Olczyk, M., Kuc-Czarnecka, M., & Saltelli, A. (2022). Changes in the Global Competitiveness Index 4.0 Methodology: The Improved Approach of Competitiveness Benchmarking. *Journal of Competitiveness,* 14(1), 118–135. https://doi.org/10.7441/joc.2022.01.07

Changes in the Global Competitiveness Index 4.0 Methodology: The Improved Approach of Competitiveness Benchmarking

▪ *Magdalena Olczyk, Marta Kuc-Czarnecka, Andrea Saltelli*

Abstract

The Global Competitiveness Index (GCI) developed by the World Economic Forum (WEF) is used as a standard for measuring a country's competitiveness. However, in literature, the GCI has been accused of numerous methodological flaws. Consequently, in 2018, the WEF introduced significant methodological changes. This study aims to examine whether the methodological modifications in the GCI's structure increase its ability to capture the real competitiveness of economies. In addition, the study considers whether the selection of weights of individual elements included in the GCI is optimal or could be improved. By employing a sensitivity-based analysis, we find that the change in methodology resulted in fewer pillars of marginal importance. In the case of the GCI 2017, there were four pillars, whereas in that of the GCI 4.0, there were only two pillars: product market and labor market. Furthermore, we reveal that the WEF weights do not reflect the measured importance of the variables. In the optimization process, numerous variables (primarily opinion-based indicators) were insignificant in explaining the GCI variance and could be eliminated from the set of diagnostic variables without affecting the index's value. For instance, in the case of the GCI 4.0, 35 out of 103 variables could be eliminated. The new rankings obtained by weight optimization and reduction of the diagnostic variables demonstrated a strong positive correlation with the original rankings. This research contributes to the literature from both a theoretical perspective (indicating the most vital indicators in the GCI) and a practical standpoint (reducing the costs and time of obtaining redundant data).

Keywords: competitiveness, composite indicators, Global Competitiveness Index, sensitivity analysis
JEL Classification: C18, C38, O11

Received: September, 2021
1st Revision: January, 2022
Accepted: February, 2022

1. INTRODUCTION

Competitiveness is of interest to managers, politicians, and scientists. Its popularity is evidenced by as many as half a million Google search results and the growing number of studies related to national competitiveness published yearly (Olczyk, 2016). Simultaneously, competitiveness is one of the most misunderstood, elusive, and ambiguous concepts, especially in economic theory (Olczyk, 2016; Roszko-Wójtowicz & Grzelak, 2020). In recent studies, a particular polarization of approaches to national competitiveness may be observed (Ketels, 2016).

The first approach, which is less popular and criticized by Krugman (1994), associates competitiveness with the ability of the economy to export goods and services in terms of balanced trade (Szczepaniak, 2018; 2019). Moreover, this approach is associated with an animated discussion among mainstream free-trade economists (Krugman, 1994) on the negative impact of free trade on a country's competitiveness measured by citizens' prosperity (Hirsch, 2019). In the second more popular approach, national competitiveness is associated with economic growth and defined as total productivity growth (Kijek & Matras-Bolibok, 2019). The productivity approach is used by the OECD research program "Going for Growth" and the World Economic Forum (WEF), which develops the Global Competitiveness Index (GCI).

The GCI is one of the most well-known national competitiveness measures. The concept, methodology, and performance of the index over the last two decades were evaluated by Porter et al. (2001). In addition, indices such as the Current Competitiveness Index proposed by Porter (2002), Growth Competitiveness Index introduced by McArthur & Sachs (2002), and Global Competitiveness Index proposed by Sala-i-Martin & Artadi (2004) must be mentioned. Between 2006 and 2018, the GCI methodology changed marginally. The last significant change occurred in 2018 and the new GCI 4.0 emerged more recently (WEF, 2019). However, the way in which the WEF interprets national competitiveness did not change. It is still defined as "the set of institutions, policies, and factors that determine the level of productivity of a country, which in turn sets the level of prosperity that the country can earn" (Schwab, 2015).

Although the GCI is the most recognized synthetic indicator of national competitiveness in literature, it is also the most criticized owing to its instability, potential correlation or reverse causality between pillars, and lack of theoretical background (Petrylė, 2017; Bergsteiner & Avery, 2019). Additionally, opinions in economic literature suggest that national competitiveness is disconnected from the concepts of sustainability, social inequality, and labor market conditions (Schröder, 2020). This situation poses numerous new challenges for the WEF regarding the structure and content of the GCI.

This study aims to optimize the GCI's structure concerning weights and variables to increase its ability to capture the actual competitiveness of economies. Our analysis highlights evident shortcomings in the linear aggregation of many variables. Sahin et al. (2008) proposed using the artificial neural network method to improve the weights used for constructing the GCI. Petrarca & Terzi (2018) tried to solve the problem of changing the weights of sub-indices according to country development stages. They proposed computing the GCI using the structural equation modeling with endogenously derived weights. Dudas & Cibula (2018) performed an empirical verification of whether the new GCI 4.0 methodology was better at capturing countries' real competitiveness based on the example of Slovakia. Nečadova (2020) tried to improve the latest GCI 4.0 through the arithmetic and geometric mean on different levels of sub-indices aggregation to develop two types of "adjusted GCI," which serve to eliminate the effect of various weighting systems on the overall rating. However, this study offers an original approach: applying methods from a sensitivity-based analysis to investigate whether the weights of individual variables truly reflect the purported significance of each factor; thus, we test the index for coherence or consistency in relation to its design.

The remainder of the paper is organized as follows. Section 2 provides an overview of the new GCI 4.0 and the methodological changes introduced to the GCI in the 2018 edition. Section 3 describes the methodology of the sensitivity-based analysis. Section 4 discusses the results, and Section 5 presents the conclusions of the study.

2. THEORETICAL BACKGROUND

This study compares two GCI methodologies: the old method used by the WEF in the 2017–2018 edition (WEF, 2017) and the new method, which forms the basis for developing the GCI 2018 edition (WEF, 2018). The development of the new GCI (GCI 4.0) is associated with the emergence of recent structural changes in numerous economies resulting from the Great Recession (GR) (2007–2009), the Fourth Industrial Revolution (4IR), changes in communications (such as the development of big data), financial markets, human capital, and the innovation ecosystem. According to the WEF (WEF, 2018), the two most important of these are the lasting implications of the GR and 4IR.

The GR indicates that economic crises can have a lasting negative impact on the perceptions of market participants that translates into slower economic growth and lower productivity even after 10 years of the crisis. Empirical analyses for advanced economies conducted by Ball (2014), Rawdanowicz et al. (2014), and Reifschneider et al. (2015) confirmed that gross domestic product (GDP) or GDP per capita was below the pre-GR trend (Cerra et al., 2020). Oulton (2018) identified that the countries with the most significant GDP growth decrease after 2008 also suffered the most total factor productivity growth reduction. The long-lasting effects of the GR on productivity could be explained by prolonged periods of underinvestment in many economies or a gradual decrease in the adoption rate of new technologies (Anzoategui et al., 2019).

Moreover, the 4IR had several significant effects on economies. Some 4IR drivers, such as artificial intelligence, robotics, the Internet of Things, 3D printing, digital platforms, and blockchain technologies, trigger innovation cycle acceleration and business models changes (Schwab, 2017) toward "platform capitalism" (McAfee & Brynjolfsson, 2017). The 4IR has created more options for businesses to automate the production process, reduce labor costs, and boost productivity. Therefore, the most competitive economies should be resilient to external shocks and agile (i.e., adapt to changes), have the best conditions for the emergence of new ideas, and implement a human-centered economic development strategy (WEF, 2018). These changes forced the WEF to rebuild the GCI.

The new method engenders a revision of individual variables and pillars of competitiveness, rebalancing hard data against soft data, an alternative approach to standardization of input data, and a distinct final aggregation of pillar values into the last index. The main differences between the two GCI methodologies are presented in Table 1 (major differences are presented in bold).

Tab. 1 – Main differences in the GCI construction: GCI 2017–2018 and GCI 4.0. Source: own research

	GCI (2017–2018)	New GCI 4.0
Indicators	114 indicators grouped into 12 pillars	**103** indicators grouped into 12 pillars
Weighting scheme	The weight varies from 5% to 15%, depending on the sub-index to which the pillar belongs and the country's development stage.	All pillars are **weighted equally (8,33%), not depending** on the country's stage of development.
Hard data vs. soft data	hard data < soft data; 37 indicators based on hard data, 77 on soft data	**hard data > soft data**; 56 indicators based on hard data, 47 on soft data

The main differences between the two analyzed GCI indices include the pillars' change. The number of pillars remains the same, while indicators decreased from 114 during 2017–2018 to 103 after 2018. The redefinition, introduction, and deletion of indicators were considerable; 67% of the indicators were new. For example, the Institutions pillar went through a complete reorganization and now includes two novel aspects: checks and balances and social capital. Similarly, the Macroeconomic Environment pillar now has a list of indicators that describe government finance rather than deficits or debt levels.

Furthermore, the new GCI 4.0 methodology is based more on hard data rather than on soft data. The number of indicators obtained from the Executive Opinion Survey decreased from 80 to 45. Some researchers criticized the lower explanatory capacity of soft data in the GCI (Necadova, 2015). Necadova (2019) demonstrated that, compared to other developed regions of the world, poor European results in competitiveness indicators based on soft data are determined by differences in the cultural and national sentiment rather than by economic opportunities. Numerous organizations significantly increased their capacity to gather reliable information, thereby replacing soft data with statistical indicators (WEF, 2018). An example of a new element in the GCI is a modification in the innovation capacity pillar—companies' propensity to spend on research and development (R&D) was replaced by R&D expenditures as a share of the GDP.

With the 2018–2019 edition of the Global Competitiveness Report, the WEF discontinued the approach wherein the weights of different pillars were strictly connected to a countries' development stage (factor-, efficiency-, and innovation-driven). The old sub-index weighting system was considered controversial and subjective (Sahin, 2008). In the new methodology, all pillars are weighted equally, with each pillar weighing 8.33%. This corresponds to the WEF's approach (2018), stating that each country, especially low-income economies, has growth paths. According to Necadova (2020), the new weighting system along with new indicators helps less developed countries and simultaneously punishes countries that are disadvantaged regarding competitiveness drivers, such as ICT adoption, employee skills, or financial and labor market development. Moreover, the new system promotes countries that can perform well in the innovation ecosystem.

In both the old and new methodology, the GCI remains a composite index. In literature, an increasing interest is observed in applying composite indicators (CI) in a wide variety of research areas (Bandura, 2011; Yang, 2017). This seemingly simple method of presenting complex phenomena has multiple methodological pitfalls, and CIs are considered biased, inconsistent, and thus problematic (Greco et al., 2019). Therefore, along with the growing popularity of applying CIs, critical research papers concerning their methodological aspects have been produced (Paruolo et al., 2013; Muller, 2018; Kuc-Czarnecka et al., 2020).

Synthetic measures are a useful tool; nevertheless, they suffer from shortcomings. The main accusations against CIs relate to the subjective selection of diagnostic variables (OECD, 2008), aggregation process (Becker et al., 2017), arbitrary nature of the weighting process (Gnaldi & Del Sarto, 2018; Cinelli et al., 2020), questionable ability to measure a complex and elusive concept (Kuc-Czarnecka et al., 2020), or spatial homogeneity assumption in the analysis of geospatial objects (Cartone & Postiglione, 2020). Numerous solutions are proposed to rectify these flaws, from Cronbach's coefficient alpha to artificial neural networks (Gnaldi & Del Sarto, 2018; Drago, 2021; Krylovas et al., 2020). In our study, we propose to use a sensitivity analysis (SA) to examine whether the GCI's methodological changes essentially improved its discriminatory properties or just marginally simplified calculations while keeping most of its earlier deficiencies.

3. METHODOLOGY

In this study, we used consistency analysis based on SA. This method allows us to determine whether the weights assigned by the developers correspond to the measured importance of a given variable (from a mathematical viewpoint) (OECD, 2008). We refrained from using tools such as data envelopment analysis, factor analysis, or neural networks as these would close the index in a black box, which is not desired by most developers, who usually prefer the linear method of aggregation. Moreover, as research demonstrates, SA is not used as often as it should be (Saltelli et al., 2020, European Comission, 2021).

Similar to most CIs, the GCI is calculated as a weighted arithmetic average:

$$y_j = \sum_{i=1}^{d} w_i x_{ji}, \qquad j = 1,2, \dots , n; i = 1,2, \dots , d \tag{1}$$

where y_j represents the value of the CI for the j-th object (country), x_{ji} denotes a normalized value of the i-th variable in the j-th item, and w_i is the weight assigned to the i-th variable.

Given that several layers of uncertainty may superimpose one another, the CI is perceived as a non-linear and possibly a non-additive model. The impact of x_j on y may be determined and isolated by calculating the first-order sensitivity index (Paruolo et al., 2013):

$$S_i = \frac{V_{x_i}\left(E_{x\sim i}(y|x_i)\right)}{V(y)} \tag{2}$$

where S_i denotes the first-order sensitivity measure, x~i is the vector containing all the variables but x_i, $E_{x\sim i}$ $(y|x_i)$ represents the expected value of y at a given value of x_i with the expectation taken over $x_{\sim i}$, and V(y) denotes the unconditional variance of y.

If the variables were uncorrelated, S_i would be the expected reduction of the variance in the CI if a given indicator (x_i) could be fixed. $S_i \in [0,1]$, therefore, two undesirable situations may occur:

- S_i=1; that is, all variance in y is driven by x_i, meaning that knowing the rank of x_i implies for knowing the rank of y.
- S_i=0; that is, the index ranks convey no information about the underlying indicator ranks.

More frequent use of S_i may invalidate developers' assumptions, such as two variables being equally important (when the S_i are different instead) or variable a being more important than variable b when instead $S_b>S_a$. In our study, $E_{(x\sim i)}$ $(y|x_i)$ is estimated through a non-linear regression fit using penalized splines. Penalized splines are an extension of linear parametric regression, but they have the capabilities of nonparametric regression as well. Here, we decompose S_i and distinguish its two components:

$$S_i = S_i^u + S_i^c \tag{3}$$

where S_i is the first-order sensitivity measure, S_i^u denotes the uncorrelated contribution, which is the unique variability that can only be explained by the x_i indicator, and S_i^c denotes the correlated contribution, the variability caused by all the variables associated with the x_i indicator.

In the case of synthetic measures, such a distinction is crucial because it may transpire that the impact of variable x_i on the CI results from its correlation with other influencing variables and does not provide additional information. In this case, it would be $S_i^c \approx S_i$. Moreover, such decomposition allows us to identify conceptual and statistical problems that are frequently invisible while constructing the CIs; this occurs when $S_i^c<0$. Having S_i, the decomposed parts can be estimated as follows (Becker et al., 2017):

- Uncorrelated part S_i^u

Performing the multivariate linear regression of x_i on $x_{(\sim i)}$ and finding the residuals:

$$\hat{z_i} = x_i - \hat{x_i} = x_i - \left(\beta_0 + \sum_{l \neq i}^{d} \hat{\beta_l} x_i\right) \tag{4}$$

where $\hat{z_i}$ represents residuals of a regression of x_i on $x_{\sim i}$, β_0 is the y-intercept from multivariate linear regression, and β_l denotes the coefficient from multivariate linear regression.

Next, the non-linear regression of y to $\hat{z_i}$ fitted values is used to estimate S_i^u:

$$S_i^u = \frac{\sum_{j=1}^{n}\left(\hat{y}_j^{(\sim i)} - \bar{y}^{(\sim i)}\right)^2}{\sum_{j=1}^{n}(y_j - \bar{y})^2} \tag{5}$$

where S_i^u denotes the uncorrelated contribution, $\hat{y}_j^{(\sim i)}$ indicates the non-linear regression fitted values, $\bar{y}^{(\sim i)}$ represents the average value of $\hat{y}_j^{(\sim i)}$, y_j is the CI value in the j-th object, and $\bar{y}$ indicates the average value of y_j.

- Correlated part S_i^c

$$S_i^c = S_i - S_i^u \tag{6}$$

With the information calculated from (5) and (6), it is possible to adjust the weight to correspond to the desired influence of each indicator. Therefore, the following optimization algorithm is applied. First, the normalized correlation ratio is estimated:

$$\tilde{S_i} = \frac{S_i}{\sum_{i=1}^{n} S_i} \tag{7}$$

where $\tilde{S}_i$ denotes the normalized correlation ratio of x_i.

Thus, optimal weights can be computed as follows (Becker et al., 2017):

$$\boldsymbol{w}_{opt} = \text{argmin}_{w} \sum_{i=1}^{d} \left(\tilde{S}_i^* - \tilde{S}_i(\boldsymbol{w}) \right)^2 \tag{8}$$

where $\tilde{S}_i^*$ indicates the target normalized correlation ratio, that is, a situation wherein initial weights reflect each indicator's intended importance (developers' weights are considered the developers' stated importance of the variables), and w represents the set of weights:

$$\boldsymbol{w} = \{w_i\}_{i=1}^{d}. \tag{9}$$

The optimization process was conducted using the Nelder–Mead simplex method (Nelder & Mead, 1965). The optimal weights were selected such that they sum up to one and are non-negative. By minimizing the squared difference between the correlation ratios at a given set of weights, the optimization algorithm relocates the weight to match the target correlation ratios.

This approach derived from the SA as a tool for evaluating the CIs has been proven based on the Environmental Performance Index (Saisana & Saltelli, 2010), Good Country Index (Becker et al., 2017), PISA ranking (Dobrota et al., 2015), and Human Development Index (Kuc-Czarnecka, 2019).

In this study, data obtained from the WEF (WEF, 2018a, 2018b) were used to perform the analysis in MATLAB using the CI Analysis and Optimization Tool (Lindén et al., 2021), which is used for advanced assessment of the CIs. We applied consistency analysis based on the SA to verify whether the weights assigned to individual variables reflect their purported importance. Given that the number of variables included in the GCI exceeds 100 in both cases; the analysis was performed in two steps:

1. the consistency of the assigned weights inside the pillars was tested,
2. the correctness of pillars' weights was tested.

Therefore, in the initial stage of the analysis, the pillars were treated as independent synthetic variables.

4. RESULTS AND DISCUSSION

4.1. Analysis of the 2017 edition of the GCI

We started our analysis by checking the correlation between sub-indices and pillars; in both cases, there was a strong positive correlation between the GCI components (ranging from 0.6 to 0.95). As described in the methodology, this may indicate that the final impact of a given sub-index (pillar) depends on its degree of correlation with other sub-indices rather than on its direct discriminatory abilities. Therefore, it is necessary to isolate the correlated and non-correlated parts of the main effect.

For each variable included in the diagnostic variables set, linear and non-linear spline regression models were estimated. By analogy, sub-pillars, pillars, and sub-indices were treated. A positive linear relationship with the GCI value was revealed in nine out of 12 pillars.

Table 2 presents the results of the decomposition of the S_i main effect into its correlated (S_i^c) and uncorrelated (S_i^u) parts. It is noteworthy that the uncorrelated part is small or negative. Briefly, influence is determined by a correlation between sub-indices rather than by the weights assigned to them. Moreover, there are no significant differences in the linear and non-linear estimates; therefore, the linear aggregation can be considered valid.

Tab. 2 – Estimates of the first-order sensitivity measure segregated into correlated and uncorrelated parts for the GCI 2017. Source: own research

Sub-index	Linear			Non-linear		
	S_i	S_i^u	S_i^c	S_i	S_i^u	S_i^c
Basic requirements	0.917	<0.001	0.917	0.929	<0.001	0.929
Efficiency enhancers	0.956	0.021	0.936	0.959	0.021	0.938
Innovation and sophistication factors	0.912	<0.001	0.912	0.914	<0.001	0.914

If the values of sub-indices are optimized following Equation (8), the weights for individual sub-pillars would be 0.16, 0.10, and 0.74 regardless of a given country's degree of development. When multiple variables are added up, they disappear in the index, which is undesirable in policy terms because of their relevance in real life. It is known that users tend to read more in these rankings than the aggregation's quality would support. This conundrum compounds the other shortcoming of linear aggregation that the failure of one variable can be compensated by the progress in another, while this may be undesirable. For example, less health for more growth may not be a viable electoral proposition.

Our optimized weights (Equation 8) normalize correlation ratios to the initially assigned weights. They provide information on the deviation of actual weights from the "optimal" values, directions of imbalance, and identification of removable variables. An analysis analogous to that included in Table 2 was conducted for the pillars. The lowest S_i values were obtained for the macroeconomic environment, labor market efficiency, and market size pillars. In addition, in this case, the correlated part was very close to the total S_i measure, which again proves that the correlation between the pillars, rather than the assigned weights, plays a crucial role. Table 3 reports the optimal weight values for the GCI 2017 pillars and sub-indices. The correlation demonstrated earlier suggests that significant changes to the weighing system are required to adjust the weights to the desired importance. Moreover, it should be emphasized that our objective was to obtain non-negative weights that add up to one.

Table 3 contains the optimal weights assigned to individual pillars included in the GCI's sub-indices. Our results correspond to the conclusions of Adamkiewicz (2019) regarding the inadequate weights used in the construction of the GCI. The sub-indices could be equally weighted provided that the values within each pillar were as given in Table 3. It transpired that in the case of the GCI 2017, the following pillars could be removed without substantially changing the final GCI (weight below 5%): infrastructure, health and primary education, higher education and training, and financial market development. These pillars were not very important in the logic of the GCI as designed by its developers. Therefore, removing 35 variables should not significantly affect the GCI's final version (Figure 1). This is probably a warning of the challenge in using the GCI if essential variables, such as those identified above, appear to be dispensable. Our results correspond to the analyses by Nečadova & Soukup (2013) and Nečadova (2015), criticizing the low explanatory power of soft data in the GCI. If the values of sub-indices were given as input variables, the highest weight would be assigned to the innovation sub-index. Since the WEF assumes that the sub-indices are equally important, the weights assigned for the pillars, sub-pillars, and individual variables should be modified. Otherwise, the assigned weights will not reflect individual factors' actual degree of influence. Currently, they reflect the developers' understanding of the importance, which is erroneous and far removed from the definition of importance that makes mathematical sense (rooted in ANOVA). Optimizing the weights at the level of pillars in the sub-indices fails to ensure that the resulting sub-indices display the required equal weight. It is impossible to rescue the architecture and the weights of the WEF simultaneously.

Tab. 3 – Optimal weights for GCI 2017 sub-indices (bold) and pillars. Source: own research

Basic requirements		Efficiency enhancers		Innovation and sophistication factors	
0.3333		0.3333		0.3333	
Pillar 1	0.4529	Pillar 5	0.0300	Pillar 11	0.2287
Pillar 2	0.0027	Pillar 6	0.4616	Pillar 12	0.7713
Pillar 3	0.5408	Pillar 7	0.2258		
Pillar 4	0.0037	Pillar 8	0.0408		
		Pillar 9	0.1641		
		Pillar 10	0.0778		

Reducing low-weighted pillars and variables could downsize the set of variables used to calculate the GCI 2017 by as much as 56% by roughly maintaining the original ranking, especially in the top and bottom performers (Table 4). However, this does not mean that the excluded variables are unimportant. In most cases, the average difference in the ranking did not exceed +/−3 positions. The Kendall's tau correlation coefficient for the newly created ranking based on the optimized weight and the original GCI 2017 was $\tau=0.84$ ($p<0.0001$). We decided to apply Kendall's tau instead of Spearman's rho because it is less sensitive to errors and discrepancies in data. Significant changes (approximately 20 places higher in the ranking) were recorded for Guinea, Tanzania, Senegal, Uganda, Kenya, Ethiopia, and Pakistan. The opposite situation, that is, a 20-place reduction in the ranking, was observed for Trinidad and Tobago, Vietnam, Nicaragua, Algeria, Egypt, Brazil, and Ukraine. However, Table 4 indicates that there were no significant changes in the top and bottom five countries.

Tab. 4 – Top and bottom five countries in the original and optimized GCI 2017. Source: own research

Top 5		Bottom 5	
GCI 2017	Optimized GCI 2017	GCI 2017	Optimized GCI 2017
Switzerland	Switzerland	DR Congo	Swaziland
the United States	the Netherlands	Venezuela	DR Congo
Singapore	Singapore	Haiti	Burundi
the Netherlands	Sweden	Burundi	Sierra Leone
Germany	Germany	Sierra Leone	Mauritania

4.2. Analysis of the GCI 4.0 edition

As aforementioned, the GCI's structure saw considerable changes in terms of the set of variables and weighting scheme. For the GCI 4.0, we conducted an analogous analysis for the GCI 2017, which allowed us to verify whether the fit was better in the new version. The following SA stages for the GCI 4.0 are presented below.

First, we analyzed the correlation between individual sub-indices and pillars. Again, correlations played a more prominent role than the weights. In most cases, the relationship was linear, with some non-linearity observed for the human capital sub-index. However, the linear method of aggregation is the preferred method. The results of the S_i estimation and the division of the main index into correlated and non-correlated parts for the GCI 4.0 sub-indices are presented in Table 5. Their analysis demonstrates that the uncorrelated part is always small (0.104 for human capital) or negative. Again, influence is determined by the correlation between sub-indices rather than the weights assigned to them. This shortcoming has not been amended in the new version of the GCI.

Tab. 5 – Estimates of the first-order sensitivity measure segregated into correlated and uncorrelated for the GCI 4.0. Source: own research

Sub-index	Linear			Non-linear		
	S_i	S_i^u	S_i^c	S_i	S_i^u	S_i^c
Enabling environment	0.936	<0.001	0.936	0.945	<0.001	0.945
Human capital	0.843	0.104	0.739	0.884	0.104	0.779
Markets	0.880	<0.001	0.880	0.882	<0.001	0.882
Innovation ecosystem	0.892	<0.001	0.892	0.903	<0.001	0.903

If the sub-index values are treated as the only input data, the following weights should be assigned: 0.003, 0.346, 0.345, and 0.306. In this case, the Enabling environment sub-index would not influence the final value of the GCI 4.0; thus, countries' competitiveness ordering. This assumption would be too simplifying; therefore, we treated each sub-index and pillar as an independent synthetic variable.

Table 6 reports the optimal weights assigned to individual pillars included in the GCI 4.0 sub-indices. When comparing values presented in Tables 3 and 6, it is observed that the change in methodology resulted in fewer pillars of marginal importance. In the case of the GCI 2017, there were four pillars of marginal importance, whereas in the case of the GCI 4.0, there are only two pillars: product market and labor market. Hence, removing the 20 variables included in Pillar 7 and 8 of the GCI 4.0 should not significantly affect the GCI's final version (Figure 2). It is noteworthy that Sub-indices 2 (human capital) and 4 (innovation ecosystem) are relatively well balanced. In both cases, the actual value of the weights assigned to the two pillars within those sub-indices is almost equal. There is a moderate imbalance in the markets sub-index case, which should have a higher weight of approximately 35%, whereas the remaining three have a similar influence, which is approximately 21%–22%.

Tab. 6 – Optimal weights for GCI 4.0 pillars and sub-indices. Source: own research

Enabling environment		Human capital		Markets		Innovation ecosystem	
0.2146		0.2127		0.3496		0.2230	
Pillar 1	0.1393	Pillar 5	0.5260	Pillar 7	0.0069	Pillar 11	0.5760
Pillar 2	0.1129	Pillar 6	0.4740	Pillar 8	0.0105	Pillar 12	0.4240
Pillar 3	0.1256			Pillar 9	0.3584		
Pillar 4	0.6222			Pillar 10	0.6243		

We further investigated the diagnostic variables that constitute each GCI 4.0 pillar. A detailed analysis revealed that the set of diagnostic variables could be downsized removing the following:

- Pillar 1: efficiency of the legal framework in settling disputes;
- Pillar 2: railroad density; efficiency of train services, air transport services, and seaport services; exposure to unsafe drinking water;
- Pillar 3: mobile-broadband subscribers, fixed-broadband Internet subscriptions, fiber Internet subscribers;
- Pillar 6: the extent of staff training, digital skills among the active population, the pupil-to-teacher ratio in primary education;
- Pillar 9: non-performing loans;
- Pillar 11: insolvency recovery rate, willingness to delegate authority, growth of innovative companies.

Reducing low-weighted pillars and variables could downsize the set of variables used to calculate the GCI 4.0 by as much as 35%. In this case, the average difference in the ranking did not exceed +/−3 positions either. The Kendall's tau correlation coefficient for the newly created ranking based on the optimized weight and the original GCI 4.0 was $\tau=0.88$ ($p<0.0001$). Significant changes (approximately 15 places higher in the ranking) were recorded for Brazil, India, Pakistan, Vietnam, Colombia, and Algeria. The opposite situation (i.e., a 15-place reduction in the ranking) was observed for Latvia, Uruguay, Armenia, Moldova, Cyprus, and Brunei. However, Table 7 suggests no significant changes in the top and bottom five countries.

Tab. 7 – Top and bottom five countries in the original and optimized GCI 4.0. Source: own research

Top 5		Bottom 5	
GCI 4.0	Optimized GCI 4.0	GCI 4.0	Optimized GCI 4.0
the United States	the United States	Mauritania	Mozambique
Singapore	Germany	Liberia	Liberia
Germany	Japan	Mozambique	Lesotho
Switzerland	the United Kingdom	Sierra Leone	Angola
Japan	the Netherlands	DR Congo	Yemen

It is difficult to compare our results with those of other researchers because there are very few examples in the literature of evaluating the new GCI 4.0 methodology. Both Dudas & Cibula (2018) and Nečadova (2020) emphasize in their analyses that the GCI 4.0 (based on a lower representation of soft data and an equal weighting of the pillars) reduces the distortions owing to the national bias and appreciates the high values across all pillars of global competitiveness. Their proposals to further improve the GCI 4.0 methodology focus on further reducing soft data, which corresponds to our conclusions. However, our proposal goes beyond and suggests improving the weights, which is a new step toward a better GCI 4.0 methodology.

5. DISCUSSION

The results of our research provoke discussion and new questions. Could convergent results be obtained based on a narrower and possibly otherwise defined set of diagnostic variables? If this is the case, then what is the purpose of the index? Can we say that the profusion of variables used in the index is rhetorical because the index could be constructed with fewer variables? Should countries be warned against reading too much into the index itself and encouraged to focus on the complete set of variables instead?

Hence, critical variables or sub-indices that are crucial in the political economy of a country's development appear redundant in the sub-indices, the same for sub-indices, such as the enabling environment in the newest version of the GCI. The holistic ambition of the GCI, of comparing all countries based on a similar large metric, appears fraught with internal coherence problems, even when neglecting the critique that the GCI excludes sustainability and social inequalities issues. Moreover, it appears that the Pareto principle that 80% of variability can be obtained using 20% of diagnostic variables applies to the GCI. Since many, mostly soft variables have a marginal influence on explaining the variations, their discriminatory ability is low. Therefore, the methodological change leading to a greater focus on hard data is justified and reducing the soft-variable set should be continued.

Additionally, we want to emphasize that indicators used in the GCI are essential and relevant; however, many lose their importance in the aggregated measure. The aggregation process, which aims to produce a grand synthesis of different competitiveness aspects over multiple countries at different stages of development, leads to an object where the information is blurred rather than illuminated. According to the GCI, country competitiveness assessment can hardly help in improving policies and may be arbitrary and misleading. Indices such as the GCI, developed by an international organization, are the subject of ideological and political battles; suffice to say—while writing the current paper, the clamor surrounding the interruption, then the announced resumption, of the World Bank Doing Business Report, following a series of polemics regarding irregularities in the scoring (Ghosh, 2020). It is often written that the indices are good at grabbing the headlines. Currently, this may pose as a mixed blessing and invite controversy.

6. CONCLUSIONS

The study's objective to identify whether the methodological changes in the GCI structure improve its ability to capture the real competitiveness of economies was met. By estimating the importance of the pillars in the GCI 2017 and GCI 4.0 and methodologically comparing the two variants of the GCI, we highlighted soft variables in the GCI that have a marginal impact on explaining the variations. Our results reveal that using a smaller set of indicators (mainly hard data) and new weights in a GCI reconstruction is justified. Optimized weights and a reduced set of variables produced a strongly correlated ranking with the original GCI. There are no differences in how competitiveness is measured in highly developed countries. Their high rankings changed by 1–2 positions at most. Changes by 15–20 places were observed in countries previously described as being in the efficiency-driven stage or undergoing the transition from the efficiency- to the innovation-driven stage.

The results have important implications for the economic policy. We found that labor and product pillars of the GCI have a marginal impact on competitiveness. According to the WEF methodology, flexibility and effective talent management are the most important features in the competitive labor market. Although the concept of flexicurity is a popular doctrine in many countries, we cannot support the WEF's approach in creating a high labor market competitiveness policy. We strongly recommend eliminating highly skilled worker shortages, existing in numerous countries. For example, in developed countries, a significant gap exists in university education and advanced vocational training, especially in the engineering, natural sciences, IT, and healthcare sectors. All programs that support high skills, lifelong learning, and deregulations of labor markets are essential for sustainable growth and productivity.

Our recommendations for using a smaller set of indices and new weights in the GCI reconstruction have some additional practical implications. Our results may play a role in the discussion concerning the measurement of the global competitiveness of regions. The growing acknowledgment of the region's role as a key spatial unit of organization has directed attention to global competitiveness at a more regional level. Owing to the increasing number of accessible and reliable databases collected by large organizations, such as the World Bank, OECD, and International Labor Organization, and our recommendations (the use of hard data), the global competitiveness of regions can be assessed more reliably through the prism of selected GCI sub-indices (The Regional Competitiveness Index (RCI)). A more consistent approach to measure the GCI and RCI would make it possible to calculate regions' contribution to the increase of a country's global competitiveness and would be an effective tool for implementing, for example, the European Union cohesion policy.

Our study has some limitations. The main weakness of using the SA is the need to calculate the correlated and uncorrelated share separately for each year analyzed. They depend on the degree of variability and correlation among variables. Consequently, the weights change over time, which can be considered a drawback of this approach. In addition, there is no clear indication in the literature concerning when a particular variable can be regarded as "mute" and how large the difference between the original and optimal weights is such that no changes are required. These questions remain unanswered but are of interest to the authors of this paper. In future research, we intend to conduct a series of simulations and experiments and provide proper guidance to CI's users.

References

1. Adamkiewicz, H. G. (2019). The Dimensions of National Competitiveness: The Empirical Analysis Based on The World Economic Forum's Data. *Economics and Business Review,* 5 (3), 92–117. https://doi.org/10.18559/ebr.2019.3.6

2. Anzoategui, D., Comin, D., Gertler, M., & Martinez, J. (2019). Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence. *American Economic Journal: Macroeconomics*, 11 (3), 67–110. http://dx.doi.org/10.1257/mac.20170269

3. Ball, L. (2014). Long-term Damage from the Great Recession in Countries. European *Journal of Economics and Economic Policies*, 11 (2), 149–160. http://dx.doi.org/10.4337/ejeep.2014.02.02

4. Bandura, R. (2011). *Composite Indicators and Rankings: Inventory 2011. Technical Report, Office of Development Studies*. New York: United Nations Development Programme (UNDP).

5. Becker, W. 2017. Matlab Toolbox for Analysis and Adjustment of Weights in Composite Indicators. European Commission, Joint Research Centre, https://doi.org/10.13140/RG.2.2.27035.46883

6. Bekker, S. (2018). Flexicurity in the European Semester: Still a Relevant Policy Concept? *Journal of European Public Policy*, 25 (2), 175–192. http://dx.doi.org/10.1080/13501763.2017.1363272

7. Bergsteiner, H., & Avery, G. C. (2019). Misleading Country Rankings Perpetuate Destructive Business Practices. *Journal of Business Ethics*, 159, 863–881. http://dx.doi.org/10.1007/s10551-018-3805-6

8. Cartone, A., & Postiglione, P. (2020). Principal Component Analysis for Geographical Data: the Role of Spatial Effects in the Definition of Composite Indicators. *Spatial Economic Analysis,* 16 (2), 126–147. http://dx.doi.org/10.1080/17421772.2020.1775876

9. Cerra, V., Fatas, A., & Saxena, S. (2020). Hysteresis and Business Cycles. *IMF Working Papers*, 20 (73). https://doi.org/10.5089/9781513536996.001

10. Cinelli, M., Spada, M., Kim, W., Zhang, Y., & Burgherr, P. (2020). MCDA Index Tool: an Interactive Software to Develop Indices and Rankings. *Environment Systems and Decisions,* 41, 81–109. http://dx.doi.org/10.1007/s10669-020-09784-x

11. Drago, C. (2021). The Analysis and the Measurement of Poverty: An Interval Based Composite Indicator Approach. *Economies*, 9 (4), 1–17. http://dx.doi.org/10.3390/economies9040145

12. Dudas, T., & Cibula, A. (2018). The Changing Methodology of the Global Competitiveness Index and its impact on Slovakia. *Journal of Interdisciplinary Research*, 8 (2), 50–53.

13. European Commission. (2018). European Skills Agenda for Sustainable Competitiveness, Social Fairness and Resilience. OECD Publishing, 1–23. Retrieved July 11, 2021 from https://ec.europa.eu/social/main.jsp?catId=1223&langId=hr

14. European Commission. (2021). Better Regulation: Guidelines and Toolbox. Retrieved November 15, 2021 from https://ec.europa.eu/info/law/law-making-process/planning-and-proposing-law/better-regulation-why-and-how/better-regulation-guidelines-and-toolbox_en

15. Ghosh, J. (2020). Stop Doing Business. Project Syndicate, September 2020. Retrieved September 29, 2020 from https://www.project-syndicate.org/commentary/world-bank-should-scrap-doing-business-index-by-jayati-ghosh-2020-09?barrier=accesspaylog

16. Gnaldi, M., & Del Sarto, S. (2018). Variable Weighting via Multidimensional IRT Models in Composite Indicators Construction. *Social Indicators Research*, 136, 1139–1156, http://dx.doi.org/10.1007/s11205-016-1500-5

17. Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. *Social Indicators Research,* 141, 61–94, http://dx.doi.org/10.1007/s11205-017-1832-9

18. Hirsh, M. (2019). Economists on the Run. Foreign Policy. Retrieved July 21, 2021 from https://foreignpolicy.com/2019/10/22/economists-globalization-trade-paul-krugman-china/

19. Ketels, C. (2016). Review of Competitiveness Frameworks. Irish National Competitiveness Council. Retrieved May 18, 2021 from http://www.competitiveness.ie/Publications/2016/Review of Competitiveness Frameworks.pdf

20. Kijek, T., & Matras-Bolibok, A. (2019). The Relationship Between TFP and Innovation Performance: Evidence from EU Regions. *Equilibrium. Quarterly Journal of Economics and Economic Policy,* 14 (4), 695–709, http://dx.doi.org/10.24136/eq.2019.032

21. Krugman, P. R. (1994). Competitiveness: A Dangerous Obsession. *Foreign Affairs*, 73 (2), 28–44. http://dx.doi.org/10.2307/20045917

22. Krylovas, A., Kosareva, N., & Dadelo, S. (2020). European Countries Ranking and Clustering Solution by Children's Physical Activity and Human Development Index Using Entropy-Based Methods. *Mathematics*, 8 (10), 1705. http://dx.doi.org/10.3390/math8101705

23. Kuc-Czarnecka, M. (2019). Sensitivity Analysis as a Tool to Optimize Human Development Index. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 14 (3), 425–440. https://doi.org/10.24136/eq.2019.020

24. Kuc-Czarnecka, M., Piano, S.L., & Saltelli, A. (2020). Quantitative Storytelling in the Making of a Composite Indicator. *Social Indicators Research*, 149, 775–802. http://dx.doi.org/10.1007/s11205-020-02276-0

25. Lindén, D., Cinelli, M., Spada, M., Becker, W., & Burgherr, P. (2021). Composite Indicator Analysis and Optimisation (CIAO) Tool, v.2, https://doi.org/10.13140/RG.2.2.14408.75520

26. McAfee, A., Brynjolfsson, E. (2017). *Machine, Platform, Crowd: Harnessing our Digital Future*. New York: W. W. Norton and Company.

27. McArthur, J. W., & Sachs, J. (2002). The Growth Competitiveness Index: Measuring Technological Advancement and the Stages of Development. The Global Competitiveness Report, 28–51. Geneva: World Economic Forum.

28. Muller, J. Z. (2018). *The Tyranny of Metrics*. Princeton University Press, Princeton, NJ.

29. Nečadová, M. (2015). Selected Approaches to Measurement of National Competitiveness and the Results of Visegrad Group in Years 2007-2014. *Acta Oeconomica Pragensia,* 23 (2), 22–39. http://dx.doi.org/10.18267/j.aop.468

30. Necadova, M. (2019). Changes in Economic Sentiment Indicators Before and After Economic Crisis (Position of Visegrad Group and Germany in EU). *Central European Business Review,* 8 (4), 55–85. http://dx.doi.org/10.18267/j.cebr.220

31. Nečadová, M. (2020). Impact of Aggregation Methods on Countries' Ranking in Composite Index of National Competitiveness. *Malaysian Journal of Economic Studies,* 57 (1), 39–58. http://dx.doi.org/10.22452/MJES.vol57no1.3

32. Nelder, J.A. &Mead, R. (1965), A Simplex Method for Function Minimization. *The Computer Journal,* 7 (4), 308–313. https://doi.org/10.1093/comjnl/7.4.308

33. OECD. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. Paris: OECD Publishing.

34. Olczyk, M. (2016). Bibliometric Approach to Tracking the Concept of International Competitiveness. *Journal of Business Economics and Management,* 17 (6), 945–959. http://dx.doi.org/10.3846/16111699.2016.1236035

35. Oulton, N. (2018). Productivity and the Great Recession. *Intereconomics*, 53 (2), 63–68. http://dx.doi.org/10.1007/s10272-018-0723-x

36. Paruolo, P., Saisana, M., & Saltelli, A. (2013). Rating and Rankings: Voodoo or Science? *Journal of Royal Statistical Society Series A - Statistics in Society,* 3. http://dx.doi.org/10.1111/j.1467-985X.2012.01059.x

37. Petrarca, F., & Terzi, S. (2018). The Global Competitiveness Index: an Alternative Measure with Endogenously Derived Weights. *Quality and Quantity,* 52 (5), 2197–2219. http://dx.doi.org/10.1007/s11135-017-0655-8

38. Petrylė, V. (2017). Does the Global Competitiveness Index Demonstrate the Resilience of Countries To Economic Crises? *Ekonomika*, 95 (3), 28–36. http://dx.doi.org/10.15388/Ekon.2016.3.10326

39. Porter M. E., Sachs, J. D., & Mcarthur, J. W. (2001). *Executive Summary: Competitiveness and Stages of Economic Development. The Global Competitiveness Report*. Geneva: World Economic Forum.

40. Porter, M. E. (2002). *Enhancing the Microeconomic Foundations of Prosperity: the Current Competitiveness Index. The Global Competitiveness Report*. Geneva: World Economic Forum.

41. Rawdanowicz, Ł., Bouis, R., Inaba, K.-I., & Christensen, A. K. (2014). Secular Stagnation: Evidence and Implications for Economic Policy. *OECD Working paper,* (1169), 1–30. http://doi.org/10.1787/5jxvgg6q27vd-en

42. Reifschneider, D., Wascher, W., & Wilcox, D. (2015). Aggregate Supply in the United States: Recent Developments and Implications for the Conduct of Monetary Policy. *IMF Economic Review,* 63, 71–109. http://dx.doi.org/10.1057/imfer.2015.1

43. Roszko-Wójtowicz, E., & Grzelak, M. M. (2020). Macroeconomic Stability and the Level of Competitiveness in EU Member States: a Comparative Dynamic Approach. *Oeconomia Copernicana*, 11 (4), 657–688. http://dx.doi.org/10.24136/oc.2020.027

44. Sahin, S., Ülengin, F., Ulusoy, G., Aktas, E., Kabak, O., & Topcuc, Y. (2008). A New Perspective in Competitiveness of Nations. S*ocio-Economic Planning Sciences,* 42 (4), 221–246.

45. Saisana, M., & Saltelli, A. (2010). Uncertainty and sensitivity analysis of the 2010 environmental performance index. Retrieved from https://publications.jrc.ec.europa.eu/repository/handle/JRC56990 (16.12.2018)

46. Sala-i-Martin, X., & Artadi, E. (2001). The Global Competitiveness Index. In Global Competitiveness Report 2004-2005. Geneva: World Economic Forum.

47. Saltelli, A., Bammer, G., Bruno, I., Charters, E., Di Fiore, M., Didier, Wendy, E., & Espeland, N. et al. 2020. Uncertainty and sensitivity analysis of the 2010 environmental performance index. JRC Publications Repository. Retrieved March 25, 2022, from https://publications.jrc.ec.europa.eu/repository/handle/JRC56990

48. Schröder, J. (2020). Decoupling of Labour Productivity Growth from Median Wage Growth in Central and Eastern Europe. *WIIW Working Papers*, 448(July), 1–48.

49. Schwab K. (2015). *The Global Competitiveness Report 2015-2016.* Geneva: World Economic Forum.

50. Schwab K. (2017). *The Fourth Industrial Revolution.* UK: Portfolio Penguin.

51. Szczepaniak, I. (2018). Comparative Advantages in Polish Export to the European Union - Food Products vs. Selected Groups of Non-food products. *Oeconomia Copernicana*, 9 (2), 287–308. http://dx.doi.org/10.24136/oc.2018.015

52. Szczepaniak, I. (2019). Changes in Comparative Advantages of the Polish Food Sector in World Trade. *Equilibrium. Quarterly Journal of Economics and Economic Policy,* 14 (3), 463–480. http://dx.doi.org/10.24136/eq.2019.022

53. World Economic Forum (WEF). (2017). The Global Competitiveness Report 2017–2018, 1-393. Retrieved March 09, 2021 from https://www.weforum.org/reports/the-global-competitiveness-report-2017-2018.

54. World Economic Forum (WEF). (2018). Benchmarking Competitiveness in the Fourth Industrial Revolution: Introducing the Global Competitiveness. The Global Competitiveness Report, 37–47. Retrieved March 09, 2021 from https://www3.weforum.org/docs/GCR2018/02Chapters/Chapter%203.pdf

55. World Economic Forum (WEF). (2018a). The Global Competitiveness Index Historical Dataset 2007-2017. Retrieved February 26, 2018 from https://www3.weforum.org/docs/GCR2017-2018.xls

56. World Economic Forum (WEF). (2018b). The Global Competitiveness Index 4.0 dataset. Retrieved October 13, 2018 from https://www3.weforum.org/docs/GCR2017-2018.xls

57. World Economic Forum (WEF). (2019). The Global Competitiveness Report 2019. Retrieved March 09, 2021 from http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf

58. Yang, L., 2014. An Inventory of Composite Measures of Human Progress, Technical Report. United Nations Development Programme Human Development Report Office, 1-120, Retrieved March 15, 2020 from: https://hdr.undp.org/en/content/inventory-composite-measures-human-progress

Contact information

Prof. Magdalena Olczyk
Gdansk University of Technology
Faculty of Management and Economics
Department of Economy
Poland
Email: magdalena.olczyk@pg.edu.pl
ORCID: 0000-0002-4880-5890

Ph.D. Marta Kuc-Czarnecka
Gdansk University of Technology
Faculty of Management and Economics
Department of Statistics and Econometrics
Poland
Email: marta.kuc@zie.pg.edu.pl
ORCID: 0000-0003-2970-9980

Prof. Andrea Saltelli
UPF-Barcelona School of Management
Spain
Email: andrea.saltelli@gmail.com
ORCID: 0000-0003-4222-6975