Repositioning a country for global manufacturing competitiveness: a case of South Africa

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Abstract

Purpose: This study aims to develop an artifact to measure the level of manufacturing competitiveness of a country in the global context and provide a suitable interpretation mechanism for the measured values, and to provide prescriptive solution where necessary so that the country can develop an actionable plan of program to move from the current level of global competitiveness to another such that they could provide more economic opportunities for their citizenry.

Design/methodology/approach: A manufacturing competitive index (MCI) was developed which includes relevant variables to capture a country's manufacturing activity level in an economy with a balanced perspective. Reliable international sources were used. Ward algorithm was used to identify clear clusters of performance upon which competitive gaps were measured and improvement projects were identified and prioritized to obtain the best value for cluster transitional plan.

Findings: This study shows that the case country is not doing as well as it wants to believe, even when the relevant technology import measures were included in the expanded metric, but also, the next level of competitiveness is achievable within the national budget if proper prioritization is done.

Originality/value: The paper presents a cocktail of indexes that is more exhaustive of MCI, including both research capacity and technology import variables. It also uses clustering mechanism to provide a proper context to interpret the MCI scores in the context of peer nations. It presents a gap determination methodology and shows how priority projects could be logically selected to close measured gaps based on anticipated value from budget expenses

Keywords: Competitiveness, Value analysis, Gap analysis, Global manufacturing,Porter's diamond model, Ward clustering algorithm

1. Introduction

The harsh global economic environment has made economic growth and national development a challenge for many countries and this has affected the quality of life that is affordable by the citizens of such countries. In this same global environment are countries whose economies are growing rapidly, driven by high levels of innovation, technological development and expanding manufacturing activity (MA), thereby creating global competitiveness, which Competitiveness, Value analysis, Gap analysis, Global manufacturing,Porter's diamond model, Ward clustering algorithmtranslates into expanding trade relations with other nations. It is, therefore, important to understand what makes a nation more competitive than others, especially in terms of global manufacturing capability.

The practice of doing business changes over time. Some countries that do not adopt the necessary technology start lagging behind. As technologies change, the practices used in the countries need to change. The evolution of technologies affects competitiveness of nations, shifting the competitive balance among countries. When this happens, the standard of living of such countries also changes. Therefore, it becomes imperative for every country to continue to monitor the evolution of new technologies and its effects on their competitiveness. It also becomes important to have a measure of preparedness as new technologies begin to emerge so that they can position or reposition themselves. This has led to the development of many techniques or approaches for countries to evaluate how ready they are considering the emerging technologies. Many countries, however, do not seem to have veritable means of evaluating how prepared they are for possible disruption as a result of shifts in the efficiency frontier and productivity of industries because of the emergence of new technologies.

The evolution of new technologies such as additive manufacturing and robotics has been considered disruptive in the manufacturing industries and may change the global manufacturing terrain and the destiny of many countries involved in the manufacturing space. It becomes pertinent for countries to be able to determine how they measure relative to others, and how to shift their standing in terms of relative competitiveness. This is important because manufacturing is a big employer of labor in most countries, especially in the developing world. As a result, any shift in such balance could lead to the loss of manufacturing competitiveness for such countries and by extension, the quality of life of their citizens and the level of employment in their economy. Coates *et al.* (2001) argues that "[…] every scientist working towards eventual innovation: each design engineer, production manager, product developer and technology marketing professional; should become informed on where the related technologies are likely heading […]." A manufacturing composite index (MCI) is one means of acquiring such insight. Composite indices offer a benchmarking approach to gather information on the current state of the manufacturing environment within an industry which can equip the leadership of a country with the best possible knowledge to make informed decisions.

An enhanced quantitative MCI was developed to benchmark different countries in terms of key manufacturing parameters. The main artifact is an MCI that makes use of variables that act as a proxy for manufacturing capability. This includes the level of country's internal innovation and the level of importation of machine tools such as computer numerically controlled (CNC) machines, plastic injection molding machines, additive manufacturing machines, industrial robotics and vacuum injection molding machines. These measures are used in conjunction with other economic and development data to create an index to benchmark different countries against each other through a clustering algorithm. The addition of a clustering algorithm expands the MCI beyond just a ranking score of countries that categorizes countries visually and display the clusters for subsequent analysis. Clustering is used because while MCI score may provide rankings of country, it does not interpret the performance gaps. By allocating countries into groups through a clustering algorithm, it indicates potential categories of competitive clusters and points out how to move across such clusters. Pareto supplemented gap analysis is subsequently used for action plans for countries to migrate across clusters. This procedure is illustrated using South Africa as a case and recommendations were made for future research. Gap analysis involves the comparison of actual cluster performance with potential or desired performance. Pareto analysis helps prioritize decisions so that the factors which will have the greatest influence can be identified, by measuring their percentage contribution.

Section 1 provides clarity on the research objectives and rational of the study. It also introduces the concept of manufacturing competitiveness. The literature review is discussed in Section 2. The research method is discussed in Section 3. In Section 4, the case country is presented and the results of the research are discussed, with the conclusion in Section 5.

2. Literature review

Composite indexes and clustering can be applied in measuring the preparedness and competitiveness of nations and companies. The manufacturing sector in today`s world is going through a challenging period (Zagloel and Jandhana, 2016). Uncertainty in manufacturing conditions raises the industrial sector risk and composite index measurement offers one method to measure the global transitional risk. Knowledge of what makes a country competitive provides a direction for improving the country's preference as an investment destination. Every nation faces a similar challenge of improving the life of its citizens, which means competitiveness has to be improved. It is evident that the manufacturing industry is becoming more technology intensive and that new forms of technology are emerging all the time (Coates *et al.*, 2001). Country examples of national shift in manufacturing competitiveness are South Korea and Germany who have become leaders in manufacturing.

Vishnevskiy *et al.* (2015) stated that there is a need for specialized tools that enable corporations to identify concrete steps to achieve the desired results in the future. An enhanced MCI approach can highlight concrete steps that countries can take in the manufacturing industry to identify the initiatives to improve the manufacturing environment within their nations. There are certain important variables that have been found in literature to have such influence, including GDP growth, manufacturing exports and imports. Research indicates a positive correlation between manufacturing growth and GDP growth (Kaldor, 1957). Kaldor's statement has also been tested and confirmed by others (Wells and Thirlwall, 2003; Millin and Nichola, 2005; Dasgupta and Singh, 2005).

2.1 Porter's diamond model

The Porter's diamond model is another popular framework used by researchers in the analysis of national competitiveness. It consists of four broad attributes that individually and as a system constitute the diamond of national advantage. The four attributes are factor conditions, demand conditions, related and supporting industries and finally firm strategy, structure and rivalry. Factor conditions include measurement of productivity of production inputs, such as skilled labor or infrastructure. Demand conditions focus on the domestic market demand for the industry's product or service. Related and supporting industries consider whether the country has the necessary feeder and related industries that are internationally competitive. Firm strategy, structure and rivalry factor seeks to evaluate the conditions in the nation governing how companies are created, organized and managed, as well as the nature of domestic rivalry (Porter, 1990). This framework views competitiveness as being related to productivity, so a strong focus on cost is a direct consequence (Wenzel and Wolf, 2016).

Researchers have used both qualitative and quantitative scales of proxy variables to operationalize these Porter's conditions. Examples of use of quantitative scales are Postelnicu and Ban (2010), Wenzel and Wolf (2016) and Ketels (2006), while Kharub and Sharma (2017) presents an example of qualitative measurement scales. There are also cases of mixed quantitative and qualitative scales such as Ezeala-Harrison (2014), Chikán (2008) and Sigalas *et al.* (2013). Some authors have combined some of Porter's conditions (the four diamond corners) while others have extended the structure by including other broad variables. Hanafi *et al.* (2017) for instance included two other variables, government and chance, creating six sub-structures or conditions for competitiveness analysis. Parc (2018) included the double diamond model to measure global and domestic competitiveness of Japan. Consequently, models based on Porter's framework have made use of three to six sub-structures when studying national competitiveness.

Scholars have indicated that in the development of composite indicators, too much qualitative variables have been used (Wenzel and Wolf, 2016). Dobss (2014) noted that the implementation of Porters framework largely used qualitative assessments of the given forces. Porter (2008) also wrote that as much as possible, analysts should look at industry structure quantitatively, rather than be satisfied with lists of qualitative factors. Akpinar *et al.* (2017) observed that the diamond model in essence is easy to understand, but the diversity of the four sub-determinants is difficult to measure.

While the conditions of the Porter's framework are also relevant in this research, a classification framework with different semantics has been adopted.

As the goal is to study national competitiveness in the manufacturing industry, the choice of a model particularly apposite for such was made. While the MCI presented herein implicitly considers the conditions of Porter's diamond framework, a different semantic is used and the variables are quantitative in nature. It also easily uses data from publicly available sources, and such data are usually more reliable and objective. The publicly available data sources also give a sufficiently large data set in the sample frame and readily incorporate latest developments.

It should also be noted that based on how the measurement has been done in this work, both the classifications based on Porter's diamond structure and that based on the adapted MCI framework will not necessarily produce different results with the subsequent clustering technique used as all proxy variables would still be used in either case. Clustering of sub-structure related items may, however, be different. A proposed alignment of the MCI framework with the Porter's diamond sub-structure is further presented in the methodology section and in Appendix 2.

2.2 Manufacturing composite index frameworks and their shortcomings

The conceptual model of the MCI presented in this work is adapted from Delgado-Márquez and García-Velasco (2018), Fischer *et al.* (2018), Terzić (2017), Ezell and Atkinson (2011), Lall (1992), Abramovitz (1986), Faberberg (1994), Archibugi and Coco (2004), Tan and Tan (2014), Milenkovic *et al.* (2016), Shaker and Zubalsky (2015) and Lall and Albaladejo (2003).

Lall (1992) argues that at the country level, capabilities can be grouped under three broad headings: physical investment, human capital and technological effort. Tan and Tan (2014) also agree with Lall (1992) that education, physical infrastructure and technological infrastructure are important elements for national technological competitiveness (NTC). Physical investment refers to plant and equipment that are needed for industries to exist. Human capital includes education, formal training and on-the-job training. Technological effort includes manufacturing, research and design. The NTC uses data from the World Bank but does not include data on importation of manufacturing technologies. In this work, technological infrastructure and physical infrastructure are important elements to be considered in the conceptual development of the MCI as used in the Asia Competitiveness Institute Index (Tan and Tan, 2014)

Abramovitz (1986) and Faberberg (1994) indicate that there are three essential ingredients explaining differences in the rate of technological changes across countries. Filiippetti and Peyrache (2011) also argue the three ingredients proposition, which can be summarized as:

1. differences in capital investments;
2. differences in the level of education; and
3. differences in the expenditures on research and development (R&D) and related innovations.

The development of appropriate social capabilities enhances rapid growth in countries that are lagging in technological development (Abramovitz, 1986). This highlights that research in universities and at public R&D institutions provides input into the innovation process (Faberberg, 1994). The innovation process is considered a major contributor to economic growth, productivity, competitiveness and employment. Countries are at different stages along this innovation path because of the availability of infrastructure in the country to support innovation and technological capabilities (Archibugi and Coco, 2004). Therefore, the measurement of variables that act as a proxy for infrastructure development assists in completing the analysis on the competitiveness of a country. Innovation is a process that includes generation of new ideas, industrialization and commercialization. In the development of the MCI, variables that can act as a proxy for measuring innovation will be used. R&D creates capacity for absorption of new technologies and aids innovation (Terzić, 2017). Advancement in knowledge leads to innovation which allows firms to build competitive advantage (Delgado-Márquez and García-Velasco, 2018). Empirically, both neoclassical and technology gap studies divide the variables into three groups (Faberberg, 1994):

1. GDP per capita as a proxy for productivity and/or technology;
2. variables to close the gap between leading and lagging countries (such as investments in education and physical infrastructure, output from innovation activities e.g. papers published); and
3. variables of economic, political and institutional nature (growth of labor force, degree of openness to trade and share of public sector in GDP).

In the development of an MCI, the elements of manufacturing, R&D and innovation should be included as they complement each other (Ezell and Atkinson, 2011). Studies indicate that R&D and manufacturing indices are important indicators to measure because of their ability to quantify economic growth or decline (Tassey, 2013). Less advanced countries can accept technologies from others to spurt their growth during the initial stages of development (Terzić, 2017). This can be captured in their level of import of manufacturing technologies as part of the development of the MCI.

The broad-based indicators include unit labor cost, deflators of sales and real exchange rates, weighted average of real GDP, aggregate imports of goods and services and volume of global trade. These broad-based indicators are suited well for measuring the competitiveness of countries (Fischer *et al.*, 2018). The competitiveness of a country can also be measured by benchmarking their investments and achievements in the information and communication technologies sector (Milenkovic *et al.*, 2016). The technological capability index is a good example of such artifact for measuring competitiveness (Khayyat and Lee, 2015).

Computation of MCI, complemented with clustering algorithm (such as Wards and Fuzzy c-mean) have been used to cluster countries (Shami *et al.*, 2013; Shaker and Zubalsky, 2015). "What If" simulation has also been used to make recommendations on structural reforms in the policy of the country (Tan and Tan, 2014).

This study uses extant literature to create the conceptual framework for the MCI to measure competitiveness by focusing on physical infrastructure, technological infrastructure, education, research and manufacturing capability, including technology import level. The identified shortcoming in literature is the exclusion of variables that specifically measure the impact of importation of manufacturing technologies pertaining to CNC machining, robotics, additive manufacturing, plastic injection molding, high technology exports and military expenditure as technology proxies.

2.3 Extant indexes and data sources

A total of 20 published composite indexes that used both quantitative and qualitative data were analyzed. Data sources used include the United Nations Comtrade database on international trade statistics (United Nations Comtrade website, 2018), the World Development Indicators (Worldbank, 2018), United States Patent and Trademark office (USPTO) (2018) and the Organization for Economic Co-operation and Development (OECD) (2018). Also, data from United Nations Development Program (UNDP) (2016), United Nations Industrial Development organization (UNIDO) (2016), United Nations Educational, Scientific and Cultural Organization (UNESCO) (2018), The World Economic Forum (WEF) (2018) and Center for World University Rankings (CWUR) (2016) were used.

2.4 Indicator levels

Indexes consist of three levels of indicators. The groupings according to The Handbook on Constructing Composite Indicators (2008) are:

1. *Individual indicators*: which represent data about a specific variable of quantitative or qualitative data, e.g. mean days to import a container into a country.
2. *Thematic indicators*: these indicators are grouped together around a specific theme, e.g. business infrastructure (BI).
3. *Composite indicators*: when all the thematic indicators (sub-indexes) are compiled into a single synthetic index, which is an aggregation of the thematic indicators.

2.5 Weights in the composite indicators

The different composite indexes analyzed use different schemes to assign weights to the sub-indexes. Nineteen of the composite indexes analyzed uses linear method of aggregation. The country performance assessment indicator from the Asian Development bank (2016) makes use of a geometric aggregation method for sub-indexes and indicators. Some weights are determined through principal component analysis, analytical hierarchy process and neural networks or by keeping all the weights equally distributed. A weighted composite index is of the form:

$$\sum_{x=1}^{Q} W_x I_{xn}$$

Where W_x is the weight assigned to the specific sub-index and I_{xn} is the sub-index. Each sub-index I_{xn} consists of a group of indicators (also called variables) which are aggregated or may also be weighted in the sub-index itself. In this research, all the weights will be kept equal without any loss of generality. In cases where sub-indexes need to be weighted, an appropriate weighting mechanism can be easily incorporated.

2.6 Development of sub-index themes for the modified manufacturing composite index

In this study, previous composite indexes were expanded by including indicators that specifically focus on manufacturing technologies, which is grouped under a MA sub-index. Also, the impact of regulatory burdens and bureaucratic processes, which usually results in long lead time are grouped under the economy and market environment (EM) sub-index.

The improved analytical framework for the enhanced MCI, thus, contains the following sub-indexes:

- BI sub-index, which measures the infrastructure activity in a country that supports the manufacturing competitiveness of the country. It contains 11 variables that measures investments in infrastructure, including health which is an important indicator of the living standards of the population of the country.
- EM sub-index contains eight variables and identifies how much GDP a country generates per person, indicating the market environment within the country. Bureaucratic obstacles, which can make the establishment of new manufacturing operations in a country difficult, are also included.
- Education and talent (ET) sub-index, containing four variables with focus on measuring the level of investment in education. Both input and output oriented measures of educational investments are considered.
- Innovation and research (IR) sub-index, containing six variables and measuring the research output of a country, patent applications and trademark applications.
- MA sub-index, having 13 indexes and measuring the manufacturing economic activity of the country. This was discussed earlier. Also see Appendix 1.

3. Research design and methodology

In this section, we present the methods for data collection, calculation of the composite index score and cluster formation. Gap analysis and closure of gaps are done in Section 4 where the case of South African competitiveness analysis is presented.

3.1 Data sources and preparation

The data used in the calculation of the MCI were obtained from the Worldbank (2018), United Nations Comtrade website (2018) and Center for World University Rankings (CWUR) (2016). These data sources are preferred because they are provided by reliable sources, open and constantly maintained, making them dependable and verifiable. Search is conducted on the different database platforms by filtering against the MCI indicator variables and international trade data on relevant machine tools. The data are downloaded in excel format from the databases. Data cleanup is performed and min-max normalization is done. Ward clustering analysis was then implemented using excel add-on package, XLSTAT, to group the countries into different categories of competitiveness.

3.1.1 Treatment of missing data

3.1.1.1 Imputation of missing data

There were few missing data points because the Worldbank (2018) source and United Nations Comtrade website (2018) have complete entries on most variables; but where there were missing data, the mean values of the non-zero entries of the indicator variables were used. This seems reasonable as the study is not trying to benchmark South Africa (ZAF) against a specific country, but rather against a basket of countries to move it from its current cluster to a more competitive cluster. This approach of treatment of missing data is used by Wenzel and Wolf (2016).

3.1.2 Data normalization

To normalize the data, the min-max normalization of data was used so that all variables have a value between 0 and 1. The can be represented as

$$Norm\, x_{q,c} = \frac{x_{q,c} - \min x_{q,c}}{max\, x_{q,c} - \min x_{q,c}}$$

Where *Norm* $x_{q,c}$ is the normalized value of an indicator *q* for country *c* at time *t*; *q* = 1, …, 42; *c* = 1, …, 27; and *t* is fixed at 2016 for all indicator variables except the GPD growth rate that was an average over 26 years.

3.2 Data aggregation

Linear aggregation was used in the computation of MCI as recommended by the Handbook on Constructing Composite Indicators (2008). The composite sub-indexes are calculated as:

$$Y_{n,c} = \sum_{n=1}^{j_n} x_{n,c}$$

Where $Y_{n,c}$ is the sub-index *Y* of the MCI for country *c*; $n \in q$: $\Sigma\, j_n = q$, $n = 1, \ldots, j_n$, j_n is the number of indicators belonging to the sub-index *n*, $\forall\, Y_n$, $n = 1, \ldots, j = 5$ categories (BI, EM, ET, IR and MA) in this case, with $j_1 = 11$, $j_2 = 8$, $j_3 = 4$, $j_4 = 6$, $j_5 = 13$ and $q = \Sigma j_n = 42$.

The MCI_c can then be calculated for each country as:

$$MCI_c = \sum_{n=1}^{j} W_n Y_n$$

where $\Sigma_n W_n = 1$, $0 \leq W_n \leq 1$ and $j = 5$ is the number of sub-indexes.

3.3 Alignment with the Porter's diamond model

The proxy items used to measure MCI sub-indexes in our proposed MCI framework can be aligned with Porter's diamond framework. This was achieved by comparing the MCI items to those of some other authors that have operationalized the four diamond corners of Porter. The summary of this alignment is presented next, while the tree structure of the comparison is provided in Appendix 2.

Factor conditions: The items used in measuring BI, ET and IR in the proposed MCI framework were found to correspond with the factor conditions of Porter's diamond. This can be observed from models of Kharub and Sharma (2017) and Postelnicu and Ban (2010).

Demand conditions: Considering that the focus of this work is the competitiveness of nations and not firms in a country, *per se*, most of the MCI variables do not fall in this category. This makes sense as Buckley (2017) has noted that firm-specific advantages (FSAs) are local in relevance and do not give a good indication of national competitiveness, and most items in this category seem to reflect more of FSAs as opposed to country-specific advantages, which the other diamond corners reflect. Only two of the MA items are classified as demand condition items.

Related and supporting industries attribute: High technology export and adoption has been used as indicator items for this sub category by researchers such as Postelnicu and Ban (2010). Generally, the proxy variables adopted depends on the focus of the research and the items under the MA sub-index of our MCI seem to fit well here, also being industry specific. The diverse industry contexts can be seen in Shafei (2009), Rugman and D'Çruz (1993), Pettus and Helms (2008), Gawad *et al.* (2014), Setyawan (2011), Molendowski and Zmuda (2013), Liu and Hsu (2009) and Moon and Lee (2004).

Firm strategy, structure and rivalry attribute: To measure this attribute proxy variables that measure how easy it is to setup and operate a firm has been measured, and the IR sub-index in our MCI is appropriate here. Similar items can be found in Liu and Hsu (2009).

3.4 Clustering method

Wards agglomerative hierarchical clustering was used to reduce the dimensionality of the data collected on the 27 different countries. Clustering of countries is used by Farinha *et al.* (2018) to also group countries into different categories. Clustering membership of the 27 countries is calculated by variance of the elements. An element will belong to a cluster if it produces the smallest possible increase in variance. A small geometric distance implies high similarity.

The squared Euclidean distance proximity type was used in the Wards clustering algorithm of the MCI_c.

The geometric distance for clusters of MCI_C is calculated as:

$$\begin{aligned}\Delta(A,B) = & \sum_{i\varepsilon A\cup B}\left\|\vec{x}\mathrm{i} - \vec{m}_{\mathrm{A\cup B}}\right\|^2 - \sum_{i\varepsilon A}\left\|\vec{x}\mathrm{i} - \vec{m}_{\mathrm{A}}\right\|^2 - \sum_{i\varepsilon B}\left\|\vec{x}\mathrm{i} - \vec{m}_{\mathrm{I}}\right. \\ & = \frac{p_A p_B}{p_A + p_B}\left\|\vec{m}_{\mathrm{A}} - \vec{m}_{\mathrm{A}}\right\|^2\end{aligned}$$

Where p_A and p_B are the number of points in clusters A and B, and $m\rightarrow_k$ is the center of cluster *k* where *k* = *A*, *B* when two clusters are considered.

4. Case study of South Africa

A total of 27 countries were compared in this study, including South Africa (ZAF). Table I shows the aggregate scores achieved by the countries in the five different themes and the overall composite index score achieved by each country included in the study. The abbreviations used to identify countries in the data are based on the UN Comtrade and World Bank standard. From the overall score, overall, South Africa (ZAF) ranks 24 out of the 27 countries and ranks 13 in the MA sub-index. This MA ranking has been significantly influenced by the level of import of manufacturing technology into South Africa from other countries as a percentage of ZAF's GDP despite that South Africa has lower number of

Table I. Overall composite scores of all the countries

Country		Theme 1		Theme 2		Theme 3		Theme 4		Theme 5		GMC score	Overall rank
United Arab Emirates	ARE	5.0	16	4.7	20	1.3	20	0.7	21	3.7	10	15.4	19
Argentina	ARG	2.9	22	4.1	23	0.9	27	0.9	18	2.2	21	11.0	25
Australia	AUS	5.9	11	5.8	7	2.1	10	2.2	5	1.5	25	17.4	12
Brazil	BRA	2.9	23	3.5	27	1.3	21	0.8	19	1.5	26	9.9	26
Canada	CAN	6.3	5	5.1	17	2.3	5	1.5	12	2.6	18	18.0	11
China	CHN	3.3	20	4.2	22	1.2	22	1.1	17	4.5	5	14.3	21
Germany	DEU	6.3	7	5.7	8	2.5	4	2.1	6	3.3	14	19.9	6
Spain	ESP	5.4	13	5.3	16	1.9	14	1.5	13	2.7	17	16.7	15
European Union	EUU	5.5	12	5.6	9	1.6	16	1.6	11	1.6	24	15.8	18
France	FRA	6.3	6	5.3	15	2.7	2	1.7	9	2.5	19	18.5	10
UK	GBR	6.7	2	5.8	6	2.7	1	1.6	10	1.8	23	18.6	9
Hong Kong Special Administrative Region, China	HKG	7.2	1	6.6	2	1.8	15	1.3	15	3.8	9	20.8	3
Indonesia	IDN	1.7	26	4.9	19	0.9	25	0.5	25	4.4	6	12.3	23
India	IND	0.8	27	3.5	26	1.3	19	0.2	27	3.3	15	9.1	27
Israel	ISR	5.4	14	5.5	10	2.2	9	2.0	7	3.8	8	18.9	7
Italy	ITA	5.1	15	4.5	21	2.0	11	1.2	16	3.1	16	15.9	17

Country		**Theme 1**		**Theme 2**		**Theme 3**		**Theme 4**		**Theme 5**		**GMC score**	**Overall rank**
Japan	JPN	6.0	9	5.3	14	2.3	6	2.3	4	1.3	27	17.2	13
Korea, Rep.	KOR	6.7	4	6.1	5	2.2	8	4.7	1	4.2	7	23.9	1
Mexico	MEX	2.2	25	5.4	11	1.1	23	0.3	26	8.1	2	17.2	14
Malaysia	MYS	3.7	18	5.4	12	2.0	12	0.7	20	8.6	1	20.4	5
Netherlands	NLD	6.7	3	6.1	4	2.6	3	2.7	3	2.4	20	20.5	4
Russian Federation	RUS	4.5	17	3.9	24	1.0	24	0.5	24	3.6	11	13.5	22
Saudi Arabia	SAU	3.4	19	5.4	13	1.5	17	0.7	22	3.6	12	14.5	20
Singapore	SGP	5.9	10	6.7	1	1.9	13	2.8	2	5.1	4	22.5	2
Turkey	TUR	3.3	21	4.9	18	0.9	26	1.4	14	5.4	3	15.9	16
USA	USA	6.3	8	6.5	3	2.3	7	1.9	8	1.9	22	18.8	8
South Africa	ZAF	2.3	24	3.6	25	1.4	18	0.7	23	3.5	13	11.6	24

patents and production of such high-end technologies. Countries such as the USA and JPN will then be ranked lower than ZAF under this sub-index as they are net exporters of advanced manufacturing technologies, but earned more points under the IR sub-index because of good R&D activities within these countries. Without such counterbalancing measurement from the level of import of technology adopted in this study, the entire picture would have been more skewed as a country can engage in manufacturing using a technology imported, even when not necessarily developed in-house.

4.1 Interpretation of dendrogram

The Ward clustering method with Euclidean distance implemented in XLSTAT was used to categorize the countries into clusters of competitiveness. The number of clusters was not specified, the optimum number of clusters being that resulting in minimum total error variance, and this easily jumps at the eye. This is an advantage of the Ward clustering algorithm because the vertical clusters can then be sliced at the appropriate point to create the desired number of clusters. From Figure 1, three clusters would seem ideal. These clusters are named as: leaders, followers and laggards. South Africa is classified as a laggard- based on this analysis. Table II shows how the countries that constitute each of these groups with ZAF being in the laggards group.

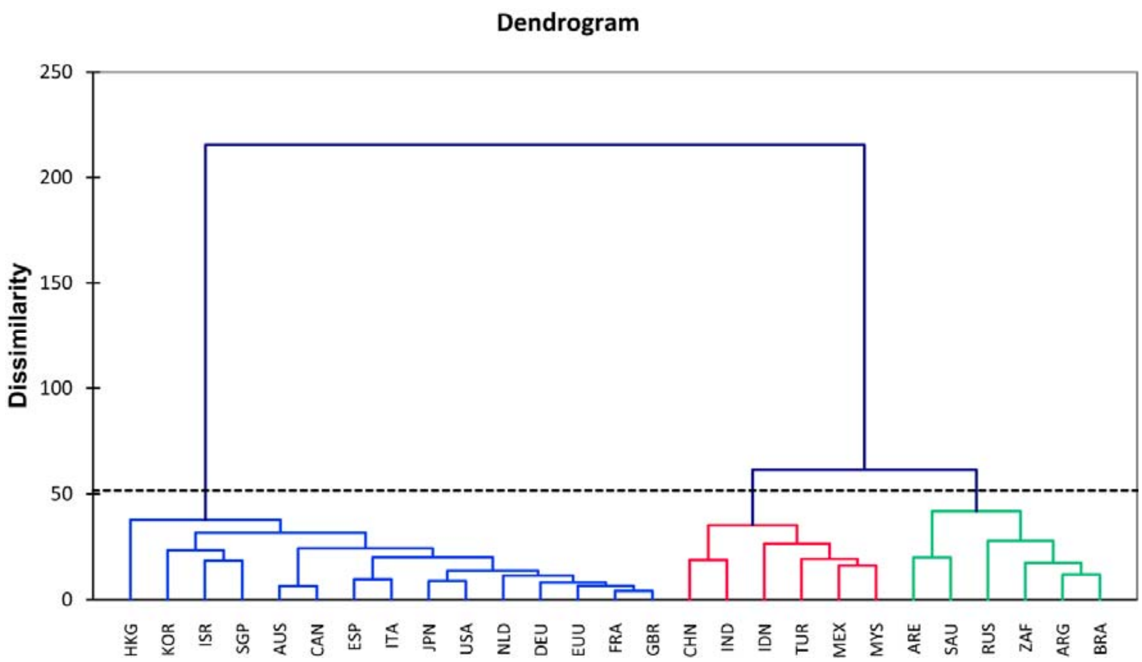

Figure 1. Dendrogram showing clustering of countries

Table II. Clustering classification into laggards, challengers and leaders

Class	Cluster 1 laggards	Cluster 2 challengers	Cluster 3 leaders
Objects	6	6	15
Sum of weights	6	6	15
Within-class variance	1.916	2.274	1.629
Minimum distance to centroid	0.953	1.064	0.758
Average distance to centroid	1.245	1.366	1.185
Maximum distance to centroid	1.636	1.560	1.921
	ARE, ARG,BRA,RUS, SAU, ZAF	CHN, IDN, IND,MEX, MYS, TUR	AUS, CAN, DEY, ESP,EUU, FRA, GBR, HKG, ISR, ITA,JPN, KOR, NLD, SGP, USA

4.2 Interpretation of the dendrogram

ZAF has United Arab Emirates, Argentina, Brazil, Russia and Saudi Arabia as its peers in the laggards' group. It can be seen that EM is one of the sub-indexes that weighs ZAF down significantly; ranked 25 out of the 27 countries with only India and Brazil achieving a lower score. The analysis of the variables making up this sub-index indicates that South Africa has very high compensation of employees relative to other expenses, a higher percentage of bank non-performing loans, very long lead times to import, very high cost for documentary compliance, high cost of import and a very long time to start up a business compared to other countries in the study.

4.3 Sub-index analysis for South Africa

Dendrograms were also drawn along the five sub-indexes (not included in this paper). These indicated that South Africa can be considered a laggard at four sub-index levels relative to the other countries. It is only in the MA sub-index that ZAF is in the follower group. This explain why ZAF is overall a laggard because while other countries are laggards in some instances (e.g. USA is a laggard in Theme 5), they are generally leaders or at least followers in many other sub-indexes.

4.4 Gaps analysis

To determine the gap between South Africa and a cluster group, the average score for the group was calculated and compared to the ZAF score for each variable to determine the gaps between South Africa and the group. The average and minimum score for the follower and leader groups was calculated to determine the gaps that South Africa will have to close to move into each group. To determine the actual gap to close for a particular indicator, there is a need to first identify whether the target is to move to a challenger or a leader group for such indicator. Also, ZAF has already surpassed the minimum gap value to move to the follower group on some indicators. This presents opportunities for ZAF to decide whether to stay at the same level or decrease investments in such indicators and divert funds into some more pressing areas when there are not enough funds to improve on all indicators. All this is discussed later.

4.5 Prioritizing gaps for closure

Gaps between ZAF and the challenger and leader groups' minimum and average values were calculated for 42 variables and shown in Table III. To determine the actual gap to close, it was decided that ZAF should consider a continuous improvement process, having incremental shift by moving first toward the challenger group, and afterwards seeking to be among the leaders (Figure 2).

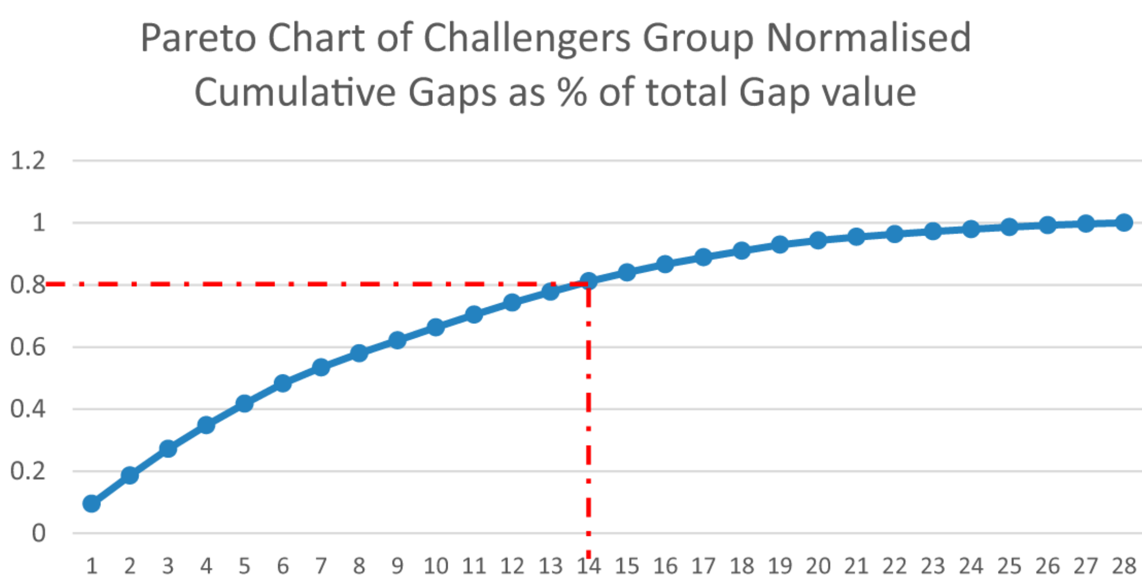

***Figure 2**. Pareto chart of normalized cumulative positive challenger average gap values*

To be in the challenger group, if all the indicators can be at least at the challenger group level, then the overall placement would be at the challenger level. This helps to narrow which gap to close and becomes the strategic target for ZAF. The main effort left is to determine how to prioritize each of the indicator gaps to progressively close to move to the challenger group.

4.6 Actions to close the gap

Having identified the 14 key indicator gaps to close, value (benefit per cost outlay) analysis was done to prioritize the sequence of closure of the gaps. Value analysis helps with cost reduction and control. It is a systematic application of techniques to provide the desired function at the lowest total cost. In this case, the desired function is to close the gap between the laggards' clustered group and challengers' clustered group. The first step was to identify projects to close each gap and do a proper costing of the project. To estimate the

Table III. Gaps between South Africa and the challengers and leaders clustering group

	Parameter	ZAF	Challengers				Leaders			
			Average	Min	GAP average	GAP minimum	Average leaders	Minimum leaders	Gap average	Gap minimum
BI1	Quality of road. Length of paved and unpaved road (%)	20.00	57.9	34.0	37.9	14.0	80.9	39.9	60.93	19.90
BI2	Healthcare expenditure as % of GDP	8.80	4.8	2.8	−4.0	−6.0	9.8	4.9	0.96	−3.87
BI3	Improved sanitation facilities (% of population with access)	66	75.5	39.6	9.1	−26.8	98.8	90.8	32.44	24.38
BI4	Fixed telephone subscriptions (per 100 people)	7	10.8	1.9	4.2	−4.7	45.1	33.1	38.47	26.49
BI5	Electric power consumption (kWh per capita)	4 229	2514.3	805.6	−1714.6	−3423.3	8034.9	5002.4	3806.06	773.55
BI6	Secure internet servers (per 1 million people)	125	44.3	7.8	−80.2	−116.7	1219.0	293.2	1094.46	168.67
BI7	Mobile Cellular Subscriptions per 100 people	142	109.9	87.0	−32.5	−55.4	128.5	84.1	−13.90	−58.32
BI8	Fixed broadband subscriptions (per 100 people)	3	10.2	1.4	7.4	−1.4	34.1	25.4	31.24	22.58
BI9	Foreign direct investment, net inflows (% of GDP)	0.76	2.1	0.4	1.3	−0.4	6.9	0.7	6.17	−0.06
BI10	Automated teller machines (per 100,000 adults)	69.29	56.0	21.2	−13.2	−48.1	106.1	47.6	36.84	−21.74
BI11	Domestic credit to private sector by banks (% of GDP)	66.94	76.1	26.7	9.1	−40.2	110.1	53.2	43.17	−13.79
EM1	GDP per person employed (constant 2011 PPP $)	43 831.00	37229.8	17149.0	−6601.2	−26682.0	92965.1	70706.0	49134.10	26875.00
EM2	Bank capital to assets ratio (%)	8.20	10.3	7.2	2.1	−1.0	7.3	5.2	−0.88	−3.04
EM3	Compensation of employees (% of expense)	14.16	20.8	15.6	6.6	1.4	13.1	5.9	−1.09	−8.25

	Parameter	ZAF	Challengers Average	Challengers Min	GAP average	GAP minimum	Leaders Average leaders	Leaders Minimum leaders	Gap average	Gap minimum
EM4	Bank non-performing loans to total gross loans (%)	2.86	4.3	1.6	1.4	−1.2	3.8	0.6	0.91	−2.26
EM5	Time to import (days)	21.00	17.4	8.0	−3.6	−13.0	8.5	4.0	−12.46	−17.00
EM6	Cost to import, documentary compliance (US$)	213.00	128.7	60.0	−84.3	−153.0	59.0	0.0	−154.00	−213.00
EM7	Cost to import (US$ per container)	2 080.00	1098.6	560.0	−981.4	−1520.0	1041.3	440.0	−1038.68	−1640.00
EM8	Time required to start a business (days)	45.00	18.2	6.5	−26.8	−38.5	6.2	1.5	−38.78	−43.50
ET1	Government expenditure per student, secondary (% of GDP per capita)	20.89	16.6	10.3	−4.3	−10.6	21.4	16.1	0.53	−4.78
ET2	Government expenditure per student, tertiary (% of GDP per capita)	37.75	35.5	19.5	−2.2	−18.3	26.8	14.6	−10.90	−23.12
ET3	Number of universities by country in Top Global 1,000 list (universities/per 10 million people)	1.07	1.3	0.1	0.2	−1.0	7.1	0.0	6.06	−1.07
ET4	Researchers in R&D per million people of the country	437.06	1389.1	215.9	952.1	−221.2	4635.9	2018.1	4198.85	1581.03
IR1	R&D expenditure as % of GDP	1.96	1.4	0.6	−0.5	−1.4	2.3	0.8	0.35	−1.20
IR2	Scientific and technical journal articles published/per 1 million people	173.12	237.7	11.2	64.6	−161.9	1325.0	814.0	1151.90	640.90
IR3	Number of patent applications residents of a country per 1 million people	15.90	139.1	4.1	123.2	−11.8	574.0	32.5	558.12	16.63

	Parameter	ZAF	Challengers				Leaders			
			Average	Min	GAP average	GAP minimum	Average leaders	Minimum leaders	Gap average	Gap minimum
IR4	Industrial design applications, resident, by count per 1 million people	12.93	156.0	5.2	143.0	−7.8	252.4	0.0	239.44	−12.92
IR5	Trademark applications, direct resident of the country per 1 million people	385.32	460.0	0.0	74.6	−385.3	1137.6	293.3	752.25	−92.01
IR6	Charges for the use of intellectual property, payments as % of GDP	0.68	0.2	0.0	−0.5	−0.7	1.3	0.2	0.58	−0.44
MA1	GDP growth % of a country average from 1990 to 2016	2.46	5.8	2.8	3.3	0.4	2.7	0.7	0.25	−1.73
MA2	Manufacturing value added annual % of GDP average from 1990 to 2016	17.85	23.3	18.0	5.4	0.1	16.4	2.4	−1.42	−15.41
MA3	High technology exports as % of GDP	5.88097	16.6	2.2	10.7	−3.7	19.4	7.1	13.53	1.27
MA4	Import of plastic injection molding machines for rubber or plastics	0.032	0.0431	0.0097	0.0114	−0.0220	0.0135	0.0010	−0.0182	−0.0307
MA5	Import of vacuum injection molding machines for rubber or plastics	0.004	0.0070	0.0017	0.0029	−0.0024	0.0012	0.0006	−0.0029	−0.0035
MA6	Import of blow molding machines for plastics and rubber	0.014	0.0089	0.0023	−0.0049	−0.0115	0.0024	0.0004	−0.0114	−0.0135
MA7	Machinery for working rubber or plastics or for the manufacture of products from these materials	0.023	0.0413	0.0115	0.0178	−0.0120	0.0091	0.0026	−0.0144	−0.0209
MA8	CNC lathes for metal: import of lathes including horizontal lathes and turning centers	0.008	0.0149	0.0035	0.0067	−0.0047	0.0080	0.0018	−0.0002	−0.0064

	Parameter	ZAF	Challengers				Leaders			
			Average	**Min**	**GAP average**	**GAP minimum**	**Average leaders**	**Minimum leaders**	**Gap average**	**Gap minimum**
MA9	CNC boring for metal: machine tools for boring	0.000	0.0016	0.0004	0.0014	0.0002	0.0036	0.0000	0.0034	−0.0002
MA10	CNC milling for metal: machine tools for milling by removing metal, knee-type and not-knee type	0.001	0.0039	0.0011	0.0029	0.0001	0.0024	0.0004	0.0015	−0.0006
MA11	CNC drilling for metal: machine-tools for drilling by removing metal, other than lathes	0.00009	0.0017	0.0005	0.0016	0.0004	0.0007	0.0000	0.0006	−0.0001
MA12	Military expenditure (% of GDP)	1.071	1.5	0.6	0.4245	−0.4953	2.1278	0.9345	1.0573	−0.1360
MA13	Importation of industrial robotics	0.015	0.0108	0.0038	−0.0045	−0.0115	0.0060	0.0009	−0.0092	−0.0144

Note: Table indicating the gap average and minimum value of Challengers group and Leaders group

Table IV. Actions to close the top 14 indicator gaps

	Parameter	ZAF	GAP ave	Cost to close gap	Cost/normalized gap
BI1	Quality of road. Length of paved and unpaved road (%)	20.00	37.87	According to SANRAL (2018) the total proclaimed roads in the country is approximately 535,000 km in length, 366,872 km of non-urban roads and 168,000 km of urban roads. The SA Development Bank of South Africa (2018) indicates that a light trafficked road cost $162,000/per km to build and heavy trafficked roads > $425,400/km to construct. To increase the quality of the SA paved roads by 38% means an increase of 203,300 km of road length. This represents a cost of USD22.6bn for non-urban and USD27.2bn for urban roads	Normalized GAP is 0.4. USD124.5bn per unit GAP (11)
BI8	Fixed broadband subscriptions (per 100 people)	3	7.36	To close this gap implies that the broadband subscriptions per 100 people be increased by 7.36. According to My broadband (2018) it cost around R5,000 per broadband license. To close this gap requires that an additional (55.91/100) 7.36 broadband subscriptions be rolled out in SA which is 559,000 subscriptions	Normalized GAP is 0.18. USD1.04bn/unit GAP (7)
EM2	Bank capital to assets ratio (%)	8.20	2.13	According to Businesstech (2018), the top six banks in ZAF have a total of USD429bn of assets in 2016. Increasing the bank capital by 2.13% equates in increase of capital USD9.13bn. The lending interest rate is 10.5% which implies that the cost to keep this additional capital will be USD958m per annum	Normalized GAP is 0.22. USD4.35bn/unit GAP (9)
EM6	Cost to import, documentary compliance (US$)	213.00	−84.32	Reduce documentary compliance for imports by $84.32 per container. According to Container Shipping Trade News and Analysis (2018), SA trade in TEU containers is 2 million per annum of which 55% is imports. Therefore 1.1 million TEU's is imported yearly. This implies a reduction in cost of USD84.32m	Normalized GAP is 0.14. USD602m/unit GAP (6)
EM7	Cost to import (US$ per container)	2 080.00	−981.43	Reduce cost to import a container by USD981.43 per container. Cost reduction is USD981.4m	Normalized GAP is 0.46. USD2.13bn/unit GAP (8)
EM8	Time required to start a business (days)	45.00	−26.80	Reduce time to start a business by 26.8 days	Normalized GAP is 0.34 (unable to cost)

	Parameter	ZAF	GAP ave	Cost to close gap	Cost/normalized gap
MA1	GDP growth % of a country average from 1990 to 2016	2.46	3.34	This variable cost is difficult to estimate as GDP is made up of different elements	Normalized GAP is 0.37 (unable to cost)
MA2	Manufacturing value added annual % of GDP average from 1990 to 2016	17.85	5.45	To increase manufacturing value added by 5.45% for South Africa equates to USD16.1bn	Normalized GAP is 0.18. USD89.4bn/unit GAP (10)
MA3	High-technology exports as % of GDP	5.88097	10.71	To increase the high-technology exports by 10.71% equates to USD31.6bn	Normalized GAP is 0.22. USD143.6bn/unit GAP (12)
MA5	Import of vacuum injection molding machines for rubber or plastics	0.004	0.0029	USD8,549,200 increase in import of vacuum injection machines	Normalized Gap is 0.24. USD35.6m/unit GAP (4)
MA7	Machinery for working rubber or plastics or for the manufacture of products from these materials-3D Printers	0.023	0.0178	USD8,555,000	Normalized GAP is 0.27. USD31.6m/unit Gap (3)
MA8	CNC lathes for metal: import of lathes including horizontal lathes and turning centers	0.008	0.0067	USD19,765,000	Normalized GAP is 0.21. USD94.1m/unit GAP (5)
MA10	CNC milling for metal: machine tools for milling by removing	0.001	0.0029	USD8,549,200	Normalized GAP is 0.50.

	Parameter	ZAF	GAP ave	Cost to close gap	Cost/normalized gap
	metal, knee-type and not-knee type – numerically controlled				USD17m/unit GAP (2)
MA11	CNC drilling for metal: machine-tools for drilling by removing metal, other than lathes – numerically controlled	0.00009	0.0016	USD4,720,000 increase in the import on CNC machines into SA based on 2016 trade statistics	Normalized GAP is 0.48. USD9.83m/unit GAP (1)

Note: Table indicating the cost per normalized gap for ZAF for parameters identified cost of projects, information from ZAF Treasury Department (2018), South African National Roads Agency Soc Ltd. (2018), My Broadband (2018), Development Bank of South Africa (2018), Businesstech (2018), Container shipping Trade News and Analysis (2018) together with Worldbank (2018) and United Nations Comtrade website (2018) were used to calculate the cost in USD per unit normalized gaps. This is summarized in Table IV. The goal is to prioritize the low hanging fruits that could benefit the economy and those that would have the highest value return if even investments are high. By dividing the cost for each of the 14 action items from Table IV with the normalized gap value for each indicator variable provides the cost/unit gap value. This is then ranked from action items with the smallest cost/unit gap to the action item with the biggest cost/unit gap to identify the action items to be completed first and those to be completed last for South Africa. Our objective is to minimize the total USD per gap or maximize the total gap closed per unit USD. The chronology of action items is then presented. This is also indicated in parentheses in Table IV. Listed in order, ZAF should complete the following action:

- Increase import of CNC drilling machine tools by USD$4.7m per annum.
- Increase import of CNC milling machine tools by USD$8.55m per annum.
- Increase import of machinery for working rubber and plastics (three-dimensional [3D] printers) by USD$8.55m per annum.
- Increase import of vacuum injection molding machines by USD$8.5m per annum.
- Increase import of CNC lathes for metal by USD$19.7m per annum.
- Reduce cost for documentary compliance during import by USD84.32m per annum.
- Increase broadband subscriptions by investing USD$186m to increase total subscription base by 559,000 subscriptions.
- Reduce cost for importation of containers by USD981.4m per annum.
- Increase the bank's capital to asset ratio by USD$9.13bn at a cost of USD$958m.
- Increase the value that manufacturing adds to the GDP as a percentage by USD$16.1bn per annum.
- Invest into increasing the paved roads of South Africa by investing USD$22.6bn for non-urban and USD$27.2bn for urban roads.
- Increase the high-technology exports of South Africa by 10.71 per cent which equates to USD$31.6bn per annum.

4.7 Evaluation of cluster characteristics and validity

One advantage of using the dendrogram with the Ward clustering is that having a good number of clusters easily jumps at the eye, and this can be seen from the dendrogram (Figure 1). In addition to this, cluster validity was further analyzed through the cophenetic correlation. The cophenetic correlation coefficient is a measure of how accurately the dendrogram preserves the pairwise distances between the original unmodeled data points. It is an internal cluster validation index. Connectivity-based clustering is based on the core idea of indicator variables being more related to nearby variables than to objects further away.

The cophenetic correlation coefficient, C_{CC}, is calculated as:

$$C_{CC} = \frac{\sum_{i<j}\left(B_{ij}-b\right)\left(Z_{ij}-z\right)}{\sqrt{\sum_{i<j}\left(B_{ij}-b\right)^2\sum_{i<j}\left(Z_{ij}-z\right)^2}}$$

where *B* is the unmodeled data set, *Z* is the cophenetic distance matrix from the Wards clustering, B_{ij} is the distance between objects *i* and *j* in *B*, Z_{ij} is the cophenetic distance between objects *i* and *j* from the hierarchical clustering, and *b* and *z* are the average values of *B* and *Z*.

The cophenetic correlation for the complete data set is 0.75, which implies a good fit of the Ward clustering technique using the original data set (Cerqueira-Silva *et al.*, 2009; Sokal and Rohlf, 1962). Clustering of the subthemes produces lower cophenetic scores. This implies that none of the individual subthemes seems to have been better than the aggregate index on its own. Lower cophenetic scores as indicated in Table V show that the use of the aggregate index seems to have produced a better fit than the individual subthemes, and this may be further investigated in the future.

Table V. Cophenetic scores of the subthemes

Subtheme	Cophenetic correlation
BI	0.477
EM	0.652
ET	0.667
IR	0.609
MA	0.617

Measures to increase validity of the clustering may include using bigger data set and probably trying out other clustering procedures such as the centroid vertical clustering and the K-means clustering. The use of K-means, however, imposes further restriction that the numbers of clusters are specified ab-initio.

5. Implications for research and practice

This study has significant impact on the use of results from analysis of competitiveness in that following this methodology, government and practitioners are able to not only measure their performance gaps, but they are also able to develop prioritized actionable plans to close the gap in the most efficient manner such that even when funds are limited, as is usually the case, they are able to decide what order of projects to implement to transition across levels. Also, because clustering has been integrated into scoring of countries, performance of target countries are placed in baskets of similar countries and compared to baskets of better performers, else, comparing a country to 50 countries or more makes it difficult to clearly define improvement gaps and target. Also, while most research works have sought to rank countries, inclusion of clustering logic makes ranking to provide more meaningful benchmark and illuminates areas for possible further research such as how different clustering techniques might behave influenced the clusters identified.

Cophenetic correlation coefficient is one of the good measures for checking the internal validity of the clustering technique. It indicated a good correlation coefficient for the complete data set. This also presents opportunities for further research in clustering nations for competitiveness grouping. It is possible that some other clustering techniques could produce better clusters, and this is an area that can still be further researched. In addition, it is possible that using different measurements of validity could have also produced some slightly different results. The impact of larger sample size on the effectiveness of clustering could also be investigated.

It might also be worth investigating how to define target improvement values. For instance, one can consider targeting the values of the least members of the better clusters as opposed to using the central values. It is possible to have closed the competitiveness gaps using these smaller target values, and this may yield more cost effective solutions. A combination of some central values and some minimum higher group values could also be considered. How to select these target values may also be worthy of investigation.

On a general note, the techniques used in this analysis can be extended in more than one ways for further research and it may be possible to identify some more cost efficient paths to achieve the desired translation in competitiveness of the country, in addition to studying other means of setting translational targets, and all these could deliver superior values for the usage of national assets.

6. Conclusions

This study examined the manufacturing competitiveness of a group of 27 countries using the MCI and Wards clustering algorithm. The conceptual diamond framework of Porter was also analyzed. Proxy variables of importation of leading technologies were incorporated into MCI resulting in 42 indicator variables considered necessary to rank the countries considered. The values of the 42 indicator variable for different countries were obtained from reliable data sources such as the Worldbank (2018) and United Nations Comtrade website (2018) and all data points were normalized to obtain a score between 0 and 1. The use of Ward clustering algorithm helps to reduce the categories for comparison so that manageable number of groups were extracted for benchmarking of countries.

In the case presented in this study, three distinct clusters were easily identified, and these were named leaders, challengers and laggards. The reference country (South Africa) was classified with the laggards. Group centroid values were used to create targets values and competitive gaps were determined based on national priority targets for shifts. Through the use of Pareto analysis and subsequent ranking, variables contributing 80 per cent of the total gap to close to transition to the target cluster were selected and the costs to close those gaps were cumulatively calculated. The cost to close each gap is then divided by the normalized gap magnitude for that variable to obtain the cost/unit gap closed and prioritize the projects in the relevant order of execution supposing funds constraint is an issue. We also believe that categorizing proxy variables according to Porter's diamond framework will not produce different results from the MCI model used as all variables are considered.

The study was able to produce an action plan for South Africa, to close the gaps and move from the laggards cluster to the challengers cluster in a systematic manner. It also shows that the method developed to measure the competitiveness of a country are useful and can be applied to any country to determine their manufacturing competitiveness.

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