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ORIGINAL ARTICLE

A Classification Methodology for Assessing Countries in Terms of Tourism Competitiveness

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Abstract

Tourism industry is important for national economies, and, in this regard, it is vital to monitor its competitiveness. The Travel and Tourism Competitiveness Index (TTCI), developed and reported by the World Economic Forum, serves this purpose by providing a consistent framework, explanatory factors, and corresponding data sets. In this paper we exploit the past data sets of this index, first, to verify that in several countries, competitiveness in tourism and travel industries hardly changes over time. Next, we identify countries that show consistency in travel–tourism competitiveness and separate them into classes of best, worst, intermediate, and ambiguous past performance. Building on such a classification, we apply linear discriminant analysis (LDA) as an alternative to the TTCI computational framework in order to compose the new synthetic index TTCI-LDA, which assesses countries' competitiveness. The analysis of country scores obtained from this index has revealed that ICT readiness and touristic service infrastructure are important for tourism competitiveness. The score thresholds for the best–worst country cases in each class provide additional useful information for management, benchmarking, and policy decision making.

Keywords: Travel and Tourism Competitiveness Index, Linear discriminant analysis, Weighting of composite indicators, Classification

JEL classification: C38, L83

Introduction

The travel and tourism industry plays an increasingly important role in the development of countries' economies. Therefore, it is vital first to identify, measure, and aggregate the factors that affect countries' progress in this sector. This need is served and supported by the Travel and Tourism Competitiveness Index (TTCI), hereinafter referred to as TTCI-WEF, developed and first published in 2007 by the World Economic Forum (WEF, 2019). The last update of TTCI-WEF was reported in 2019 and after that, it has been restructured to form the Travel & Tourism Development Index (TTDI) (WEF, 2022). The TTCI framework is regarded as the most popular, comprehensive, and systematic collection of data related to travel and tourism competitiveness (Salinas-Fernández et al., 2020).

For the assessment and benchmarking of the countries, the TTCI original World Economic Forum methodology proposes a conceptual model and a number of factors organized in a hierarchy, on the top level of which there are four main dimensions (subindices) of competitiveness, namely Enabling Environment (e.g., safety and security and human resources and labor market), Travel and Tourism Policy and Enabling Conditions, Infrastructure, and Natural and Cultural Resources. At the next lower levels, TTCI has 14 pillars and 90 individual indicators (see Fig. A1 in the Appendix, which briefly presents the TTCI-WEF structure). The latest report (WEF, 2019) for the year 2019 evaluates 140 countries (economies), which account for over 98% of world GDP.

It is important to emphasize that TTCI-WEF follows the common approach applied to composite indicators (CIs), that is, to use the data of the current period

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to estimate the performance of the countries, ignoring the historical progress that a country may have had. An inspection of TTCI-WEF scores reported for previous years reveals that the best- and worst-performing countries remain approximately in the same ranking positions, and this is hardly improved or worsened from year to year. This is explained by the fact that an exceptional improvement of a country in the travel and tourism industry needs a great deal of economic, administrative–legislative, infrastructural, and political changes, the result of which is visible and reflected in the TTCI in a horizon of several years. This observation raises the idea that countries' performance in previous years could form the basis for classifying countries in terms of performance, and this classification information could be a starting exploitation point for the reassessment of the TTCI-WEF index. Therefore, for the assessment of countries based on the TTCI-WEF, it is feasible to accept, as initial preference information, a classification of countries in groups of potentially best, worst, and intermediate performance. The concept of using such preference information in the form of a broad classification for the development of CIs has been presented by Smirlis (2020) for the estimation of the Digital Economy and Society Index (DESI).

This paper proposes a new methodology for the reassessment of TTCI-WEF: the initial classification of the countries into groups of high, medium, and low performance, combined with a detailed profile of each country in the current year as it is expressed by the scores in the TTCI-WEF pillars, create the necessary input to a statistical linear discriminant analysis (LDA). In a next step, intermediate measurements of the LDA procedure are used to calculate proper subindicator weights that could interpret and explain the classification. This approach aims to bring a new idea for constructing CIs and at the same time to deal with the problem of imposing equal importance to indicators/pillars due to a simple arithmetic average formula, which has been a main subject of strong criticism in the construction methodology of the original TTCI-WEF index (see next section).

The paper has the following structure. Section 1 includes a review of past publications that propose new computational methodologies for the TTCI-WEF and presents a short overview of the proposed LDA-based approach. Section 2 presents the methodological part of constructing the proposed TTCI-LDA index. In this, based on a weighted sum formula for the aggregation of the pillars, we present the LDA formulations for the estimation of the weights. Section 3 presents the data analysis of the past TTCI-WEF scores, the implementation of LDA, the estimations of the weights, and the comparison of the proposed TTCI-LDA country scores to those of the original TTCI-WEF. Section 4 concludes the method and discusses the results.

1 Literature review and methodology overview

CIs measure multidimensional and complex concepts and phenomena (Greco et al., 2019). Their construction is based on individual subindicators that measure various dimensions and comply with a theoretical framework and an underlying model of the concept to be measured (Nardo et al., 2008).

In the process of the construction, weighting and aggregation are among the main issues to be considered. The weighting determines the assignment of an explicit importance to the subindicators, while the aggregation refers to the mathematical operations for combining the values of indicators into a single summary (Nardo et al., 2008). For the weighting problem, a plurality of methods has been proposed, among them the data-driven, originated by multivariate statistics factor/principal component, cluster, correspondent, canonical correlation analysis, and so forth (Greco et al., 2019; Nardo et al., 2008).

Particularly in the field of travel and tourism competitiveness, the work of Mendola and Volo (2017) describes methodological foundations to build CIs and evaluates the currently available CIs. Among them, TTCI-WEF is a noteworthy contribution, aiming to evaluate the set of factors that enable the sustainable development of travel and tourism (WEF, 2019). This index has offered a consistent framework and a credible and accurate data set since 2007 (Abreu-Novais et al., 2016). It has been extensively used for research in the travel and tourism sector, allowing direct comparison of countries (Dwyer et al., 2014; Kayar & Kozak, 2010).

In its recent 2019 report, TTCI-WEF evaluates 140 economies by using a hierarchical structure (see Fig. A1—Appendix) composed of 4 subindices, 14 pillars, and 90 low-level indicators. In detail, subindex A—Enabling Environment—includes 5 pillars and captures the general conditions necessary for operating in a country. Subindex B—T&T Policy and Enabling Conditions—is analyzed in 4 pillars and includes indicators for policies and strategic aspects that impact the travel–tourism industry. Subindex C—Infrastructure—has 3 pillars that measure the availability and quality of physical infrastructure in each economy. Finally, subindex D—Natural and Cultural Resources—, which has 2 pillars, captures the principal "reasons to travel."

The calculation of the TTCI-WEF score of each country is performed on a bottom-up basis. First, the response data from the World Economic Forum's Executive Opinion Survey are used to grade the countries' performance on the low-level indicators on a scale of 1 (worst) to 7 (best). Then, the scores in pillars are calculated as an arithmetic average of their constituent low-level indicators' scores; the scores in subindices are derived as averages of their constituent pillars, and finally the TTCI-WEF total score results from the average score in the 4 subindices. This arithmetic average formula used in TTCI-WEF implicitly defines weights that account for the number of subindices and pillars. For example, at the upper level, which includes 4 subindices, the weight for each subindex score is $1/4 = 0.25$; at the lower level, the weight of the pillars in subindex A (Enabling Environment) is $0.25/5 = 0.05$ as it includes 5 pillars, while the weight of the pillars in subindex D (Natural and Cultural Resources) will be $0.25/2 = 0.125$ as only two pillars exist in this subindex. In this manner, TTCI-WEF assigns equal weight values to the pillars in every subindex and equal weights to all subindices. Conceptually, this is interpreted as attributing equal contribution of subindices or pillars to tourism competitiveness, independently of their context.

Although TTCI-WEF represents a widely accepted approach to measuring tourism competitiveness, it has been criticized (Croes & Kubickova, 2013) for both its conceptual model of tourism competitiveness and the index composition methodology and consequently the reliability of the measurement. At the conceptual level of the TTCI-WEF, Ring (2011) restructured the pillars and subindicators to form four additional models. Then, by comparing the derived scores, she examined how pillars influence the countries' competitiveness. One of the results is that Natural Resources and Environmental Sustainability, considered by some other studies as the main factors of attractiveness in tourist destinations, have not been proven significant. Kunst and Ivandić (2021) ascertain the methodological shortcomings of TTCI-WEF by using the Mediterranean countries as a sample and observe that the variation of scores does not match significantly with international arrivals and inbound tourism expenditures taken as proxies of performance-related tourism activity. The authors suggest the application of equal weights to pillars and subindicators along with the addition of new indicators.

As far as the issue of the TTCI-WEF methodology is concerned, a number of publications criticize its above-mentioned equal weights arrangement (Crouch, 2007; Rodríguez-Díaz & Pulido-Fernández, 2020) as unrealistic and not representing the actual tourism and travel competitiveness (Wu et al., 2012). Furthermore, the arithmetic average formula for the aggregation of the components entails that the higher the number of indicators used to calculate the score of the upper-level CI, the lower their weight value is, and thus their importance is reduced. To address this drawback, several attempts to reconstruct the TTCI-WEF have been published in the past years, focusing on the problem of reestimating the weights. From a methodological viewpoint, it is possible to distinguish between publications employing multivariate statistics and those that use multicriteria decision making or linear programming. For the multivariate statistical approaches, Mikulić et al. (2015), by comparing past studies, highlight the requirement of strong correlation among the pillars and subindicators. Moreover, Kožić and Mikulić (2014), comparing Croatian coastal destinations, juxtapose three different procedures for weighting sustainability and raise the argument that the application of factor analysis is questionable. In this group, indicative publications are as follows. Lin and Huang (2009) propose grey relational and sensitivity analysis in order to evaluate the tourism-competitive potential in Asian countries. Mazanec and Ring (2011) examine the predictive power of the TTCI data by applying different computational methods (partial least squares path modelling, PLS regression, mixture modelling, and non-linear covariance-based structural equation modelling) and conclude that different unobserved factors and complicated relations affect tourism competitiveness. Lan et al. (2012) combine an expectation–maximization (EM) clustering algorithm with an artificial neural network structure to group countries into three classes and thus obtain an objective weighting system for the 14 pillars of TTCI. The resulting weights indicate high importance in six pillars, namely Tourism Infrastructure, Ground Transport Infrastructure, Air Transport Infrastructure, Cultural Resources, Health and Hygiene, and ICT Infrastructure. Milić and Jovanović (2019) contribute to the problem of weighting TTCI pillars by employing factor/principal component analysis to obtain the weights of each pillar and therefore new country rankings. Salinas-Fernández et al. (2020) estimate new weights for the TTCI pillars by introducing a DP_2 distance-based method to derive a synthetic indicator that linearly aggregates the distances of each country relative to the least desirable situation. Then they apply factor analysis to explore the underlying dimensions. In terms of pillars' significance, this approach concludes that ICT Readiness and Prioritization of Travel & Tourism exert the greatest influence in determining the final index, while Natural Resources have the least influence. Litavcová and Síč (2021) use a quantile regression approach to examine how the four pillars of the T&T Policy and Enabling

Conditions contribute to the TTCI-WEF scores. In the multicriteria-decision-making group of publications, the work of Pulido-Fernández and Rodríguez-Diaz (2016) introduces two reference points for each pillar, an aspiration and a reservation level, and, by building on these, estimates a weak index and a strong index, which are finally combined into a composite one used for the country rankings. Gomez-Vega and Picazo-Tadeo (2019) used multicriteria and data envelopment methods to estimate new weights for the TTCI-WEF. Gomez-Vega and Picazo-Tadeo (2019) propose a regression and bootstrapping method based on the benefit of the doubt principle of the data envelopment analysis modelling approach (Despotis, 2005) to estimate the weights of the pillars endogenously.

In this paper, we propose LDA as the main methodological technique to estimate new weights for the TTCI-WEF pillars, following the stream of multivariate statistical approaches. Discriminant analysis has not been very common for aggregating factors in CIs, particularly in tourism. In other fields, indicative works are that of Gupta et al. (1994), who used this method to calculate relative weights of human rights indicators to evaluate countries in terms of human rights abuse and violations, and that of Iwuagwu and Nwosu (2021), who use LDA as a basis to model the Human Development Index. We construct the new TTCI-LDA index by considering the 14 pillars of the TTCI-WEF structure as variables contributing independently to travel and tourism competitiveness. Based on the country scores in these pillars, we calculate the new TTCI-LDA scores for the countries by using a weighted sum formula, with the pillar weights to be derived directly from the LDA statistical procedure. The steps followed in the TTCI-LDA construction process are:

(i) classification of countries in terms of their past performance scores,
(ii) application of the LDA, estimation of new weight values for the pillars, and calculation of the new country scores,
(iii) validation of the scores obtained.

In step (i), we analyze the past TTCI-WEF data for the years 2007–2017, and by employing a statistical procedure (percentile distribution thresholds, hypothesis testing and confidence interval estimations), we select those countries that show consistency in travel–tourism competitiveness and separate them into classes of best, worst, and intermediate past performance. The rest of the countries, showing variability in their past TTCI-WEF scores and ambiguous rankings, are left unclassified.

In step (ii), the four-class categorization of the countries (best, intermediate, worst, and ambiguous past performance) together with the country scores in the 14 pillars for the recent year 2019 are considered input to a LDA procedure from which the new pillar weights derive. By definition, these weight values reflect the impact and contribution of each pillar to the separation of classes. The new pillar weight values are then used to calculate the total score for all countries, including those previously left unclassified due to ambiguous performance.

In step (iii), the necessary validation with external data sources is performed.

2 Estimation of the weights using Linear Discriminant Analysis

To formulate the problem of aggregating and weighting of subindicators in order to construct a composite indicator, we assumed that in the general case, n countries $A = \{a_1, a_2, \ldots, a_n\} (j = 1, \ldots, n)$ have to be assessed on $X_1, X_2, \ldots, X_m$ subindicators so that the total performance of country a_j is derived from the m-dimensional level of achievement of achievement vector $(x_{1j},\ x_{2j}, \ldots, x_{m_j})$. The common approach for the aggregation of the m subindicators is to employ the weighted average formula (1)

$$I_j = \sum_{i=1}^{m} w_i x_{ij} \tag{1}$$

In formula (1) the weights $w_i, i = 1, \ldots, m$ are scaling positive variables.

In our indicator approach, the 14 pillars ($m = 14$) were considered as the constituent subindicators, and the weights $w_i, i = 1, \ldots, 14$ were estimated by applying an LDA statistical procedure, as is explained latter in this section. Then, the countries' scores $I_j,\ j = 1, \ldots, 140$ derived directly from (1), as the pillar scores $x_{1j}, x_{2j}, \ldots, x_{14_j}$ were known from the original TTCI-WEF calculations. However, it is worth noting that formula (1) is actually the same as the one used by the original TTCI-WEF and that the corresponding weight values are those estimated by its arithmetic average calculation (see column 6, Table 4).

Additionally, we assume that it is feasible to classify a number of countries in terms of their performance and use this classification as initial preference information. Let $C^1, C^2, \ldots, C^K$ denoted K in number classes of decreasing level of performance, with the best performing countries belonging to class C^1, the worst performing to class C^K, and the classes $C^2, \ldots, C^{K-1}$ including countries of intermediate levels of total performance. Note that several countries may have been left unclassified, as there may have been no strong indication of their level of performance. These countries comprised class $C^?$. For simpler modelling, we accept that all the defined classes are non-empty ($C^1, C^2, \ldots, C^K, C^? \neq \emptyset$), that a country should belong to only one class or be left unclassified ($C^1 \cap C^2 \cap \ldots \cap C^K \cap C^? = \emptyset$) and that no country is left without initial classification membership $C^1 \cup C^2 \cup \ldots \cup C^K \cup C^? = A$. The order of the classes, due to the common, positive weight values in (1), implies a monotonic relation on the total scores I_j, that is, $I_{j_1} \geq I_{j_2}, \forall a_{j_1} \in C^{k_1}, a_{j_2} \in C^{k_2}$, where class C^{k_1} is superior to class C^{k_2}.

In the case of TTCI-WEF, which was under consideration, there were three defined classes ($K = 3$), set as C^1 best, C^2 intermediate, and C^3 worst. This partitioning derived from the past TTCI-WEF data for the years 2007–2017 in the statistical process of step (i) of our methodology, as explained in Section 3.

The initial classification of the countries was to be further exploited by LDA to estimate new weights of the pillars. LDA, introduced by Fisher (1936), is a popular multivariate statistical method to model, analyze, and predict classifications of observations. The mechanism of LDA arranges linear transformations on the data set to define $K-1$ in numbered linear functions $F_1, F_2, \ldots, F_{K-1}$, called *discriminant functions*. These adopted the initial classification suggested and achieved the best possible separation of countries. The first function, F_1, is the most powerful in expressing the differentiation of the classes, while the next, $F_2, \ldots, F_{K-1}$, have decreasing importance. Every discrimination function F_k is associated with an eigenvalue, λ_k, which denotes the amount of variance between the classes explained by this function. The normalization of the eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_{K-1}$ in the ratio $\Phi_k = \frac{\lambda_\kappa}{\sum_{i=1}^{K-1} \lambda_\kappa}$ can represent the relative contribution of the discriminant function F_k to the total discriminating power of the model (Hair et al., 2010). In addition to the discriminant functions and the eigenvalues, a typical LDA procedure also reports the *structure coefficients*, which, for the case under consideration, denote the correlation between the discriminant functions and the pillars, regarded as variables. We considered r_{ik} to be such a structure coefficient between the i^{th} pillar X_i and the k^{th} discriminant function F_k. The combination of the correlation coefficients r_{ik} and the ratios Φ_k creates the *potency index* PI_i in formula (2).

$$PI_i = \sum_{k=1}^{K-1} r_{ik}^2 \Phi_k \tag{2}$$

The *potency index* (2) was initially proposed by Perreault et al. (1979) as an aggregative measure that summarizes information across different functions. Hair et al. (2010) defines the potency index as the "composite measure of the discriminatory power of an independent variable when more than one discriminant function is estimated. Based on the discriminant loadings it is a relative measure used for comparing the overall discrimination provided by each step independent variable across all significant discriminant loadings". It has been used in conjunction with LDA in different fields (e.g., Njoku, 2013; Shobha & Siji, 2018) to indicate the order of importance of the variables used. In the case of TTCI-LDA, the potency index expresses how significantly pillar i participates in the separation of classes. In this manner, the weight values needed for the calculation of total performance of the countries in (1) can derive from the normalization formula (3) of PI_i.

$$w_i = \frac{PI_i}{\sum_{i=1}^{m} PI_i} \tag{3}$$

The definition of the weights in (3) implies that $\sum_{i=1}^{m} w_i = 1$, so each weight w_i will explain, in terms of percentage, to what extent pillar i contributes to the countries' classification.

LDA also has predictive power to assign the unclassified countries in $C^?$ to the previously defined classes $C^1, C^2, \ldots, C^K$, thus obtaining a full classification. This was achieved first by calculating the class centroids as the within-class average scores of the discriminating functions and then by calculating the probability of a country to belong to a class by evaluating its distance from the corresponding class centroid (Huberty & Olejnik, 2006).

It is important to point out that for the reliability of the analysis, LDA imposes strong assumptions on the data: the size of the smallest group must be larger than the number of predictor variables (size of the problem); the predictor variables should approximately follow the normal distribution within each class (multivariate normality); the variance/covariance structure of indicators should be the same among classes (homoscedasticity); the correlation (multicollinearity) between indicators should be insignificant, and the indicators' scores have to be independent of each other (independence) (Huberty, 1994; Watson, 1982). Such assumptions limit the application of LDA in practical problems somewhat. Quadratic discriminant analysis (Friedman et al., 2009) does not impose strict statistical properties such as the equal covariance matrices between classes but does not allow linear form for the discriminant functions.

3 Classification of countries and estimation of the new TTCI-LDA index

In this section, we apply the steps (i)–(iii) described in Section 1 in order to reassess countries in terms of

Table 1. One sample t*-test at level of significance* $\alpha = 5\%$ *against the estimated thresholds.*

Class		Condition	Hypotheses
C^1	Top 10%	Average score greater than $t_1 = 5.23$	H_0:$\bar{X} \geq t_1$ H_1:$\bar{X} < t_1$ (1-tail)
C^2	Average	Average score approximately equal to $t_1 = 4.29$	H_0:$\bar{X} = t_2$ H_1:$\bar{X} \neq t_2$ (2-tail)
C^3	Bottom 10%	Average score lower than $t_3 = 2.89$	H_0:$\bar{X} \leq t_3$ H_1:$\bar{X} > t_2$ (1-tail)

tourism competitiveness. First, based on TTCI-WEF scores for the years 2007–2017 (TCdata360, 2019), we develop a statistical process to detect those countries that had consistent performance in these years and distinguish them in classes of high-, intermediate-, and low-level total performance. Then a classification of the countries is performed, and according to the weighting method presented in the previous section, the new TTCI-LDA country scores are estimated.

3.1 *Classification of countries in terms of their past performance scores*

The definition of classes is based on the TTCI-WEF country total scores in the past years 2007, 2009, 2011, 2013, 2015, and 2017. Table A1 and Fig. A2 in the Appendix present the basic descriptive statistics and the relative box-plot graphs, respectively, for that period. The inspection of these reveals that there is no significant variation of TTCI scores among these years, except for a small decrease observed for the recent period 2015–2017.

The three classes of performance are defined as follows. The best performing class, C^1, includes the countries of the 90th percentile of the TTCI-WEF scores; the worst performing class, C^3, the countries belonging to the 10th percentile, and C^2 the countries with an intermediate level of performance. Let t_1 be the maximum 90th percentile value of past scores, t_3 the minimum 10th percentile value, and t_2 the average 50th percentile value, that is

$$\begin{aligned} t_1 &= \max\{P_{90}^t, t = 2007, 2009, 2011, 2013, 2015, 2017\} \\ t_2 &= \text{average}\,\{P_{50}^t, t = 2007, 2009, 2011, 2013, 2015, 2017\} \\ t_3 &= \min\{P_{10}^t, t = 2007, 2009, 2011, 2013, 2015, 2017\} \end{aligned} \quad (4)$$

(the notation P_q^t stands for the qth percentile of the distribution of TTCI scores at year t).

From the corresponding data, the resulting threshold values are $t_1 = 5.23$, $t_2 = 4.29$, and $t_3 = 2.89$. These values were further utilized in hypothesis tests to indicate the initial class membership of each country. Table 1 presents the classes, the condition set, and the associated hypothesis test.

Positive test results (acceptance of the null hypothesis H_0 at significance level 95%, p-value $> .05$) were confirmed for 58 countries in total, of which 16 were classified in class C^1, 25 in class C^2, and 17 in class C^3. These countries are listed in Table 2. The other 82 out of 140 total ($\sim$ 59%) assumed to have unknown group membership and assigned to class $C^?$. These, either had a rejection of the null hypothesis H_0 or appeared with insufficient data.

The classification result of Table 2 is comparable with the WEF report 2019 (WEF, 2019), which identifies Spain, France, Germany, Japan, the United

Table 2. List of countries assigned to classes C^1, C^2, C^3.

	Class C^1	Class C^2		Class C^3
Number of countries	16	25		17
Countries:	Austria	Bahrain	Montenegro	Angola
	Australia	Brazil	Oman	Bangladesh
	Canada	Bulgaria	Panama	Burundi
	France	Chile	Poland	Burkina Faso
	Germany	Costa Rica	Qatar	Cameroon
	Hong Kong SAR	Dominican Rep.	Russian Fed.	Chad
	Japan	Hungary	Seychelles	Guinea
	Luxemburg	Israel	Slovak Rep.	Haiti
	Netherlands	Jamaica	Slovenia	Lesotho
	New Zealand	Jordan	Tunisia	Malawi
	Singapore	Latvia	Turkey	Mali
	Spain	Lithuania	Uruguay	Mauritania
	Switzerland	Mauritius		Mozambique
	Sweden			Nigeria
	United Kingdom			Pakistan
	United States			Sierra Leone
				Yemen

States, United Kingdom, Australia, Italy, Canada, and Switzerland as the top 10 countries. The same report certifies the main underlying concept of the study for score stability in successive years by stating, "the top 10 TTCI scorers remain the same . . . Spain is the top performer for the third consecutive report . . .".

In an alternative but equivalent statistical reformulation of the previous process, the countries' total scores in years 2007, 2009, 2011, 2013, 2015, and 2017, considered as values of a random variable X, may be regarded as a small sample ($n = 6$) retrieved from a Student-t approximated distribution. In this manner, it is possible to calculate a 95% confidence interval for the unknown average TTCI-WEF score $\bar{X}$ for each country and test it against the previously defined thresholds $t_1 = 5.23$, $t_2 = 4.29$, and $t_3 = 2.89$. Fig. 1 exhibits such intervals for the countries included in the 2019 assessment with vertical lines. The dot inside each vertical line represents the average score in years 2007–2017. The class membership of the countries can be tested visually in this chart by inspecting whether the horizontal lines of the thresholds intersect the vertical lines corresponding to countries' score ranges. For example, the confidence interval for Austria is estimated to [4.92, 5.56], and as this includes the class 1 threshold $t_1 = 5.23$, it classifies Austria in the first high class. Pakistan with an estimated interval score [2.78, 3.40] is placed in the third class due to the value of the $t_3 = 2.89$ threshold. China with expected scores in [4.37, 4.63] is left unclassified as this interval lies between and does not include the class 1 and 2 threshold values.

Regarding Fig. 1, a few more comments are possible. First, the relatively large confidence interval observed in countries such as Albania, Barbados, Denmark, Egypt, Finland, Iceland, Luxemburg, Sweden, Tunisia, and so forth is a sign of high variability. On the opposite side, small ranges in confidence intervals in countries such as Argentina, Brazil, Colombia, France, Germany, South Africa, Sri Lanka, and Spain are an indication of consistent behavior in past years.

3.2 Application of the LDA, estimation of new weight values for the pillars, and calculation of the new country scores

The application of LDA to the data set of the 58 classified countries (Table 1) using the 14 pillars as predictor factors was feasible as all statistical properties assumed were satisfied. First, the size of the smallest class, C^1, was equal to 16, which was larger than the number of pillars (14). Second, the multivariate normality of the pillars was tested and confirmed by using quantile–quantile (Q–Q) graphs (not included here for the economy of the presentation). Third, the Box's M test performed marginally confirmed the equity of the covariance matrices at a significance level of 95% as it was associated with a p-value of .059, which marginally enabled its acceptance. Fourth, a Wilks' Lambda test indicated the significance of the pillars ($p = .00$) for the discriminating problem, and finally, the conceptual scheme and consequently the definition of pillars in TTCI implied that they were independent, representing different dimensions of travel and tourism competitiveness. The multicollinearity test (IBM, 2021) between the 14 pillars, regarded as predictor variables for the classification, showed values of VIF (variance inflation factor) between 1.65 and 9.53, that is, less than 10, which is an empirical threshold value to indicate serious multicollinearity requiring correction. The maximum VIF value has been detected in A.5 ICT Readiness marginal correlation.

Table 3. Class centroids coordinates.

Class	F_1	F_2
C^1	5.94	1.68
C^2	1.44	−1.60
C^3	−7.71	0.78

Following the analysis of LDA, due to the three classes defined, there were two discrimination functions, F_1, F_2.

The first function, F_1, explained 93.1% of the variance; the eigenvalue was estimated as $\lambda_1 = 29.623$, and the canonical correlation was equal to 0.984. The second function, F_2, explained 6.9% of the variance; the eigenvalue was estimated as $\lambda_2 = 2.203$, and the canonical correlation was equal to 0.828.

The estimated class centroids in terms of the two discrimination functions' normalized scores are reported in Table 3.

Based on the class centroids, the membership probabilities calculated for the unclassified $C^?$ countries predicted their classification as follows: 9 countries were assigned to class C^1, 44 countries to C^2, and 29 countries to C^3. There were no misclassification errors reported.

The classification of the countries in terms of the two discriminating functions is graphically presented in the charts of Fig. 2. The first chart presents the initially classified countries in Table 2, the unclassified countries (which appear with grey symbols), and the estimated class centroids, shown in Table 3. The second chart of Fig. 2 presents the final classification result, after the implementation of LDA and the prediction of class membership for the unclassified countries.

The first outcome of LDA is the class membership prediction for the 82 countries that were not included

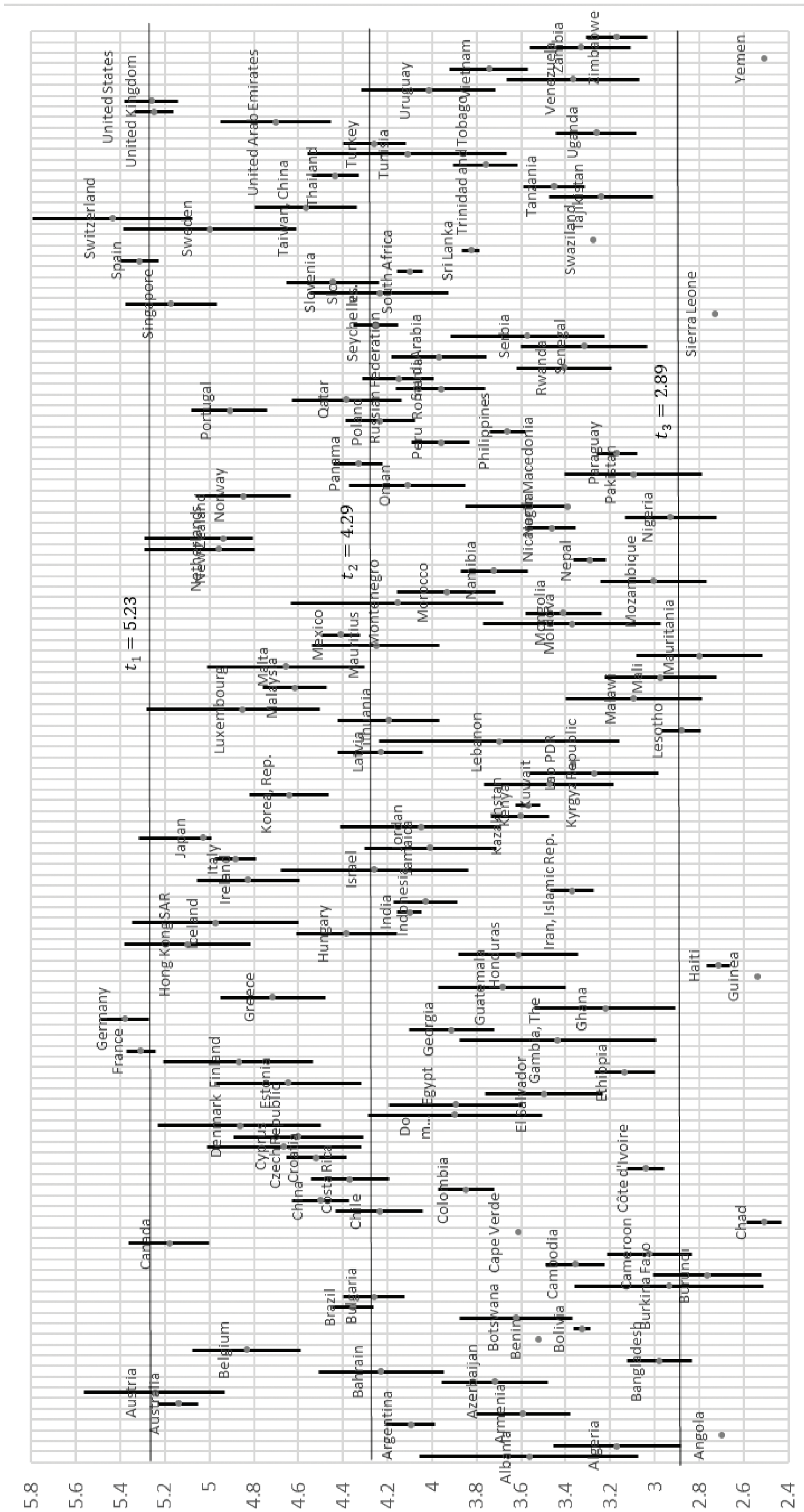

Fig. 1. Chart of 95% confidence intervals for country TTCI scores in 2007–2017.

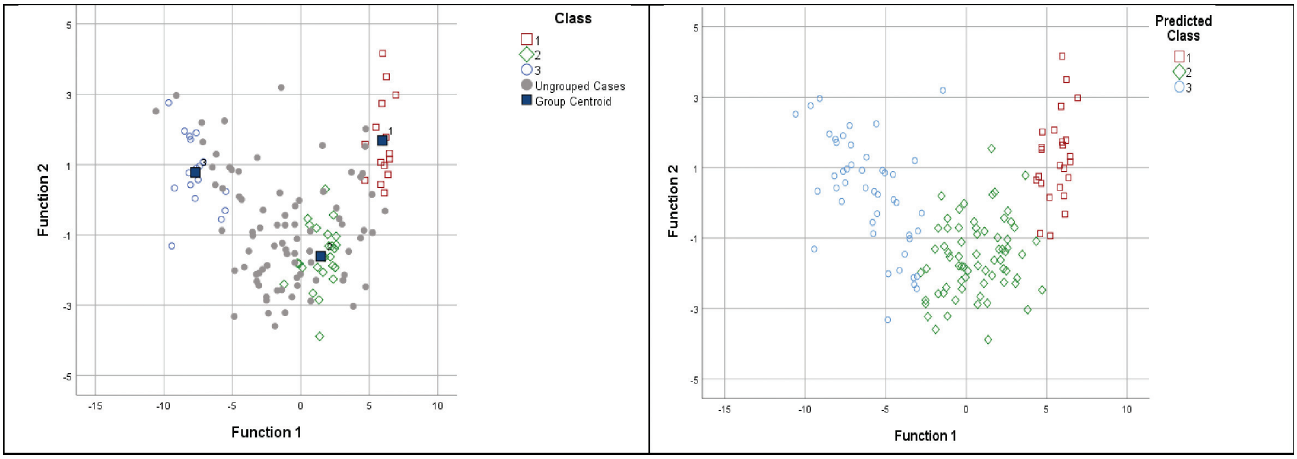

Fig. 2. Graphical representation of classes in terms of the discrimination functions, before and after the discriminant analysis.

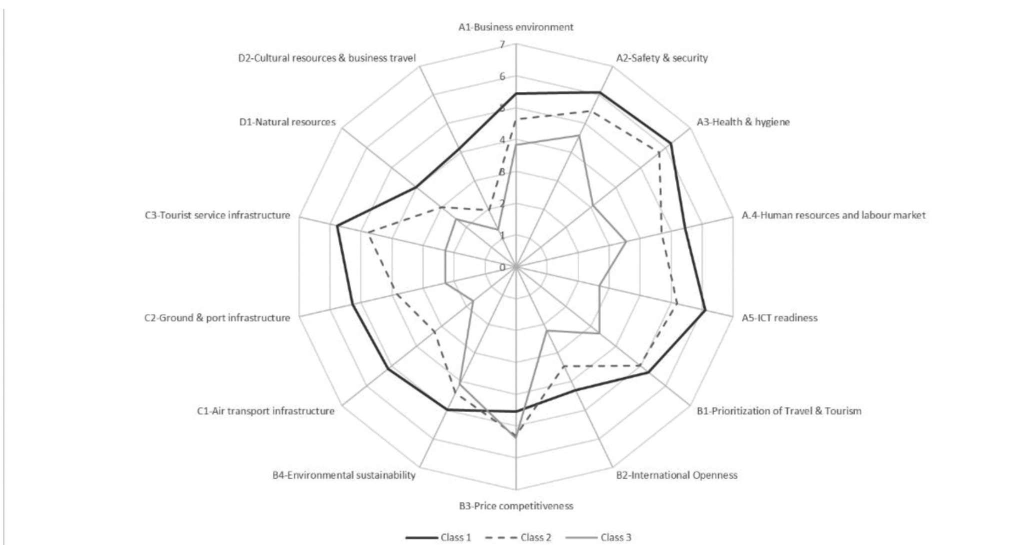

Fig. 3. Mean score of TTCI 2019 pillars for countries' classes; 1—high, 2—medium, and 3—low competitiveness.

in the first assignment (Table 2). The third column of Table A2 in the Appendix presents the predicted class, thus providing a full classification in classes of high, medium, and low level of tourism competitiveness. This classification further enables to explore the differences between these three groups. By calculating the average country score in all fourteen pillars (Table A3 in the Appendix) for the whole data set (including the countries with predicted classes), it is feasible to determine similarities and differences. Fig. 3 presents the mean scores in the pillars graphically.

The predominating pattern of Fig. 3 is that, in almost all pillars, class 1 surpasses class 2, which in turn surpasses class 3. The exception is B3—Price Competitiveness, in which class 1 has lower mean performance. This evidence is mentioned in the WEF report (WEF, 2019), which indicates "the top 25% (countries) tend to greatly outscore the global average on all pillars apart from Price Competitiveness". This is explained by the fact that countries in the highest class (1) are mainly advanced economies with strong business environments, good safety conditions and healthcare standards, superior human resources and labour market circumstances, increased level of ICT services and readiness, and so forth, comprising rather expensive destinations compared to the countries of the other two classes.

According to Fig. 3, a significant difference in mean scores between class 1 and classes 2–3 is detected in D2—Cultural Resources and Business Travel and C1—Air Transport Infrastructure. Furthermore, countries of class 3, compared to those of classes 1–2, are inferior in terms of competitiveness in A3—Health

Table 4. LDA intermediate calculations and estimated weights.

Pillar	Function 1 $\lambda_1 = 29.623\ r_{1k}$	Function 2 $\lambda_2 = 2.186\ r_{2k}$	Potency index PI_i	TTCI-LDA normalized weight w_i	TTCI-WEF weight w_i	Difference
A1—Business environment	.243	.204	.0570	.0483	.050	.002
A2—Safety & security	.195	.074	.0316	.0268	.050	.023
A3—Health & hygiene	.381	−.294	.1435	.1216	.050	−.072
A4—Human resources and labor market	.192	.191	.0362	.0306	.050	.019
A5—ICT readiness	.501	−.052	.2844	.2409	.050	−.191
B1—Prioritization of travel & tourism	.55	−.150	.0671	.0568	.063	.006
B2—International openness	.265	−.178	.0510	.0432	.063	.020
B3—Price competitiveness	.235	.077	.0140	.0119	.063	.051
B4—Environmental sustainability	−.091	−.3	.0202	.0171	.063	.046
C1—Air Transport infrastructure	.136	.214	.1341	.1136	.083	−.031
C2—Ground & port infrastructure	.364	.385	.0784	.0664	.083	.017
C3—Tourist service infrastructure	.284	.202	.2143	.1815	.083	−.099
D1—Natural resources	.476	−.095	.0183	.0155	.125	.110
D2—Cultural resources & business travel	.134	.195	.0304	.0257	.125	.099

& Hygiene, A5—ICT Readiness, C1—Air Transport Infrastructure, and C3—Tourist Service Infrastructure due to their lower level of development.

Table 4 presents the intermediate calculations and the weights of the pillars (first column) estimated by this method. The second and third column of Table 4 present the structure coefficients as reported by the application of the LDA procedure; the fourth column lists the scores of the potency index calculated for each pillar from formula (2); the fifth column the weight values estimated by formula (3), and, for comparison reasons, the sixth column lists the weights assigned by the original TTCI-WEF methodology. The last column of Table 4 presents the difference between the values of the fifth and sixth columns, that is, the initial TTCI-WEF weight and the proposed normalized weight value, according to the TTCI-LDA. Positive values show that the pillar was assigned greater weight value in the proposed TTCI-LDA version of the index (e.g. D1—Natural Resources), while negative values show a lower weight value (e.g. A5—ICT Readiness).

According to the results presented in Table 4, the most decisive factors that distinguish countries and explain their differentiation in terms of travel–tourism competitiveness are those that appear with the highest potency index, PI_i, and related with the highest absolute values r_{1k} and r_{2k}. These are A5—ICT Readiness, C3—Tourist Service Infrastructure, A3—Health & Hygiene, and C1—Air Transport Infrastructure. For them, the difference in the last column of Table 4 is negative, denoting higher TTCI-LDA weight values, compared to the corresponding TTCI-WEF. These four pillars were detected as the most significant for the countries to develop their competitiveness and improve their position in the countries' ranking. Note that the above-mentioned pillar priority is comparable with other past publications. Rodríguez-Díaz and Pulido-Fernández (2020) indicated that ICT Readiness is significant for tourism competitiveness, and the work of Lan et al. (2012) mentions that C1—Air Transport Infrastructure and C3—Tourist Service Infrastructure have a significant influence in their proposed index.

On the opposite end, the lowest weight values were assigned to B3—Price Competitiveness (.0119), D1—Natural Resources (.0155), B4—Environmental Sustainability (.0171), and D2—Cultural Resources & Business Travel (.0257). This result is similar to that reported in the work of Ring (2011), who identified pillars D1—Natural Resources and B4—Environmental Sustainability as least significant. Notably, two Enabling Conditions—A2—Safety and Security (.0268) and A4—Human Resources and Labor Market (.0306)—also had comparatively low weight values. The latter result suggests that while much of the tourism industry is deficient in the HRM areas of working conditions, training, and pay (Baum, 2007), there is not much difference in these key human relations practices between more and less competitive countries.

The new estimated weight values differ from those of the original TTCI-WEF index. Due to the equal contribution of the four subindicators A, B, C, and D, the pillars at the immediate lower level share the same weight values. This value is smaller in subindicators with a greater number of pillars and larger with a smaller number. For example, in subindicator D—Natural and Cultural Resources, the pillars D1—Natural Resources and D2—Cultural Resources & Business Travel, being only two, have the greatest weight value of .125, while in subindicator A—Enabling Environment, the pillars' weight is only .050. Under this view, pillars D1 and D2 seem to have

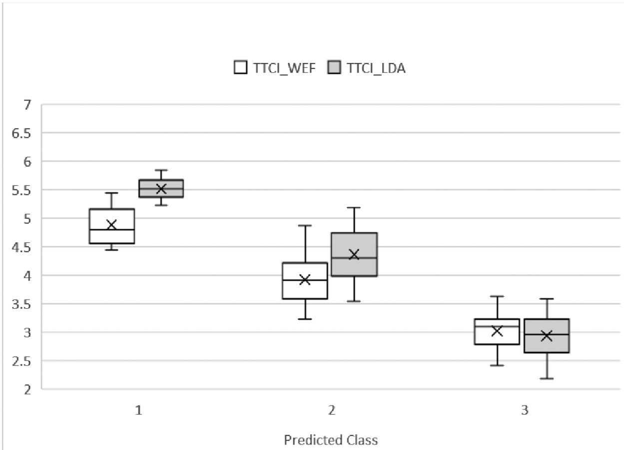

Fig. 4. Box plots to compare TTCI-WEF and TTCI-LDA scores in the three country classes.

the greatest contribution to travel–tourism competitiveness, an issue that is not justified by the objective, data-driven estimation of our methodology.

Based on the weights in Table 4, Table A2 in the Appendix presents, for the whole country set, the calculated scores and ranks of both the original TTCI-WEF and the new TTCI-LDA indices, ordered by the predicted class and then alphabetically. Statistical measurements show that the new proposed TTCI-LDA scores have a significant correlation with the original TTCI-WEF scores. Indeed, the R-square value between the two index scores is equal to .895; the Pearson correlation coefficient is equal to .946, and Kendall's Tau (Kendall, 1976) for the proximity of the ranking positions is equal to .827.

The close relation between TTCI-WEF and TTCI-LDA scores can also be observed from the box-plot graph of Fig. 4. According to that, the country scores in each class are placed in similar ranges. Particularly for the countries in C^1 and C^2 with the best and intermediate performance, the TTCI-LDA scores appear increased, while in C^3 (worst performing countries) the new scores show, in average terms, a very small decrease. The observed dispersion between the two scores can also be verified by the fact that the standard deviation and range for TTCI-LDA are 0.968 and 3.64 respectively, compared to the corresponding values 0.713 and 3.02 for TTCI-WEF. The best and worst country in each class, represented by the whiskers in the box plot in Fig. 4, together with the associated scores in parentheses, are presented in Table 5.

Besides the similarity between TTCI-WEF and TTCI-LDA scores, in a number of countries, the score difference is significant. For example, India's score of 4.421 in TTCI-WEF has worsened to 3.935 in TTCI-LDA due to the different weighting scheme and the

Table 5. First and last ranked countries in classes.

Class	Best country in class	Worst country in class
Class 1—best performance	Switzerland (5.835)	Belgium (5.219)
Class 2—intermediate performance	Malta (5.178)	Paraguay (3.545)
Class 3—worst performance	Botswana (3.578)	Congo (2.187)

low performance of this country in pillars A5—ICT Readiness and C3—Tourist Service Infrastructure, which have been revealed as very significant. The same applies to Congo and Malawi, for which their scores 2.675 and 2.927 have been reduced to 2.187 and 2.515, respectively. Unlike the country cases with worsened performance, a number of countries have shown significant score improvement. This is the case for Israel, for which a 25.2% score increase from 3.984 to 4.988 has been observed. Iceland has had a 23.28% score increase from 4.499 to 5.547, which places it in the first class. Kuwait has had a 23.6% score increase from 3.419 to 4.227.

3.3 Validation of the resulting scores

This step validated and explained the derived TTCI-LDA scores. The validation was performed by employing an external, different index, the Global Competitive Index (GCI) developed by the World Economic Forum. This index measures annually the countries' level of productivity against relative factors, organized into 12 pillars: Institutions, Infrastructure, ICT Adoption, Macroeconomic Stability, Health, Skills, Product Market, Labor Market, Financial System, Market Size, Business Dynamism, and Innovation Capability. GCI is considered to have a link with the TTCI-WEF in the sense that a high level of travel and tourism competitiveness is expected to lead to increased general competitiveness and productivity. The relation of the two indices is mentioned in WEF's Global Competitiveness Report (Schwab, 2019) and confirmed by Jovanović et al. (2014), who identified a high correlation between TTCI and GCI, suggesting that "the increase in the tourism competitiveness of the country enables an increase in its overall competitiveness".

A correlation test between TTCI-LDA and GCI performed on the common country data set (140 countries) in the same period, 2019, indicated a significant connection (Pearson correlation coefficient .955).

The scatter plot in Fig. 5 of the countries' scores in the indices shows a significant linear connection indicating that the resulting TTCI-LDA scores follow the observed link between TTCI-WEF and GCI scores.

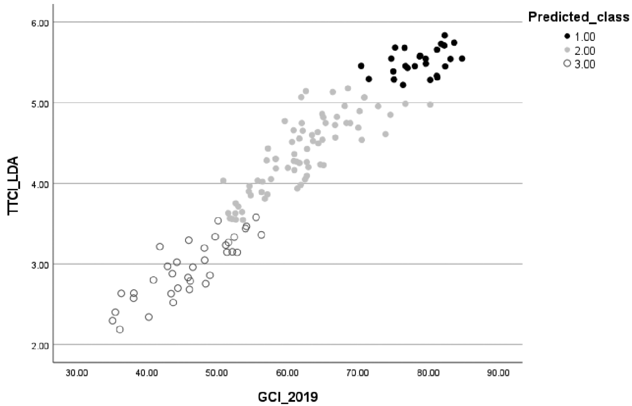

Fig. 5. Comparison graph of TTCI-LDA and GCI 2019 country scores.

Furthermore, Fig. 5 provides visual confirmation that the separation of classes in terms of GCI score is distinct.

4 Conclusion

This paper brings an alternative methodology for weighting CIs by using LDA and calculating the new weights endogenously. This approach is new and belongs to the category of methods that use multivariate statistical analysis. The new index weights derive from the intermediate measurements and results of the typical LDA procedure and particularly from the potency index by using a simple calculation formula. Furthermore, this paper applies the above-mentioned method to the TTCI-WEF data set to provide new weights for pillars, which give different priorities compared to the original TTCI-WEF.

The new TTCI-LDA scores enable a global classification of the countries in such a way that the overall score discrimination is increased and that a significant correlation to original TTCI scores is retained. The priority of pillars that emerge as either decisive or least significant factors for the discrimination are comparable with other related publications. Furthermore, the new TTCI-WEF allows for direct country comparisons and benchmarking. The score thresholds and the best–worst country cases in each class provide additional information for policy decision making. In this regard, the best country in each class can be regarded as a benchmark for the other members in the same class, and its policies and practices should constitute short-/mid-term goals to achieve.

However, the data analysis part depends on several critical points. The first point is whether the initial data enable the application of LDA. LDA imposes strict statistical assumptions on the data, which are often not met in various problems and applications. Another issue concerns the initial classification. In many applications, this derives from initial preference information provided by a decision maker or an expert. In the case of TTCI-WEF, we introduced a statistical procedure that exploits past TTCI scores and, based on their level and variation, provides the required three-class country segmentation (countries at the top, middle, and bottom ranking positions). This approach is objective and statistically adequate but relates the countries' classification to the original calculating method of the TTCI index. Moreover, it depends on the number of years for which the data are available and requires a minimum number of countries to appear in each class.

The proposed methodology has the potential to be applied to other similar CIs' cases, for example, to the United Nations' Human Development Index (HDI; United Nations Development Programme, 2024), commonly used in research, studying various aggregating and weighting methods. In the case of HDI, the original report indicates empirical cut-off points to distinguish countries in classes of low, medium, high, and very high human development. This initial classification suggestion, in conjunction with the performance indicators assumed in the HDI framework, can be used as input to an LDA procedure to obtain a new weighting scheme, according to our methodology.

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Appendix

Fig. A1 exhibits the high-level structure of TTCI in subindicators and pillars. The numbers in parentheses denote the number of low-level indicators that are associated with every pillar.

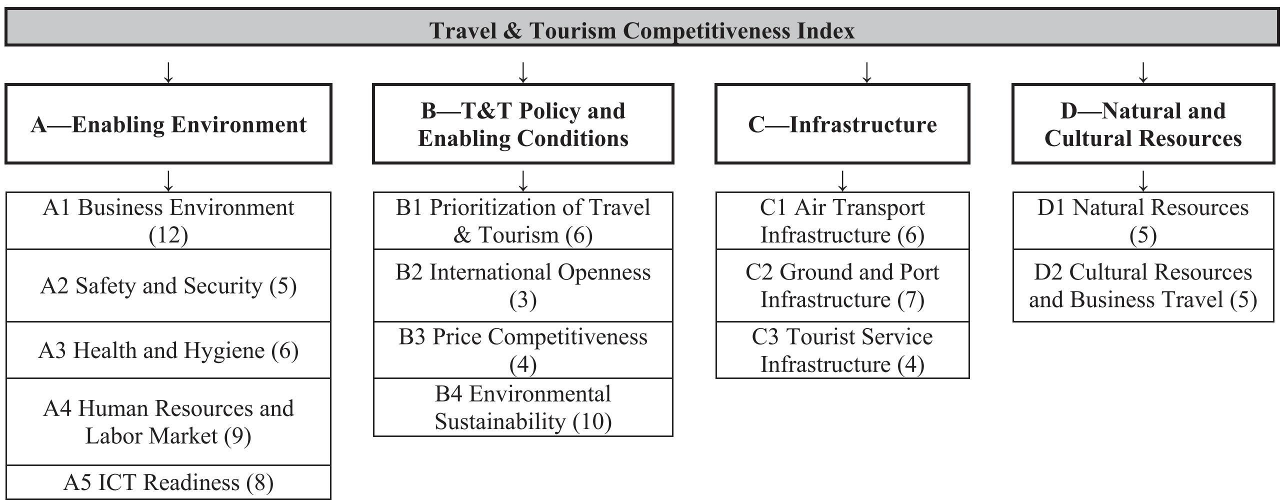

Fig. A1. The 4 subindices and 14 pillars of TTCI.

Table A1. Descriptive statistics of TTCI-WEF scores in years 2007–2017.

Year of WEF report	*N*	Mean	*SD*	Min	Q1	Median	Q3	Max
2007	123	4.24	0.68	2.88	3.67	4.52	4.8	5.66
2009	133	4.08	0.69	2.52	3.54	4.41	4.55	5.68
2011	139	4.09	0.71	2.56	3.49	4.38	4.59	5.68
2013	140	4.12	0.72	2.59	3.56	4.39	4.67	5.66
2015	141	3.74	0.68	2.43	3.22	3.98	4.25	5.31
2017	136	3.82	0.69	2.44	3.28	4.05	4.38	5.43

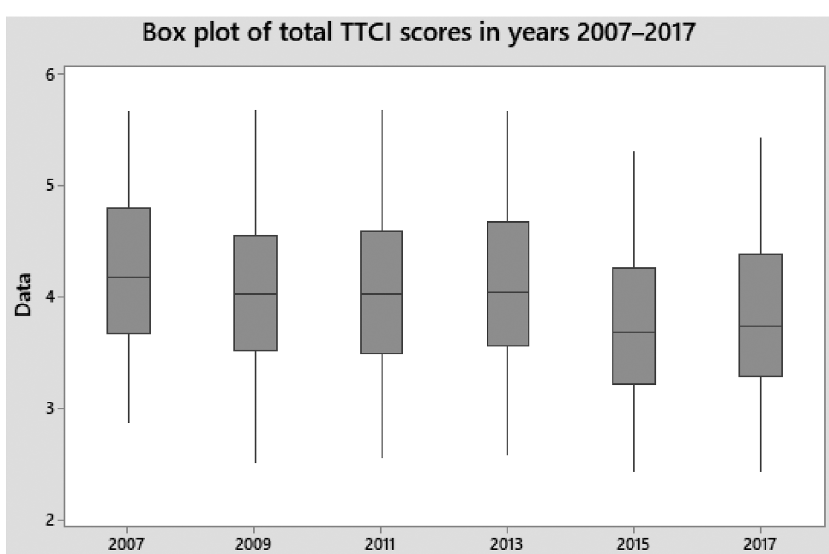

Fig. A2. Box-plot diagram for TTCI total score in years 2007–2017.

Table A2. Classification, countries scores and ranks.

Country	Initial class 1, 2, 3	Predicted class	TTCI-WEF	TTCI-LDA	Rank TTCI-WEF	Rank TTCI-LDA
Australia	1	1	5.1415	5.5725	7	9
Austria	1	1	4.9538	5.6812	11	6
Belgium		1	4.5471	5.2197	24	26
Canada	1	1	5.0513	5.5452	9	12
Denmark		1	4.5811	5.3340	21	21
Finland		1	4.5183	5.2823	28	25
France	1	1	5.4032	5.5813	2	8
Germany	1	1	5.3882	5.7313	3	3
Hong Kong SAR	1	1	4.8119	5.5429	14	13
Iceland		1	4.4996	5.5470	30	11
Ireland		1	4.5383	5.2873	26	24
Italy		1	5.0856	5.2926	8	23
Japan	1	1	5.3716	5.7083	4	4
Korea, Rep.		1	4.7806	5.4840	16	14
Luxembourg	1	1	4.5556	5.4300	23	19
Netherlands	1	1	4.7915	5.4524	15	18
New Zealand	1	1	4.7459	5.4567	18	16
Norway		1	4.5924	5.4543	20	17
Portugal		1	4.8936	5.4579	12	15
Singapore	1	1	4.7578	5.5475	17	10
Spain	1	1	5.4401	5.6836	1	5
Sweden	1	1	4.5626	5.3141	22	22
Switzerland	1	1	5.0159	5.8350	10	1
United Arab Emirates		1	4.4349	5.3896	33	20
United Kingdom	1	1	5.1921	5.6585	6	7
United States	1	1	5.2539	5.7450	5	2
Albania		2	3.5846	4.0523	86	78
Argentina		2	4.1522	4.4329	50	61
Armenia		2	3.7096	4.2684	79	68
Azerbaijan		2	3.7993	4.2626	71	69
Bahrain	2	2	3.9069	4.7474	64	44
Bolivia		2	3.4959	3.5660	90	99
Bosnia and Herzegovina		2	3.2813	3.8517	105	91
Brazil	2	2	4.4564	4.3632	32	63
Brunei Darussalam		2	3.7834	4.4260	72	62
Bulgaria	2	2	4.2113	4.8608	45	38
Cambodia		2	3.3942	3.5602	98	100
Cape Verde		2	3.5508	4.0337	88	81
Chile	2	2	4.1001	4.5384	52	57
China		2	4.8759	4.6094	13	52
Colombia		2	4.0088	4.0942	55	77
Costa Rica	2	2	4.2682	4.7467	41	45
Croatia		2	4.5258	5.0692	27	30
Cyprus		2	4.2162	5.1336	44	29
Czech Republic		2	4.3267	5.0648	38	32
Dominican Republic	2	2	3.7753	4.1850	73	75
Ecuador		2	3.8645	4.0353	70	80
Egypt		2	3.8973	3.9654	65	85
El Salvador		2	3.2321	3.6291	108	97
Estonia		2	4.1961	5.0673	46	31
Georgia		2	3.8763	4.5145	68	59
Greece		2	4.5454	5.1436	25	28
Guatemala		2	3.3930	3.6446	99	95
Honduras		2	3.4569	3.5506	94	101
Hungary	2	2	4.1936	4.8186	48	41
India		2	4.4211	3.9353	34	86
Indonesia		2	4.2700	4.2344	40	71
Iran, Islamic Rep.		2	3.5427	3.7125	89	94
Israel	2	2	3.9841	4.9881	57	33
Jamaica	2	2	3.7493	4.3043	76	64
Jordan	2	2	3.5888	4.1656	84	76
Kazakhstan		2	3.6696	4.2007	80	73

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Table A2. (Continued)

Country	Initial class 1, 2, 3	Predicted class	TTCI-WEF	TTCI-LDA	Rank TTCI-WEF	Rank TTCI-LDA
Kuwait		2	3.4196	4.2274	96	72
Latvia	2	2	4.0408	4.8234	53	40
Lebanon		2	3.3821	3.8920	100	89
Lithuania	2	2	3.9751	4.7479	59	43
Malaysia		2	4.5135	4.8514	29	39
Malta		2	4.3582	5.1788	35	27
Mauritius	2	2	4.0095	4.6366	54	51
Mexico		2	4.6894	4.5405	19	56
Moldova		2	3.2898	3.8084	103	92
Mongolia		2	3.4700	3.7530	93	93
Montenegro	2	2	3.8914	4.6589	67	49
Morocco		2	3.8954	4.1920	66	74
Namibia		2	3.6672	3.9011	81	88
Nicaragua		2	3.4944	3.6313	91	96
North Macedonia		2	3.3578	3.9686	101	84
Oman	2	2	3.9776	4.5254	58	58
Panama	2	2	4.1937	4.5543	47	55
Paraguay		2	3.2318	3.5458	109	102
Peru		2	4.1670	4.2533	49	70
Philippines		2	3.7519	3.9801	75	83
Poland	2	2	4.2322	4.7466	42	46
Qatar	2	2	4.1346	4.9557	51	36
Romania		2	3.9892	4.4962	56	60
Russian Federation	2	2	4.3172	4.7240	39	47
Saudi Arabia		2	3.8752	4.6897	69	48
Serbia		2	3.6277	4.2763	83	67
Seychelles	2	2	3.9295	4.7731	62	42
Slovak Republic	2	2	3.9733	4.5693	60	54
Slovenia	2	2	4.3464	4.8943	36	37
South Africa		2	3.9721	4.0486	61	79
Sri Lanka		2	3.7261	3.8620	77	90
Taiwan, China		2	4.3323	4.9770	37	34
Thailand		2	4.4971	4.9583	31	35
Trinidad and Tobago		2	3.5832	4.3042	87	65
Tunisia	2	2	3.5868	4.0211	85	82
Turkey	2	2	4.2227	4.6532	43	50
Ukraine		2	3.7235	4.2836	78	66
Uruguay	2	2	3.7658	4.5989	74	53
Vietnam		2	3.9145	3.9295	63	87
Algeria		3	3.1477	3.3618	116	106
Angola	3	3	2.7367	2.6375	134	131
Bangladesh	3	3	3.1004	3.1513	120	114
Benin		3	3.0212	2.8321	123	124
Botswana		3	3.4772	3.5787	92	98
Burkina Faso	3	3	2.7799	2.6315	132	133
Burundi	3	3	2.6604	2.3428	137	138
Cameroon	3	3	2.8978	2.6848	128	130
Chad	3	3	2.5232	2.2959	139	139
Congo, Democratic Rep.		3	2.6750	2.1873	136	140
Côte d'Ivoire		3	3.1140	3.1970	119	113
Ethiopia		3	3.0239	2.6997	122	128
Gambia, The		3	3.2278	3.2955	111	109
Ghana		3	3.1489	3.2342	115	111
Guinea	3	3	2.9217	2.7886	126	126
Haiti	3	3	2.7612	2.6345	133	132
Kenya		3	3.6285	3.4650	82	104
Kyrgyz Republic		3	3.2316	3.4396	110	105
Lao PDR		3	3.4153	3.5359	97	103
Lesotho	3	3	3.0192	2.9708	124	120
Liberia		3	2.6098	2.4291	138	136
Malawi	3	3	2.9279	2.5215	125	135
Mali	3	3	2.8064	2.8808	130	122

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Table A2. (Continued)

Country	Initial class 1, 2, 3	Predicted class	TTCI-WEF	TTCI-LDA	Rank TTCI-WEF	Rank TTCI-LDA
Mauritania	3	3	2.6859	2.8012	135	125
Mozambique	3	3	2.9129	2.5744	127	134
Nepal		3	3.3469	3.2671	102	110
Nigeria	3	3	2.8180	2.7562	129	127
Pakistan	3	3	3.0969	3.1468	121	115
Rwanda		3	3.2494	3.1441	107	116
Senegal		3	3.2619	3.3377	106	107
Sierra Leone	3	3	2.7840	2.6986	131	129
Swaziland		3	3.1248	2.9897	118	119
Tajikistan		3	3.2839	3.3330	104	108
Tanzania		3	3.4316	3.0465	95	117
Uganda		3	3.1937	2.8595	112	123
Venezuela		3	3.1314	3.2156	117	112
Yemen	3	3	2.4180	2.4027	140	137
Zambia		3	3.1617	2.9609	113	121
Zimbabwe		3	3.1533	3.0232	114	118

Table A3. Mean score of TTCI 2019 pillars for countries' classes 1—high, 2—medium, and 3—low competitiveness.

TTCI Pillar	Class 1	Class 2	Class 3
A1—Business Environment	5.436	4.6234	3.8306
A2—Safety & Security	6.075	5.4391	4.5797
A3—Health & Hygiene	6.2116	5.7483	3.0963
A4—Human Resources and Labor Market	5.4465	4.6926	3.5554
A5—ICT Readiness	6.0968	5.1905	2.6767
B1—Prioritization of Travel & Tourism	5.316	4.9734	3.3563
B2—International Openness	4.2986	3.4677	2.2302
B3—Price Competitiveness	4.5473	5.3042	5.3753
B4—Environmental Sustainability	4.992	4.4044	4.0835
C1—Air Transport Infrastructure	5.1555	3.2842	1.7168
C2—Ground & Port Infrastructure	5.2747	3.8508	2.2867
C3—Tourist Service Infrastructure	5.7683	4.7828	2.2806
D1—Natural Resources	4.0199	2.9971	2.4172
D2—Cultural Resources & Business Travel	4.1163	1.9711	1.2932