Journal of Cleaner Production 287 (2021) 125040

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Benchmarking OECD countries' sustainable development performance: A goal-specific principal component analysis approach

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A R T I C L E I N F O

Article history:
Received 22 October 2019
Received in revised form
1 November 2020
Accepted 6 November 2020
Available online 13 November 2020

Handling editor. Prof. Jiri Jaromir Klemeš

Keywords:
Sustainable development
Principal component analysis
OECD
Multicollinearity
Sustainability index
Sustainable development goals

A B S T R A C T

This paper proposes a framework to assess the status of sustainable development performance of OECD countries towards reaching the 2030 agenda based on the 17 Sustainable Development Goals (SDGs). Each SDG addresses a critical area of sustainable development and is represented with several social, economic, or environmental indicators. As a result of data collection efforts, 17 SDGs are represented with total of over 90 variables following the guidance of United Nation's (UN) recent reports. Using such a high number of variables to create a benchmark score for each of the 35 OECD countries is a challenging and complex task due to the degree of correlation among the indicators and unit of measurement differences. To cope with these challenges, we proposed a Goal-Specific Principal Component Analysis (GS-PCA) approach and compared statistically with the UN reports for experimental validation purpose. It was found that SDG1 No Poverty, SDG7 Affordable and Clean Energy, SDG11 Sustainable Cities and Communities, SDG17 Partnerships to Achieve the Goal and the group mean of 17 SDGs were found to be improving. On the other hand, SDG4 Quality Education and SDG8 Decent Work and Economic Growth were in decline. The highest performance was observed in SDG 8 Decent Work and Economic Growth (78.06) and the lowest performance was observed in SDG 17 Partnerships to Achieve the Goal (29.93). In addition, substantial differences were observed in the scores and ranks of mediocre and poor performing countries compared to the benchmark reports, while both the results of this study and benchmark reports were found to be strongly positively correlated.

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1. Introduction

On September 25th, 2015, 193 United Nations (UN) member countries adopted a set of goals to end poverty, protect the planet and ensure that all people enjoy peace and prosperity as part of a new sustainable development comprehensive plan. The plan was structured around 17 Sustainable Development Goals (SDGs). "Envision 2030" sets specific measurable outcomes for the 17 SDGs to be achieved over the next 15 years (Fig. 1). The newly proposed SDGs were built on the successes of the Millennium Development Goals while including new policy focus areas such as climate change, economic inequality, innovation, sustainable consumption, peace, and justice, among other priorities; that were covered with 169 targets ("Sustainable Development Goals | UNDP," 2018). The proposed 17 SDGs were aimed to cover interconnected social, economic, environmental, and ecological aspects of sustainable development based on the assumption that successful policy-making and implementation require a series of efforts rather than individually focused SD paradigm initiatives e.g. environment, society, or economy. The SDGs work in the spirit of partnership and pragmatism to make the right choices to improve life, in a sustainable way, for future generations. ("Sustainable Development Goals | UNDP," 2018).

The Organization for Economic co-operation and Development (OECD), founded in 1961, supports the UN in ensuring the success of the 2030 Agenda for Sustainable Development by bringing together its existing knowledge, and its unique tools and experience. These tools include a strong track record of data collection that enables quantifying and monitoring development performance ("Sustainable

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https://doi.org/10.1016/j.jclepro.2020.125040
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Fig. 1. Sustainable development goals (Sachs et al., 2017).

Development Goals | UNDP," 2018). In addition, OECD partnerships are creating synergies among private and public, domestic, and international sectors and country resources to provide countries with a strong support mechanism towards building a better future. Successful implementation of the SDGs will require striking a balance in all areas of social, environmental, and economic pillars of overall sustainable development including socio-economic progress, sustaining the planet's resources and ecosystems, combating climate change, and promoting renewable energy use (Sachs et al., 2017, 2018) (Alvarado et al., 2018; Khan et al., 2019a, 2019b, 2020). 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. These organizations continuously track the status of sustainable development efforts and often, a composite sustainability index is used to compare the performance of countries. In this regard, the methods that use sustainability indicators to produce composite index scores are gaining importance and are increasingly recognized as practical and effective for policy making and public communication, especially in providing information on 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 literature to create sustainability scores/index 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). These methods include equal weighting and aggregation, principal component analysis (PCA), analytic hierarchy process (AHP), economic Input-output life-cycle assessment (EIO-LCA) with PCA, PCA in combination with data envelopment analysis, etc. The details of the methods employed are listed in Table 2.

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). Sustainability indexing greatly helps in guiding policy decisions as well as monitoring sustainable development performance. Besides, sustainability scoring creates a common platform, which promotes consistent monitoring and decision making across the countries and organizations. In this context, UN SDGs regularly collect data and produces reports about a member country's sustainable development performance. Among the well-known SD indices, the 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 the World Economic Forum comprises of 68 indicators from 148 countries that were aggregated into 5 components. These aggregated components track environmental trends and assist the move towards a more analytically rigorous and data-driven approach to environmental decision making (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. 2017 SDG Index and Dashboards report provides critical information about the overall performance of countries towards reaching the 17 SDGs (Sachs et al., 2017). The method of sustainability scoring involves data collection, data preparation, weighting, and aggregation. The method follows with the min-max normalization method of the data for each indicator by transforming it linearly to a scale of 0–100, which also ensures comparability. Recent 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 was selected for each SDG. 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 to each of the 17 SDGs, there are critical limitations to this approach. In summary:

- All the SDGs were given equal importance, even though 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 (Parris and Kates, 2003).
- 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, pairwise correlation plays a vital role in giving weights to the indicators (Guide, 2008).

We conducted a correlation analysis of 2017 and 2018 benchmark study (Sach et al., 2017, 2018) (See Table 1). It is evident that there are significant number of highly correlated pairs of variables under SDGs. For instance, in 2017, SDG1 consists of 3 variables and there are 3 pairs of distinct correlation and only 1 pair was found to be significantly correlated. On the other hand, in SDG 3, 53 of 91 pairs were significantly correlated. Overall mean and median values of the rows indicate that around 50% of the pairs were significantly correlated across all SDGs. This is a significant degree of multicollinearity, which needs to be carefully addressed when working with these variables in creating sustainability indices. In this regard, it is hard to argue that parametric approaches that do not take the correlation of variables into account will be viable to produce sustainability performance index scores (Park et al., 2015; Abson et al., 2012; Hag, 2017). To the best knowledge of authors, nonparametric benchmarking methods such as PCA have not been implemented to calculate sustainable development performance of countries in the literature. And this is needed due to the high degree of correlation found among the variables and unit of measurement differences in input variables as mentioned above. In this context, 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 variables in a dataset. PCA retains most of the 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). Therefore, this study proposes a novel Goal Specific Principal Component Analysis (GS-PCA) approach. Each of the 17 SDGs were modeled with PCA individually, then the resulting scores were integrated into an overall sustainable development index score.

The rest of the paper is organized as follows. Section two provides the review of the literature on 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. Conclusions, future work, and limitations are provided in section five.

2. Literature review

An index is typically termed "*synthesis of numerous factors into one given factor*". 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 technology 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 affects 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 used approach in the

Table 1
Results of correlation analysis.

SDG	2017				2018			
	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%
Median	5	10	3	50%	5	10	3	38%
Mean	5.44	15.78	9.17	49%	6.06	20.17	10.44	48%

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 & Silveira (2015)	Sustainability	Evaluation of the sustainability performance of energy technologies applied in rural electrification	PCA
Hosseini & 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
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

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 pairwise 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 (Vyas and Kumaranayake, 2006), 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 and Rovira, 2009), eco-efficiency analysis (Park et al., 2015), human development index (HDI) (Biswas and Caliendo, 2002). The application of Vyas and Kumaranayake (2006) 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 in the work of 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 another work (Lai, 2003), 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., 2010). 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 identified as a robust statistical approach, used to evaluate the sustainability performance of many 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's method 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 (Sachs et al., 2017, 2018). This shortcoming was also addressed in a methodological paper (Lafortune et al., 2018).

In this study, the 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.

3. Methodology

Principal Component Analysis (PCA), as a multivariate data analysis approach, is proposed to create a composite sustainability index for OECD countries for each year in the study period (2017–2018). The study period was chosen based on the data availability in the recent UN dashboard reports (Sachs et al., 2017, 2018). To successfully implement PCA, 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 for the entire set of 17 SDGs. In this context, it is important to note that there are 35 countries and over 90 SDG variables in both 2017 and 2018 datasets. Therefore, it is not feasible to implement PCA to the entire dataset due to having substantially a smaller number of decision units (countries) compared to the total number of variables (there are 93 in 2017 and 105 in 2018 data). Moreover, it is also more practical and effective to apply PCA to each goal since it yields composite index score for each SDG as well as the overall sustainable development performance index score. Thus, 17 PCA model is developed for each year (total of 34 PCA models). 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 SDGs, and countries were then ranked. The findings are then compared and statistically validated with the 2017 and 2018 SDG Index and Dashboards reports (Satchs et al., 2017).

3.1. Data

In this study, the researchers focused on addressing all 17 SDGs while creating a novel sustainability index for 35 OECD countries. The 2017 and 2018 UN SDG Index and Dashboards Reports were used to classify and choose variables (Sachs et al., 2017, 2018). The raw dataset consisted of indicators that have a substantial range of data, which necessitates carrying out a normalization procedure. For instance, the 2017 data consisted of 93 indicators, where 3 to 14 variables were classified under each of the 17 SDGs (See Table 3) (Sachs et al., 2017, 2018). This classification was directly obtained from the reports. Then, Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity for each SDG is conducted to assess the proximity of correlation matrices to the identity matrix. Significance (p) values of the test that are less than 0.05 indicate that a factor analysis could be effectively applied to the set of variables under an SDG (Lolli and di Girolamo, 2015) (See Table 3).

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

PCA (Principal Component Analysis) is a mathematical procedure typically used for variable or data reduction. Orthogonal transformation is used to convert a set of correlated variables into a set of linearly uncorrelated variables called "principal components (PCs)" (Jolliffe, 2011). The principal components (PCs) are ordered so that the first component accounts for the largest possible amount of variation in the original variables. The following components (e.g. 2nd, 3rd, etc.) are completely uncorrelated with the first component, while all PCs together account for the maximum variation in the original data (Vyas and Kumaranayake, 2006). The first step was to standardize the data in other words, normalization of the scale of the data. The data for each of the variables were transferred linearly to a scale between scale 0 and 100 by using the min-max normalization (Eq. (1)) (Mainali and Silveira, 2015).

$$X' = \frac{X - Min\ (x)}{Max(x) - Min(x)} \qquad \text{(Eq.1)}$$

where x is the original data value; max/min denote the bounds for minimum and maximum data points in the corresponding column (variable), respectively; and x' is the normalized value after rescaling. Min-max normalization technique was chosen because it was one of the most robust normalization approaches in terms of its ability to preserve the relationships in the data (Jayalakshmi and Santhakumaran, 2011).

After, the correlation matrix of the normalized variable is calculated. Then, the correlation matrix of the normalized variable is calculated. Moreover, the eigenvalues and eigenvectors of the correlation matrix are calculated. An eigenvalue indicates how much variance there is in the data in that direction. The eigenvector with the highest eigenvalue is identified as the principal component. We can use the size of the eigenvalue to determine the number of principal components. Hence, we retain the principal components with the largest eigenvalues. Moreover, eigenvalues are determined by the following determinant equation,

$$(R - \lambda I) = 0 \qquad \text{(Eq. 2)}$$

where R is the correlation matrix (n × n), λ is the symbol for eigenvalue(s) and I is the unit matrix (Doukas et al., 2012).

Solving for λ from nth degree polynomial equation provides n eigenvalues, which correspond to the correlation matrix. 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

Table 3
Number of variables classified under each SDG.

SDG #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
2017	3	4	14	5	5	4	4	6	9	3	3	6	6	5	3	9	4	93
2018	3	6	16	8	5	4	4	5	11	3	4	7	5	6	5	9	4	105

et al., 2012). Furthermore, to derive the eigenvectors, the following matrix equation (Eq. (3)) is solved.

$$(R - \lambda jI)Fj = 0 \quad \text{(Eq. 3)}$$

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 (Vyas and Kumaranayake, 2006). 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 for each SDG for each year. In other words, PCA is conducted for each SDG individually.

$$NSI_{ks} = \frac{\sum_{i=1}^{n_s} \lambda_{iks} * f_{iks}}{\sum_{i=1}^{n_s} \lambda_{iks}} \; where\; k = 1, \ldots, 35;\; s = 1, \ldots, 17;\; i = 1, \ldots, n_s \quad \text{(Eq. 4)}$$

where NSI_{ks} is the non-standardized sustainability index of the kth country and sth SDG. λ_{iks} is the corresponding eigenvalue loading and f_{ik} is the factor score of ith principal component for kth country and sth SDG. There are n_s *number of* principal components in the SDG s. It is important to note that the number of variables varies from one SDG to another; thus, the number of principal components. The non-standardized 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. (5), which yields the Goal-Specific PCA Sustainable Development Index (GS-PCA SDI) (Park et al., 2016). NSI_{ks} is the non-standardized index score for country k and SDG *s*. *Min* $[NSI_s]$ is the minimum NSI value in SDG *s* and *Max* $[NSI_s]$ is the maximum NSI score in SDG *s*.

$$GS - PCA\; SDI_{ks} = \frac{NSI_{ks} - Min\;[NSI_s]}{Max\;[NSI_s] - Min\;[NSI_s]} * 100\; where\; k = 1, \ldots, 35; s = 1, \ldots, 17 \quad \text{(Eq. 5)}$$

4. Results

This section is organized into subsections. In the initial subsection, descriptive statistics of the results are provided. The next sub-section introduces the results of GS-PCA in terms of index scores and ranks of the OECD countries. Lastly, the comparison of the current study's findings with the 2017 and 2018 UN SDG Index and Dashboard Report was provided.

4.1. Descriptive statistics of results obtained with GS-PCA approach

Tables 4 and 5 depict the descriptive statistics of the 17 SDGs' sustainability index score obtained with the proposed GS-PCA approach. The mean statistics of the goal 17 i.e. partnership for the goal (Revitalize the global partnership for sustainable development goal) and goal 13 i.e. Climate action (Take urgent action to combat climate change and its impacts) is relatively lower than that of the other goals. The range of standard deviation is between 18 and 30, while the range of mean scores were between 57 and 80. In Table 3, the Z-skewness and Z-Kurtosis results indicate that majority of the SDGs index score results are out of −1.96 and + 1.96 range, which is strong indication of non-normal results dataset (Taylor et al., 2012). It is also important to note that using PCA as a nonparametric approach could be of importance and more suitable in such problems where non-normal input and/or output data are obtained. Table 5 represents the descriptive statistics of the individual SDI scores for the year 2018. SDG 13 i.e. Climate change has the highest average SDI score of 81.13 while SDG 17 i.e. Partnerships to achieve the Goal has lowest average SDI score.

4.2. Results of the proposed GS-PCA

The results of KMO tests and p values after arranging variables are provided in Table 6. 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 PCA. 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 and di Girolamo, 2015).

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 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 2017 results (See Table 6), after implementing PCA to each SDG, the researchers found 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, the researchers found

Table 4
Descriptive statistics of the GS-PCA SDI 2017 results.

SDG	N	Min	Max	Mean	Std. Dev.	Skewness[1]	Kurtosis[2]	$Z_{Skewness}$	$Z_{Kurtosis}$
1	35	0	100	57.39	26.71	−0.23	−0.77	−0.58	−0.99
2	35	0	100	71.41	18.99	−2.57	7.53	−6.47	9.68
3	35	0	100	74.85	23.84	−1.73	2.69	−4.35	3.46
4	35	0	100	71.83	22.11	−1.76	3.24	−4.42	4.17
5	35	0	100	71.60	20.53	−1.35	2.99	−3.39	3.84
6	35	0	100	74.90	23.71	−1.67	2.32	−4.20	2.99
7	35	0	100	58.91	17.20	−0.75	3.95	−1.89	5.07
8	35	0	100	78.06	24.27	−1.84	3.24	−4.62	4.17
9	35	0	100	59.37	24.00	−0.61	0.34	−1.53	0.43
10	35	0	100	66.17	23.29	−1.27	1.89	−3.20	2.43
11	35	0	100	65.37	25.84	−0.95	0.23	−2.39	0.30
12	35	0	100	53.94	27.78	−0.02	−0.99	−0.05	−1.28
13	35	0	100	38.60	21.11	0.64	1.38	1.60	1.77
14	35	0	100	51.28	21.29	0.07	0.31	0.19	0.40
15	35	0	100	57.48	25.55	−0.43	−0.58	−1.09	−0.74
16	35	0	100	56.92	29.43	−0.43	−0.98	−1.09	−1.27
17	35	0	100	29.93	24.92	1.33	1.71	3.33	2.20

Table 5
Descriptive statistics of the GS-PCA SDI 2018 results.

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	24.5	−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	2.4
8	35	0	100	67.28	25.11	−1.32	1.37	−0.21	−0.3
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	2.3	−0.3	−0.1
11	35	0	100	84.64	5.85	−0.173	0	−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	13.5	−1.72	1.8
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	−1.2	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

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

Table 6
KMO and significance values.

SDG	2017			2018		
	Number of Variables	KMO	Significance	Number of Variables	KMO	Significance
1	3	0.534	0.029	3	0.591	0.000
2	4	0.489	0.040	6	0.459	0.000
3	14	0.71	0.048	16	0.565	0.000
4	5	0.703	0.050	7	0.686	0.000
5	5	0.58	0.000	5	0.509	0.000
6	4	0.433	0.020	4	0.536	0.092
7	4	0.482	0.000	4	0.446	0.000
8	6	0.665	0.000	5	0.723	0.000
9	9	0.806	0.000	11	0.815	0.000
10	3	0.533	0.000	3	0.571	0.000
11	3	0.592	0.000	4	0.422	0.324
12	6	0.544	0.000	7	0.675	0.000
13	6	0.672	0.060	5	0.548	0.071
14	5	0.447	0.050	6	0.571	0.110
15	3	0.544	0.000	5	0.544	0.000
16	9	0.682	0.000	9	0.693	0.000
17	4	0.506	0.002	4	0.512	0.089

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). Additionally, three variables, "CO_2 emission from energy", "Annual change in forest area", and "HIV incidence (per 1000)" were removed from the SDGs 13 (Climate Action), 15(Life on Land) and 3 (Good health and well-being) respectively from the data set to maintain the KMO and Bartlett's tests results at the acceptable levels. The PCA models were built again after aforementioned variable additions and deletions, and the results of the two PCA models built for SDG 1 and SDG 13 became quite close to acceptable level of significance.

In 2018 results (See Table 6), except for SDG 11, all goals were found to be suitable for PCA. Individual SDI score is then calculated from the factor score generated from the analysis. The individual SDI score for OECD countries for the year 2018 is given in Table 9. In 2018, the top 5 performing countries remains the same with some changes in their rank. Mexico and Turkey remain among the worst performing countries. The changes in the score and their ranks are more explained on the comparison section of this report. The detailed sustainable development performance scores (GS-PCA SDI) of 2017 and 2018 years are shown in Table 7 and Table 8, respectively. Countries are ranked based on the average index scores on the 17 SDGs. In the next two sub-sections, OECD countries performance scores are systematically analyzed.

4.3. Statistical validation: Comparison with the benchmark study (Baseline UN reports - (Sachs et al., 2017, 2018)

The result obtained from the GS-PCA models are compared with the benchmark study (Sach 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 UN report), mediocre or poor performing countries were found to have substantial score differences with the benchmark study. For instance, Hungary, Luxemburg, and the US were found to have significant differences in their ranks with the UN SDG report. On the other hand, countries like Sweden, France, Portugal, Italy, and Greece were found to have the same ranking but with significant score differences. Additionally, results obtained with the newly proposed GS-PCA approach and results of benchmark study were compared with scatter plots as shown in Fig. 2 (Horizontal axis: Benchmark study, Vertical Axis: Current Study). The R2 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 R2 values validates our proposed GS- PCA model of the score for the year 2017 and 2018. The corresponding R2 values for the year 2017 and 2018 are 0.78 and 0.874, respectively. The high R2 values is the strong indication of model validation.

4.4. How do the OECD countries' do in 2018 compared to 2017?

4.4.1. 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 the difference in scores of 2017 and 2018.

Fig. 3 depicts the rank difference of 2017 and 2018 years. Ireland has significantly improved its rank by 14, followed by Poland (8), Estonia (7), Israel (6) and Slovenia (5). On the other hand, Belgium, United States, and Luxembourg's rankings dropped by 7–8 ranks in

Table 7
OECD countries' SDG index scores in 2017.

Countries\SDG	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	$GS-PCA-SDI_{k\bar{s}}$
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**
GSPCA SDI$_{\overline{ks}}$	**57.4**	**71.4**	**74.8**	**71.8**	**71.6**	**74.9**	**58.9**	**78.1**	**59.4**	**66.2**	**65.4**	**53.9**	**38.6**	**51.3**	**57.5**	**56.9**	**29.9**	**61.1**

Table 8
OECD countries' SDG index scores in 2018.

Countries\SDG	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	$GS-PCA-SDI_{k\bar{s}}$
Sweden	79.9	83.0	98.0	66.7	93.9	63.5	98.8	92.6	90.2	93.8	81.8	46.3	86.5	45.6	61.4	88.2	100.0	**80.6**
Finland	100.0	75.0	100.0	92.7	90.3	64.9	92.2	72.5	79.6	99.2	82.5	48.9	77.5	70.5	74.3	93.8	50.6	**80.3**
Denmark	87.7	90.1	85.9	73.5	87.0	69.9	84.0	88.7	100.0	89.5	91.6	41.4	80.9	35.6	81.2	78.9	79.0	**79.1**
Norway	87.8	71.4	98.6	83.4	100.0	79.8	98.6	76.3	78.3	99.3	80.3	20.7	47.2	86.1	27.9	95.6	79.2	**77.1**
Iceland	95.7	81.4	99.3	66.9	94.8	36.6	100.0	100.0	91.4	100.0	95.4	60.8	89.9	33.1	6.0	77.5	34.8	**74.3**
United Kingdom	90.8	81.8	81.0	84.4	78.1	43.4	74.6	82.2	59.6	63.3	87.2	35.5	82.4	56.8	58.6	86.0	86.5	**72.5**
Ireland	94.2	88.0	90.5	61.5	59.6	68.2	73.7	89.9	58.4	86.6	62.7	52.2	91.0	42.9	79.0	71.6	47.4	**71.6**
France	93.7	87.4	81.0	39.9	90.6	78.9	82.8	59.4	48.9	89.2	85.1	50.2	89.5	57.5	54.6	68.2	53.9	**71.2**
Belgium	86.5	82.9	83.2	44.5	85.1	93.8	73.0	68.4	46.7	93.5	73.4	46.4	77.8	21.1	71.5	64.9	72.3	**69.7**
Switzerland	95.7	81.6	96.3	44.1	76.8	80.4	86.5	95.1	62.9	75.4	87.8	8.5	92.1	46.5	11.7	100.0	34.9	**69.2**
Germany	93.5	92.1	84.1	57.3	71.4	58.1	76.7	89.9	45.7	85.8	76.8	43.0	88.6	21.4	58.8	80.4	52.0	**69.2**
Canada	70.6	71.7	75.1	100.0	75.2	77.5	82.8	77.7	40.8	78.3	73.0	54.4	63.6	83.7	24.3	79.8	37.9	**68.6**
New Zealand	94.2	72.7	70.5	64.2	84.7	23.3	87.0	90.0	56.7	70.0	71.4	71.7	88.4	63.8	9.2	82.1	40.0	**67.1**
Austria	85.7	92.3	85.6	44.4	58.1	71.6	84.7	83.6	55.0	90.9	68.1	32.3	86.5	46.5	42.9	69.9	41.0	**67.0**
Czech Republic	90.0	84.9	80.6	31.1	53.2	72.4	76.1	68.6	47.0	86.7	77.5	84.7	90.6	46.5	79.4	43.4	14.0	**66.3**
Estonia	67.2	71.7	71.6	80.5	54.2	45.9	58.1	73.1	58.5	59.0	75.1	82.0	79.5	80.9	89.5	58.1	19.5	**66.1**
Netherlands	92.6	84.4	90.2	64.0	74.5	24.3	71.0	90.3	58.1	92.2	79.0	29.8	48.5	12.2	60.0	94.6	56.9	**66.0**
Slovenia	89.6	80.0	87.0	64.3	86.9	30.9	77.5	67.4	46.6	84.2	61.3	81.8	95.0	14.1	55.9	49.2	41.8	**65.5**
Japan	62.5	83.5	98.2	98.0	15.8	82.7	74.3	82.1	58.8	70.0	72.3	60.4	83.3	36.8	34.7	72.4	19.1	**65.0**
Portugal	58.5	67.7	73.4	53.3	81.8	82.1	83.5	65.5	43.9	63.9	75.7	58.8	93.8	45.8	74.9	47.1	27.4	**64.5**
Luxembourg	96.2	76.6	90.4	22.4	71.0	68.7	54.5	83.6	33.5	92.5	100.0	0.0	80.4	46.5	28.6	82.7	61.2	**64.0**
United States	61.4	82.6	56.0	54.8	63.7	94.6	74.6	75.5	50.1	40.4	82.6	48.3	64.4	61.3	30.7	73.7	55.7	**63.0**
Spain	46.4	68.3	87.4	69.3	73.6	95.6	80.0	49.1	32.9	72.0	89.4	49.5	89.5	28.3	40.3	52.6	30.7	**62.0**
Korea, Rep.	67.9	100.0	85.7	83.4	24.1	29.0	73.3	61.7	78.9	62.5	59.8	70.2	85.6	85.6	13.2	45.9	7.3	**60.8**
Poland	93.1	73.5	67.7	53.9	64.4	34.5	70.0	55.5	29.0	71.5	46.6	100.0	90.7	0.0	80.5	34.5	7.2	**57.2**
Latvia	56.2	73.2	49.4	66.9	51.6	88.2	78.0	70.0	15.7	58.1	25.3	75.7	83.7	18.3	100.0	29.0	5.6	**55.6**
Israel	68.6	68.5	88.9	52.7	72.0	0.0	74.7	75.9	80.2	51.7	71.3	37.8	87.6	27.2	9.9	68.7	8.6	**55.6**
Hungary	73.7	78.9	52.2	0.0	51.0	47.1	74.5	49.5	9.3	82.8	70.5	86.1	100.0	46.5	73.4	23.3	12.9	**54.8**
Australia	87.5	64.2	85.9	68.5	71.2	52.6	71.2	81.6	65.1	63.0	0.0	43.0	0.0	49.9	17.0	63.5	34.1	**54.0**
Slovak Republic	55.7	72.8	60.6	26.7	56.4	29.9	76.6	52.3	38.0	82.9	32.8	83.6	81.2	46.5	70.6	29.9	14.1	**53.6**
Italy	40.7	81.4	89.3	56.9	56.5	49.2	77.2	25.2	19.3	73.4	56.2	51.4	84.6	17.6	55.6	30.9	33.5	**52.9**
Greece	30.6	76.5	79.4	30.2	54.8	100.0	76.7	15.0	13.3	62.6	86.8	43.9	79.3	53.5	52.9	24.3	16.8	**52.7**
Chile	72.1	49.1	44.0	7.3	32.4	23.2	73.0	44.0	0.9	13.5	84.4	85.5	97.0	100.0	28.2	36.6	18.3	**47.6**
Turkey	83.4	44.5	28.2	33.8	0.0	86.0	73.6	0.0	0.0	35.4	42.2	95.3	90.6	38.2	0.0	23.2	0.0	**39.7**
Mexico	0.0	0.0	0.0	20.6	48.4	73.7	0.0	2.8	8.0	0.0	42.8	98.7	92.6	60.9	5.2	0.0	23.0	**28.0**
$GSPCA\ SDI_{\overline{ks}}$	**75.7**	**75.2**	**77.0**	**56.1**	**65.8**	**60.6**	**76.1**	**67.3**	**48.6**	**72.4**	**70.0**	**56.5**	**81.1**	**46.5**	**47.5**	**60.6**	**37.6**	**63.2**

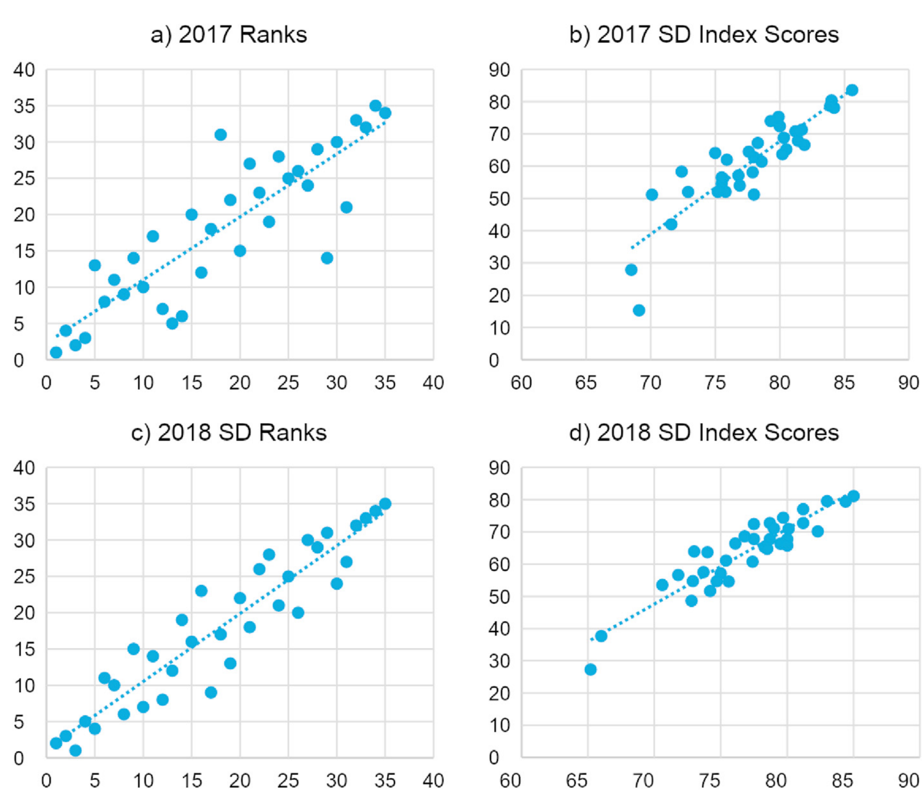

Fig. 2. Scatter Plots of Ranks and Index Scores (Horizontal axis: Benchmark study, Vertical Axis: Current Study).

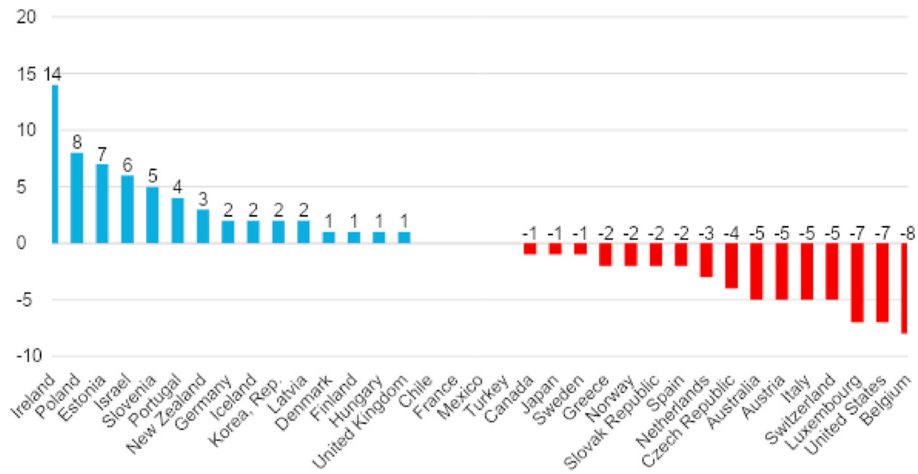

Fig. 3. Changes in the GS-PCA-SI ranks from 2017 to 2018.

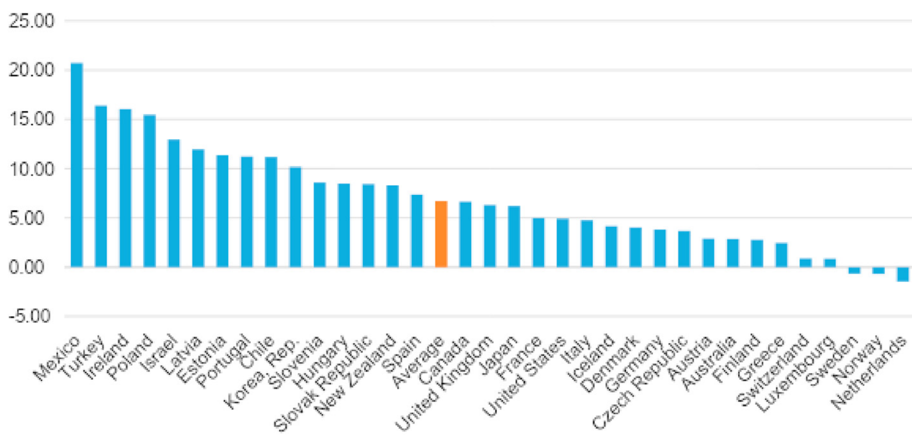

Fig. 4. Changes in the SI scores from 2017 to 2018.

2018. 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 while demonstrating some improvements in their SDI scores.

Fig. 4 shows the differences in GS-PCA-SI scores from 2017 to 2018. Most of the countries experienced a positive increase in the SDI scores in 2018. For instance, Mexico, Turkey, Ireland, Poland, and Israel have significantly increased in the sustainability score. Netherland, Sweden, and Norway, on the other hand, have seen lower SDI scores in 2018 compared to 2017. The average SDI score in the 2018 has increased by almost 6.7% with a reduction in standard deviation to 11.26 in 2018 as compared to 13.70 in 2017. This is an indication of positive progress in terms of increasing the sustainable development performance and closing the standard deviation of performance among the OECD partners.

4.4.2. *Statistical comparison of 2017 and 2018 SDG performances*

Statistical comparison tests are conducted to compare the SDIs of OECD countries in 2017 and 2018 to see if there is significant difference from 2017 calendar year to the 2018 calendar year. The comparative analysis of GS-PCA-SI scores for 2017 and 2018 years were given with box and whisker plots (considering all 17 SDGs) and depicted in Fig. 5. Normality test is conducted to find whether the data are normal or not to identify the suitable test compare the score difference (Normality test results are provided in Table 9). Most of them is found to have p value less than 0.05 which indicate the non-normal data set. To deal with the non-normal data set, non-parametric test Kruskal Wallis test is performed. The results are provided in Table 10. 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 greater than 0.05, thus there is 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 majority of the SDGs. However, only 7 SDGs (1,4,7,8,11,13,17) had significant difference from 2017 to 2018. On the other hand, the mean SDG performance was found to be increasing with statistical significance. Among the SDGs with statistically significant changes, SDG 1 No Poverty, SDG 7 Affordable and Clean Energy, SDG 11 Sustainable Cities and Communities, SDG 17 Partnerships to Achieve the Goal and mean of all 17 SDGs were found to be improving from 2017 to 2018 with statistical significance. On the other hand, SDG 4 Quality Education and SDG 8 Decent Work and Economic Growth were found to be worsening with statistical significance.

4.4.3. *Comparison of top 5 performers and worst performers between 2017 and 2018*

Tables 11 and 12 depict the top 5 and worst 5 performing

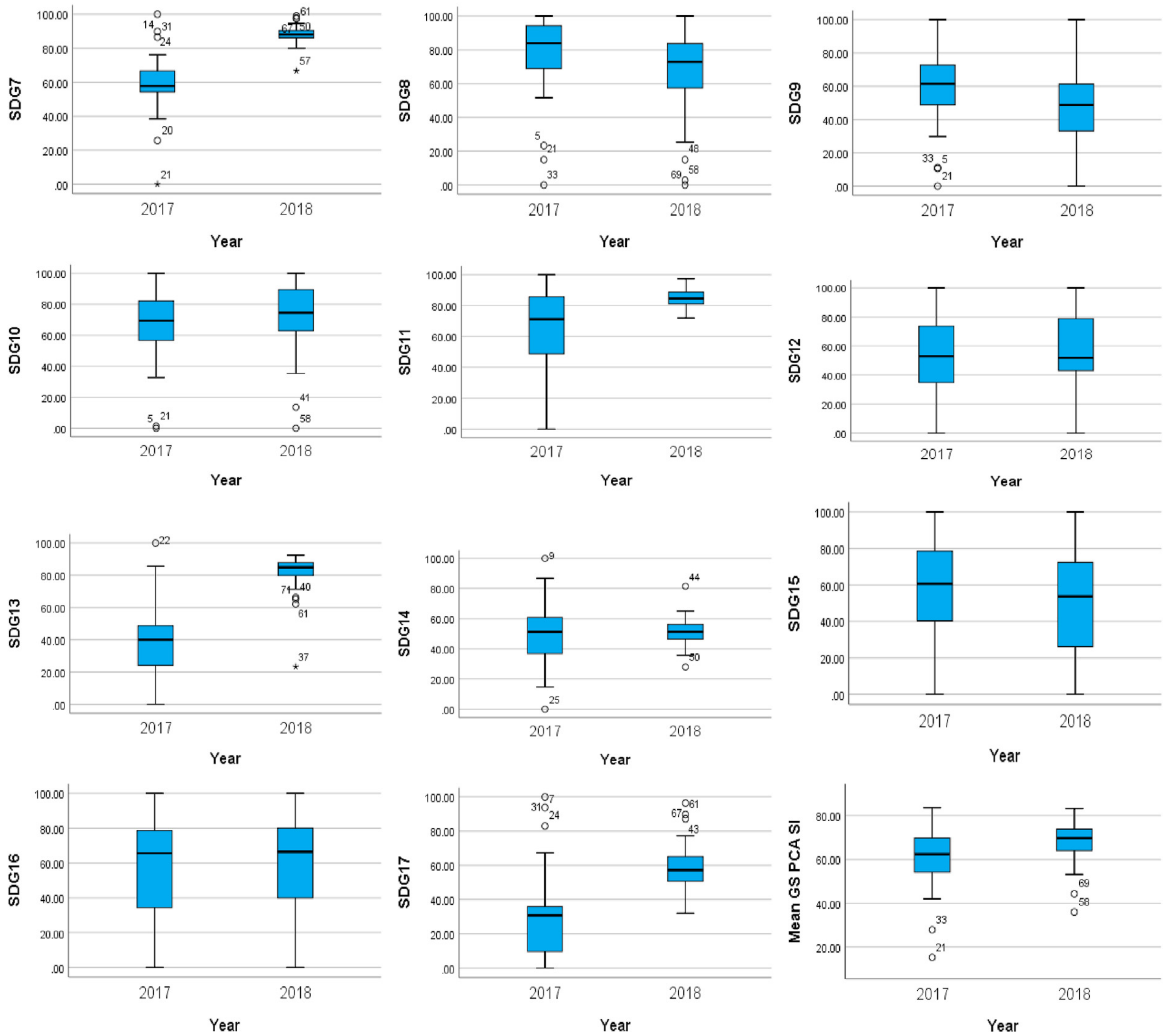

Fig. 5. The Box and Whisker plots of GS-PCA-SI Scores (2017 and 2018).

Table 9
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**

countries in the 2017 and 2018 along with their best and worst SDG. It can be seen from the Table 11 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%. The Table 12 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

Table 10
Results of Kruskal Wallis test.

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

Table 11
Top 5 best performers and their best and worst SDG performance.

	TOP 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)

Table 12
Top 5 worst performers and their best and worst SDG performance.

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)

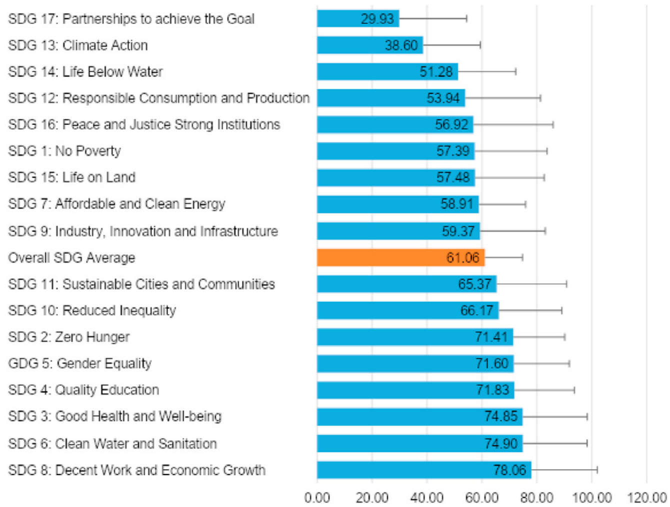

Fig. 6. Average and Standard Deviation of SDI scores in 2017.

worst performing countries have scored highest on the SDG like Responsible Consumption and Production, Clean water and Sanitation, Good health, and well-being etc.

4.5. SDG-focused analysis

In this section, we present results on each of the 17 SDGs. Results of average SDI score for each SDGs in 2017 is provided in Fig. 6 and results of 2018 data is provided in Fig. 7. According to Fig. 6, 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 an average score of almost 80%. The average SDG score of the OECD countries in the year 2017 was found to be 61.09%.

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.

5. Discussion

The objective of proposing a PCA approach in this paper was to aggregate a large 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 UN's benchmark reports (Sachs et al., 2017, 2018). The reason behind this difference is attributed to the inherent correlations among most 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). We strongly advise the United Nations' DSDG to replace their assessment and evaluation approach with the nonparametric method proposed in this paper.

SDI scores depicts the OECD countries' progress towards achieving the targets of 17 SDGs and 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 SDG 1 "No Poverty" with an increase of 14.36% compared to 2017. However, there are goals 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. Thus, 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

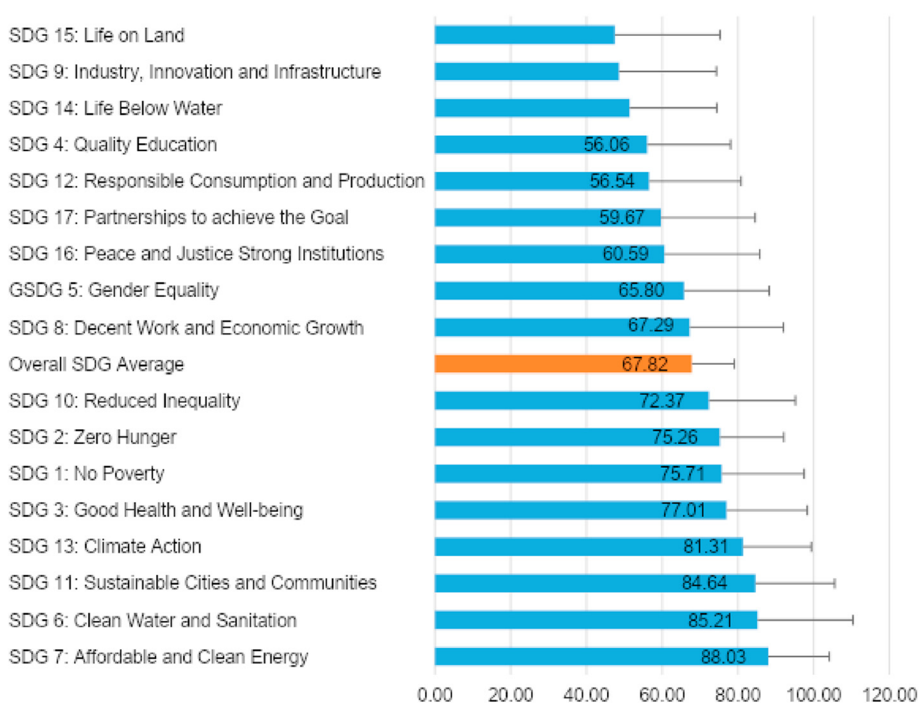

Fig. 7. Average and Standard Deviation of SDI scores in 2018.

end of 2030. SDG17, “Partnership to achieve goal” was found to be the lowest performing goal for the OECD countries. And this is a particularly tragic result since sustainable development significantly requires effective partnerships among the OECD countries and among the organizations within each and every OECD country.

Both our findings and benchmark reports indicate that majority of the OECD countries significantly fell behind addressing the expectations set by 18 SDGs. In this context, the most critical stakeholder, the Division for Sustainable Development Goals (DSDG) of United Nations should be more affectively working with the entities that will create momentum for assessing the 17SDGs and creation of formal task forces. In addition, the following stakeholders such as United Nations as a whole, European Union as a whole, at the United Nations: The Division for Sustainable Development Goals (DSDG), United Nations Department of Economic and Social Affairs (UNDESA), Voluntary National Reviews Lab; and in each OECD country: the departments of interior and state, the national statistical institutes, non-governmental agencies whose mission is to promote 17 SDGs at the local and national level.

According to 2018 report, only 35% of the OECD countries had identified key national system to monitor 17 SDGs. This statistic clearly depicts that even though the 17 UN SDGs were set in 2015 for 2030 agenda, about two-third of OECD countries have not even implemented the monitoring system effectively. There is a significant gap in the implementation and monitoring system. Most of the efforts especially in poor performing or mediocre performing countries are highly scattered and disorganized. Therefore, they are not effectively supporting the broader 17 SDGs.

6. Conclusion, limitations, and future work

What Peter Drucker quoted for business organizations is true for the sustainable development: if we cannot 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 paper 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 UN SDG reports, which consist of 35 rows (OECD countries) and 93 variables, which account for 17 SDGs. Each SDG has a set of variables ranging between 2 and 9. And, these variable sets 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 recent UN benchmark reports (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 UN report), mediocre or poor performing countries were found to have substantial score differences with the UN report. For instance, Hungary, Luxemburg, and the US were found to have significant differences in their ranks with the UN SDG 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 differences were observed in the standard deviation of the scores and ranks, 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 UN SDG index 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. These aforementioned extensions could be made with the integration of expert judgment or further literature review on weight assignments to SDGs, which will reflect the relative importance of SDGs. The researchers also envisions to integrate multi-criteria decision analysis with the proposed GS PCA approach to address the non-equal weight assignments and compare with the literature. In addition, machine learning-based clustering approaches could be coupled with the findings of the current study to further group the countries into sustainability performance clusters and conduct nonparametric sensitivity analysis of input variables. Lastly, the study period can and should be increased as more data becomes readily available in the recent future.

CRediT authorship contribution statement

Shyam Lamichhane: Formal analysis, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Gökhan Eğilmez:** Conceptualization, Methodology, Visualization, Investigation, Formal analysis, Writing - review & editing, Supervision. **Ridvan Gedik:** Conceptualization, Writing - review & editing, Supervision. **M. Khurrum S. Bhutta:** Conceptualization, Writing - review & editing. **Bulent Erenay:** Conceptualization, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.125040.

References

Abson, D.J., Dougill, A.J., Stringer, L.C., 2012. Using principal component analysis for information-rich socio-ecological vulnerability mapping in southern Africa. Appl. Geogr. 35 (1–2), 515–524. https://doi.org/10.1016/j.apgeog.2012.08.004.

Adler, N., Yazhemsky, E., Tarverdyan, R., 2010. A framework to measure the relative socio-economic performance of developing countries. Soc. Econ. Plann. Sci. 44 (2), 73–88. https://doi.org/10.1016/j.seps.2009.08.001.

Ali, H.M.M., 2009. Development of Arab water sustainability index using principal component analysis. In: Proceedings of the 13th International Water Technology Conference, pp. 1563–1579. Retrieved from. http://faculty.ksu.edu.sa/72005/Papers of Interest Water/Development of Arab Water Sustainability

Index.pdf.

Alvarado, R., Ponce, P., Criollo, A., Córdova, K., Khan, M.K., 2018. Environmental degradation and real per capita output: new evidence at the global level grouping countries by income levels. J. Clean. Prod. 189, 13–20. https://doi.org/10.1016/j.jclepro.2018.04.064.

Biswas, B., Caliendo, F., 2001. A multivariate analysis of the human development index. Indian Econ. J. 49 (4), 96–100.

Biswas, B., Caliendo, F., 2002. A multivariate analysis of the human development index. Indian Econ. J. 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. Am. J. Ind. Bus. Manag. 5 (2), 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, 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.

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. Renew. Agric. Food Syst. 31 (6), 524–539. https://doi.org/10.1017/S1742170515000460.

Doukas, H., Papadopoulou, A., Savvakis, N., Tsoutsos, T., Psarras, J., 2012. Assessing energy sustainability of rural communities using Principal Component Analysis. Renew. Sustain. Energy Rev. 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.

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. Retrieved from. https://www.ecologic.eu/sites/files/publication/2015/kraemer_08_analysis_of_the_epi.pdf.

Hag Ibrahim, S.N., 2017. Sustainability assessment of community-based water supply projects in Sudan using sustainability index and multivariate analysis. J. Water Sustain. 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. Ecol. Indicat. 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 Econ. Pap. 22 (4), 459–473. https://doi.org/10.18267/j.pep.462.

Jayalakshmi, T., Santhakumaran, A., 2011. Statistical normalization and back propagation for classification. Int. J. Comp. Theor. Eng. 1793–8201.

Jollands, N., Lermit, J., Patterson, M., 2004. Aggregate eco-efficiency indices for New Zealand - a principal components analysis. J. Environ. Manag. 73 (4), 293–305. https://doi.org/10.1016/j.jenvman.2004.07.002.

Jolliffe, I., 2011. Principal component analysis. In: International Encyclopedia of Statistical Science, vol. 58. Springer, Berlin Heidelberg. https://doi.org/10.1201/b17700-1.

Khan, M.K., Khan, M.I., Rehan, M., 2020. The relationship between energy consumption, economic growth and carbon dioxide emissions in Pakistan. Financial Innov. 6 (1) https://doi.org/10.1186/s40854-019-0162-0.

Khan, M.K., Teng, J.Z., Khan, M.I., 2019a. Effect of energy consumption and economic growth on carbon dioxide emissions in Pakistan with dynamic ARDL simulations approach. Environ. Sci. Pollut. Control Ser. 26 (23), 23480–23490. https://doi.org/10.1007/s11356-019-05640-x.

Khan, M.K., Teng, J.Z., Khan, M.I., Khan, M.O., 2019b. Impact of globalization, economic factors and energy consumption on CO2 emissions in Pakistan. Sci. Total Environ. 688, 424–436. https://doi.org/10.1016/j.scitotenv.2019.06.065.

Krishnan, V., 2010. Constructing an area-based socioeconomic status index: a principal components analysis approach. In: Every Day in Every Way: Creating Learning Experiences for Every Child. (May), pp. 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, p. 56. September.

Lai, D., 2003. Principal component analysis on human development indicators of China. Soc. Indicat. Res. 61 (3), 319–330. https://doi.org/10.1023/A:1021951302937.

Li, T., Zhang, H., Yuan, C., Liu, Z., Fan, C., 2012. A PCA-based method for construction of composite sustainability indicators. J. Life Cycle Assess. 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. J. Atmos. Ocean. Technol. 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. Renew. Sustain. Energy Rev. 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. J. Clean. Prod. 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>. Annu. Rev. Environ. Resour. 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. SDG index and dashboards report 2017: global responsibilities, international spillovers in Acheving the goals. New York. Retrieved from. http://www.sdgindex.org/assets/files/2017/2017-SDG-Index-and-Dashboards-Report–regions.pdf.

Sachs, J., Schmidt-Traub, G., Kroll, C., Durand-Delacre, D., Teksoz, K., 2018. SDG Index and Dashboards Report 2018: Global Responsibilities, International Spillovers in Implementing the Goals. New York.

Searcy, C., Elkhawas, D., 2012. Corporate sustainability ratings: an investigation into how corporations use the Dow Jones Sustainability Index. J. Clean. Prod. 35, 79–92. https://doi.org/10.1016/j.jclepro.2012.05.022.

Singh, R.K., Murty, H.R., Gupta, S.K., Dikshit, A.K., 2012. An overview of sustainability assessment methodologies. Ecol. Indicat. 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. Ecol. Indicat. 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., 2012. Kurtosis : A Critical Review Kurtosis : A Critical Review (November 2014), pp. 37–41. https://doi.org/10.1080/00031305.1988.10475539.

Vyas, S., Kumaranayake, L., 2006. Constructing socio-economic status indices: how to use principal components analysis. Health Pol. Plann. 21 (6), 459–468. https://doi.org/10.1093/heapol/czl029.

Zhao, G., 2015. A sustainability classification for a country based on PCA Guojin Zhao, International Symposium on Social Science (ISSS 2015). Proceedings of the 1st International Symposium on Social Science (isss-15) 100–103. https://doi.org/10.2991/isss-15.2015.25.