Socio-Economic Planning Sciences 42 (2008) 221–246

SOCIO-ECONOMIC PLANNING SCIENCES

www.elsevier.com/locate/seps

# A new perspective on the competitiveness of nations

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Available online 13 March 2008

## Abstract

The capability of firms to survive and to have a competitive advantage in global markets depends on, amongst other things, the efficiency of public institutions, the excellence of educational, health and communications infrastructures, as well as on the political and economic stability of their home country. The measurement of competitiveness and strategy development is thus an important issue for policy-makers. Despite many attempts to provide objectivity in the development of measures of national competitiveness, there are inherently subjective judgments that involve, for example, how data sets are aggregated and importance weights are applied. Generally, either equal weighting is assumed in calculating a final index, or subjective weights are specified. The same problem also occurs in the subjective assignment of countries to different clusters. Developed as such, the value of these type indices may be questioned by users. The aim of this paper is to explore methodological transparency as a viable solution to problems created by existing aggregated indices. For this purpose, a methodology composed of three steps is proposed. To start, a hierarchical clustering analysis is used to assign countries to appropriate clusters. In current methods, country clustering is generally based on GDP. However, we suggest that GDP alone is insufficient for purposes of country clustering. In the proposed methodology, 178 criteria are used for this purpose. Next, relationships between the criteria and classification of the countries are determined using artificial neural networks (ANNs). ANN provides an objective method for determining the attribute/criteria weights, which are, for the most part, subjectively specified in existing methods. Finally, in our third step, the countries of interest are ranked based on weights generated in the previous step. Beyond the ranking of countries, the proposed methodology can also be used to identify those attributes that a given country should focus on in order to improve its position relative to other countries, i.e., to transition from its current cluster to the next higher one.


*Keywords:* Ranking; Competitiveness; Artificial neural network; Cluster analysis

## 1. Introduction

In today's globalized world, competitiveness has become a milestone of both advanced and developing countries. Because of pressures introduced by this globalization, it is important to have a framework for

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0038-0121/$ - see front matter 
doi:10.1016/j.seps.2007.11.001

analyzing a country's competitive position in the international market rather than simply focusing on measures of internal productivity. It is common knowledge that the marketplace is no longer restricted to a particular geographic location. A business can thus expect competition from neighboring entities, and/or from similar operations within its region. The marketplace is now global, and even the smallest of organizations competes on an international level. In order to provide firms the necessary opportunities to survive and realize global competitive advantage, it is essential to define the *relative competitive position of their home country.*

A nation's competitiveness can be viewed as its position in the international marketplace compared to other nations of similar economic development. The capability of firms to survive and to have a competitive advantage in global markets depends on, among other things, the efficiency of their nation's public institutions, excellence of the educational, health and communication infrastructures, as well as on the nation's political and economical stability. On the other hand, an outstanding macroeconomic environment alone cannot guarantee a high level of national competitive position unless firms create valuable goods and services with a commensurately high level of productivity at the microlevel. Therefore, the micro- and macroeconomic characteristics of an economy jointly determine its level of productivity and competitiveness.

The competitiveness of a nation is defined as the degree to which it can, under free and fair market conditions, produce goods and services that meet the standards of international markets while simultaneously expanding the real income of its citizens, thus improving their quality of life [1,2]. This includes the set of institutions, policies, and factors that determine the level of productivity of a country [2].

Although many view competitiveness as a synonym for productivity [3], these two related terms are, in fact, different. Productivity refers to the internal capability of an organization while competitiveness refers to the relative position of an organization vis-à-vis its competitors.

Most current composite indicators apply either predetermined fixed weights uniformly to all countries, or subjective weights to different clusters of countries. Such weights may cause biased measurement. Again, in most composite indicators, such as those developed by the World Economic Forum (WEF) [4], countries are clustered based on their stage of competitiveness. Unfortunately, this classification tends to be rather subjective, or is based solely on per capita income.

Subjectivity is also present when creating the threshold used to separate one stage from another. Some degree of objectivity is possible, however, if countries are clustered as a function of their similarities on selected criteria. By doing so, important factors underlying the competitiveness position of each stage, and of particular countries at various stages, can be revealed. It will thus be easier to understand the internal dynamics of each stage, and to provide useful and objective guidelines to countries as they attempt to improve their positions with respect to those located at higher stages.

In Section 2, different indices developed and used by the WEF to analyze the competitiveness of nations are summarized, and the subjectivity within their weighting and clustering method, is analyzed. Section 3 introduces the proposed methodology to cluster countries into stages, and to generate criteria weights that are critical at each stage of the procedure.

In Section 4, a new composite index is proposed using the calculated weights. The results are then compared to those of the Global Competitiveness Index (GloCI) of the WEF to determine whether the weights adopted by the WEF incorrectly penalize some countries and/or reward others. This section also provides some useful guidelines to selected countries as they seek to improve their relative competitiveness. The paper closes with conclusions and suggestions for further improvements of the proposed methodology.

## 2. Assessing countries' competitiveness indices: current state of the art

Although much research has been done on competitiveness measurements, it generally focuses on the firm [3,5–9] or industry level [1,10]. Very few such studies have considered the issue of multi-country competitiveness [2,4,7,9,11–16].

Each year, some organizations, such as the WEF and the Institute for Management Development (IMD) [17], publish rankings of national competitiveness among countries. These rankings serve as benchmarks for national policy-makers and interested parties in judging the relative success of their countries in achieving competitiveness as represented by well-known and accepted indices.

Since 1989, IMD, initially with WEF, has produced comparisons of nations' competitiveness through annual publication of the World Competitiveness Yearbook (WCY). The WCY analyzes and ranks the ability of nations to provide a sustainable environment for the competitiveness of enterprises. It develops a competitiveness score of selected countries, members of the Organisation for Economic Cooperation and Development (OECD), as well as newly industrialized countries based on political and socio-economic indicators. Until 2001, it provided such scores for each country by synthesizing all collected information into eight major factors: domestic economy, internationalization, government, finance, infrastructure, management, science and technology, and people.

Since 2001, IMD has employed four factors: economic performance (77 criteria), government efficiency (72 criteria), business efficiency (68 criteria), and infrastructure (95 criteria). Each of these factors has been broken down into five sub-factors, thus highlighting the various aspects of competitiveness. The resulting 20 sub-factors comprise more than 300 criteria, although the sub-factors do not necessarily have the same number of criteria; furthermore, inter-correlation among the criteria is generally difficult to avoid [18]. Criteria can be hard data, which analyze competitiveness as it can be *measured* (e.g., GDP), or soft data, which do so as it can be *perceived* (e.g., availability of competent managers). Countries are given scores on each of the four factors, based on both quantitative and survey data; a weighted average is then taken to produce the Overall Competitiveness Index. In the computation of this index, hard data are given a weight of two-thirds in the overall ranking whereas the survey data account for the remaining one-third. In 2006, the WCY evaluated 61 countries and regional economies, all "key players" in world markets [19].

Oral and Chabchoub [9,11], using mathematical programming by the sub-factor level, showed that the methodology used in the WCY is hard to understand, and thus suggested the need for alternative statistical or mathematical programming approaches.

For the last quarter-century, the WEF has led in evaluation of the competitiveness of nations through its publication, *The Global Competitiveness Report* [4]. The WEF uses three competitiveness indices to analyze national competitiveness from both macro- and microeconomic perspectives. The Growth Competitiveness Index (GCI), developed by McArthur and Sachs [20], and Blanke and Lopez-Claros [10], makes an evaluation based on critical, and mostly macroeconomic environmental, factors that influence sustained economic growth over the medium-to-long term. Porter's Business Competitiveness Index (BCI) [14], however, investigates those company-specific factors that lead to improved efficiency and productivity indicators at the microlevel, and is complementary to the GCI. Recently, a GloCI [2], which is a synthesis of the GCI and BCI, has also been proposed. This new index is designed to unify the two earlier measures, and, eventually, to replace them in *The Global Competitiveness Report.*

## 2.1. Growth Competitiveness Index

The GCI is composed of three-factor groups, all accepted as critical to economic growth [4]. The detailed configuration of the GCI is given in Fig. 1.

The GCI uses a combination of hard data and data from the WEF's Executive Opinion Survey [4], with responses ranging from 1 to 7. Standardization is achieved by converting the hard data to a scale of 1–7.

In general, the importance of technology differs between countries, depending on their stage of development. Thus, in estimating the GCI, countries are divided into two groups: the "core" economies, where technological innovation is critical for growth, and the "non-core" economies, which are still growing by adopting technology developed abroad. The separation is based on the threshold of 15 patents per million people [4].

For the core innovators (with more than 15 patents), the GCI is calculated as

$$\text{Core GCI} = \tfrac{1}{2}\,\text{technology index} + \tfrac{1}{4}\,\text{public institution index} + \tfrac{1}{4}\,\text{macroeconomic environment index}$$

For the non-core economies, however, the GCI is calculated as

$$\text{Non-core GCI} = \tfrac{1}{3}\,\text{technology index} + \tfrac{1}{3}\,\text{public institution index} + \tfrac{1}{3}\,\text{macroeconomic environment index}$$

The GCI seeks to rank the countries, and also track changes in those rankings over time.

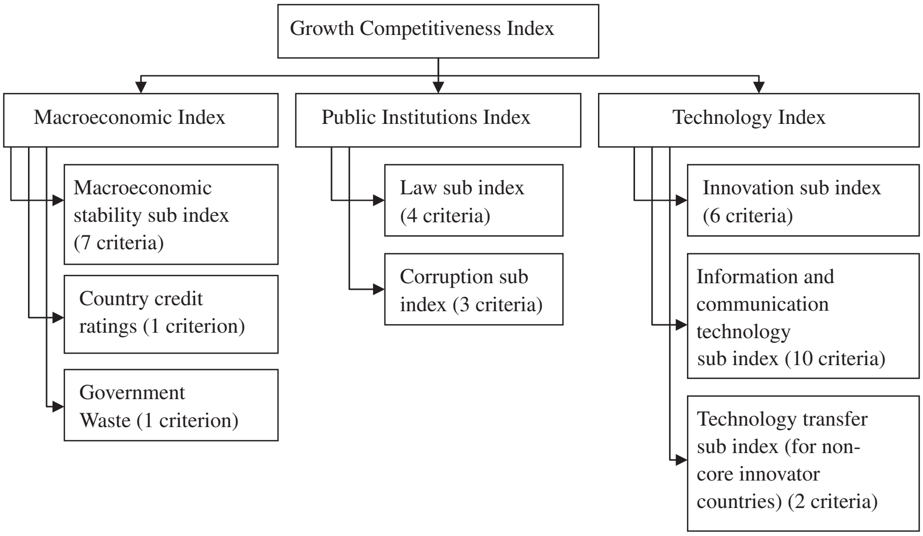


Fig. 1. Configuration of Growth Competitiveness Index [4].

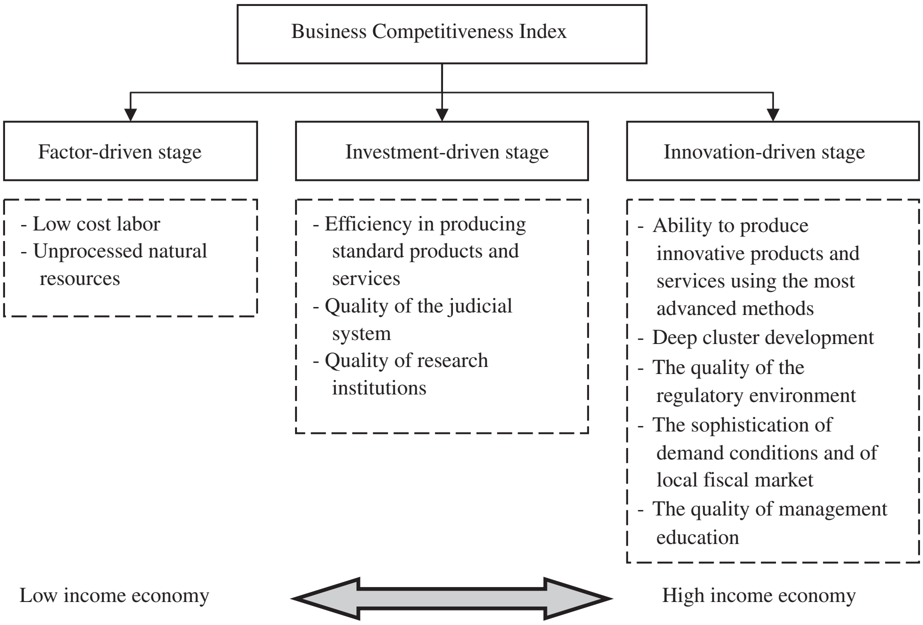


Fig. 2. Configuration of Business Competitiveness Index [4].

### 2.2. Business Competitiveness Index

The BCI explores the underpinnings of a nation's prosperity, measured by its GDP per capita. The focus is on whether current prosperity is sustainable. The BCI accounts for 81% of variation across countries in GDP per capita. It accepts that true competitiveness is measured by productivity. A nation's standard of living is determined by the productivity of its economy, which is measured by the value of goods and services produced per unit of the nation's human, capital, and natural resources. Fig. 2 shows the configuration of the BCI.

Although stable political, legal and social institutions and sound fiscal and monetary policies create the potential to create wealth, they do not, in themselves, create wealth. Rather, wealth is created at the microeconomic level. Therefore, unless microeconomic capabilities improve, macroeconomic, political, legal and social reforms will generally not be sufficient [21].

As nations develop, they progress in terms of their competitive advantages and modes of competing. At the *factor-driven* stage, basic qualities such as low-cost labor and unprocessed natural resources are the dominant sources of competitive advantage. At this stage, companies compete in terms of price and have limited roles in the value chain.

For low-income countries at the factor-driven stage of development, the ability to move beyond competing vis-à-vis cheap labor and natural resources is the essential challenge. Those countries score low on most measures but especially on infrastructure, educational quality, capital access, cluster development and measures related to technology and innovation. In these countries, priority should be given to upgrading the quality of infrastructure and opening competition.

In the *investment-driven* stage, efficiency in producing standard products and services becomes the dominant source of competitive advantage. Heavy investment in the efficiency structure, strong investment incentives and better access to capital allow major improvements in productivity. Improving production process sophistication is the most important corporate priority. Companies must also begin to increase the professionalism of management, create the capacity for technology absorption and overcome their dependence on exports to a few, advanced foreign markets. Middle-income countries generally score low, especially on infrastructure, and legal and regulatory efficiency and transparency. The objective is to move from the *factor-driven* to the *investment-driven* stage. Improving university–industry research collaboration, and the quality of both research institutions and the judicial system become important success factors.

Finally, at the *innovation-driven* stage, the ability to produce creative products and services using the most advanced methods becomes the dominant source of competitive advantage. To succeed in a high-income economy, it is necessary to move to the innovation-driven stage. Deep-cluster development, the quality of the regulatory environment, the sophistication of both demand conditions and of the local fiscal market, and the quality of management education are important distinguishing factors for most successful high-income economies.

### *2.3. Global Competitiveness Index*

As noted earlier, the WEF recently introduced the GloCI to rank countries. While the GCI refers to macroeconomic determinants of productivity, the BCI captures its microeconomic components. Additionally, while the GCI is supposed to capture the "dynamic" determinants of productivity, the BCI captures the "static" determinants. In reality, however, the macro- and microeconomic determinants of competitiveness cannot truly be separated. The ability of firms to succeed depends on, among other things, the efficiency of public institutions, the quality of the educational system, and the overall macroeconomic stability of the country in which they operate. Productivity thus has both static and dynamic implications for a country's standard of living. Only by reinforcing each other can the micro- and macroeconomic characteristics of an economy jointly determine its level of productivity and competitiveness. Recalling from an earlier discussion, that is why, in the 2004 WEF report, the GloCI was developed with the goal of unifying GCI and BCI.

This new index is based on three principles: (1) the determinants of competitiveness are complex, and consist of twelve pillars; (2) economic development is a dynamic process of successive improvement, i.e., it evolves in stages; and (3) as economies develop, they move from one stage to the next in a smooth fashion.

The twelve pillars of economic competitiveness in Principle 1 are described in Table 1. They are, in fact, related to each other and tend to be mutually reinforcing. For example, innovation (12th pillar) cannot be performed in a country lacking human capital (the fifth pillar), and will never take place in economies with inefficient markets (sixth, seventh, and eighth pillars), without infrastructures (second pillar), or in nations at war (fourth pillar).

On the other hand, according to the second principle, countries belong to one of three stages (Table 1). Each of the twelve pillars has different weights for each stage of development. At the most basic stage, called the *factor-driven* stage, firms compete in terms of price and take advantage of cheap labor and/or unprocessed natural resources. At the second stage, called *efficiency-driven*, efficient production becomes the main source of competitiveness. Finally, at the *innovation-driven* stage, successful economies can no longer compete in terms

Table 1
Twelve pillars of economic competitiveness [4]

| Number | Pillar | Main group | Weights of the three main groups of pillars at each stage of development | | |
|---|---|---|---|---|---|
| | | | Factor-driven stage (%) | Efficiency-driven stage (%) | Innovation-driven stage (%) |
| 1<br>2<br>3<br>4<br>5a | Institutions<br>Physical infrastructure<br>Macro-stability<br>Security<br>Basic human capital | Basic requirements | 50 | 40 | 30 |
| 5b<br>6<br>7<br>8<br>9 | Advanced human capital<br>Goods market efficiency<br>Labor market efficiency<br>Financial market efficiency<br>Technological readiness | Efficiency enhancers | 40 | 50 | 40 |
| 10<br>11<br>12 | Openness and market size<br>Business sophistication<br>Innovation | Innovation and sophistication factor | 10 | 10 | 30 |

of price, or even quality, and must therefore produce innovative products and practices using the most advanced methods of production and organization.

In computing the GloCI, the weighted averages of three groups of criteria—*basic requirements, efficiency enhancers,* and *innovation and sophistication factors*—are calculated, with each group being weighted differently depending on the stage to which the country belongs (see Table 1).

In the allocation of countries to stages, the following criteria are taken into account:

(1) If the country's GDP per capita is below US$2000, or the fraction of its exports in the form of primary goods is above 70%, the country belongs to the *factor-driven* stage.
(2) If a country has a per capita income between US$3000 and $9000 and does not export more than 70% in primary goods, it belongs to the *efficiency-driven* stage.
(3) If a country has more than US$17,000 per capita income and less than 70% of its exports are in primary goods, it belongs to the *innovation-driven* stage.
(4) Countries with income per capita between US$2000 and 3000 are said to be in transition from Stage 1 to Stage 2.
(5) Countries with income per capita between US$9000 and 17,000 are said to be in transition between Stages 2 and 3.

Similar to the GCI and BCI, both hard data and survey data collected by the WEF were used to calculate the GloCI for 104 countries. In GloCI, the United States ranked as the most competitive country, Angola the least, followed by Chad, Ethiopia, Zimbabwe, and Mozambique [4].

As can be seen with all the indices discussed above, the weights given to the various criteria are different for countries at different stages of development where specification of these weights is generally subjective in nature. For example there is no rationale given for assigning a 50% weight to "basic requirements" for countries in the *factor-driven* stage while these weights are 40% and 30%, respectively, for countries in the *efficiency-driven* and *innovation-driven* stages.

Similarly, assignment of the countries to different clusters at different stages of development is seen to be either arbitrary, or based on their level of per capita income alone. Moreover, the threshold values used to separate stages are generally subjective in nature.

## 3. The proposed methodology

The aim of this research is, first, to provide an *objective clustering of countries* according to their values/scores on selected criteria, and to then propose an *objective weighting procedure to calculate an aggregated index.* For these purposes, a three-step methodology is proposed, as shown in Fig. 3.

It is the case that current clustering methodologies are based solely on country GDP levels. However, in today's globalizing, complex world, GDP is insufficient, by itself, to cluster nations. The proposed methodology thus considers 178 criteria in the clustering process (Table 2). In particular, a hierarchical cluster analysis is used to determine the "best" number of clusters; this number is then used as a parameter to determine the appropriate clusters of countries using self-organizing maps (SOMs) [22].

Next, relationships between the criteria and the classification of countries are determined using artificial neural networks (ANNs) in an objective manner. Importantly, existing methodologies generally assess criteria weights/importances subjectively.

Finally, in the third step of our procedure, countries are rank-ordered based on the ANN-generated weights.

The proposed methodology can also be used to identify those attributes a country should focus on in seeking to improve its position relative to other countries, i.e., to transition from its current cluster to the next higher one.

In this regard, as noted earlier, the indices used by the WEF consist of many criteria where each is assigned a weight based on the development stage of the country of interest. However, the logic underlying how these weights are created is not explicitly given. For example, the GloCI utilizes 177 criteria, consisting of basic requirements, efficiency enhancers, and innovation and sophistication factors. These groups of criteria are, however, assigned weights based on whether the country is at the factor-driven, efficiency-driven, or innovation-driven stage.

Although such differentiation may be important, there is, as noted above, very little additional detail given. Therefore, in the second step of our proposed methodology, an ANN is used to determine the relationships between the criteria and the country classifications, and to then specify the criteria weights for each cluster.

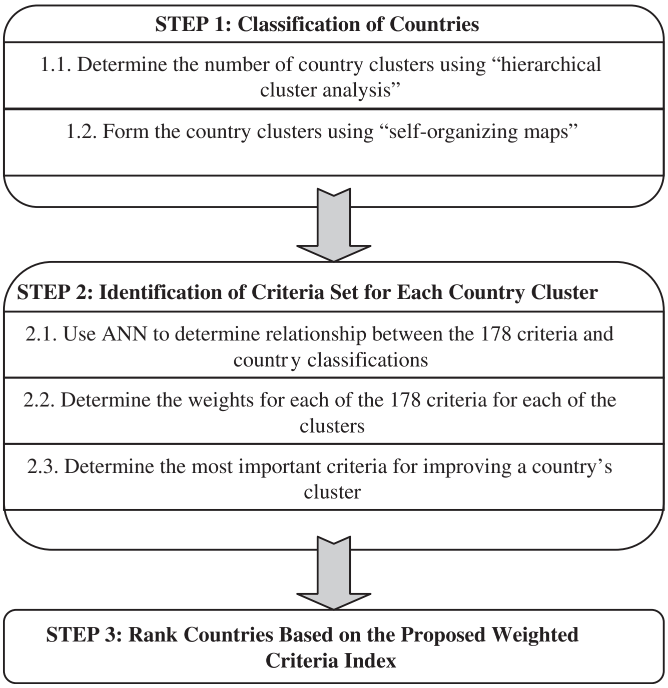


Fig. 3. Flowchart of the proposed methodology.

Table 2
WEF criteria [4]

| | |
|---|---|
| *Section I. Aggregate country performance indicators* | |
| 1.01 | Total GDP, 2003 |
| 1.02 | Total population, 2003 |
| 1.03 | GDP per capita (PPP), 2003 |
| *Section II. Macroeconomic environment* | |
| 2.01 | Recession expectations |
| 2.02 | Business costs of terrorism |
| 2.03 | Financial market sophistication |
| 2.04 | Soundness of banks |
| 2.05 | Ease of access to loans |
| 2.06 | Venture capital availability |
| 2.07 | Access to credit |
| 2.08 | Local equity market access |
| 2.09 | Regulation of securities exchanges |
| 2.10 | Effectiveness of bankruptcy law |
| 2.11 | Hidden trade barriers |
| 2.12 | Cost of importing foreign equipment |
| 2.13 | Business impact of domestic trade barriers |
| 2.14 | Business impact of foreign trade barriers |
| 2.15 | Business impact of customs procedures |
| 2.16 | Business impact of rules on FDI |
| 2.17 | Tax burden |
| 2.18 | Efficiency of customs procedures |
| 2.19 | Openness of customs regime |
| 2.20 | Agricultural policy costs |
| 2.21 | Organized efforts to improve competitiveness |
| 2.22 | Government surplus/deficit, 2003 |
| 2.23 | National savings rate, 2003 |
| 2.24 | Real effective exchange rate, 2003 |
| 2.25 | Inflation, 2003 |
| 2.26 | Interest rate spread, 2003 |
| 2.27 | Exports, 2003 |
| 2.28 | Imports, 2003 |
| 2.29 | Government debt, 2003 |
| 2.30 | Country credit rating, 2004 |
| *Section III. Technology: innovation and diffusion* | |
| 3.01 | Technological readiness |
| 3.02 | Firm-level technology absorption |
| 3.03 | Prevalence of foreign technology licensing |
| 3.04 | FDI and technology transfer |
| 3.05 | Quality of scientific research institutions |
| 3.06 | Company spending on research and development |
| 3.07 | Subsidies and tax credits for firm-level research and development |
| 3.08 | University/industry research collaboration |
| 3.09 | Government procurement of advanced technology products |
| 3.10 | Availability of scientists and engineers |
| 3.11 | Availability of mobile or cellular telephones |
| 3.12 | Internet access in schools |
| 3.13 | Quality of competition in the ISP sector |
| 3.14 | Government prioritization of ICT |
| 3.15 | Government success in ICT promotion |
| 3.16 | Laws relating to ICT |
| 3.17 | Utility patents, 2003 |
| 3.18 | Cellular telephones, 2003 |
| 3.19 | Internet users, 2003 |
| 3.20 | Internet hosts, 2003 |
| 3.21 | Personal computers, 2003 |

Table 2 (*continued*)

| | |
|---|---|
| *Section IV. Human resources: education, health, and labor* | |
| 4.01 | Quality of the educational system |
| 4.02 | Quality of public schools |
| 4.03 | Quality of math and science education |
| 4.04 | Disparity in healthcare quality |
| 4.05 | Business impact of malaria |
| 4.06 | Business impact of tuberculosis |
| 4.07 | Business impact of HIV/AIDS |
| 4.08 | Medium-term business impact of malaria |
| 4.09 | Medium-term business impact of tuberculosis |
| 4.10 | Medium-term business impact of HIV/AIDS |
| 4.11 | Ease of hiring foreign labor |
| 4.12 | Brain drain |
| 4.13 | Maternity laws' impact on hiring women |
| 4.14 | Childcare availability |
| 4.15 | Infant mortality |
| 4.16 | Life expectancy |
| 4.17 | Tuberculosis prevalence |
| 4.18 | Malaria prevalence |
| 4.19 | HIV prevalence |
| 4.20 | Primary enrollment |
| 4.21 | Secondary enrollment |
| 4.22 | Tertiary enrollment |
| *Section V. General infrastructure* | |
| 5.01 | Overall infrastructure quality |
| 5.02 | Railroad infrastructure development |
| 5.03 | Port infrastructure quality |
| 5.04 | Air transport infrastructure quality |
| 5.05 | Quality of electricity supply |
| 5.06 | Postal efficiency |
| 5.07 | Telephone/fax infrastructure quality |
| 5.08 | Telephone lines, 2003 |
| *Section VI. Public institutions* | |
| 6.01 | Judicial independence |
| 6.02 | Efficiency of legal framework |
| 6.03 | Property rights |
| 6.04 | Intellectual property protection |
| 6.05 | Freedom of the press |
| 6.06 | Wastefulness of government spending |
| 6.07 | Burden of central government regulation |
| 6.08 | Burden of local government regulation |
| 6.09 | Transparency of government policymaking |
| 6.10 | Favoritism in decisions of government officials |
| 6.11 | Extent of bureaucratic red tape |
| 6.12 | Effectiveness of law-making bodies |
| 6.13 | Extent and effect of taxation |
| 6.14 | Efficiency of the tax system |
| 6.15 | Centralization of economic policymaking |
| 6.16 | Reliability of police services |
| 6.17 | Business costs of crime and violence |
| 6.18 | Organized crime |
| 6.19 | Informal sector |
| 6.20 | Government effectiveness in reducing poverty and inequality |
| 6.21 | Irregular payments in exports and imports |
| 6.22 | Irregular payments in public utilities |
| 6.23 | Irregular payments in tax collection |
| 6.24 | Irregular payments in public contracts |
| 6.25 | Irregular payments in loan applications |
| 6.26 | Irregular payments in government policymaking |

Table 2 (*continued*)

| | |
|---|---|
| 6.27 | Irregular payments in judicial decisions |
| 6.28 | Business costs of irregular payments |
| 6.29 | Diversion of public funds |
| 6.30 | Business costs of corruption |
| 6.31 | Public trust of politicians |
| 6.32 | Prevalence of illegal political donations |
| 6.33 | Policy consequences of legal political donations |
| 6.34 | Pervasiveness of money laundering through banks |
| 6.35 | Pervasiveness of money laundering through non-bank channels |
| *Section VII. Domestic competition* | |
| 7.01 | Intensity of local competition |
| 7.02 | Extent of locally based competitors |
| 7.03 | Extent of market dominance |
| 7.04 | Sophistication of local buyers' products and processes |
| 7.05 | Administrative burden for startups |
| 7.06 | Effectiveness of anti-trust policy |
| 7.07 | Prevalence of mergers and acquisitions |
| 7.08 | Private sector employment of women |
| 7.09 | Wage equality of women in the workplace |
| 7.10 | Regional disparities in quality of business environment |
| *Section VIII. Cluster development* | |
| 8.01 | Buyer sophistication |
| 8.02 | Local supplier quantity |
| 8.03 | Local supplier quality |
| 8.04 | Presence of demanding regulatory standards |
| 8.05 | Decentralization of corporate activity |
| 8.06 | State of cluster development |
| 8.07 | Extent of collaboration among clusters |
| 8.08 | Local availability of components and parts |
| 8.09 | Local availability of process machinery |
| 8.10 | Local availability of specialized research and training services |
| *Section IX. Company operations and strategy* | |
| 9.01 | Nature of competitive advantage |
| 9.02 | Value chain presence |
| 9.03 | Extent of branding |
| 9.04 | Capacity for innovation |
| 9.05 | Ethical behavior of firms |
| 9.06 | Production process sophistication |
| 9.07 | Extent of marketing |
| 9.08 | Degree of customer orientation |
| 9.09 | Control of international distribution |
| 9.10 | Extent of regional sales |
| 9.11 | Breadth of international markets |
| 9.12 | Extent of staff training |
| 9.13 | Willingness to delegate authority |
| 9.14 | Extent of incentive compensation |
| 9.15 | Reliance on professional management |
| 9.16 | Quality of management schools |
| 9.17 | Efficacy of corporate boards |
| 9.18 | Hiring and firing practices |
| 9.19 | Flexibility of wage determination |
| 9.20 | Cooperation in labor–employer relations |
| 9.21 | Pay and productivity |
| 9.22 | Protection of minority shareholders' interests |
| 9.23 | Foreign ownership restrictions |
| 9.24 | Strength of auditing and reporting standards |
| 9.25 | Charitable causes involvement |
| 9.26 | Company promotion of volunteerism |

Table 2 (*continued*)

| | |
|---|---|
| 9.27 | Importance of corporate social responsibility |
| *Section X. Environment* | |
| 10.01 | Stringency of environmental regulations |
| 10.02 | Clarity and stability of regulations |
| 10.03 | Effects of compliance on business |
| 10.04 | Compliance with international agreements |
| 10.05 | Prevalence and effectiveness of environmental reporting |
| 10.06 | Political context of environmental gains |
| 10.07 | Subsidies for energy or materials |
| 10.08 | Prevalence of environmental marketing |
| 10.09 | Prevalence of environmental management systems |
| 10.10 | Prevalence of corporate environmental reporting |
| 10.11 | Importance of environmental management for companies |
| 10.12 | Prioritization of energy efficiency |
| 10.13 | Importance of environment in business planning |
| 10.14 | Prevalence of socially responsible investing |
| *Section XI. Military* | |
| 11.01 | Military expenses |

Current indices provide the ranks of the countries and do not make any suggestion about the way the countries can improve their relative position. In the proposed methodology, ANN helps to find out the criteria of top priority that a country should focus on in order to switch to a higher cluster.

Thirdly, a new composite index, which consists of the weighted average of the indicators taken from the ANN, is proposed for the ranking of the countries. As a result, an attempt is made to base an evaluation of countries' objective measurements. In the third step, the weights of the criteria for each development stage are used to specify the ranking of the countries. Fig. 3 gives the detailed flowchart of the proposed methodology.

## 4. An application of the proposed methodology

The proposed methodology is now employed to cluster the 103 countries evaluated by the WEF in 2004 using the GloCI based on their level of competitiveness. All countries except Hong Kong are included in the analysis. The latter was omitted due to the inconsistencies in its data. This likely resulted from Hong Kong being a Special Administrative Region of China as of 1 July 1997.

In addition to the 177 criteria used by the WEF to compute the GloCI, military expenditures were also considered here. For purposes of completeness, the criteria are listed in Table 2. We included military expenditures simply because military power is considered one of the most important factors affecting the power of nations [15]. Note that there is a significant positive correlation between the World Competitiveness Index (WCI) and economic and demographic power, but a significant negative correlation between the WCI and the military power of nations. In other words, as the military power of a country increases, its WCI declines [15].

### *4.1. Classification of countries through cluster analysis*

In the first part of this research, countries are grouped based on their similarity of characteristics. Cluster analysis, as described below, is used for this purpose.

#### *4.1.1. Cluster analysis*

Cluster analysis involves grouping similar objects into mutually exclusive subsets, referred to as clusters [23]. The cluster definition problem is NP-complete; hence, a computationally efficient, exact solution method, to the best of the authors' knowledge, does not exist. However, a number of heuristic methods have been proposed for this purpose, including agglomerative techniques [23]. All hierarchical agglomerative heuristics begin with **n** clusters, where **n** is the number of observations. Then, the two most similar clusters are combined to form **n−1** clusters. On the next iteration, **n−2** clusters are formed with the same logic, and this process continues until one cluster remains. Only the rules used to merge clusters differ across the various heuristics.

Although all hierarchical methods successfully define clusters for compact and isolated data, they generally fail to accurately provide defined clusters for "messy" data. In fact, the major issue with all clustering techniques is how to best select the *number of clusters*. Different clustering methods may lead to different clusters, with the differences generally due to inherent characteristics of the methodology. In fact, as implied above, there is no single methodology that can be recommended for selecting the most appropriate number of clusters. This is why cluster analysis is generally viewed as more art than science [24].

In order to improve the accuracy of, and reduce any subjectivity in, the cluster analysis, we employ a SOM Neural Network, as suggested by Mangiameli et al. [25]. The SOM is thus not taken as an alternative, but rather as a complementary analysis that follows hierarchical clustering. The focus is on improved accuracy in the assignment of observations to appropriate clusters, given that the number of clusters in the data is known. The SOM's network learns to detect groups of similar input vectors in such a way that neurons physically close in the neuron layer respond to a similar input vector [26].

SOM networks are used to separate outputs into categories. They are unsupervised networks, that is, they have no output value in the training pattern with which training can be compared. In most other network models, all neurons adjust their weights in response to a training presentation, while in an SOM, that is not the case. In this kind of network, the neurons compete for the privilege of learning.

SOM networks have two layers, the input layer of $N$ variables, and a Kohonen layer. In the latter, the neurons are configured to reduce the size of $N$ input neurons in the input layer to two dimensions. Each neuron in the input layer is related to the Kohonen layer. All neurons in the output layer are interrelated, and located side-by-side. Neurons in the output layer are trained to conserve the topological structure of the input layer. As a result, the same topological structure is experienced by all neurons, while those that are close to each other respond to similar inputs [27].

The self-organization process begins by randomly assigning weights between the input and Kohonen layers. During the training process, the input vectors are added to the network sequentially. At the entry of each input, neurons in the output layer compete to respond to this newcomer. The neuron most similar to the input, i.e., the one closest to the input vector according to a selected distance measure, will be the "winning" neuron. It, and those that are in its vicinity, are moved so as to be closer to the input element [25].

Based on this ongoing process, the neurons of the Kohonen layer specialize in responding to specific input groups—simply by being closer to them than other neurons (Fig. 4). As a result, the input vectors are grouped according to a prespecified number of clusters, which are represented by the neuron in the output layer specialized for this cluster.

The Kohonen network is used for classification problems. Once the value of the output neurons is specified, the neuron stimulated at the highest value is identified as the "winner" and the weights of the relations in the

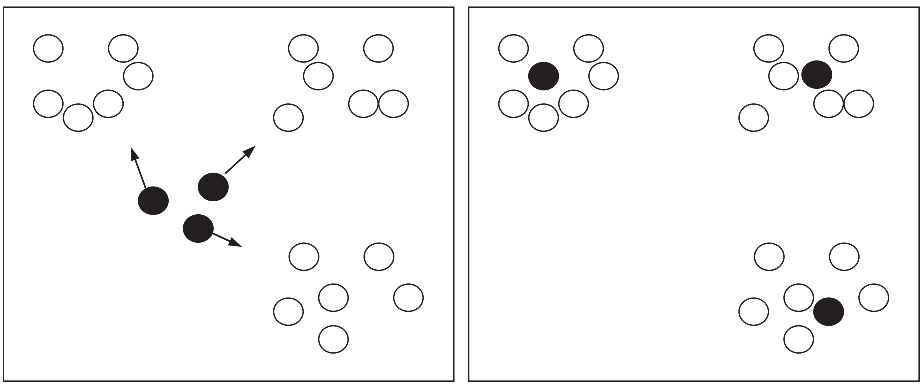

Fig. 4. Movement of neurons in the output layer toward clusters generated by the input vectors.

network are updated accordingly. After several iterations, the system reaches a state of equilibrium, i.e., after several iterations of training, any further significant change in the vector becomes impossible. Once this situation occurs, the training is terminated and that classification made according to the most stimulated output can be applied to any data set of interest.

#### *4.1.2. Determining the country clusters*

The basic drawback of any study based solely on ranking is that the ordinal scale does not reflect (here) the appropriate competitiveness level of a country (entity) relative to other countries (entities). The most accurate position of a country within the total configuration can only be determined after the grouping of nations is performed, and similarities to the evaluated country in terms of competitiveness are identified.

In the current study, the Ward hierarchical method, an agglomerative clustering technique, and the Squared Euclidean distance measure were selected as most appropriate based on evaluations using MATLAB [28]. In Ward's method, the distance is the ANOVA sum of squares between two clusters summed over all variables [23].

An analysis of the dendogram (Fig. 5) and ANOVA were thus used to test the significance of differences between the cluster means, producing three significant clusters. Dendrogram analysis generates a dendrogram plot of the hierarchical, binary cluster tree. It consists of many U-shaped lines connecting objects in a hierarchical tree. The height of each U represents the distance between the two objects being connected. Each leaf in the dendrogram corresponds to one data point. As can be seen from Fig. 5, the countries are grouped in three different U-shaped clusters.

An ANOVA can be run to compare the means of two or more columns of data in a matrix $X$, where each column represents an independent sample containing mutually independent observations. The function returns the $p$-value under the null hypothesis that all samples in $X$ are drawn from populations with the same mean. Interestingly, our ANOVA results show otherwise, i.e., that the three clusters have no common means for their scores. The cluster means are therefore not equal at the 5% significance level for all variables (see Table 3).

Next, the appropriate number of clusters generated in the first stage was used to repeat the analysis using SOM and MATLAB software. Since we sought of categorizing the countries into three classes, there were three outputs in the ANNs configuration. This generated a $3 \times 1$ matrix of the weight vector. The topology function used was "HEXTOP," which means that the neurons were arranged in a hexagonal topology at the Kohonen layer, while the distance function was "MANDIST," i.e., the Manhattan (city block) distance.

The training of a SOM using MATLAB involved two steps, namely the ordering phase and the tuning phase. In the former, the ordering phase learning rate and neighborhood distance are decreased from that rate and the maximum distance between two neurons to the tuning phase learning rate and tuning phase neighborhood distance, respectively. The ordering phase lasts for a given number of steps. In the tuning phase,

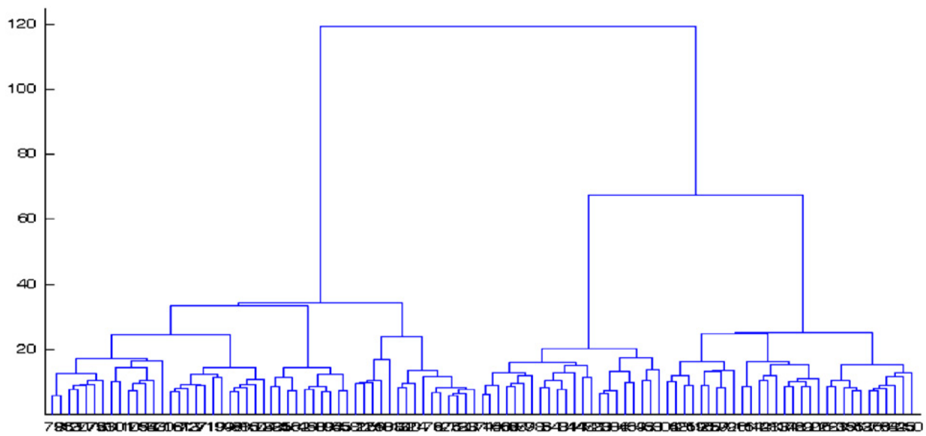


Fig. 5. Dendogram of the country clusters.

Table 3
Tests of homogeneity of stage variances and means

| | Cluster variances | | Cluster means | |
|---|---|---|---|---|
| | Levene statistic | Significance | *F* statistic | Significance |
| Overall | 2.249 | 0.111 | 232.2 | 0.000 |
| Basic | 2.647 | 0.076 | 172.4 | 0.000 |
| Efficient | 2.166 | 0.120 | 290.7 | 0.000 |
| Innovation | 0.921 | 0.401 | 219.7 | 0.000 |

Table 4
Non-competitive, competitive and highly competitive countries

| Non-competitive countries | | Competitive countries | | Highly competitive countries | |
|---|---|---|---|---|---|
| Algeria | Mexico | Bahrain | Korea | Australia | Japan |
| Angola | Mozambique | Botswana | Latvia | Austria | Luxembourg |
| Argentina | Nicaragua | Brazil | Lithuania | Belgium | Netherlands |
| Bangladesh | Nigeria | Chile | Malaysia | Canada | New Zealand |
| Bolivia | Pakistan | China | Malta | Denmark | Norway |
| Bosnia & Her. | Panama | Costa Rica | Mauritius | Finland | Singapore |
| Bulgaria | Paraguay | Cyprus | Morocco | France | Sweden |
| Chad | Peru | Czech Rep. | Namibia | Germany | Switzerland |
| Colombia | Philippines | Egypt | Portugal | Iceland | Taiwan |
| Croatia | Poland | Estonia | Slovak Rep. | Ireland | UK |
| Dominican Rep. | Romania | Ghana | Slovenia | Israel | US |
| Ecuador | Russian Fed. | Greece | S. Africa | | |
| El Salvador | Serbia & Mon. | Hungary | Spain | | |
| Ethiopia | Sri Lanka | India | Thailand | | |
| Gambia | Tanzania | Indonesia | Tunisia | | |
| Georgia | Tri. &Tob. | Italy | UAE | | |
| Guatemala | Turkey | Jordan | | | |
| Honduras | Uganda | | | | |
| Jamaica | Ukraine | | | | |
| Kenya | Uruguay | | | | |
| Macedonia | Venezuela | | | | |
| Madagascar | Vietnam | | | | |
| Malawi | Zambia | | | | |
| Mali | Zimbabwe | | | | |

the learning rate is decreased much more slowly than in the ordering phase, while the neighborhood distance stays constant [29]. In the current study, the ordering phase learning rate, ordering phase steps, and the tuning phase learning rate were taken as 0.9, 1000, and 0.02, respectively.

The countries contained within the resulting three clusters are summarized in Table 4.

For each cluster, Table 5 shows the mean, standard deviation, and coefficient of variation ($\mathrm{CV} = \sigma/\mu$) of the resulting clusters for the following factors: overall, basic requirements, efficiency enhancers, and innovation and sophistication. Note that the countries assigned to the first cluster have a low overall index (mean: 3.4) and, as might be expected, their basic requirement values are higher than those for efficiency enhancers and innovation/sophistication. These countries are thus classified as non-competitive at the *factor-driven* stage. Not surprisingly, the average overall value of this first cluster (3.40) is well below the global average (3.89) of all 103 countries. Among the countries in this cluster, Turkey represents a typical example.

Countries belonging to the second cluster achieve higher values for overall (mean: 4.06), basic requirements (mean: 4.90), efficiency enhancers (mean: 3.54), and innovation and sophistication (mean: 3.24) when compared to those in the first cluster. However, their innovation and sophistication factor scores are lower

Table 5
The mean, standard deviation and coefficient of variance (CV) of countries in the three clusters

| | Overall | | | Basic requirements | | | Efficiency enhancers | | | Innovation and sophistication | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std dev. | CV | Mean | Std dev. | CV | Mean | Std dev. | CV | Mean | Std dev. | CV |
| Non-competitive countries | 3.40 | 0.28 | 0.08 | 4.03 | 0.4 | 0.1 | 2.87 | 0.27 | 0.09 | 2.66 | 0.3 | 0.11 |
| Competitive countries | 4.06 | 0.21 | 0.05 | 4.90 | 0.31 | 0.06 | 3.54 | 0.22 | 0.06 | 3.24 | 0.28 | 0.09 |
| Highly competitive countries | 4.73 | 0.2 | 0.04 | 5.63 | 0.25 | 0.05 | 4.36 | 0.22 | 0.05 | 4.33 | 0.37 | 0.08 |
| All countries | 3.89 | 0.58 | 0.15 | 4.65 | 0.72 | 0.16 | 3.40 | 0.63 | 0.19 | 3.20 | 0.71 | 0.22 |

than those of the first cluster countries. The second cluster countries are seen as competitive at the *efficiency-driven* stage. It is interesting to note that China, accepted as one of the most promising nations in the world in terms of competitiveness, is found in this category.

Finally, those countries assigned to the third and last cluster have the highest scores for the overall index (mean: 4.73), basic requirements (mean: 5.63), efficiency enhancers (mean: 4.36), and innovation and sophistication factors (mean: 4.33). In fact, their scores on innovation/sophistication and efficiency are nearly the same and, hence, can be accepted as highly competitive countries, at the *innovation-driven* stage. The United States, Finland, and Denmark achieved the highest overall index values [4].

The means of two of the three clusters—non-competitive (3.4) and highly competitive (4.73)—are significantly different from the mean of all countries (3.89). This suggests that these clusters have different characteristics with respect to the overall configuration of their countries. The former has a competitiveness performance significantly below the overall mean, while the latter has much higher competitiveness when compared to the overall mean. Not surprisingly, the cluster of competitive countries shows similarity to the overall mean (4.06), suggesting that they have average competitiveness power.

The homogeneity of countries within a cluster—i.e., the variation around the cluster average—is calculated using the standard deviation of the four measures, i.e., overall, etc. at each stage (see Table 5). When the equality of variances is calculated using the Levene homogeneity test [23], the significance values suggest no statistical differences across the three clusters. The hypothesis of equal variances is thus (easily) rejected at the 5% confidence level.

In order to account for both within-group variances and their corresponding cluster averages, the coefficients of variation (CV) are also calculated for each stage. The cluster having the highest overall index mean (0.04) has a CV close to that of the cluster with the lowest overall mean (0.08). The same situation holds for both the second and third clusters. Furthermore, the variances of the two extreme clusters (1 and 3) are almost the same, as they are for the second and third clusters. As a result, it can be said that, for the three clusters, each has the same level of homogeneity. Although their within-group variances are found to be the same, it is noteworthy that their respective cluster averages differ. Countries within each cluster thus show similarity with respect to each other in terms of competitiveness power. On the other hand, countries in different clusters show important disparities in this regard.

### 4.2. *Identification of basic criteria underlying country stages through ANN*

At this step of the study, the basic factors underlying the reasons a country belongs to a specific cluster are analyzed using ANN. The feed-forward back propagation algorithm is used for this purpose.

#### 4.2.1. *Artificial neural networks*

ANN techniques have been applied to a variety of problem types and, in many instances, provided superior results to conventional methods [30]. The literature [31–33] suggests the potential advantages of ANN vs statistical methods. The basic ANN model consists of computational units that emulate the functions of a nucleus in a human brain. The unit receives a weighted sum of all its inputs and computes its own output value by a transformation, or output function. The output value is then propagated to many other units via connections between units. The learning process of ANN can be thought of as a reward and punishment mechanism [34]. When the system reacts appropriately to an input, the related weights are strengthened. As a result, it becomes possible to generate outputs, which are similar to those of the previously encountered inputs. In contrast, when undesirable outputs are produced, the related weights are reduced. The model will thus *learn* to give a different reaction when similar inputs occur. In this way, the system is "trained" to produce desirable results while "punishing" undesirable ones.

In multilayer networks, all inputs are related to outputs through hidden neurons, i.e., there is no direct relationship among them. As a result, specification of the characteristics of each input neuron and the strength of relation between input $X_i$ and output $O_i$ can be found using the method proposed by Yoon et al. [30]:

$$\mathrm{RS}_{ji} = \frac{\sum_{k=0}^{n}(W_{ki}U_{jk})}{\sum_{i=0}^{m}\left|(\sum_{k=0}^{n}(W_{ki}U_{jk})\right|}.$$

In this expression, $\mathrm{RS}_{ji}$ represents the strength of relation between input $i$ and output $j$. $W_{ki}$ is the weight between the $j$th output $U_{jk}$ and the $k$th hidden neuron. $\mathrm{RS}_{ji}$ is thus the ratio of the strength of relation between the $i$th input and the $j$th output to the sum of all such strengths. The absolute value in the denominator is used to avoid positive relations canceling the impact of negative ones.

Furthermore, in order to increase the efficiency of the measure, the squares of both the numerator and denominator are taken, as suggested by Onsel et al. [22]. The sum of the weights is set equal to 1 and, in the current study, the resulting modified formula is used as the basis of the analysis.

$$\mathrm{RS}_{ji} = \frac{\left[\sum_{k=0}^{n}(W_{ki}U_{jk})\right]^2}{\left[\sum_{i=0}^{m}(W_{ki}U_{jk})\right]^2}$$

#### 4.2.2. Determining basic criteria weights

Output from the SOM in the previous stage helps generate the clusters of countries. These data are then used as the output of the multilayer feed-forward ANN while the 178 criteria (the 177 WEF criteria plus military expenditures) are treated as inputs.

Ninety-three countries are used for training and 10 for testing stages. In order to obtain robust results based on different trials, for each hidden neuron number, the ANN is computed 10 times, and the best results obtained from each taken. In this way, an attempt is made to detect different points of weight space corresponding to the network via several experiments. The smallest error ratio is obtained in a configuration with one hidden layer containing 10 hidden neurons. The logistics function (logsig) is used to show the relation between the input and hidden neurons, while the linear function (purelin) is preferred for the relation between the hidden and output neurons. The training algorithm is a gradient-descent method with momentum and an adaptive learning ratio ("traingdx"). The resulting ANN configuration is given in Fig. 6.

The training was stopped after 1000 runs, when the test error began to increase (see Fig. 7). At this point, the mean square error, selected as the performance measurement, was found to be 0.00021.

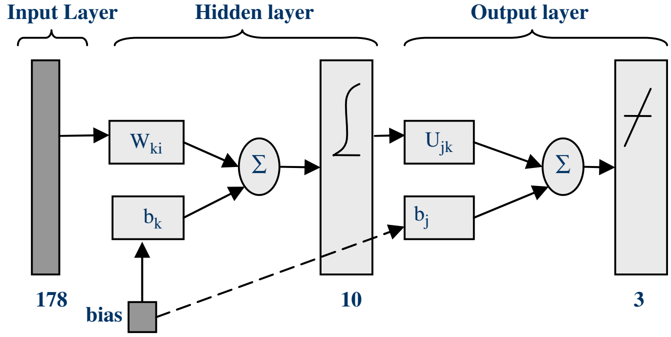


Fig. 6. The resulting multilayer feed-forward neural network configuration.

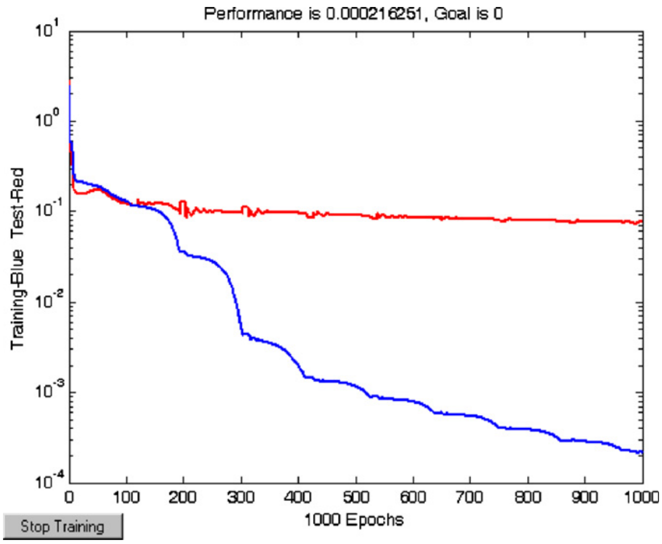


Fig. 7. The learning curve of the ANN used.

Table 6
The 10 most important criteria in the specification of Cluster 1

| | Criteria (input of ANN) | Cluster 1 | | |
|---|---|---|---|---|
| | | Weight impact score | Stage average | Impact rank |
| 11.01 | Military expenses | 0.065 | 6.412 | 1 |
| 4.18 | Malaria prevalence | 0.050 | 6.473 | 2 |
| 4.07 | Business impact of HIV/AIDS | 0.030 | 4.911 | 3 |
| 4.16 | Life expectancy | 0.024 | 4.607 | 4 |
| 2.24 | Real effective exchange rate, 2003 | 0.022 | 3.232 | 5 |
| 5.04 | Air transport infrastructure quality | 0.022 | 3.632 | 6 |
| 10.03 | Effects of compliance on business | 0.021 | 4.037 | 7 |
| 6.11 | Extent of bureaucratic red tape | 0.021 | 2.845 | 8 |
| 6.28 | Business costs of irregular payments | 0.019 | 3.321 | 9 |
| 9.25 | Charitable causes involvement | 0.018 | 3.830 | 10 |
| | | Mean | 4.330 | |
| | | Standard deviation | 1.274 | |
| | | CV | 0.294 | |

The 10 most important inputs (criteria), playing the dominant role in the allocation of countries to the three clusters, were obtained using the modified Yoon et al. [30] formula. They are given, by cluster, in Tables 6–8, respectively.

As can be seen in Table 6, the most important criterion in the construction of Cluster 1, which is composed of non-competitive countries, is military expenditure (cluster average is 6.41). This is followed by basic requirements criteria—e.g., health and transportation—as well as those related to bureaucracy levels.

On the other hand, since the basic requirements concerning health, transportation, and communications structure have been achieved in Cluster 2, the criterion related to improving the quality and efficiency of the electricity, transportation, communication, and fiscal infrastructures becomes of primary importance.

Finally, it can be seen that the criteria fundamental to composition of Cluster 3 involve science, research and development, and technology rankings (see Table 8).

Table 7
The 10 most important criteria in the specification of Cluster 2

| | Criteria (input of ANN) | Cluster 2 | | |
|---|---|---|---|---|
| | | Weight impact score | Stage average | Impact rank |
| 5.05 | Quality of electricity supply | 0.051 | 4.739 | 1 |
| 2.02 | Business costs of terrorism | 0.038 | 5.041 | 2 |
| 5.02 | Railroad infrastructure development | 0.030 | 3.186 | 3 |
| 5.06 | Postal efficiency | 0.027 | 4.173 | 4 |
| 6.13 | Extent and effect of taxation | 0.024 | 3.097 | 5 |
| 3.17 | Utility patents, 2003 | 0.024 | 1.450 | 6 |
| 6.04 | Intellectual property protection | 0.023 | 3.751 | 7 |
| 2.20 | Agricultural policy costs | 0.023 | 3.464 | 8 |
| 3.18 | Cellular telephones, 2003 | 0.023 | 3.204 | 9 |
| 8.01 | Buyer sophistication | 0.022 | 4.116 | 10 |
| | | Mean | 3.622 | |
| | | Standard deviation | 1.012 | |
| | | CV | 0.279 | |

Table 8
Ten most important criteria in the specification of Cluster 3

| | Criteria (input of ANN) | Cluster 3 | | |
|---|---|---|---|---|
| | | Weight impact score | Stage average | Impact rank |
| 9.13 | Willingness to delegate authority | 0.043 | 4.406 | 1 |
| 8.01 | Buyer sophistication | 0.040 | 5.514 | 2 |
| 3.10 | Availability of scientists and engineers | 0.038 | 5.466 | 3 |
| 4.01 | Quality of the educational system | 0.032 | 4.930 | 4 |
| 2.12 | Cost of importing foreign equipment | 0.030 | 4.687 | 5 |
| 3.06 | Company spending on research and development | 0.028 | 4.476 | 6 |
| 2.03 | Financial market sophistication | 0.022 | 4.966 | 7 |
| 6.35 | Pervasiveness of money laundering through non-bank channels | 0.021 | 4.698 | 8 |
| 3.12 | Internet access in schools | 0.021 | 5.425 | 9 |
| 9.06 | Production process sophistication | 0.020 | 5.046 | 10 |
| | | Mean | 4.961 | |
| | | Standard deviation | 0.404 | |
| | | CV | 0.082 | |

#### *4.2.3. Comparison of the relative importances of the criteria in different country clusters*

An overall evaluation of our proposed approach can be realized by comparing the relative importances of criteria used in the ranking of those countries belonging to different clusters. For example, the *quality of education,* which is one of the sub-criteria used in the GCI evaluation, has a mean of 2.869 and is the 75th most important factor in the ranking of the first (non-competitive) cluster countries. This means that the quality of education is not a dominant factor in the ranking of these countries. However, in the second cluster (competitive countries), the same sub-criterion has a mean of 3.76 and is the 42nd most important factor in the ranking, while in the last cluster (highly competitive countries), it is the fourth most important sub-criterion with a mean of 4.93. Clearly, a similar type analysis can be conducted for any other sub-criteria.

When analyzing Tables 9–11, we see there are highly contrasting differences among the criteria that are of primary importance in each cluster. For example, in Cluster 1 (non-competitive countries) *military expenditures* is the most important criterion while its relative rank is only 153 and 98 in the second

Table 9
Criteria of primary importance for non-competitive countries

| | Criteria | Cluster 1 | | | Cluster 2 | | | Cluster 3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Weight impact score | Stage average | Rank | Weight impact score | Stage average | Rank | Weight impact score | Stage average | Rank |
| 11.01 | Military expenses | 0.065 | 6.412 | 1 | 0.000 | 6.345 | 153 | 0.002 | 6.364 | 98 |
| 4.18 | Malaria prevalence | 0.050 | 6.473 | 2 | 0.003 | 6.673 | 88 | 0.002 | 6.923 | 102 |
| 4.07 | Business impact of HIV/AIDS | 0.030 | 4.911 | 3 | 0.001 | 5.379 | 137 | 0.007 | 6.078 | 51 |
| 4.16 | Life expectancy | 0.024 | 4.607 | 4 | 0.000 | 5.213 | 148 | 0.000 | 6.083 | 149 |
| 2.24 | Real effective exchange rate, 2003 | 0.024 | 3.232 | 5 | 0.000 | 3.447 | 142 | 0.006 | 3.629 | 53 |

Table 10
Criteria of primary importance for competitive countries

| | Criteria | Stage 1 | | | Stage 2 | | | Stage 3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Weight impact score | Stage average | Rank | Weight impact score | Stage average | Rank | Weight impact score | Stage average | Rank |
| 5.05 | Quality of electricity supply | 0.001 | 3.758 | 126 | 0.051 | 4.739 | 1 | 0.001 | 5.942 | 116 |
| 2.02 | Business costs of terrorism | 0.002 | 4.763 | 105 | 0.038 | 5.041 | 2 | 0.000 | 5.265 | 163 |
| 5.02 | Railroad infrastructure development | 0.004 | 2.299 | 85 | 0.030 | 3.186 | 3 | 0.001 | 4.392 | 134 |
| 5.06 | Postal efficiency | 0.003 | 3.033 | 90 | 0.027 | 4.173 | 4 | 0.014 | 5.624 | 20 |
| 6.13 | Extent and effect of taxation | 0.000 | 2.625 | 141 | 0.024 | 3.097 | 5 | 0.000 | 3.542 | 151 |

Table 11
Criteria of primary importance for highly competitive countries

| | Criteria | Cluster 1 | | | Cluster 2 | | | Cluster 3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Weight impact score | Stage average | Rank | Weight impact score | Stage average | Rank | Weight impact score | Stage average | Rank |
| 9.13 | Willingness to delegate authority | 0.011 | 2.578 | 28 | 0.000 | 3.322 | 143 | 0.043 | 4.406 | 1 |
| 8.01 | Buyer sophistication | 0.000 | 3.125 | 150 | 0.022 | 4.116 | 10 | 0.040 | 5.514 | 2 |
| 3.10 | Availability of scientists and engineers | 0.008 | 4.141 | 42 | 0.002 | 4.706 | 104 | 0.038 | 5.466 | 3 |
| 4.01 | Quality of the educational system | 0.004 | 2.869 | 75 | 0.008 | 3.762 | 42 | 0.032 | 4.930 | 4 |
| 2.12 | Cost of importing foreign equipment | 0.001 | 2.370 | 124 | 0.000 | 3.315 | 175 | 0.030 | 4.687 | 5 |

and third clusters, respectively. Similarly, *life expectancy* is the fourth most important criterion in the first cluster, while its rank is very low in the second and third clusters (148 and 149, respectively) (see Table 9).

On the other hand, although the *quality of electricity supply* is of primary importance for the second cluster of countries, its rank is 126 and 116 for the first and third clusters, respectively. Similar contrasting results can also be seen for *business costs of terrorism*, *railroad infrastructure development*, *postal efficiency*, and *extent and effect of taxation* (Table 10).

Finally, as can be seen in Table 11, the factors that are very important for the highly competitive countries (i.e., willingness to delegate authority, buyer sophistication, availability of scientists and engineers, quality of the educational system, cost of importing foreign equipment) have very low ranks in the other clusters.

### 4.3. How can countries switch to a higher cluster?

The proposed methodology can serve as a useful benchmarking guide to countries attempting to increase their levels of competitiveness. For a country to switch to a higher cluster, it is initially expected to reach the competitiveness value of the top-ranked country in its own cluster. Subsequently, it must reach the value of the last-ranked country of the next higher cluster. For this second iteration, the criteria weights corresponding to the higher cluster are considered. For purposes of illustration, Turkey is chosen as the special case of the third cluster.

Turkey was chosen to represent the non-competitive cluster as it is the authors' home country, and has been subject to debate regarding its entrance to the EU. Additionally, Turkey's relative position (score = 4.13) in its cluster is above the average of 3.70.

In moving Turkey toward improvement, El Salvador, as the top-ranked country in the first cluster, is used as the first stepping-stone. For Turkey to attain El Salvador's index value (4.27), it must increase its own index value by 0.14 (4.27–4.13 = 0.14). For this purpose, once the criteria are ranked according to their importance weights, it is sufficient to increase the value of five criteria to the average value of the second cluster (see Table 12).

So, at this initial step of improvement, fiscal discipline appears to be very important for Turkey. In addition, a decrease in military expenses would seem crucial in its attempt to improve position. Once Turkey reaches the index value of the top-ranked country of its own cluster, it must then take steps to attain the index value of Egypt (3.61), which is at the bottom of the second cluster of countries. This second jump, however, would necessitate an improvement in the values of eight criteria given in Table 13.

Thus far in the analysis, it can be said that improving the transparency and efficiency of Turkey's public institutions is needed most in order to switch to the second cluster. The government's attitude toward markets and the efficiency of its own operations would thus be key here. In fact, when the clustering analysis is redone using the SOM neural network and the revised values (for Turkey) on the above-mentioned 13 criteria, its switch to the second cluster is verified. According to this revision, Turkey's rank rose from 60th to 54th.

### 4.4. Ranking countries based on the proposed weighted criteria index

At the third step of this research, the weights of 178 criteria for each cluster calculated in the previous step are used to rank the countries. For this purpose, initially the weights are normalized. The score obtained by

Table 12
Criteria on which Turkey should improve in order to reach a more competitive position in the first Cluster

| | Name of criterion | Turkey (1) | Average of the second Cluster (2) | Weights in third Cluster (3) | Weighted difference ((2)−(1)) × 3 | Cumulative weights |
|---|---|---|---|---|---|---|
| 11.01 | Military expenses | 5.55 | 6.35 | 0.065 | 0.052 | 0.052 |
| 2.04 | Soundness of banks | 1.82 | 4.84 | 0.011 | 0.033 | 0.084 |
| 2.14 | Business impact of foreign trade barriers | 2.83 | 4.30 | 0.015 | 0.022 | 0.106 |
| 6.28 | Business costs of irregular payments | 3.14 | 4.23 | 0.020 | 0.021 | 0.127 |
| 7.10 | Regional disparities in quality of business environment | 1.65 | 3.39 | 0.011 | 0.019 | 0.146 |

Table 13
Criteria on which Turkey should improve in order to enter the second Cluster

| | Name of criterion | Turkey (1) | Average of the second Cluster (2) | Weights in second Cluster (3) | Weighted difference ((2)−(1))× (3) | Cumulative weights |
|---|---|---|---|---|---|---|
| 5.05 | Quality of electricity supply | 3.54 | 4.74 | 0.051 | 0.061 | 0.061 |
| 6.13 | Extent and effect of taxation | 1.52 | 3.10 | 0.024 | 0.038 | 0.099 |
| 5.02 | Railroad infrastructure development | 1.93 | 3.19 | 0.030 | 0.037 | 0.136 |
| 6.04 | Intellectual property protection | 2.33 | 3.75 | 0.023 | 0.032 | 0.168 |
| 2.20 | Agricultural policy costs | 2.17 | 3.46 | 0.023 | 0.029 | 0.198 |
| 6.14 | Efficiency of the tax system | 1.92 | 3.41 | 0.018 | 0.027 | 0.225 |
| 6.08 | Burden of local government regulation | 1.77 | 3.11 | 0.020 | 0.027 | 0.252 |
| 2.02 | Business costs of terrorism | 4.43 | 5.04 | 0.038 | 0.023 | 0.275 |

each country from each of the criteria is then multiplied by the normalized weight of that criterion. The 103 countries are subsequently ranked according to these weighted index values (see Table 14).

If the ranking of the proposed model is compared with that obtained using the WEF's GloCI, it can be seen that, while there is an overall similarity, there are some important differences between the two. For example, the latter ranks Turkey and the United States 66th and first, respectively. On the other hand, when the proposed weighted index is used, Turkey climbs to 60th while the United States drops to fourth. Those countries that differ by positions of at least 10 in the absolute value between the two indices are shown in Fig. 8.

It is important to emphasize that the subjectivity of the WEF clustering, as well as of the weighting process, sometimes result in contradictory results with respect to the WEF index. In particular, important discrepancies may occur between the stage to which a country is assigned and the rank that it receives based on the GloCI. For example, although authorities agree that China is one of the most economically promising countries, the WEF's index assigned it to Stage 1 (factor-driven economies). In contrast, the WEF's global competitiveness ranking places it 31st.

As a second example, Bahrain, another Stage 1 country, is ranked 24th according to the WEF's GloCI. This indicates higher rank than most countries in higher stages (i.e., all other stages). Similarly, GloCI assigns Taiwan to the transition stage between Stage 2 (efficiency-driven economies) and Stage 3 (innovation-driven economies), while it is 10th according to the GloCI. When a country is assigned to a stage, logically it is not expected to be ranked lower than countries in "worse" stages, nor higher than ones in "better" stages. However, the rankings assigned by GloCI are clearly higher than expected regarding the stages to which the countries belong.

In contrast to these findings, Spain and Italy, which are assigned as Stage 3 countries by WEF, are placed 33rd and 55th, respectively, by the GloCI. Both thus show a lower ranking than expected in terms of the stages to which they belong.

As was mentioned in Section 2.3, according to the WEF, those countries having a GDP below a threshold level are accepted at Stage 1 countries, suggesting that what is most important to them is performance of basic requirements. However, this is a non-compensatory approach since there may be some countries performing well vis-à-vis basic requirements while still having a low GDP. It may therefore be unfair to assign a country to a stage based solely on its GDP. This is why it may actually be more accurate to use a compensatory approach for such purposes.

On the other hand, a country may be unfairly rewarded for having a high GDP, even though it may be performing poorly in terms of basic requirement factors. For example, the United States does not score well on basic requirements, yet it is the world's leader in both efficiency enhancers and innovation and sophistication. This is due mainly to the fact that the US is at the third stage of development (innovation ) and

Table 14
Country rankings based on the proposed weighted criteria index

| Cluster 3 | | | Cluster 2 | | | Cluster 1 | | |
|---|---|---|---|---|---|---|---|---|
| Country | Our ranking | WEF ranking | Country | Our ranking | WEF ranking | Country | Our ranking | WEF ranking |
| Finland | 1 | 2 | Bahrain | 32 | 24 | El Salvador | 56 | 54 |
| Denmark | 2 | 3 | Slovak Rep. | 33 | 40 | Jamaica | 57 | 64 |
| Sweden | 3 | 5 | South Africa | 34 | 35 | Mexico | 58 | 59 |
| US | 4 | 1 | Jordan | 35 | 27 | Colombia | 59 | 68 |
| Switzerland | 5 | 4 | Cyprus | 36 | 51 | Turkey | 60 | 66 |
| Singapore | 6 | 7 | Czech Rep. | 37 | 37 | Tri. and Tob. | 61 | 62 |
| UK | 7 | 8 | Thailand | 38 | 32 | Romania | 62 | 56 |
| Netherlands | 8 | 11 | Namibia | 39 | 42 | Panama | 63 | 53 |
| Germany | 9 | 6 | Lithuania | 40 | 38 | Sri Lanka | 64 | 65 |
| Japan | 10 | 9 | Hungary | 41 | 45 | Uruguay | 65 | 70 |
| Iceland | 11 | 12 | Greece | 42 | 50 | Croatia | 66 | 78 |
| Australia | 12 | 15 | Brazil | 43 | 48 | Russian Fed. | 67 | 63 |
| Norway | 13 | 13 | China | 44 | 31 | Gambia | 68 | 80 |
| New Zealand | 14 | 19 | Malta | 45 | 41 | Peru | 69 | 75 |
| Canada | 15 | 14 | Morocco | 46 | 44 | Vietnam | 70 | 60 |
| Taiwan | 16 | 10 | Botswana | 47 | 57 | Bulgaria | 71 | 69 |
| Luxembourg | 17 | 20 | Latvia | 48 | 43 | Kenya | 72 | 83 |
| Austria | 18 | 17 | India | 49 | 36 | Nigeria | 73 | 76 |
| Belgium | 19 | 18 | Italy | 50 | 55 | Macedonia | 74 | 81 |
| France | 20 | 16 | Mauritius | 51 | 49 | Philippines | 75 | 73 |
| Ireland | 21 | 26 | Costa Rica | 52 | 52 | Argentina | 76 | 74 |
| Israel | 22 | 21 | Indonesia | 53 | 47 | Dominican Rp. | 77 | 58 |
| Malaysia | 23 | 22 | Ghana | 54 | 67 | Uganda | 78 | 77 |
| UAE | 24 | 30 | Egypt | 55 | 46 | Algeria | 79 | 61 |
| Estonia | 25 | 23 | | | | Poland | 80 | 71 |
| Korea | 26 | 25 | | | | Ser. and Mon. | 81 | 95 |
| Spain | 27 | 33 | | | | Georgia | 82 | 85 |
| Chile | 28 | 28 | | | | Ukraine | 83 | 72 |
| Slovenia | 29 | 34 | | | | Tanzania | 84 | 96 |
| Tunisia | 30 | 29 | | | | Pakistan | 85 | 86 |
| Portugal | 31 | 39 | | | | Mali | 86 | 98 |
| | | | | | | Guatemala | 87 | 82 |
| | | | | | | Madagascar | 88 | 84 |
| | | | | | | Nicaragua | 89 | 91 |
| | | | | | | Zambia | 90 | 90 |
| | | | | | | Bangladesh | 91 | 93 |
| | | | | | | Venezuela | 92 | 79 |
| | | | | | | Bos. and Her. | 93 | 97 |
| | | | | | | Paraguay | 94 | 89 |
| | | | | | | Ecuador | 95 | 87 |
| | | | | | | Honduras | 96 | 88 |
| | | | | | | Malawi | 97 | 92 |
| | | | | | | Bolivia | 98 | 94 |
| | | | | | | Ethiopia | 99 | 101 |
| | | | | | | Zimbabwe | 100 | 100 |
| | | | | | | Mozambique | 101 | 99 |
| | | | | | | Chad | 102 | 102 |
| | | | | | | Angola | 103 | 103 |

the weight on basic requirements is relatively small. Consequently, the high values received from the other two sub-indices result in its leading position. In contrast, Finland leads the world in basic requirements, but ranks only sixth in efficiency enhancers and fourth in innovation and sophistication.

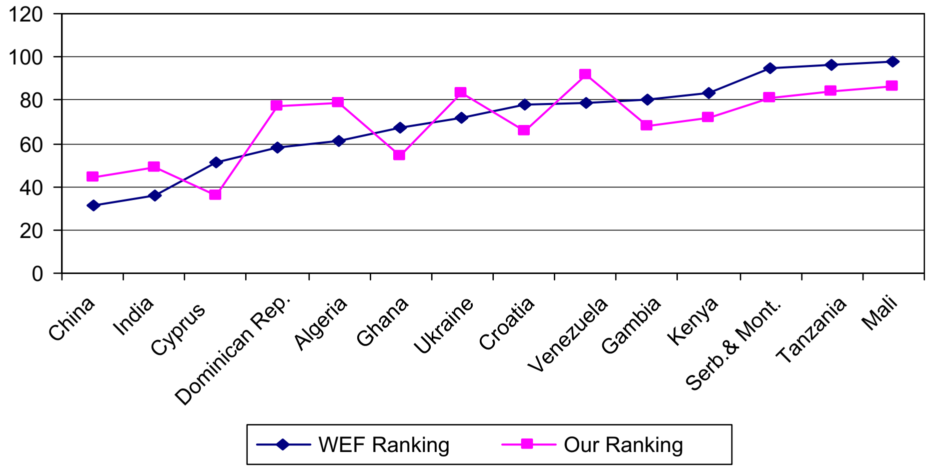


Fig. 8. Rankings of selected countries by the proposed model and WEF.

In particular, when the same countries are analyzed using our proposed methodology, a parallelism can be seen between the cluster to which a country is assigned and its global ranking. For example, China is assigned to Cluster 2 (transition countries), and, appropriately, is in the 44th place based on our global ranking.

Similarly, Taiwan is assigned to the third cluster (high competitive countries) and 16th in our global ranking. On the other hand, Italy is assigned to Cluster 2, and has a global ranking of 50, while Spain is also assigned to Cluster 2 but is in the 27th place.

## 5. Conclusions and further suggestions

Despite attempts to provide objectivity in the development of indicators for the competitiveness of countries, subjective judgments are clearly required about how data are aggregated and weights are applied. Generally, either equal weighting is utilized in calculating the final index, or some form of subjective weights is specified. The same problem also occurs in the (subjective) assignment of countries to clusters. For example, the WEF assigns countries to stages of development mainly on the basis of GDP and subjective weight structures for each stage. These subjectivities may create biases, e.g., simultaneous overestimates of the competitiveness of some countries, making them look unrealistically good, while underestimating the levels of others. Developed as such, these types of indices clearly do not provide reliable guides for executives and policy-makers.

The aim of this paper is to explore whether methodological transparency can be an adequate solution to the above-noted problems posed by existing aggregated indices. A methodology was thus proposed to objectively group countries as well as to specify weights for those criteria that play dominant roles in each resulting cluster. A new composite index that uses these weights was subsequently created. By doing so, we sought to avoid or at least reduce the criticism that such attempts may make some countries more competitive than they actually are. Further, by focusing on the criteria necessary to move a country into a higher cluster, the proposed index can be used by both policy-makers and executives responsible for making their countries more competitive.

Our methodology can also be used to evaluate how well-prepared current and future "accession countries" are to join the EU, and where particular attention should be focused to ensure that they contribute effectively to the competitiveness of an expanded EU. The impact of such additions on the EU can then be evaluated, and precautions can be taken to avoid declines from the resulting enlargement process.

Importantly, this study may be improved by including alternative variables to better reflect a nation's intellectual capital, or knowledge assets. In its current form, the study uses criteria suggested by the WEF to measure the production of knowledge. However, we note that such criteria focus on an evaluation based on the *inputs* to knowledge assets and intellectual capital. This could lead to skewed conclusions for the following reason: While the inputs may have potential use in the production of knowledge, they do not, *in and of themselves*, represent a production of knowledge. Competitiveness is linked with creation, transmission, and timely application of new knowledge, resulting in technological advance. Knowledge traditionally considered for technological advance has been restricted to the natural sciences and engineering [35]. However, if a knowledge-based economy is emerging, then both the ''hard'' and ''soft'' sides of competitiveness must be researched. It thus becomes critical to differentiate those prerequisite inputs that are necessary but not sufficient for knowledge management from those that play a more discriminatory role in specifying the relative position of countries in terms of knowledge management level.

In a further point, inferential techniques, specifically the classification and regression trees (CART) algorithm, which allows both predictor and target variables to be continuous, can be used to improve the accuracy of our cluster analysis. There is no implicit assumption that the underlying relationships between the predictor variables and the dependent variable are linear, that they follow some specific non-linear link function, or that they are even monotonic in nature. In such analyses, tree methods can often reveal simple relationships between just a few variables that can easily go unnoticed when using alternative techniques [16].

Finally, in the current study, ''subjectivity'' was taken to mean ''researcher-dependent.'' While it is clearly important to avoid bias originating from a study's researchers, ''countries,'' as researchers, do not necessarily make their choices, or take their decisions, ''objectively.'' In fact, countries generally make their choices ''subjectively,'' as their own conditions and preferences reflect positions in world politics and the economy. While our approach seeks to avoid researcher-dependent bias, the ''subjectivity'' of countries must obviously be considered as it reflects their own *perception* of reality.

In this regard, a Data Envelopment Analysis (DEA) approach could be of some value as the authors consider its use in future research efforts. Finally, a DEA might be used to benchmark countries in providing more precise policy changes [13,36,37] (for further details of such an approach, see [13]).

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