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Competitiveness of nations: A knowledge discovery examination

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Abstract

This paper presents the insights gained from the use of data mining and multivariate statistical techniques to identify important factors associated with a country's competitiveness and the development of knowledge discovery in databases (KDD) models to predict it. In addition to stepwise regression and weighted non-linear programming techniques, intelligent learning techniques (artificial neural networks), and inferential techniques (classification and regression trees), were applied to a dataset of 43 countries from the World Competitiveness Yearbook (WCY). The dataset included 55 variables on economic, internationalization, governmental, financial, infrastructure, management, science and technology, as well as demographic and cultural characteristics. Exploratory data analysis and parameter calibration of the intelligent method architectures preceded the development and evaluation of reasonably accurate models (mean absolute error <5.5%), and subsequent out-of-sample validations. The strengths and weaknesses of each of the KDD techniques were assessed, along with their relative performance and the primary input variables influencing a country's competitiveness. Our analysis reveals that the primary drivers of competitiveness are lower country risk rating and higher computer usage, in entrepreneurial urbanized societies with less male dominance and basic infrastructure, with higher gross domestic investment, savings and private consumption, more imports of goods and services than exports, increased purchase power parity GDP, larger and more productive but not less expensive labor force, and higher R&D expenditures. Without diminishing the role and importance of WCY reports, our approach can be useful to estimate the competitiveness of many countries not included in WCY, while our findings may benefit policy makers and international agencies to expand their own abilities, insights and establish priorities for improving country competitiveness.

Keywords: Data mining; Knowledge discovery; Statistics; Competitiveness; Country comparisons

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1. Introduction

A nation's competitiveness, quoted widely by many authors, has been defined by the US President's Commission on Industrial Competitiveness (1985) as "the degree to which a nation can, under free and fair market conditions, produce goods and services that meet the test of international markets while simultaneously expanding the real incomes of its citizens", thus improving their quality of life. Although many view competitiveness as a synonym for productivity (Porter, 1990), these two related terms are in fact quite different, in that, "productivity refers to the internal capability of an organization, while competitiveness refers to the relative position of an organization against its competitors" (Cho and Moon, 1998). Country risk, namely the evaluation of the creditworthiness and the economic performance of a country, is regularly assessed in two magazines, *Euromoney* and *Institutional Investor*. Country risk may be viewed as a component rather than substitute of competitiveness (as is innovation); both country risk and innovation are input variables in our study. In particular because of recent pressures introduced by globalization, it is important to have a model for analysis of a country's competitive position in the international market, and not simply its internal measure of productivity. A nation's competitiveness can be viewed as a nation's relative competitive position in the international market among other nations of similar economic development (Cho and Moon, 1998).

The foundations for competitiveness measures are built on the economic theories of exchange, supply and demand, unit total cost (or unit labor costs) and market behavior, and may be used to define competitiveness in one of the following ways (Artto, 1987):

1. Cost-competitiveness—the most common measure, based on unit labor costs.
2. Price-competitiveness—measured with relative export prices.
3. Non-price competitiveness—based on cost and price competitiveness measures.

Although many researchers have studied the subject of competitiveness and suggested relevant measures, most of the studies focus on the firm level (Karnani, 1982; Oral, 1985, 1993; Oral and Chabchoub, 1996; Oral et al., 1999; Li and Deng, 1999). Table 1 summarizes the measures proposed in these studies, which are primarily within a firm or an industry, and mostly within a single country.

Fewer studies have attempted to compare the relative competitiveness of countries for a specific industry, as shown in Table 1. While unit labor cost (ULC) is typically used to define a country's manufacturing competitiveness (Enoch, 1978), other measures such as relative total cost (RTC) have also been proposed (Artto, 1987). Menzler-Hokkanen (1989) points that the limitation of the customary measures of competitiveness is that many of them, like for example ULC, are arbitrary and thus they are not adequate indicators of a country's true competitive position. He also points out that the RTC index has a major shortcoming in that the financial and economic conditions are treated as if they were deterministic. In fact, the motivation for our study is best summarized by Menzler-Hokkanen (1989) in his concluding remarks: "The level of international competitiveness of an industrial sector or a given firm depends on several forces on the micro and macrolevel. Only the collective consideration of these variables will lead to an understanding of the dynamics underlying international competitiveness... Employing single indices as the sole measure of competitiveness appears to oversimplify the problem."

Very few studies have attempted a more comprehensive comparison of multicountry competitiveness. Extending his prior work for competitive firm advantage, Porter (1990) suggested the well-cited "national diamond" framework and applied it to each economic sector of ten industrialized nations based on six sources of national competitiveness: sector, related industries, demand, firm environment, government, and chance. Rugman and Cruz (1993) criticized its limitations for Canada and extended it to a "double diamond". Cho and Moon (1998) present a related framework based on physical, human, and governmental

Table 1
Literature review of competitiveness measures at the firm and industry levels (single or few countries)

Author	Measure	Scope of Measure	Goal
Karnani (1982)	Developed the concept of equilibrium market share	Conceptual, within a firm	To determine the firm's growth potential and competitive strength
Oral (1985, 1993), Oral and Chabchoub (1996), Oral et al. (1999), Oral and Ozkan (1986)	Describe a measure of foreign-market competitiveness of local manufacturing firms	Within an industry and a country. Based on the study of Turkish manufacturing firms	Industrial competitiveness model, analyzes the degree of competitive advantage on the basis of industrial mastery and cost superiority
Li and Deng (1999)	Developed a model to identify and relate the determinant factors of competitive advantage (DFCA) and competitive strategic goals (CSGs)	Within a firm and a country. Based on a study of an electronic plant in China	Develop a comprehensive analysis model of competitive advantage (AMCA) to help managers understand the firm's competitive position that of their competitors', the firm's strategic goals, and the relationship between the firm's DFCA and CSGs
Kao and Liu (1999)	Two primary indicators: automation technology and manufacturing management. Index is based on a linear programming fuzzy weighted average approach, containing four secondary indicators that describe technology, and eighteen that describe management	Within an industry and a country. Rank the competitiveness of 15 machinery firms in Taiwan	Calculate the relative competitiveness of industries within a country
Peterson and Barras (1987)	Relative competitive advantage index measuring the importance of service exports to total exports of a country	Across industries and a country	Competitiveness index for tradable products and services
Velocci (1998)	Index calculated via discriminant analysis of key operating and financial ratios, including asset utilization, productivity, financial stability, earnings protection, liquidity, and market valuation, weighted based on surveys of executives from those industries	Within an industry and a country. Based on publicly traded airlines and aerospace enterprises	Calculate an index of competitiveness rankings for an industry
Yamin et al. (1997)	Hypotheses and factors affecting competitive strategy, organizational innovation and performance	Within an industry and a country. Based on Australian manufacturing companies	Based on surveys of industry managers, but stops short of aggregating this information into a single index
Enoch (1978)	Unit labor cost (ULC)	Typical concept	Define a country's manufacturing competitiveness
Artto (1987)	Total competitiveness indicators, based on relative total cost (RTC), drawn from the financial statements of the firms and including all the traditional competitiveness dimensions (cost, price, and non-price factors) relating total cost to net sales	Total competitiveness indicators for the Finnish paper industry in relation to that of four other countries	Compare the Finnish paper industry competitiveness to the Swedish, West German, Canadian, and US paper industries

(*continued on next page*)

Table 1 (*continued*)

Author	Measure	Scope of Measure	Goal
Menzler-Hokkanen (1989)	Redefines ULC as the sum of all labor costs (including wages, salaries, social costs and other employment taxes) divided by the volume of output produced by that labor	Extended ULC concept	Extend definition of country's manufacturing competitiveness, and point out the shortcomings of both ULC and RTC

factors, illustrated with 16 Asian countries that are clustered by patterns of economic development. They included an innovation component that has been studied extensively by Nasierowski and Arcelus (1999) using structural equations modeling and factor analysis to compare countries, and extended to a National Technological System Index (Nasierowski and Arcelus, 2000). Ivanova et al. (1998) compared the competitiveness rankings of Latin American countries based on five composite indexes: their regional index, country risk index of Euromoney and Institutional Investor, UN's Human Development Index, and the World Competitiveness Yearbook (WCY) discussed below.

The Institute for Management Development (IMD, http://www.imd.ch), initially jointly with the World Economic Forum, produces since 1982 the most extensive and widely publicized comparisons of nations' competitiveness via the annual publication of the WCY. It develops a competitiveness score, ranking a select group of Organization for Economic Co-operation and Development (OECD http://www.oecd.org/home) and newly industrialized countries based on 288 (for 1999) socio-economic and political indicators, of which 42 were background information not used in the rankings. Surveys of 4160 executives provided 1/3 of the 1999 data, while 2/3 of the data were taken from international and individual country statistics. WCY provides a competitiveness score for each country by synthesizing all collected information into eight major factors: (1) domestic economy, (2) internationalization, (3) government, (4) finance, (5) infrastructure, (6) management, (7) science and technology, and (8) people. The undisclosed methodology of WCY is hard to "guess", as Oral and Chabchoub (1996) found after detailed mathematical programming modeling by (sub)-factor levels, suggesting the need of other statistical or mathematical programming techniques, like those explored in our study.

Our research focuses on the use of data mining techniques to identify important factors associated with determining a country's competitiveness and the development of knowledge-based models to predict a country's competitiveness score. The dataset employed consists of 55 independent variables and 43 countries listed in the '99 WCY, and it is used to predict their competitiveness score. As explained in the next sections, two data mining techniques, *Classification and Regression Inferential Trees* and *Neural Networks*, are utilized in this study, in addition to a statistical and a mathematical programming method.

2. Knowledge discovery in databases

In recent years, the process of finding and interpreting patterns from data, known as *Knowledge discovery in databases* (KDD), [1] and specifically the application of *data mining* (DM) methods or algorithms together with the interpretation of these patterns, has generated unprecedented interest in the business community. The knowledge management community regards KDD as systems that enable new knowledge creation (Becerra-Fernandez, 2001). Both statistical and intelligent data mining techniques have been utilized in the

[1] For an extensive treatise on KDD methods and applications, see Fayyad et al. (1996b).

scientific and engineering research fields for years, for example in breast cancer diagnosis (Kovalerchuck et al., 2000). Perhaps the recent proliferation of e-commerce applications, providing realms of hard data ready for analysis, together with the increasing availability of computing power and integrated DM software tools, have contributed to the increasing popularity of DM applications to business concerns. Over the last decade intelligent techniques have been applied across business problems (Smith and Gupta, 2000), [2] for example in,

1. Marketing—for *target marketing* including market segmentation, through the use of DM techniques to segment customers according to basic characteristics and purchasing patterns. Also to improve *direct marketing* campaigns, through an understanding of which customers are likely to respond to new products based on their previous consumer behavior.
2. Retail—for *sales forecasting*, which take into consideration multiple market variables. Intelligent techniques like *market basket analysis* also helps to uncover which products are likely to be purchased together.
3. Banking—for *trading* and *financial forecasting*, to determine derivative securities pricing, futures price forecasting, and stock performance. DM techniques have also been used successfully to develop scoring systems to identify credit risk and fraud. An area of recent interest is attempting to model the relationships between corporate strategy, financial health, and corporate performance. This is the same venue as our present paper, which aims at predicting a country's competitiveness based on a set of variables used to characterize each country.
4. Insurance—for segmenting customer groups to determine *premium pricing* and predict *claim* frequencies, as well as to detect claim fraud and to aid in customer retention.
5. Telecommunications—mostly for market basket analysis and to predict customer return or attrition to a competitor.
6. Operations management—for planning and scheduling, project management, and quality control. In fact, by 1996, 95% of the top banks in the US were utilizing intelligent techniques (Smith and Gupta, 2000), for example to determine a customer's likelihood of purchasing a new product (Bank of Montreal). E-commerce applications include Web site personalization based on customer's ZIP code information (eBags.com), and better managing customer traffic (Proflowers.com) via inventory optimization to downplay on Web-storefronts better selling products while highlighting slower selling ones (Stevens, 2001).

We discuss in the next sections how we applied the KDD process to uncover knowledge that will better serve to assess a country's competitiveness, as well as the primary factors that influence that outcome.

3. Modeling approaches

Two types of DM predicting techniques will be used in this study:

(A) *Neural networks*, specifically multilayered feedforward with the backpropagation learning rule and radial basis function network (RBFN) training methods.
(B) *Inferential techniques*, specifically the classification and regression trees (CART) algorithm, which allows both the predictor and target variables to be continuous.

3.1. Neural network models

The most popular neural network (NN) algorithm is the multilayered feedforward neural network with the backpropagation learning rule (Bishop, 1994; Fu, 1994; Hornik et al., 1989; Smith

[2] For an extensive review of articles on neural network models and applications to specific business problems see Bishop (1994), Widrow et al. (1994), Wong et al. (1997) and Smith and Gupta (2000).

and Gupta, 2000; Walczak, 2001a; Widrow et al., 1994; Wong et al., 1997), which is known to exhibit superior performance to other neural network paradigms (Barnard and Wessels, 1992; Benjamin et al., 1995; Walczak, 1998). Backpropagation calculates the difference between calculated results of using the network weights and the outputs of the training set, and feeds back the error network by adjusting the weights in a recursive fashion in order to minimize the error. Network training is accomplished by seeking the set of values for the weights that minimizes an error function, such as the sum-of-squares errors. Because of their non-parametric nature, neural networks can also serve as an evaluation mechanism for business decisions and prediction or classification heuristics (Walczak, 2001b).

In this study, in addition to using the backpropagation-learning algorithm, the radial basis function (RBF) network training algorithm was also evaluated for constructing the neural network models to predict competitiveness. Each of the above two learning methods, backpropagation and RBF network training, were used to develop neural network models to predict the competitiveness measure for each of the 43 countries in the dataset. In order to avoid the possibility of over- or under-training the predictive model, we experimented with multiple architectures to avoid problems associated with under-fitting and over-fitting of the training data (Barnard and Wessels, 1992; Walczak and Cerpa, 1999), each time seeking to minimize the mean square error and secondarily the mean absolute percent error between the predicted and actual competitiveness scores. RBF network is based on the idea that any function can be approximated by the linear superposition of a set of localized basis functions, thus overcoming some of the difficulties of multilayer perceptron, resulting in a simpler and computationally less intensive network training process, and an output which is easier to interpret (Bishop, 1994).

Bishop (1994) summarizes the various stages involved in the training of a NN as follows:

1. Select the number of hidden neurons in the NN architecture, and initialize with random values the network weights.
2. Train the NN seeking to minimize the error with respect to the training data set, using a recursive procedure such as the backpropagation algorithm.
3. Repeat the training process using different initial random weights to avoid a solution around the local minima (vs. the global minima).
4. Test the NN with a fresh dataset using an error function.
5. Repeat the training and test for different network configurations and compare the corresponding error function.
6. Select the NN architecture with the smaller test error.

In this study, we repeated the training with different network configurations in order to pick the best predictive NN, and calibrated each configuration by varying the percent training and other parameters listed below if applicable to an option. [3] The *Quick* NN creates a network with only one hidden layer, while its *expert* option allows the user to select up to three hidden layers and the number of neurons within each of these layers. The *Dynamic* NN defines a growing network that begins with two hidden layers of two neurons each and grows by adding one neuron to each layer, until it detects either over-training or degradation in the network accuracy. The Dynamic NN has no Expert option. *Multiple* allows the creation of a number of NNs with differing topologies. NN topologies can be defined with varying hidden layers, and differing number of neurons in each layer. The networks are trained in parallel, therefore causing this method to be extremely slow. The *Prune* option will train and remove hidden neurons until there's no improvement in the network, and may yield good results at the expense of considerable longer computing times. *Persistence* is the number of cycles for which the network will train without improvement, before it attempts to pruning the layers.

[3] The network options discussed here are offered with SPSS Clementine ©. For more information refer to SPSS (2000a,b) appearing in the reference list.

The Prune method will continue based on the parameter of persistence (changed from 200 to 100), which is the number of cycles for which the network will train without improvement before it attempts to prune one of the layers. The *RBF* NN creates a RBF network that is trained as a single layer perceptron. Each of the resulting networks will perform with different accuracies; therefore it is best to try a number of NN models and pick the one that offers the best performance. Hence we calibrated the RBF networks via the no-expert or expert option; for the latter, the persistence was increased from 30 to 50 and alpha was reduced from 0.9 to 0.2. *Alpha* refers to the momentum used in updating the weights when trying to locate a global solution. The use of expert option in NN allows specifying persistence and alpha values, rather than accepting the default values of the no-expert option.

A grid search is employed to evaluate quickly various network architectures, starting with a small number of hidden nodes, say five, and successively increasing it by the same number. Additionally, since the shape and complexity of the response surface is unknown, both one and two hidden layer NN architectures are used for back-propagation, thus enabling modeling of more complex non-linear surfaces (Fu, 1994; Walczak and Cerpa, 1999). In all, a total of twelve different NN architectures were implemented, after several calibrations of NN parameters, most importantly the percent training used to prevent over-training (as shown in Section 5.3).

3.2. Inferential KD techniques

These learning algorithms try to develop a classification (branching) scheme that will predict the response variable based on the values of several attributes (Breiman et al., 1984; Fayyad et al., 1996a). The purpose is to produce an accurate classifier or to uncover the predictability of a response (Breiman et al., 1984). An efficient way of predicting classifiers from data is to generate a decision tree, which provides automated techniques for discovering how to generate classification schemes (Breiman et al., 1984; Apte and Hong, 1996; Apte and Weiss, 1997). KD inferential techniques can be used to develop decision trees and rules for efficient search of conditional attribute branches that can be used to classify the dataset as a function of its characteristics.

Breiman et al. (1984) first described the classification and regression tree (CART) algorithm, which has become one of the most popular methods to build a decision search tree. Other classification methods also include χ-squared Automatic Interaction Detector (CHAID) and C5.0 (the most recent version of ID3, C4.0 and C4.5). C5.0 and CART are similar classification methods, one of the main differences being on how C5.0 treats categorical variables, since CART always performs a binary split of a continuous variable at each note, while C5.0 will assume one branch for each value taken on by the discrete variable (Berry and Linoff, 1997). Thus CHAID (Hartigan, 1975) can also be used to build decision trees, but its use is restricted to categorical variables. Because of the continuous characteristics of the dataset in this study, we selected the CART algorithm. The CART classification process begins at the top of the tree, which is the root node. An attribute is selected to divide the sample at the root node. Then the test at the root node tests all samples, which pass to the left if True, or to the right if False. At each of the resulting nodes (called the *parent* nodes), further tests serve to continue classifying the data (creating *children* nodes). The algorithm is applied recursively to each child node until either all examples at a node are in one class, or all the examples of that node have the same values for all attributes (Fayyad et al., 1996a). Every leaf of the tree represents a branching (classification) rule. Rule-based solutions translate the tree by forming a conjunct of every test that occurs on a path between the root node and the leaf node of the tree (Apte and Weiss, 1997). The CART algorithm makes its best split first, at the root node, each following split having smaller and less representative population and the decision tree will continue growing as long as new splits improve the ability of the tree to separate the records (Berry and Linoff, 1997). The error of the entire decision tree will amount to a weighted sum of the predictive error rate of the leaves. Pruning enables obtaining a more accurate tree, by pruning the branches that provide the least predictive power (Berry and Linoff, 1997). Therefore, pruning helps to remove the effects of overtraining, while not losing valuable information. Additionally, method calibration was attempted via different tree architectures, through variation of the tree depth options (number of parents and children).

Traditional statistical prediction methods like regression and discriminant analysis, attempt to fit a model to data. In contrast, decision trees successively partition the data based on the relationships between predictor variables and outcome variable. The resulting tree indicates the predictor variables having strong relationship to the outcome (the stronger the closer to the root node), and which subgroups have concentrations of cases with specified characteristics (Breiman et al., 1984). In other words, variables at the root node represent the strongest classifiers (denotes as Level 1 in Section 5.4), followed by the next strongest classifiers at each of the leaf nodes (denoted as Levels 2 and 3, etc.).

One of the advantages offered by rule induction algorithms is that the results may be directly inspected to understand the variables that can be effectively used to classify the data. Another advantage of decision trees is that they can handle a large number and different types of predictor variables. In reality, data sets are often characterized by complexity, including high dimensionality, a mixture of data types, and non-standard data structures—in other words "different relationships hold between variables in different parts of the measurement space" (Breiman et al., 1984 , p. 7). Along with complex data sets, comes "the curse of dimensionality" (attributed to Bellman, 1961) as well as heterogeneity, which highlight the need for algorithms like CART that are entirely non-parametric; thus they can capture relationships that standard linear models do not easily handle. Finally, CART is robust in the presence of missing data and therefore it can accept missing values in the dataset (in contrast to NN that often experience difficulties with many missing values).

3.3. Statistical and mathematical programming techniques

In addition to the above two KDD techniques, we use:

(A) *Stepwise regression analysis* to predict country competitiveness scores, after the exploratory data analysis on the independent variables described in the next section.
(B) *Weighted non-linear programming*, to predict the competitiveness score $Y_{i,}$ for each of the n countries, as a weighted function of the m independent variable values X_{ij} that will minimize the sum of square errors (SSE) and equivalently the mean square error (MSE).

Find weights W_{ij} such that to

$$\text{Minimize}\quad \text{SSE} = \sum_{i=1}^{n}[Y_i - \hat{Y}_i]^2 = \sum_{i=1}^{n}\left[Y_i - \sum_{j=1}^{m} W_{ij}X_{ij}\right]^2, \tag{1}$$

$$\text{s.t.} \sum_{j=1}^{m} W_{ij} = 1 \quad \text{for } i = 1, 2, \ldots, n, \tag{2}$$

$$\text{all weights } W_{ij} \geqslant 0. \tag{3}$$

This problem was solved using the Excel Premium Solver (Fylstra et al., 1998), with non-negativity and automatic scaling option. The latter is necessary because of the different scale magnitudes of the independent variables. Other attempts to standardize X_{ij}, before applying the above model, did not producer better results. Several non-linear search algorithms were evaluated, including Newton and Conjugate (with central or forward derivatives, and tangent or quadratic estimates), as well GRG and Evolutionary Search. The latter two required almost 1200 iterations. Different starting points were attempted in order to avoid local optima, as well using the best solution of each search algorithm as the starting point for another algorithm. The best results are presented after the data presentation of the next section.

4. Data understanding and exploratory analysis

The 1999 WCY competitiveness score was used in our study as dependant variable (World Competitiveness Yearbook, 1999). We selected the 1999 WCY to match the year available (late 90s) for the data collected in this study for countries included in the '99 WCY. Guided by the content of the eight factors in WCY, we collected from a variety of databases (World Bank, UN, World Factbook, IMD, etc.) data on 47 promising variables for 43 countries included in the 1999 WCY. Table 2 lists these variables, grouped according to the eight WCY factors, plus eight extra variables added subsequently. The latter included Hofstede's (1991) four cultural country dimensions: individualism, power distance between authority and subordinates, culture importance to masculine personality traits, and uncertainty avoidance indexes—as a proxy of cultural, managerial and entrepreneurial styles in a country. In addition the variables include the purchasing power parity, as a measure of cost-of-living adjusted real domestic wealth per capita, and three R&D measures found to affect a country's technological innovativeness (Nasierowski and Arcelus, 1999, 2000). Note that variable abbreviations are in alphabetical order (except for the extra variables at the end). The complete dataset included a total of 55 variables and 43 countries, with a few (8.9%) values missing in the 2365 data-cells.

Exploratory analysis of the 55 variables was undertaken prior to any model development, as summarized in Table 2. For each variable, the correlation with the competitiveness score, percent missing values and the result of a dichotomous t-test are reported in the first three column results of Table 2. The t-test uses each variable missing/valid data occurrence as a two-group indicator to assess the equality of the two group means in each of the remaining variables (Hair et al., 1998, pp. 58–59). It identified eight problematic variables for which the number of times this t-test was rejected as shown in Table 2 (WAT_RUR and WAT_URB, 13 times each), along with a "+" to signify minor missing patterns in other variables. Nevertheless, Little's MCAR χ-square test (Hair et al., 1998, p. 60) confirmed that data was missing completely at random (pval = 0.817). Hence, estimates of all missing values were imputed using the EM algorithm of Dempster et al. (1977). In step E, this algorithm computes the expected log-likelihood value, and in step M it maximizes this function to provide new estimates. Likelihood-based imputation methods are generally preferred, even when the underlying normality assumptions do not hold or data are missing at random (Little, 1992). The number of low and high EM extremes for each variable is also shown in Table 2, along with the variables identified as overall outliers through principal component analysis. In addition, the significance level of Kruskall–Wallis non-parametric ANOVA is listed for each variable (high p-values indicate variables individually not affecting competitiveness score significantly). The collective impact of all these exploratory analyses is summarized in the last two columns of Table 2 as a *Yes*/*No* expectation for each variable to be a good predictor of competitiveness score (blanks denote marginal).

An additional test, the χ-square for the Mahalanobis distance, was also undertaken to explore the existence of multivariate country outliers. None was found at the 0.001 level of significance. However, the test pointed to five high multivariate extremes (US, Venezuela, Brazil, Japan and China) and five low extremes (Canada, Italy, United Kingdom, Turkey and Switzerland). These are not multivariate outliers, but they could be outliers or influential observations for single variables.

5. Results and discussion

In this section we present and discuss the results of models obtained using the four approaches: statistics, non-linear programming, neural networks and inferential trees.

Table 2
Exploratory analysis summary

Variable	Abbreviation	Correlation to competitiveness score[a]	Miss %	Miss value *t* rejects[b]	EM low extreme[c]	EM high extreme[c]	PCA outlier	KW significance	Expected good predictor
Balance of trade ranking	BAL_RANK	−0.092	0.00		0	0		*0.412*	N
Balance of trade imports/exports	BAL_TRADE	**−0.224**	0.00	+	2	3		*0.420*	Y
Ratio of bank liquid reserves to bank assets	BNK_RAT	**−0.308**	0.02	+	0	4		0.001	Y
Bank and trade related lending ($millions)	BT_LEND	0.113	***0.60***		0	2	Medium	*1.000*	N
Capital expenditure (% of total expenditure)	CAP_EX	**−0.237**	0.05	+	0	3		0.078	Y
Carbon dioxide damage (% of GDP)	CO	**−0.518**	0.00	+	0	3		0.000	Y
Public expenditure on education (% of GNP)	COLLEGE	**0.406**	0.05	+	0	0		0.041	
Computers per 1000 people	COMP	**0.868**	0.00	+	0	0		0.000	Y
Conversion rate local $ to US$	CON_RATE	−0.163	0.14		0	***5***	Bigest	0.054	N
Consumer price index (1990 = 100)	CPI	**−0.315**	0.02	+	0	***7***	Medium	0.000	Y
Gross domestic investment (% of GDP)	DOM_INV	−0.146	0.00		0	3		0.142	
Gross domestic savings (% of GDP)	DOM_SAV	0.077	0.00	+	0	3		***0.327***	
Electricity consumption per capita (kW h)	ELECT	**0.615**	0.00	+	0	4		0.000	Y
Employment rate (% of population)	EMPLOY	0.123	0.02	+	2	0		***0.856***	
Energy depletion (% of GDP)	ENERGY	**−0.386**	0.02	+	0	***9***		0.013	Y
Total expenditure (% of GDP)	EXPEND	**0.282**	0.09	5	0	0		0.072	N
Export of goods and services (% of GDP)	EXPORT	**0.317**	0.00	+	0	***5***		0.193	Y
Foreign direct investment (% of GDP)	FOR_INV	0.005	0.05	+	0	2		***0.630***	N
Gross domestic product (US$ billions)	GDP	**0.449**	0.00	+	0	***7***		0.100	Y

General government consumption (% of GDP)	GOVT_CON	−0.042	0.00		0	1		***0.300***		N
Adult illiteracy rates (% of population)	ILLETER	**−0.410**	0.00	+	0	2		0.002	Y	
Import of goods and services (% of GDP)	IMPORT	**0.258**	0.00	+	0	3		***0.317***	Y	
Real short term interest rates	INT_RAT	**−0.253**	0.02		0	4		***0.789***		N
Intellectual property (patent applications filed)	INTELL	**0.483**	0.00	+	0	2	Big	0.000	Y	
Labor costs	LAB_COST	**0.299**	***0.37***	10	0	0		***0.373***		N
Labor force (millions)	LAB_FOR	−0.136	0.00		0	***6***		0.080		
Labor force (% of population)	LAB_PER	**0.234**	0.00	+	2	0		0.091		
Arable land area (1000 ha)	LAND	−0.052	0.02	+	0	***5***	Medium	0.146		
Labor force structure in population aged 15–64 (millions)	LB_STRUT	−0.075	0.02	+	0	***5***		0.116		
Domestic debt (% of GDP)	NAT_DEBT	**0.250**	0.12	5	0	0		0.066	Y	
Telephone lines per 1000 people	PHONE	**0.779**	0.00	+	0	0		0.000	Y	
Population (millions)	POPUL	−0.160	0.00		0	***6***		0.063		N
Private consumption (% of GDP)	PRI_CON	**−0.338**	0.00	+	2	1		0.050	Y	
Private investment (% of gross domestic fixed investment)	PRI_INV	**0.384**	***0.42***		2	0		***0.331***		N
Overall productivity (US$ per person employed)	PROD	**0.766**	0.00	+	0	0	Big	0.000	Y	
Quality of life index	QUALITY	−0.024	0.00		0	***4***		***0.227***		N
Research and development expenditure (US$ millions)	RD_EXP	**0.462**	0.00	+	0	*5*		0.001	Y	

Table 2 (*continued*)

Variable	Abbreviation	Correlation to competitiveness score[a]	Miss %	Miss value *t* rejects[b]	EM low extreme[c]	EM high extreme[c]	PCA outlier	KW significance	Expected good predictor
Scientists, engineers and technicians in R&R (per million people)	RD_PEP	**0.574**	0.02	+	0	0		0.000	Y
Revenue (% of GDP)	REVENUE	**0.365**	0.07	7	0	0		0.011	
Composite international country risk rating (1–100 best)	RISK	**0.742**	0.00	+	2	0		0.000	Y
Density of road network (km/km^2)	ROAD	**0.359**	0.00	+	0	3		0.084	
Access to sewage (% of rural population)	SEW_RUR	**0.529**	***0.40***	8	0	0		0.021	N
Access to sewage (% of urban population)	SEW_URB	**0.495**	***0.35***	6	4	0		0.012	N
Expenditure per student on tertiary education	STU_EXP	0.032	0.16		0	1		***0.405***	N
Urban population percentage	Urban	**0.383**	0.05	+	0	2		***0.432***	
Access to water (% of rural population)	WAT_RUR	**0.513**	***0.58***	***13***	0	0		0.135	N
Access to water (% of urban population)	WAT_URB	**0.615**	***0.53***	***13***	1	0		0.040	N
Individualism index	IDV	**0.526**	0.16		6	6		0.002	Y
Power distance index	PDI	**−0.573**	0.16		*9*	*9*		0.001	Y
Masculinity index	MAS	−0.199	0.12		*8*	*8*		***0.574***	N
Uncertainty avoidance index	UAV	**−0.442**	0.02		*10*	*10*		0.029	Y
Purchasing power parity	PPP	**0.886**	0.02		0	0		0.000	Y
Ratio of business to government expenditures in R&D	RDB	**0.459**	0.05		0	0		0.001	Y
Employment in technology sector	EMT	**0.396**	0.02		0	0		0.029	Y
Employed engineers and scientists in R&D (% EMT)	EMRD	**0.204**	0.02		0	0		0.029	Y

Bold: desirable; ***bold italic:*** undesirable.

[a] $R > 0.3$ significant at $\alpha = 0.01$.

[b] +: affected.

[c] Cases not in (Q1-1.5*IQR, Q3+1.5*IQR).

5.1. Stepwise regression models (SWR)

Even after eliminating the weak or problematic variables identified in the prior exploratory data analyses, the number of observations (countries) is not, as recommended for regression purposes, several times bigger than the number of independent variables. Furthermore, severe multicolinearities exist between several independent variables. Thus, the dataset was partitioned into groups, such that (a) no extremely highly collinear Xs exist in any group, and (b) each group contained reasonably more observations that variables. The best regression model from each subset (without regard to multicolinearity) identified good predictors that were all combined to produce a combined model. All these good models were scrutinized for multicolinearity and outliers. Several good SWR models, without multicolinearities, reasonable residual behavior and all slope p-values <10%, are listed in Table 3. The best model, number 1 was further improved by eliminating two outliers (China and Slovenia), yielding two alternate models numbered 2 and 3. Model 2 is taken as the best SWR exhibiting $R^2_{\text{adj}} = 0.9311$ and $\text{MSE} = 13.48$. Standardizing the dataset by replacing all observations for each variable with their Z scores (as it is done in WCY), produced models 4 and 5, having lower R^2 than models 1–3. Two of the cultural variables (MAS and UAV) appeared in model 6, which has a lower $R^2_{\text{adj}} = 0.8832$ than the best model 2. A further attempt was made to improve model 2 by transforming Y into LnY, in order to eliminate a minor heteroscedasticity of residuals and slight exponentiality of a few independent variables. This model, number 7, produced good results but not as accurate as model 2. Therefore, model 2 is taken as the best SWR model. Note that a few other significant variables (DOM_INV, DOM_SAV, EXPORT, INTELL, PHONE, PROD and WAT_RUR) entered in inferior alternate SWR models, all with larger MSE and $0.74 \leqslant R^2_{\text{adj}} \leqslant 0.88$, which have not been considered further.

The SWR models in Table 3 also reveal the most frequently encountered significant predictors of competitiveness: COMP (12 times), RISK (11),

Table 3
Stepwise regression models

SWR Model	1	2	3	4	5	6	7
Constant	35.3313	38.5393	38.9384	65.1285	65.4267	38.5779	3.6307
CO	−8.2298	−8.7006	−8.7326	−4.1224	−4.2071		−0.1583
COMP	0.0531	0.0526	0.0526	7.1346	7.2556		0.0007
EMRD					3.1913		
GDP	0.0020	0.0025		2.7791			2.035E-05
IMPORT	−8.2298	0.0795	0.0775	2.4451	2.3871		0.0012
LB_STRUT	0.0252			3.1560	2.6617		0.0005
MAS						−0.0723	
PPP						0.0010	
RD_EXP			0.0001			0.0001	
RISK	0.2615	0.2306	0.2304	2.9919	2.7959	0.2955	0.0053
UAV						−0.1171	
Adj R-Square	0.9122	**0.9311**	0.9298	0.9043	0.9033	0.8832	0.9020
St Err of Est	3.9772	**3.6721**	3.7190	4.0763	4.1579	4.7027	
MSE	15.8181	**13.4841**	13.8309	16.6160	17.2880	22.1156	
Remarks:	w/o China	w/o China and Slovenia	w/o China and Slovenia	Std data Variables as in 1	Std data Variables similar to 1		LnY Variables as in 1 and 4

CO (9), IMPORT (7), GDP (6), LB_STRUT (5), RD_EXP (5), and 2 times each PPP, PROD, and UAV, in addition to eight other variables each encountered once.

5.2. Weighted non-linear programming models (WNLP)

The WNLP model with non-negative unknown weights for each variable, requires that all independent variables influence competitiveness in the same direction. Ten exploratory variables, identified because of their opposite direction to competitiveness and/or significant negative correlation with it, were transformed linearly as $X^* = (\text{Max} - X)/(\text{Max} - \text{Min})$ to change their direction: BAL_TRADE, BT_LEND, BNK_RAT, ENERGY, CO, CPI, PDI, MAS, UAV and ILLETERACY (to LITERACY).

As indicated in Section 3.3, to overcome local optima several search algorithms were employed to solve the constraint non-linear optimization problem (Eqs. (1)–(3)), starting from different starting points, as well using the best solution of each search algorithm as the starting point for another algorithm. The best solution, using sequentially Newton and Conjugate search (with central derivatives and quadratic estimates) achieved MSE = 23.80 and mean absolute error (MAE) = 6.26%. With this as the starting point, sequential application of GRG and evolutionary search identify the best solution reported in Table 4 yielding MSE = 14.89 and MAE = 4.69%. Note that the correlation between the actual and predicted competitiveness score was 0.959, which of course is a necessary but not sufficient condition of good fit; a counter example is two parallel series far apart that have perfect correlation but big gaps (errors). It is very interesting to observe that, although the WLP model improved in MSE objective relatively to the one without directional transformations (MSE = 17.64 and MAE = 5.33%), it produced not very different set of variables with non-zero weights, while all of the transformed variables had practically zero weights, except two cultural ones (MAS and UAV).

The best solution weights for each independent variable are shown in Table 4. The twelve heaviest

Table 4
Weighted non-linear programming model

Input variable	Weights to Min SSE (%)
RISK	24.036
LAB_COST	14.399
DOM_INV	12.841
PRI_CON	8.912
UAV[a]	7.975
MAS[a]	6.555
LETERACY[a]	5.654
BAL_RANK	5.603
URBAN	3.841
COMP	2.822
WAT_RUR	2.472
IMPORT	2.381
SEW_RUR	0.946
LAB_FOR	0.821
LB_STRUT	0.696
PROD	0.030
RD_EXP	0.007
DOM_SAV	0.006
PPP	0.004
LAND	0.001
POPUL	0.000
BAL_TRADE[a]	0
BNK_RAT[a]	0
BT_LEND[a]	0
CAP_EX	0
CO[a]	0
COLLEGE	0
CPI[a]	0
ELECT	0
EMPLOY	0
EMRDB	0
EMT	0
ENERGY[a]	0
EXPEND	0
EXPORT	0
FOR_INV	0
GDP	0
GOVT_CON	0
IDV	0
INT_RAT	0
INTELL	0
LAB_PER	0
NAT_DEBT	0
PDI[a]	0
PHONE	0
PRI_INV	0
QUALITY	0
RD_PEP	0
RDB	0
REVENUE	0
ROAD	0
SEW_URB	0

Table 4 (*continued*)

Input variable	Weights to Min SSE (%)
STU_EXP	0
WAT_URB	0
Total	100
MSE	14.58
MAE	4.66%
Correl Y and Y^	0.960

[a] Direction reversed.

weighted independent variables and their weights are:

RISK 24.04 %, LAB_COST 14.40%, DOM_INV 12.84%, PRI_CON 8.91%, UAV* 7.98%, MAS* 6.56%, LETERACY* 5.65%, BAL_RANK 5.60%, URBAN 3.84%, COMP 2.82%, WAT_RUR 2.47%, IMPORT 2.38% (where * denotes direction transformed). Seven more variables had a minor influence: SEW_RUR 0.95%, LAB_FOR 0.82%, LB_STRUT 0.70%, PROD 0.03%, RD_EXP 0.007%, DOM_SAV 0.006%, and PPP 0.004%. The remaining thirty-six independent variables did not practically influence the results (ten of which had zero weights).

Given the large number of variables with zero or nearly zero weights in the above model, we deleted them and repeated the WNLP runs. No better solution could be obtained than MSE = 14.89, while the variable weights remained practically the same.

5.3. Neural network models (NN)

After extensive experimentations to calibrate network parameters as described in Section 3.1, twelve architectures were selected for developing and evaluating NN models: dynamic no expert with 85% and 75% training; multiple expert 85% training; multiple no expert with 75% and 86% training; Prune expert 85% training; quick expert 75% training, and quick no expert 75% and 86% training, RBFN expert 86% training, and RBFN no expert 75% and 86%.

As an additional step to exploit NN model sensitivity to input variables, we developed the above models from four datasets, using 47 of the original 55 variables, omitting 8 weak variables identified in the exploratory data analysis (Table 2) and which degraded the performance of NN and CART. Runs with all Xs for NN and CART caused parameter calibration difficulties and inferior or unacceptable models. Our creation of the four datasets, although subjective, culminated after several trial runs and parameter calibrations, taking into account possible sensitivity to EM estimates (set 1 vs. 2–4) and the earlier exploratory data analysis findings in Section 4 (as in SWR, which could not run with all Xs simultaneously either). Calibration of NN (and CART) procedures requires several judgments and trials driven by the objective to minimize MSE in the training sample, but try to avoid overfitting. We report the most successful ones and check them in the validation experiment.

These four datasets consisted of the *initial dataset* of 33 variables with missing values; and three datasets (1–3) with EM estimates of all missing values, having 35, 36, and 44 input variables respectively. The four datasets and their resulting model errors (MSE and MAE%) for the twelve NN architectures are shown in Table 5 (Panel A). The best performance, MSE = 13.10 and MAE = 4.05%, was obtained using dataset *1* with the option of *multiple expert 85% training*, which was also the best model in the initial dataset with missing values. This most accurate NN model has an input layer with 35 neurons, two hidden layers with 27 and 22 neurons, and an output layer with 1 neuron.

Neural network methods are non-parametric and thus are not constrained by the error distributions of the population, like regression algorithms. Furthermore, neural networks provide their results instantaneously and can continue learning as new data is collected, thus facilitating updates of competitiveness predictions when a country's conditions change. However, in contrast to statistical and optimization modeling, in neural networks even when exhibiting relatively high performance, it is hard to provide a confident explanation of the results by pointing to significant input variables, mainly due to sensitivity of results to model architecture and inputs. Hence, we report with caution in Table 5(Panel B) the relative importance of input variables for each of the best

Table 5
Neural net experiments (Panel A) and neural net input variable importance (Panel B)

Panel A

Method	Dataset 1		Dataset 2		Dataset 3		Initial	
	MSE	MAE (%)	MSE	MAE (%)	MSE	MAE (%)	MSE	MAE (%)
Dynamic no expert 85% training	24.04	6.03	74.27	11.99	24.10	4.93	167.52	15.98
Dynamic no expert 75% training	20.51	5.70	40.74	7.71	***15.75***	***4.34***	47.23	7.94
Multiple expert 85% training	**13.10**	**4.05**	31.74	7.00	32.83	7.16	***29.76***	***6.59***
Multiple no expert 75% training	28.96	6.52	37.65	7.48	48.19	8.62	33.89	6.51
Multiple no expert 86% training	18.92	5.03	47.07	8.06	37.20	7.10	37.66	6.90
Prune expert 85% training	14.46	4.42	144.43	18.98	144.30	18.98	180.23	17.66
Quick expert 75% training	31.07	7.07	36.90	8.38	32.63	7.09	39.69	8.12
Quick no expert 75% training	24.67	6.07	28.91	6.34	34.51	7.47	42.17	7.87
Quick no expert 86% training	19.06	5.27	46.22	8.21	38.02	7.95	33.30	7.11
RBFN 86% training	200.10	16.00	58.62	10.32	18.62	5.74	–	–
RBFN no expert 75% training	213.34	16.84	***27.95***	***7.32***	17.79	5.87	98.87	10.60
RBFN no expert 86% training	126.44	13.38	47.57	7.75	20.24	5.91	–	–

Panel B

Input variable	Name	Multiexpert 85% training	Dynamic no expert 75% training	RBFN no expert 75% training	Overall average
BAL_TRAD	Balance of trade imports/exports	**0.0948**	**0.0727**	**0.0548**	**0.0741**
BNK_RAT	Ratio of bank liquid reserves to bank assets	0.0112	0.0173	**0.0516**	0.0267
CAP_EX	Capital expenditure (% of total expenditure)	0.0068	0.0308	0.0479	0.0285
CO	Carbon dioxide damage (% of GDP)	**0.0770**	0.0481	**0.0839**	**0.0697**
COLLEGE	Public expenditure on education (% of GNP)	0.0209	0.0267	0.0404	0.0293
COMP	Computers per 1000 people	**0.1625**	**0.1922**	**0.1286**	**0.1611**
CPI	Consumer price index (1990 = 100)	0.0461	**0.0522**	**0.0622**	**0.0535**
DOM_SAV	Gross domestic savings (% of GDP)	**0.0589**	**0.0901**	**0.0622**	**0.0704**
ELECT	Electricity consumption per capita (kW h)	0.0429	**0.0510**	**0.0743**	**0.0561**
EMPLOY	Employment rate (% of population)	0.0080	0.0268	0.0409	0.0252
EMRD	Employed engineers and Scientists in R&D (% EMT)	0.0153	0.0484	0.0356	0.0331
EMT	Employment in technology sector	0.0081	0.0341	0.0208	0.0210
ENERGY	Energy depletion (% of GDP)	0.0347	0.0279	**0.0604**	0.0410
EXPEND	Total expenditure (% of GDP)	0.0182	**0.0574**	0.0470	0.0409
EXPORT	Export of goods and services (% of GDP)	0.0178	0.0207	**0.0909**	0.0431
GDP	Gross domestic product (US$ billions)	**0.0501**	**0.0787**	**0.0791**	**0.0693**
IDV	Individualism index	0.0361	**0.0616**	0.0382	0.0453
ILLETER	Adult illiteracy rates (% of population)	0.0231	0.0256	0.0367	0.0285
IMPORT	Import of goods and services (% of GDP)	0.0456	0.0305	**0.1013**	**0.0591**
INT_RAT	Real short term interest rates	0.0312	0.0286	**0.0726**	0.0441
INTELL	Intellectual property (Patent applications filed)	0.0454	**0.0659**	**0.0677**	**0.0597**
LAB_COST	Labor costs	**0.0705**	**0.0887**	0.0418	**0.0670**
LAB_PER	Labor force (% of population)	0.0213	0.0286	**0.0931**	0.0477
LB_STRUT	Labor force structure in population aged 15–64 (millions)	0.0406	**0.0891**	0.0446	**0.0581**
MAS	Masculinity index	0.0328	**0.1123**	0.0485	**0.0645**
NAT_DEBT	Domestic debt (% of GDP)	0.0293	0.0078	**0.0851**	0.0407
PDI	Power distance index	0.0487	**0.0690**	0.0187	0.0455
PHONE	Telephone lines per 1000 people	**0.0756**	**0.0671**	**0.0995**	**0.0807**
PPP	Purchasing power parity	**0.0989**	**0.1158**	**0.1146**	**0.1098**

Table 5 (*continued*)

Panel B Input variable	Name	Multiexpert 85% training	Dynamic no expert 75% training	RBFN no expert 75% training	Overall average
PRI_CON	Private consumption (% of GDP)	0.0368	**0.0618**	0.0346	0.0444
PROD	Overall productivity (US$ per person employed)	**0.0841**	**0.1192**	**0.1182**	**0.1072**
RD_EXP	Research and development expenditure (US$ millions)	0.0439	**0.0986**	**0.0812**	**0.0746**
RD_PEP	Scientists, engineers and technicians in R&D (per million people)	**0.0565**	0.0303	**0.0613**	0.0494
RDB	Ratio of business to government expenditures in R&D	0.0211	**0.0631**	**0.0751**	**0.0531**
REVENUE	Revenue (% of GDP)	0.0493	**0.0642**	0.0322	0.0486
RISK	Composite international country risk rating (1–100 best)	**0.1065**	**0.1553**	**0.0646**	**0.1088**
ROAD	Density of road network (km/km^2)	0.0303	0.0377	**0.0805**	0.0495
SEW_RUR	Access to sewage (% of rural population)	0.0316	**0.0510**	**0.0605**	0.0477
SEW_URB	Access to sewage (% of urban population)	**0.0855**	**0.0608**	**0.0725**	**0.0730**
UAV	Uncertainty avoidance index	**0.0657**	**0.1218**	**0.0780**	**0.0885**
URBAN	Urban population percentage	0.0430	**0.0639**	**0.0652**	**0.0574**
WAT_RUR	Access to water (% of rural population)	0.0419	0.0325	0.0278	0.0341
WAT_URB	Access to water (% of urban population)	0.0238	0.0182	0.0374	0.0265

Bold > 0.05.

NN models, multi expert 85% training, dynamic no expert 75% training, and RBFN no expert 75% training, as well as the their averages. The relative importance of the input variables is the outcome of the sensitivity analysis, and is listed in descending order of importance ranging from 1.0 to 0.0, signifying extremely important to unimportant respectively. It is interesting to observe that each input variable weights vary little across the best models, indicating that the most influential NN input variables are (in order of relevance): COMP, PPP, RISK, and PROD.

5.4. Classification and regression tree models (C&R trees or CART)

Inferential trees can be calibrated through the use of options such as depth limit that defines the growth of the tree; for example *Depth3* means that the tree will grow to a maximum of three levels deep below the root node. Deeper trees may be more accurate, but will require more time to compute. Alternatively, the CART *Parent5 Child2* represents a model that requires the *Parent* node to have minimum size of 5 cases before splitting can occur (*Parent5*). The Child node is the minimum number of cases in the subgroup resulting from a split, meaning that a node will not be split further if any of the resulting nodes have fewer cases than this value, therefore in this example each resulting child node will result in a minimum of two records or values (*Child2*). In other words, in this case, a branch of a tree will be split only if two or more of the resulting sub-branches will contain at least two records from the dataset. This value could be increased to prevent over-training in the case the dataset is characterized by noisy data.

The same four datasets used in NN modeling were also employed to develop CART models. Calibrations of parameters to reduce the mean square (MSE), pointed to five promising architectures: [4]

Training simple tree with depth 3, *training expert 3 parents and 2 children*, *training expert 5 parents 2*

[4] The tree model options discussed here are offered with SPSS Clementine ©.

children, *training expert 6 parents 3 children*, and *training expert 8 parents 2 children*. These variations were based on changing the settings for the numbers referring to the pruning percentages and branches for each node. Each CART decision tree attempted revealed a vexing difficulty; namely depending on the model, predicted correlation of competitiveness score with some tree variable(s) illogical or vastly different than the sample statistical correlations, infrequently with opposite sign. Depending on the model, such conflicts were found for the inputs DOM_SAV, ELECT, EXPORT GDP, and PDI. Such variables were eliminated and the same CART model was run again, unless many such attempts failed. Table 6 shows the accuracy (MSE and MAE) of different CART models, allowing minor conflicts at lower tree levels. The CART model without such conflicts is training expert 5 parents 2 children with dataset 2, producing MSE = 4.81 and MAE = 2.42%. A further effort standardizing (*Z* scores) the dataset values produced identical results for this and other CART models.

The corresponding decision tree is shown in Fig. 1. The strongest predictor is PROD at the starting node, followed by COMP and NAT_DEBT in level 1, URBAN and LAB_PER appear in level 2, adding INT_RAT and BAL_TRAD in level 3, finishing level 4 with PRI-CON, LAB_STRUT, CAP-EXP and BNK_RAT. The tree decisions are read as follows: For example, if PROD > 35,980 $/employee and COMP per thousand people > 397.2 then all countries in that category receive the same predicted competitiveness score 93.2 (actually US and Singapore). That branch numbers (2, 1.0) indicate that this rule was ‘‘fired’’ twice (assigning that score to these two countries), with confidence 1.0 (proportion of cases for which the rule is true).

Table 6
C&R tree experiments

Method	Dataset 1		Dataset 2		Dataset 3		Initial	
	MSE	MAE (%)	MSE	MAE (%)	MSE	MAE (%)	MSE	MAE (%)
Training expert parent 3 child 2	1.21	1.09	1.21	1.09	1.5	1.39	1.41	0.80
Training expert parent 5 child 2	3.91	1.89	**4.81**	**2.42**	4.93	2.58	3.88	1.39
Training expert parent 6 child 3	6.44	2.82	–	–	–	–	–	–
Training expert parent 8 child 2	–	–	4.22	2.13	4.22	2.13	–	–
Training simple tree depth 3	12.39	4.49	–	–	–	–	–	–

MSE—mean square error.
MAE—mean absolute error.
Datasets (all with 43 countries).
Dataset Initial—missing values, 33 variables total.
Eliminated 14 variables: BAL_RANK, BT_LEND, CON_RATE, DOM_INV, FOR_INV, GOVT_CON, LAB_FOR, LAND, POPUL, PRI_INV, QUALITY, STU_EXP, SEW_RUR, LAB_COST.
Dataset 1—no missing values, 35 variables.
Eliminated 12 variables: BAL_RANK, BT_LEND, CON_RATE, DOM_INV, FOR_INV, GOVT_CON, LAB_FOR, LAND, POPUL, PRI_INV, QUALITY, STU_EXP.
Dataset 2—no missing values and extra variable, 44 variables total.
Eliminated 12 variables: BAL_RANK, BT_LEND, CON_RATE, DOM_INV, FOR_INV, GOVT_CON, LAB_FOR, LAND, POPUL, PRI_INV, QUALITY, STU_EXP.
Dataset 3—no missing values and extra variables, 36 variables total.
Eliminated 20 variables: DOM_INV, GOVT_CON, BAL_RANK, CON_RATE, NAT_DEBT, REVENUE, CAP_EX, FOR _INV, PRI_INV, BT_LEND, LAND, WAT_RUR, RD_PEP, POPUL, LAB_FOR, STU_EXP, ILLETER, QOL, PDI, EMT.

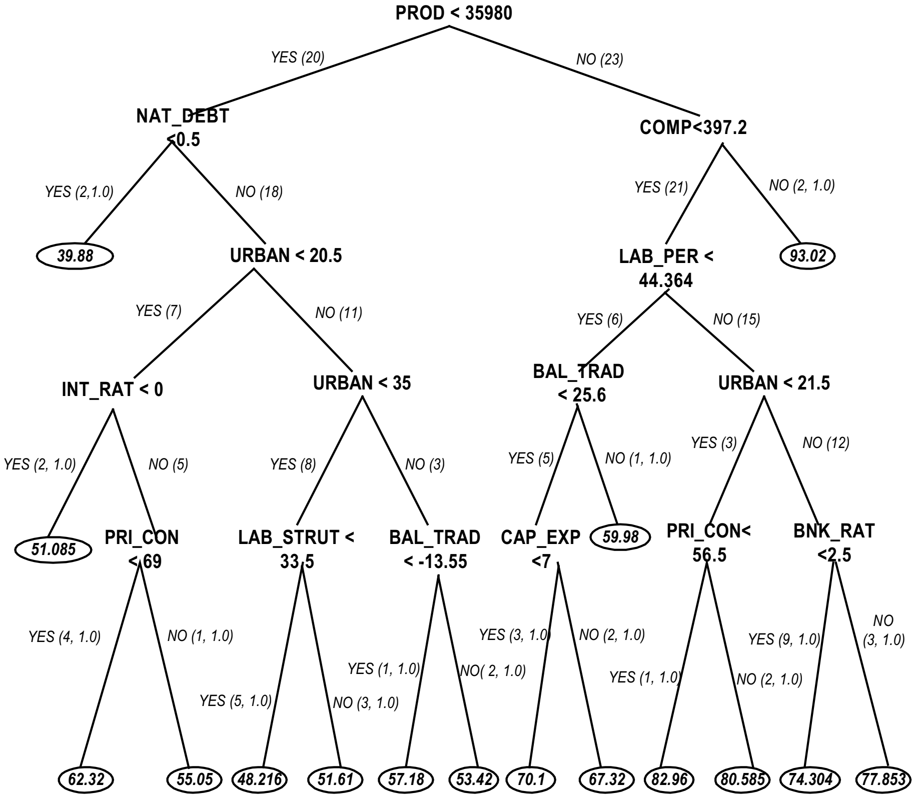

Fig. 1. C&R decision tree with 5 parents and 3 children (numbers in parenthesis indicate instances and confidence).

This classification nature of the output is an inherent weakness of the CART method when applied to continuous dependent variables. Fine-tuning it by allowing more tree levels or children is likely to cause over-training (which CART cannot control via a parameter like the training percent in NN). In the above example, CART assigned the same predicted competitiveness score 93.2 to US and Singapore, compared to their actual scores of 100 and 86.4 respectively, creating by far the procedure's largest errors among all countries.

Given the step nature of the CART output and, most importantly, the frequent conflicts in classification variables chosen in its trees, the output results should be viewed with extreme caution; i.e. its impressive overall accuracy may be too optimistic. Furthermore, we cannot rely on the CART model's importance of input variables. Only for information purposes, we state the input variables with the high predicted correlations in the CART training expert model with 5 parents 2 children: PPP, COMP, PHONE, RISK, PROD, and RD_PEP.

5.5. Model comparisons

A visual comparison of the accuracy all four models in predicting the competitiveness score of each country is portrayed in Fig. 2. It appears that the best fit is provided by CART, followed by NN, WNLP and SWR models developed with these data. In SWR, China and Slovenia produced the biggest errors (identified as outliers in regression analysis), followed by Chile, Finland, Italy, Czech and Norway. The largest WNLP model errors occurred for India, Chile, Slovenia, Malaysia, Italy, Belgium and Philippines. The best NN model, multiple expert 85% training, had difficulty

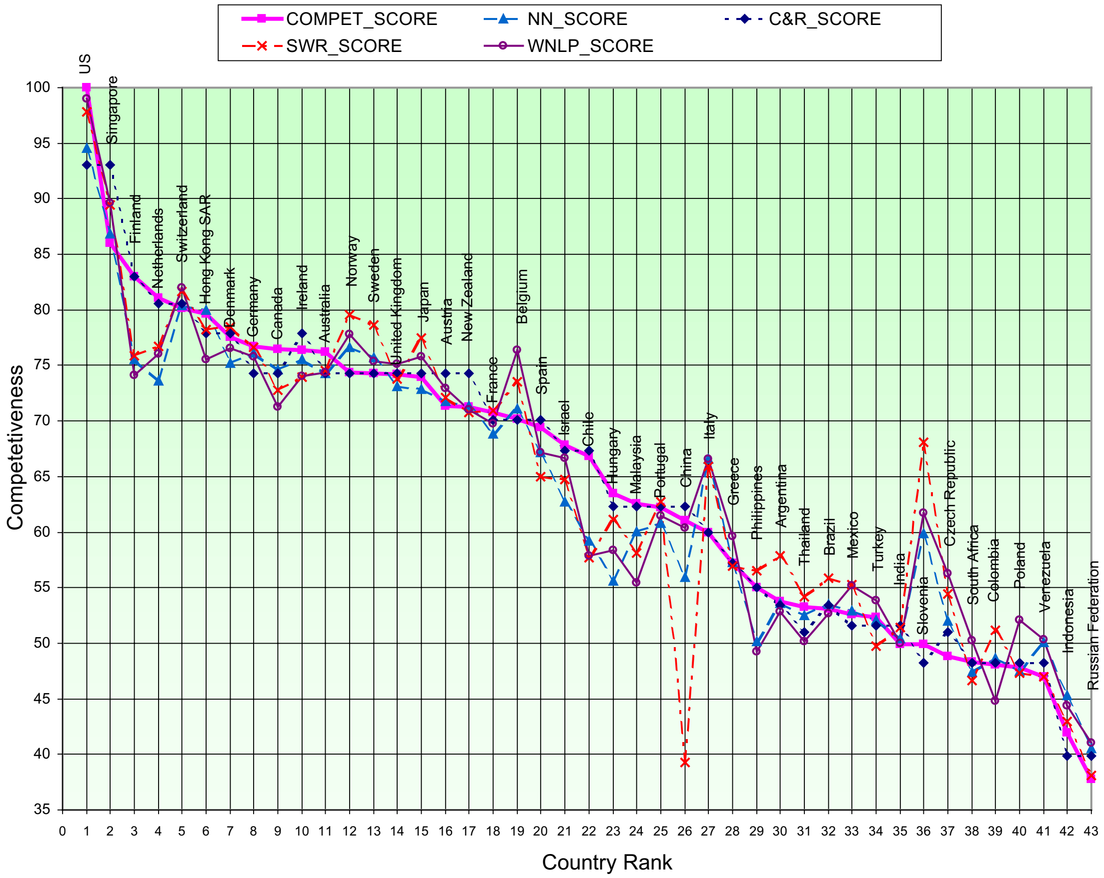

Fig. 2. Training model predictions.

predicting the competitiveness of Slovenia, Hungary, Netherlands, Finland, Chile, and Italy. The difficulty of the above three models in predicting closely Slovenia's competitiveness is due to the large number of missing data for that country, 43.6%, which is more than twice the next highest country's missing data count. CART *Expert with 5 parents 2 children* produced suspiciously accurate predictions for all countries, except Singapore and US and to a much lesser extent New Zealand and Austria. This close fitness raises further suspicions of over-training and necessitates validations that are described in the next section.

A summary of influential inputs for each of the four methods (SWR, WNLP, NN and CART) is presented in Table 7, with those appearing in the best models marked in bold. Although the input variables are shown in somewhat approximate order of overall influence, no strict comparison between variables, especially those close-listed, is appropriate. Some people feel skeptical in viewing NN weights strictly as indicators of the significance of input variables. The same would apply even more so to CART given its non-robust performance. The impact of the apparently most influential exploratory variables on the competitiveness of countries worldwide is discussed later in the next section.

6. Validation of results

Although the model development predictions obtained with the entire sample are quite good, a thorough investigation of their generalizing ability is necessary via cross-validation (Stone, 1974). In contrast to bootstrapping requiring 100–500 replications (Efron and Tibshirani, 1993; Wehrens et al., 2000), cross-validation requires a limited number of replications to provide an unbiased estimate of a model's generalizing performance. The commonly employed cross-validation is a k-fold experiment in which the complete sample is split randomly into k mutually exclusive sub-samples (folds) of approximately equal size. Using the specific method with the data in the $k-1$ folds as the training sample, a model is developed and applied to predict the competitiveness of each country in the single held-out fold. The same procedure is repeated for each of the other folds and the accuracy of all n predictions assessed, from which average measures like MSE and MAE are computed for the specific technique. The obvious question is what is a good choice for the number of folds k (typically 1–20, depending on the total sample size n). Choosing $k = n$ (leave-one-sample-out cross-validation, also called Jack-knifing, Efron, 1982), is not only time-consuming

Table 7
Summary of influential input variables

Abbreviation	Input variable	SWR	WNLP	NN	CART
COMP	Computers per 1000 people	**X**	**X**	**X**	**X**
LB_STRUT	Labor force structure in population aged 15–64 (millions)	**X**	X	X	**X**
RISK	Composite international country risk rating (1–100 best)	**X**	**X**	**X**	
UAV	Uncertainty avoidance index	X	**X**	**X**	
BAL_TRAD or BAL_RANK	Balance of trade imports/exports or rank		**X**	**X**	**X**
PPP	Purchasing power parity GDP	X	X	**X**	
PROD	Overall productivity (US$ per person employed)	X	X	**X**	**X**
RD_EXP	Research and development expenditure (US$ millions)	X	X	**X**	
URBAN	Urban population percentage		X	X	**X**
IMPORT	Import of goods and services (% of GDP)	**X**	X	X	
MAS	Masculinity index	X	**X**	X	
DOM_SAV	Gross domestic savings (% of GDP)	X	X	**X**	
CO	Carbon dioxide damage (% of GDP)	**X**	X		
DOM_INV	Gross domestic investment (% of GDP)	X	**X**		
PRI_CON	Private consumption (% of GDP)		**X**		X
LAB_COST	Labor costs		**X**	X	
PHONE	Telephone lines per 1000 people	X		**X**	
WAT_RUR	Access to water (% of rural population)	X	**X**		
INTELL	Intellectual property (patent applications filed)	X		X	
NAT_DEBT	Domestic debt (% of GDP)				**X**
LAB_PER	Labor force (% of population)				**X**
LETERACY	Adult literacy rates (% of Population)		**X**		
INT_RAT	Real short term interest rates				**X**
BNK_RAT	Ratio of bank liquid reserves to bank assets				**X**
CAP_EXP	Capital expenditure (% of total expenditure)				**X**
SEW_URB	Access to sewage (% of urban population)			X	
EMRD	Employed engineers and scientists in R&D (% employed in technology)	X			
SEW_RUR	Access to sewage (% of rural population)		X		
EXPORT	Export of goods and services (% of GDP)	X			

Note: Bold **X** indicates important variable in best model for each method.

but it may produce less accurate and more volatile estimates (Kohavi, 1995; Shao, 1997; Brieman, 1996). On the other hand, a very small number of folds k reduces the size of the training sample and produces pessimistically biased error estimates due to the difference in training set size between the full sample and the cross-validation. It is generally believed that for categorization learning in general, and artificial neural network learning specifically, performance improves as the learning/training set size ratio increases (Schürmann, 1996). Ten-fold cross-validation is commonly used in practice and was repeatedly employed in a comparative evaluation of several algorithms for solving various large-size problems in the literature (Lim et al., 2000).

To implement a ten-fold validation experiment here, three countries were randomly eliminated and the remaining 40 were split into ten subgroups of four countries each. Because of the intensity and time consuming multiple optimization procedures needed to avoid local optima, WNLP was left out of validation. This experiment was manually performed for the previously identified best configurations of the other three procedures: *SWR model 2*, *NN multiple expert 85% training* and CART *expert training 5 parents 2 children*. The results are summarized in Table 8.

The best-generalized out-of-training sample accuracy is exhibited by SWR (MSE = 29.89, MAE = 6.41%), followed by NN (MSE = 40.40, MAE = 8.43%). Not surprisingly, due to difficulty to control over-training, the small sample size, and for the reasons stated at the end of Section 5.4, CART performed poorly (MSE = 91.28, MAE = 13.94%). Note that validation results cannot surpass the accuracy of the training model that uses all observations. In our study, the small sample sizes make it even harder to achieve high accuracies, especially in inferential modeling. Our interest was to explore the relative performance of methods on data outside the training sample and not to investigate alternate forms of validation.

Table 8
Validation ten-fold experiments

Method	MSE	MAE (%)
SWR	29.89	6.41
Neural Net	40.40	8.43
CART	91.28	13.94

The small sample size of only 43 countries in our study, unavoidably restricted by those included in the '99 WCY, makes it very hard to obtain good validation results. Furthermore, the number of observations is far smaller than the commonly desired few-times multiple of independent variables, even after the elimination of the weak ones identified in exploratory data analysis. Therefore, the above SWR and NN validation results are viewed as quite satisfactory.

7. Conclusions

A measure of world competitiveness can be useful to assess how nations manage their economic future. Competitiveness of Nations is defined by the WCY as,

> "*a field of economic knowledge, which analyses the facts and policies that shape the ability of a nation to create and maintain an environment that sustains more value creation for its enterprises and more prosperity for its people*" (Garelli, 2003).

Although economic value is created within the context of an enterprise, some nations support competitiveness more than others by creating an environment which facilitates the competitiveness of enterprises and encourages long-term sustainability. In addition, competitiveness of nations includes the economic consequences of non-economic issues, such as education, sciences, political stability, and computer literacy (Garelli, 2003).

In this study we examined four knowledge discovery methods to predict the competitiveness of 43 countries in the '99 WCY and identify major factors out of 55 variables that affect these results. Our results are a little better using non-standardized data than Z-standardized (like in WCY). The methods employed, after extensive exploratory data analysis, are stepwise regression (SWR), weighted non-linear programming (WNLP), neural networks (NN), and classification and regression trees (CART). To comply with non-negative weights in WNLP, ten independent variables logically moving in the opposite direction of competitiveness and/or significant negative correlation with it, were transformed linearly. Sequential application of GRG and evolutionary search from different starting points was necessary to overcome local minima in WNLP. After considerable parameter calibration, twelve NN and five CART architectures were identified and applied to the initial dataset, as well as three variations of data with EM imputed estimates of missing values (8.9%), but without different problematic variables identified during the exploratory data analysis. The best models of each method were: CART (MSE = 4.81, MAE = 2.42%), SWR (MSE = 10.91, MAE = 3.97% and $R^2_{\text{adj}} = 0.9311\%$), NN (MSE = 13.10, MAE = 4.05%), and WNLP (MSE = 14.89, MAE = 4.69%). Their prediction accuracy for each country is shown in Fig. 2. Countries more difficult to predict (ordered by largest MAE%) were: Slovenia (all methods, due to its largest number of missing data), Chile (not for CART), Czech Republic, Hungary with Italy and Finland (except for CART), Indonesia, Netherlands, and Russia (except for SWR). For CART the largest errors occurred for the top ranked US and Singapore, and for SWR China was a big outlier.

Some caution is necessary when reviewing these results, because of difficulties or limitations of each method. If the two big outliers (China and Slovenia) are not removed, then SWR accuracy is about the same as in WNLP. The latter, however, required considerable computational efforts to overcome local optima. NN performance was sensitive to which suspicious variables were not included in its inputs. CART, although not as sensitive as NN to exclusion of variable inputs, experienced considerable difficulties in finding a decision tree for which the correlation of each variable with the predicted competitiveness did not contradict logic or the corresponding sample correlation. The lack of a training parameter in CART (like the one in NN) suggests that overtraining was unavoidable, which boosted CART's performance ahead of the other three methods. Due to these shortcomings, in addition to CART's classification nature output of step rather than continuous predictions, we do not recommend it for this problem.

A ten-fold validation experiment was performed in order to gauge the generalizing performance of all methods (except WNLP, because of its computational intensity). As anticipated, CART had the worst performance (MSE = 91.28, MAE = 13.94%), while SWR (MSE = 29.89, MAE = 6.41%) performed better than NN (MSE = 40.40, MAE = 8.43%). Given that holdout sample validations are expected to produce worse accuracies than training complete-sample models, and the unavoidably very small sample size (43 countries of usable WCY scores of competitiveness), these validation results are quite satisfactory for SWR and NN. If there were many more countries than variables in the dataset, then NN could be a serious contender as the top performing methodology.

Our analyses pinpoint the independent variables that exert major influence on the competitiveness of a country worldwide: Better composite international country risk rating (RISK) and more computers per capita (COMP) are major drivers of competitiveness. Entrepreneurial societies with less male dominance are more competitive, as evidenced by their lower uncertainty avoidance (UAV) and lower masculinity index (MAS). The dominant economic variables are: gross domestic investment, savings and private consumption as % of GDP (DOM_INV, DOM_SAV, PRI_CON) and purchase power parity GDP (PPP), while higher imports of goods and services as % of GDP (IMPORT) improve competitiveness but better balanced trade (BAL_RANK, BAL_TRAD) tends to reduce it. Interestingly, although exports have a higher correlation to competitiveness score than imports (0.317 vs. 0.258), they only appeared as a significant variable in one earlier model and only in SWR. Higher R&D Expenditures and patents (RD_EXP, INTELL), and a labor force (LB_STRUT) that is both larger and more productive (PROD), more literate (LITERACY) but not less expensive (LAB_COST) tend to increase a country's competitiveness, as is the basic infrastructure of population access to water and sewage (WAT_RUR, SEW_URB and SEW_RUR). This is further aided by more telephone lines per capita (PHONE) and increasingly urban population (URBAN). It is interesting to note the increased damage of carbon dioxide (CO), an unavoidable consequence of progress and growth, affects competitiveness adversely. Policy makers in each country and international agencies could take advantage of these findings.

The results of our study confirm the findings presented in the WCY related to the profound impact that the technological revolution (computers, telecommunications, and the internet) has had on the competitiveness of nations. These findings are not surprising, since the availability of effective telecommunication and internet systems, is considered a key asset in a nation's competitiveness. Nation's seeking to improve their competitiveness will also need to consider making investments in IT related education, since those skills will be necessary to operate the new technology infrastructure.

Our study cannot reduce or replace the valuable extensive information provided by the annual WCY reports, nor can it substitute the nearly three hundreds of WCY variables and the timely survey opinions of thousands of executives worldwide. Since the WCY methodology is undisclosed, our aim was to extract knowledge from these expert competitiveness scores and publicly available country data, to identify major contributing factors and KDD techniques that can be used to estimate the competitiveness of a country. Although far from exhaustive, our set of 55 variables resulted in very reasonable estimates of global competitiveness. Any of the 130 or so countries, not included in the limited annual list of WCY, could estimate its own global competitive position from a dozen or so of its socio-economic indicators specified in models like those developed in this paper. This research demonstrates that variables like those in our dataset could be used to predict reasonably well and with less effort the competitiveness of a country, most successfully with stepwise regression and neural net techniques. The advantage of using such techniques to predict a country's competitiveness is that they can provide the basis of a decision support system for on-line competitiveness assessment, which could respond quickly to "what-if" scenarios in changing conditions as reflected in varying input data, or to estimate the competitiveness of additional countries (not included in WCY). Moreover, such a DSS could serve as a basis for training policy makers and administrators to expand their own abilities and insights. Understanding and using such KDD approaches could help countries in prioritizing the implementation of national policies to improve their competitiveness.

On the other hand, a limitation of this study is that, although it is based on a relatively large and broad set of 55 exploratory variables, it may have overlooked other important variables. For example, it may have not included the most appropriate variables that reflect a nation's *intellectual capital* or *knowledge assets* (see Clark and Guy's, 1998, review on innovation and competitiveness). The four proxies included (literacy, intellectual property patent applications, scientists/engineers/technicians in R&D, and employment in technology sector), although all significantly correlated to WCY competitiveness score, they did not play a major role in our models. It can be argued that the most vital resource of today's enterprise is the collective knowledge residing in the minds of an organization's employees, customers, and vendors. Unfortunately, accounting practices, which typically reflect the value of assets owned by a company, still do not consider the value of knowledge assets. It is said that knowledge intensive companies around the world are valued at three to eight times their financial capital. This is the case for Microsoft, the highest-valued company in the world as of May 2000, whose market capitalization of approximately $350 billion, obviously exceeds its physical assets. Microsoft's valuation also reflects the value of its brand name (about $65 billion) and its intellectual assets. This includes structural capital in the form of copyrights, customer databases, and business process software. It also includes human capital in the form of the knowledge that resides in the minds of all of Microsoft's software developers, researchers, academic collaborators, and business managers. Learning how to manage knowledge assets will enable a nation to be better suited to compete successfully in a much more demanding environment. In the words of Peter Drucker (1994, pp. 60–70):

> *"How well an individual, an organization, an industry, a country, does in acquiring and applying knowledge will become the key competitive factor. The knowledge society will inevitably become far more competitive than any society we have yet known—for the simple reason that with knowledge being universally accessible, there will be no excuses for non-performance ...We need systematic work on the quality of knowledge and the productivity of knowledge—neither even defined so far. The performance capacity, if not the survival, of any organization in the knowledge society will come increasingly to depend on those two factors. But so will the performance capacity, if not the survival, of any individual in the knowledge society."*

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