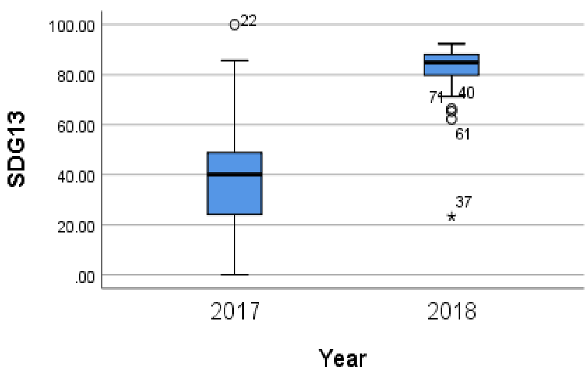
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2017
2018
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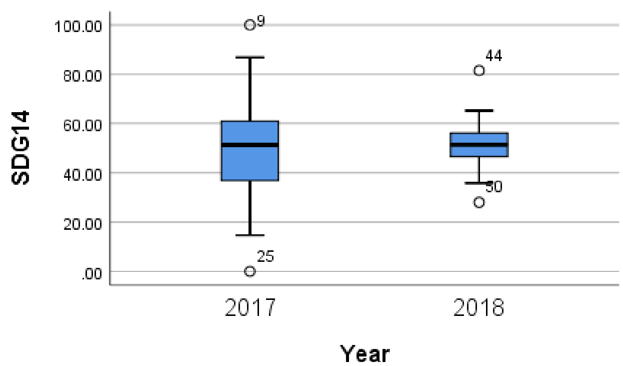
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2017
2018
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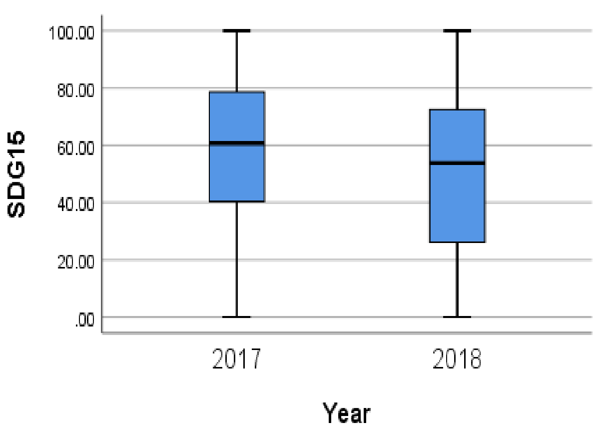
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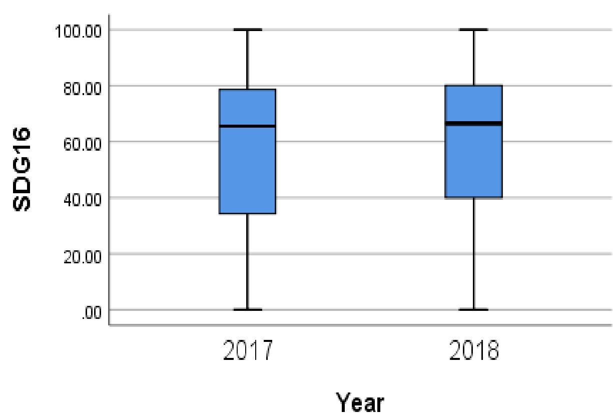
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2017
2018
Year

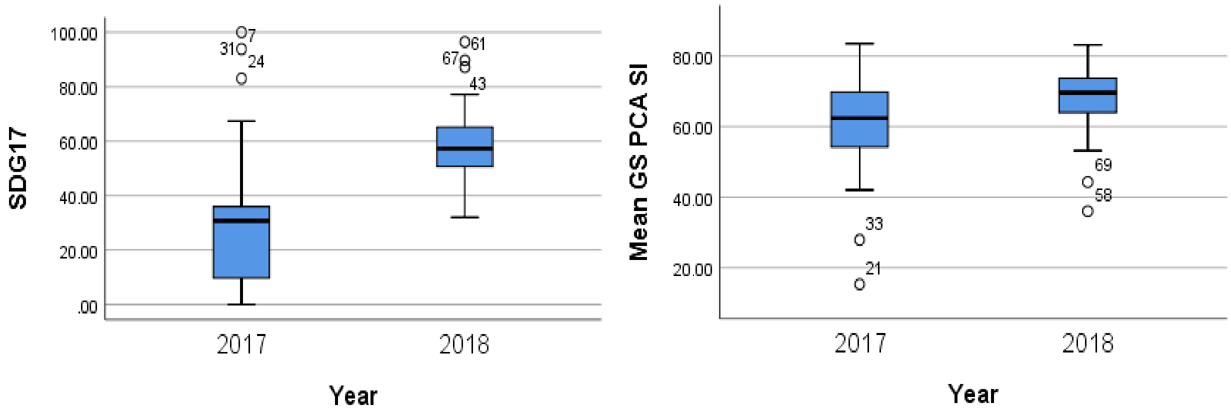

Figure 9. The Whisker and Box plot for 17 SDG of the Year 2017 and 2018

4.6. Comparison of top 5 performers and worst performers between the year 2017 and 2018

The following table 12 and table 13 depicts the top 5 and worst 5 performing countries in the 2017 and 2018 along with their best and worst SDG. It can be seen from the table 12 that there are few changes on the ranking of top performing countries where Sweden is ranked first in 2017 and Finland achieved the first rank in 2018 with 100 % achievements on No Poverty and Good Heal and Well-being. The worst SDG of the top performing countries in the year 2018 is Responsible Consumption and Production with the average score of only 34.2%.

Table 13. Top 5 best performers and their best and worst SDGs

TOP 5 BEST PERFORMERS							
2017	ID	**Country**	**BEST SDG (SI)**	**WORST SDG**	**MEAN**	**STDEV**	**95% CI OF SDG**
	1	Sweden	Goal 17-Partnerships to achieve the Goal-100%	Goal 13-Climate Action-54.2%	83.62	13.77	(76.56, 90.64)
	2	Finland	Goal 14-Life Below Water-100%	Goal 12-Responsible Consumption and Production-39.9%	80.36	18.25	(70.94, 89.66)
	3	Norway	Goal 5/11-Gender Equality/Sustainable Cities and Communities -100%	Goal 12-Responsible Consumption and Production-17.8%	78.69	22.49	(67.13, 90.27)
	4	Denmark	Goal 9-Industry, Innovation and Infrastructure-100%	Goal 14-Life Below Water-14.7%	78.08	20.85	(67.36, 88.74)
	5	Netherlands	Goal 13(100)-Climate Action-100%	Goal 14-Life Below Water-24.1%	75.29	21.32	
2018	**ID**	**Country**	**BEST SDG (SI)**	**WORST SDG**	**MEAN**	**STDEV**	**95% CI OF SDG**
	1	Finland	Goal1/3-No Poverty/Good Health and Well-being-100%	Goal 12-Responsible Consumption and Production-48.09%	83.2	16.77	(74.41, 89.84)
	2	Sweden	Goal 17-Partnerships to achieve the Goal-100%	Goal 12-Responsible Consumption and Production-46.30%	82.9	16.33	(74.36, 91.90)
	3	Denmark	Goal 9-Industry, Innovation and Infrastructure-100%	Goal 12-Responsible Consumption and Production-48.09%	82.1	15.12	(73.76, 89.79)
	4	Iceland	Goal 8/10-Decent Work and Economic Growth/Reduced Inequality-100%	Goal 15-Life on Land-6.03%	78.2	23.10	(62.74, 91.44)
	5	Norway	Goal 12-Responsible Consumption and Production-48.09%	Goal 12-Responsible Consumption and Production-20.7%	78.0	23.94	(64.64, 90.16)

The table 13 represents the 5 worst performing countries in the year 2017 and 2018. The three worst performing countries Mexico, Turkey and Chile remains on the bottom of the table for both years with very low score. However, the worst performing country, Mexico, is seen to have achieved higher score on the goal # 12 Responsible consumption and Production with score of 90.7 % and 98.7 % in the year 2017 and 2018 respectively. The worst performing countries have scored highest on the SDG like Responsible Consumption and Production, Clean water and Sanitation, Good health and well-being etc.

Table 14. Top 5 worst performers and their best and worst SDGs

WORST PERFORMERS

2017	ID	**Country**	**BEST SDG (SI)**	**WORST SDG**	**MEAN**	**STDEV**	**95% CI OF SDG**
	1	Mexico	Goal 12-Responsible Consumption and Production-90.7 %	Goal 1-4/6-7/9/13-15:No Poverty/Zero Hunger/Good Health and Well-being/Quality Education/Clean Water and Sanitation/Affordable and Clean Energy/Industry, Innovation and Infrastructure/Climate Action/ Life Below Water/Life on Land-0%	15.3	27.3	(1.26, 29.34)
	2	Turkey	Goal 14-Life Below Water-86.9%	Goal 5/8-Gender Equality/Decent Work and Economic Growth-0%	27.9	27.2	(13.92, 41.88)
	3	Chile	Goal 6-Clean Water and Sanitation-91.4%	Goal 10-Reduced Inequality-0%	42.0	26.0	(28.63, 55.37)
	4	Israel	Goal 3-Good Health and Well-being-92.6%	Goal 17-Partnerships to achieve the Goal-5%	51.2	24.8	(38.45, 63.95)
	5	Hungary	Goal 6-Clean Water and Sanitation-98.5%	Goal 16-Peace and Justice Strong Institutions-5.7%	51.2	25.7	(37.99, 64.41)
2018	ID	**Country**	**BEST SDG (SI)**	**WORST SDG**	**MEAN**	**STDEV**	**95% CI OF SDG**
	1	**Mexico**	Goal 12-Responsible Consumption and Production-98.7%	Goal 1/2/3/7/10/16-No Poverty/Zero Hunger/Good Health and Well-being/Affordable and Clean Energy/Reduced Inequality/Peace and Justice Strong Institutions-0%	38.29	34.0	(18.51, 58.07)
	2	**Turkey**	Goal 12-Responsible Consumption and Production-95.3%	Goal 4/5/8/9/15/17-Quality Education/Gender Equality/Decent Work and Economic Growth/Industry, Innovation and Infrastructure/Life on Land/Partnerships to achieve the Goal- 0%	41.83	34.9	(24.33, 59.33)
	3	**Chile**	Goal 6-Clean Water and Sanitation-94.2%	Goal 9-Industry, Innovation and Infrastructure-1%	51.99	30.0	(35.39, 68.60)
	4	**Greece**	Goal 7-Affordable and Clean Energy-86.9%	Goal 9-Industry, Innovation and Infrastructure-13.31%	55.94	26.3	(42.76, 69.14
	5	**Italy**	Goal 3- Good Health and Well-being 89.3%	Goal 17-Partnerships to achieve the Goal-5.6%	60.41	27.0	(48.76, 72.36)

4.7. SDG-focused Analysis

In this section, results are provided with a specific focus on each of the 17 SDGs. Results of average SDI score for each SDGs in 2017 is provided in Fig. 9 and results of 2018 data is provided in Fig. 10. According to figure 9, which presents the average SDI Score for the year 2017, the lowest performance was observed in SDG 17, “Partnership to achieve the Goal” with an average score of 34% and the highest achieving goal was found to be SDG 8 “Decent Work and Economic Growth” with average score of almost 80%. The average SDG score of the OECD countries in the year 2017 was found to be 61.09 %.

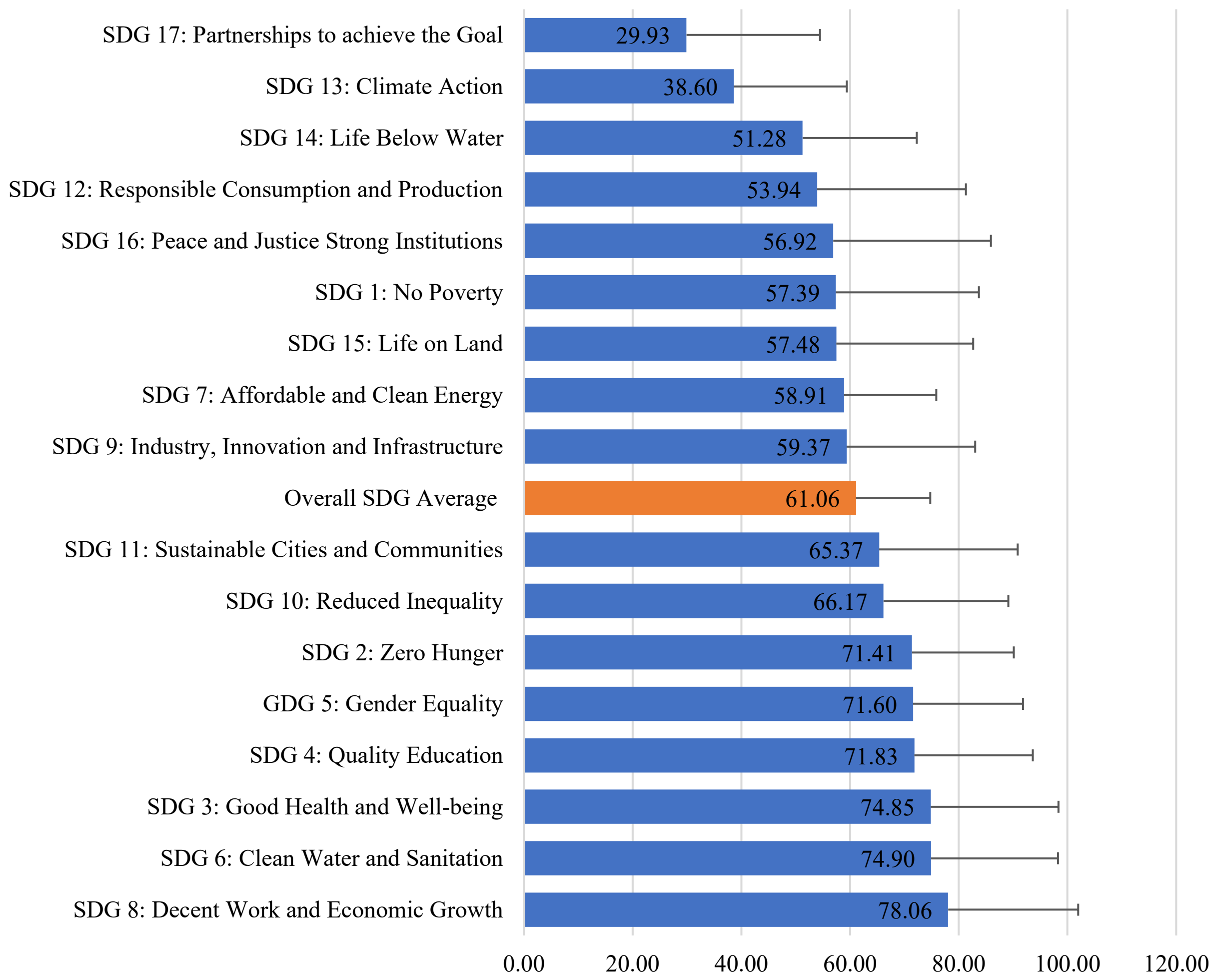

Figure 10. Average and Standard Deviation of SDI scores in 2017

For instance, the average SDI score of SDG 13 was found to be 81.1, which indicates the average of all OECD countries for that specific goal. The average goal score of OECD countries for the years 2017 and 2018 are provided in the separate figures below, which depicts the OECD countries' overall performance on individual SDGs and also the standard deviation of the SDIs, which are shown with error bars in both graphs.

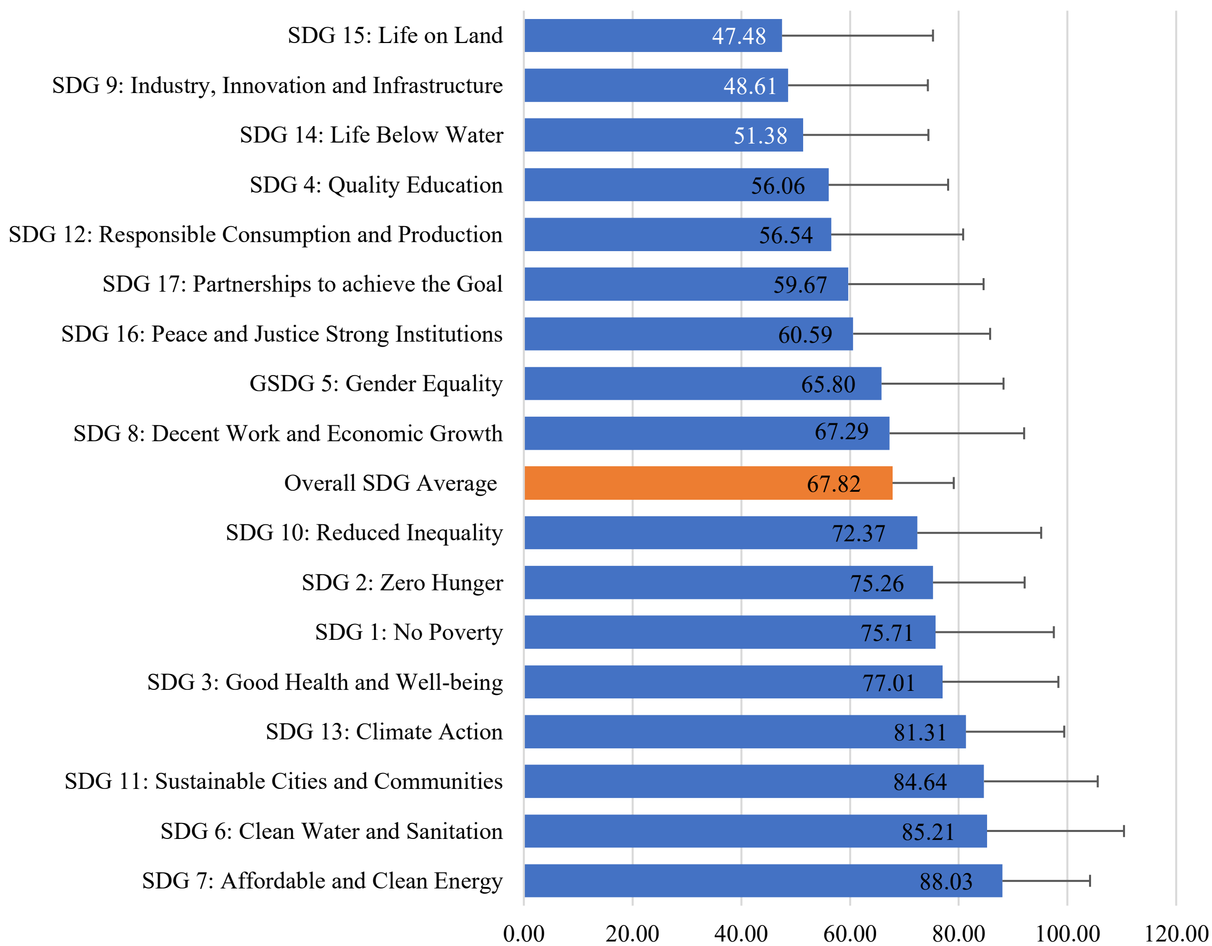

Figure 11. Average and Standard Deviation of SDI scores in 2018

5. DISCUSSION

The objective of proposing a PCA approach in this thesis was to aggregate a largest set of sustainability indicators to form a composite sustainability index score for OECD countries. It was found that significant differences exist in the ranks and SDI scores of the OECD countries with the newly proposed GS-PCA approach compared to the equal weighting method adopted by the UN's benchmark report (Sachs et al., 2017). The reason behind this difference is attributed to the inherent correlations among the majority of the pairs of variables in the data. As a nonparametric approach, PCA effectively dealt with the multicollinearity in the data by developing factor variables (principal components).

SDI scores describe the OECD countries' progress towards achieving the targets of 17 SDGs and also indicates areas requiring faster progress and more effective policy making. Significant shifts in the SDI scores were found for some SDGs. For Instance, SDG 13 "climate action", the average SDI score significantly jumped from 38.6% to 81.13% in 2018. Similarly, OECD countries experienced progress in SDG1 "No Poverty" with an increase of 14.36% compared to 2017. However, there are some SDGs such as SDG 4 "Quality Education", SDG 6 "Clean Water and Sanitation", SDG 8 "Decent Work and Economic Growth", SDG 15 "Life on Land" in which the average SDI scores were found to be lower in 2018 compared to 2017. So, OECD countries should be more focused on those goals in which they are performing poor, to reach the set target in defined time i.e. by the end of 2030. SDG17," Partnership to achieve goal" was found to be the lowest performing goal of OECD countries. And, this is a particularly tragic result since sustainable development solely requires effective partnerships among the OECD countries and among the organizations within each and every OECD country.

6. CONCLUSION, LIMITATIONS, AND FUTURE WORK

What Peter Drucker quoted for business organizations is true for the sustainable development: if we can't measure the sustainable development, we cannot improve it. Thus, sustainability performance indexing is crucially important for sustaining the sustainable development initiatives in the direction of successful implementation of socially acceptable, economically viable, and environmentally benign policies. In this regard, country specific sustainable development indexing has been the focal point of the UN Sustainable Development reports. In the recent UN SDG performance assessment reports, linear weighted averaging method have been typically employed, which is quite robust and practical to apply but had a few shortcomings. Among the shortcomings, not accounting for the multi collinearity and correlation among the variables that are used to assess the 17 SDGs was crucial and was the focus of this study. This study proposes a Principal Component Analysis-based approach to assess the sustainability performance of the OECD countries, which is aimed to alleviate the deteriorating impacts of the shortcomings on the sustainability indexing.

The data is collected from SDG Index and Dashboards report, which consist of 35 rows (OECD countries) and 93 variables for 2017 and 104 variables for 2018, which account for 17 SDGs. Each SDG has 2-9 variables, that are the representative variables for the specific SDG. Data cleaning and normalization steps were carried out prior to the implementation of Goal Specific PCA approach. The PCA models were built for all 17 SDGs and factor scores were recorded to be used for sustainability index scores (0-100). It was found that Sweden had the first rank, which was followed by Finland, Norway, and Denmark, while Mexico was ranked as the last.

The results of the GS PCA were compared with the UN's sustainable development scores of 2017 and 2018 (Sachs et al., 2017, 2018). It was found that except a few top performing countries such as Sweden (ranked and scored as almost the same with the SDG Index and Dashboards report, mediocre or poor performing countries were found to have substantial score differences with the SDG Index and Dashboards report . For instance, Hungary, Luxemburg, and the US were found to have significant differences in their ranks with the SDG Index and Dashboards report. On the other hand, countries like Sweden, France, Portugal, Italy, and Greece were found to have the same ranking but significant score differences.

All in all, it was found that there is a strong positive correlation between the proposed method (GS PCA) and the UN SDG index, however, substantial difference in the standard deviation of the scores and ranks were found, which were more attributed to the correlation and collinearity effects of the high volume of input variables and the relationship of the input variables with multiple SDGs. There are obviously limitations in the current study, which are targeted to be part of the future work. For instance, equal weighting assumption was kept the same as it was in the SDG Index and Dashboards report to have a fair comparison with the literature. The weights of the 17 SDGs might not have to be the same for all countries given the socio-economic, cultural, and other differences exist among the OECD countries, which requires further research. In addition, the literature is still in evolution stage in terms of identifying the importance of social, economic, and environmental sustainability indicators towards realizing SDGs more effectively. This limitation could be extended with the integration of expert judgment or further literature review on weight assignments to SDGs, which will reflect the relative importance of SDGs. It would be interesting to integrate expert judgment, multi-criteria decision analysis with the proposed GS PCA approach to address the non-equal weight assignments and compare with the literature.

APPENDIX

Appendix folder includes data, modeling and experimentation results, which could be reached at:

https://drive.google.com/file/d/1hPmV95UPp8XD9T-jTVL9sdHNVupF3hfU/view?usp=sharing

REFERENCES

Adler, N., Yazhemsky, E., & Tarverdyan, R. (2010a). A framework to measure the relative socio-economic performance of developing countries. *Socio-Economic Planning Sciences*, *44*(2), 73–88. https://doi.org/10.1016/j.seps.2009.08.001

Adler, N., Yazhemsky, E., & Tarverdyan, R. (2010b). A framework to measure the relative socio-economic performance of developing countries. *Socio-Economic Planning Sciences*, *44*(2), 73–88. https://doi.org/10.1016/j.seps.2009.08.001

Ali, H. (2009). Development of Arab water sustainability index using principal component analysis. *Proceedings of the 13th International Water …*. Retrieved from http://faculty.ksu.edu.sa/72005/Papers of Interest Water/Development of Arab Water Sustainability Index.pdf

Biswas, B., & Caliendo, F. (2001). A Multivariate Analysis of the Human Development Index. *Indian Economic Journal*, *49*(4), 96–100.

Choi, J., Park, Y. S., & Park, J. D. (2015). Development of an Aggregate Air Quality Index Using a PCA-Based Method : A Case Study of the US Transportation Sector, (x), 53–65.

Constantin, C. (2014). Principal Component Analysis - a Powerful Tool in Computing Marketing Information. *Bulletin of the Transilvania University of Brasov. Series V: Economic Sciences*, *7*(2), 25–30.

Dong, F., Mitchell, P. D., Knuteson, D., Wyman, J., Bussan, A. J., & Conley, S. (2016). Assessing sustainability and improvements in US Midwestern soybean production systems using a PCA-DEA approach. *Renewable Agriculture and Food Systems*, *31*(6), 524–539. https://doi.org/10.1017/S1742170515000460

Dong, X., Guo, J., Höök, M., & Pi, G. (2015). Sustainability Assessment of the Natural Gas Industry in China Using Principal Component Analysis. *Sustainability*, *7*(5), 6102–6118. https://doi.org/10.3390/su7056102

Doukas, H., Papadopoulou, A., Savvakis, N., Tsoutsos, T., & Psarras, J. (2012). Assessing energy sustainability of rural communities using Principal Component Analysis. *Renewable and Sustainable Energy Reviews*, *16*(4), 1949–1957. https://doi.org/10.1016/j.rser.2012.01.018

European Commission. (2017). *European Innovation Scoreboard 2017*. *European Innovation Scorecard*. https://doi.org/10.2873/571375

Gokhan Egilmez. (2019). (2) Great job UN COPs! Hmm, what about the 3C: Climate Change Communication? | LinkedIn. Retrieved July 24, 2019, from https://www.linkedin.com/pulse/great-job-un-cops-hmm-what-3c-climate-change-gokhan-egilmez/

Guide, U. (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. https://doi.org/10.1787/9789264043466-en

Haberland, T. (ed). (2008). Analysis of the Yale Environmental Performance Index (EPI), 46.

Hag Ibrahim, S. N. (2017). Sustainability Assessment of Community-Based Water Supply Projects in Sudan using Sustainability Index and Multivariate Analysis. *Journal of Water Sustainability*, *7*(1), 1–16. https://doi.org/10.11912/jws.2017.7.1.1-16

Hosseini, H. M., & Kaneko, S. (2011). Dynamic sustainability assessment of countries at the macro level: A principal component analysis. *Ecological Indicators*, *11*(3), 811–823. Retrieved from http://www.sciencedirect.com/science/article/pii/S1470160X10001780

Hudrliková, L. (2013). Composite Indicators as a Useful Tool for International Comparison: The Europe 2020 Example. *Prague Economic Papers*, *22*(4), 459–473. https://doi.org/10.18267/j.pep.462

Jollands, N., Lermit, J., & Patterson, M. (2004). Aggregate eco-efficiency indices for New Zealand—a principal components analysis. *Journal of Environmental Management*. Retrieved from http://www.sciencedirect.com/science/article/pii/S0301479704001495

Krishnan, V. (2010). Constructing an area-based socioeconomic status index: a principal components analysis approach. *Every Day in Every Way: Creating Learning Experiences for Every Child*, (May), 2–26. https://doi.org/10.1093/heapol/czl029

Lafortune, G., Fuller, G., Moreno, J., Schmidt-traub, G., & Kroll, C. (2018). SDG Index and Dashboards Detailed Methodological paper, (September), 56.

Lai, D. (2012). Analysis on Human Component Principal of China, *61*(3), 319–330.

Li, T., Zhang, H., Yuan, C., Liu, Z., & Fan, C. (2012). A PCA-based method for construction of composite sustainability indicators. ... *Journal of Life Cycle Assessment*, *17*(5), 593–603. Retrieved from http://link.springer.com/article/10.1007/s11367-012-0394-y

Lindman, C. (2011). Measuring Human Development The Use of Principal Component Analysis in Creating an Environmental Index.

Lolli, S., & di Girolamo, P. (2015). Principal component analysis approach to evaluate instrument performances in developing a cost-effective reliable instrument network for atmospheric measurements. *Journal of Atmospheric and Oceanic Technology*, *32*(9), 1642–1649. https://doi.org/10.1175/JTECH-D-15-0085.1

Mainali, B., & Silveira, S. (2015). Using a sustainability index to assess energy technologies for rural electrification. *Renewable and Sustainable Energy Reviews*, *41*, 1351–1365. https://doi.org/10.1016/j.rser.2014.09.018

Mainali, B., & Silveira, S. (2015). Using a sustainability index to assess energy technologies for rural electrification. *Renewable and Sustainable Energy Reviews*, *41*, 1351–1365. https://doi.org/10.1016/j.rser.2014.09.018

Park, Y. S., Egilmez, G., & Kucukvar, M. (2015). A Novel Life Cycle-based Principal Component Analysis Framework for Eco-efficiency Analysis: Case of the United States Manufacturing and Transportation Nexus. *Journal of Cleaner Production*, *92*, 327–342. https://doi.org/10.1016/j.jclepro.2014.12.057

Parris, T. M., & Kates, R. W. (2003). C <scp>HARACTERIZING AND</scp> M <scp>EASURING</scp> S <scp>USTAINABLE</scp> D <scp>EVELOPMENT</scp>.

Annual Review of Environment and Resources, *28*(1), 559–586. https://doi.org/10.1146/annurev.energy.28.050302.105551

Rovira, J. S., & Rovira, P. S. (2009). Assessment of aggregated indicators of sustainability using PCA: the case of apple trade in Spain. Retrieved from http://oa.upm.es/2461/1/SOLER_PON_2008_01.pdf

Sachs, J., Schmidt-Traub, G., Kroll, C., Durand-Delacre, D., & Teksoz, K. (2017). Global Responsibilities. International spillovers in achieving the goals. *SDG Index and Dashboards Report 2017*, 396. https://doi.org/10.1016/S0140-6736(09)61513-0

Sainz, P. (1989). An index of social welfare. In *Towards a New Way to Measure Development, Report on the International Meeting on More Effective Development Indicators, July* (Vol. 31, pp. 156–160).

SDSN. (2018a). *2018 SDG Index and Dashboards*. New York, NY. Retrieved from http://www.sdgindex.org/reports/2018/

SDSN. (2018b). *2018 SDG Index and Dashboards*. New York, NY.

Searcy, C., & Elkhawas, D. (2012). Corporate sustainability ratings: An investigation into how corporations use the Dow Jones Sustainability Index. *Journal of Cleaner Production*, *35*, 79–92. https://doi.org/10.1016/j.jclepro.2012.05.022

Si, C. (2006). External Debt and Growth Dynamics, *28*(3), 291–303. https://doi.org/10.5202/rei.v2i3.45

Singh, R. K., Murty, H. R., Gupta, S. K., & Dikshit, A. K. (2012). An overview of sustainability assessment methodologies. *Ecological Indicators*, *15*(1), 281–299. https://doi.org/10.1016/j.ecolind.2011.01.007

Sustainable Development Goals | UNDP. (2018). Retrieved June 13, 2018, from http://www.undp.org/content/undp/en/home/sustainable-development-goals.html

Tanguay, G. A., Rajaonson, J., Lefebvre, J. F., & Lanoie, P. (2010). Measuring the sustainability of cities: An analysis of the use of local indicators. *Ecological Indicators*, *10*(2), 407–418. https://doi.org/10.1016/j.ecolind.2009.07.013

Taylor, P., Balanda, K. P., Macgillivray, H. L., Balanda, K. P., & Macgillivray, H. L. (2012). Kurtosis : A Critical Review Kurtosis : A Critical Review, (November 2014), 37–41. https://doi.org/10.1080/00031305.1988.10475539

Zhao, G. (2015). A sustainability classification for a country based on PCA Guojin Zhao, (Isss), 100–103.