Tourism competitiveness measurement. A perspective from Central America and Caribbean destinations

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Abstract

Purpose – *This study aims to present diverse proposals for the measurement of tourism destination competitiveness that serve as alternatives to the travel and tourism competitiveness index (TTCI).*

Design/methodology/approach – *The proposal includes principal component analysis, the DP2-distance method, goal programming, data envelopment analysis and the Borda count. The study evaluates 17 destinations from Central America and the Caribbean.*

Findings – *These include the feasibility that the methodologies provide reliable competitiveness rankings and the possibility of using less information due to the strength of the statistical methodologies. International tourist arrivals, income from international tourism and travel and tourism contribution to the gross domestic product could be used as approximations of tourism destination competitiveness.*

Research limitations/implications – *The main limitation is the absence of major destinations from the region that constitutes fierce competitors.*

Practical implications – *New aggregation methods can build composite indicators for competitiveness measurement and their presentation in a more comprehensible way.*

Social implications – *The results serve as an alternative for countries that have yet to be considered in international tourism competitiveness comparisons.*

Originality/value – *A better explanatory power of the proposed index is given, thanks to their decomposition capacity and the reduction of the limitations of the original TTCI. Moreover, the proposals facilitate the inclusion of external information or the execution of a completely objective methodology.*

Keywords *Competitiveness, Central America and the Caribbean, Composite indicators, Distance-based methods, Multicriteria, Data envelopment analysis*

Paper type *Research paper*

旅游竞争力测量-中美洲和加勒比海目的地的視角

目的 ： 本研究旨在为衡量旅游目的地竞争力提出多样化的建议，并作为旅行和旅游竞争力指数的替代方案。

设计/方法/方法：该提案包括主成分分析、*DP*$_2$ 距离方法、目标规划、数据包络分析和 *Borda* 计数。 该研究评估了中美洲和加勒比地区的 *17* 个目的地。

调查结果：结果包括这些方法提供可靠的竞争力排名的可行性, 以及由于统计方法的优势而使用较少信息的可能性。 国际旅游人数、国际旅游收入以及旅行和旅游对 *GDP* 的贡献可以用作旅游目的地竞争力的近似值。

研究局限/影响：主要局限是该地区没有竞争激烈的主要目的地。

实际意义：新的聚合方法可以为竞争力测量建立综合指标, 并以更易于理解的方式呈现。

社会影响：结果可作为国际旅游竞争力比较中, 衡量尚未考虑国家的替代方案。

原创性/价值：由于其分解能力和原始 *TTCI* 限制的减少, 所提出的指数具有更好的解释力。 此外, 这些建议有助于纳入外部信息及执行完全客观的方法。

关键词 竞争力, 中美洲和加勒比, 综合指标, 基于距离的方法, 多标准, 数据包络分析

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Medición de la competitividad turística. Una perspectiva desde los destinos de centro América y El Caribe

Resumen

Propósito : *El presente estudio busca presentar diversas metodologías para medir la competitividad de los destinos turísticos, de modo que sirvan como alternativa al Índice de Competitividad de Viajes y Turismo.*

Diseño/metodología/enfoque : *La propuesta incluye Análisis de Componentes Principales, el método de distancia* DP_2*, Programación por Metas, Análisis Envolvente de Datos y el Recuento de Borda. Se analizan 17 destinos de Centro América y el Caribe.*

Hallazgos : *Estos incluyen la validez de las metodologías para obtener rankings de competitividad fiables y la posibilidad de emplear menor cantidad de información, dadas las fortalezas de los procedimientos estadísticos propuestos. Las Llegadas de Turistas Internacionales, los Ingresos por Turismo Internacional, y la Contribución del Turismo al PIB podrían ser buenas aproximaciones para medir competitividad turística*

Limitaciones/implicaciones : *La principal limitación es la ausencia de destinos importantes de la región, que se consideran importantes competidores.*

Implicaciones prácticas : *Novedosos procedimientos de agregación para crear indicadores sintéticos para medir la competitividad turística y su presentación de un modo más comprensible.*

Implicaciones sociales : *Los resultados sirven como alternativa para otros destinos que aún no han sido considerados en comparaciones internacionales de competitividad turística.*

Originalidad : *Un mejor poder explicativo de los índices propuestos, gracias a su capacidad de descomposición, y la reducción de las limitaciones del índice del WEF. Además, las propuestas facilitan la inclusión de información externa o la ejecución de un método completamente objetivo.*

Palabras clave *Competitividad, Centro américa y el caribe, Indicadores sintéticos Métodos basados en distancia, Multicriterio análisis envolvente de datos*

Tipo de papel *Trabajo de investigación*

1. Introduction

To assess destination competitiveness, researchers have diagnosed the competitive positions of a specific destination or groups of destinations using a wide range of approaches, tools and simple and specific indicators (Abreu-Novais *et al.*, 2016). In addition, the literature reveals the existence of several studies dedicated to this end (Carayannis *et al.*, 2018; Croes, 2011; Croes and Kubickova, 2013; Dwyer *et al.*, 2000; Gómez-Vega and Picazo-Tadeo, 2019; Kayar and Kozak, 2010; Knežević Cvelbar *et al.*, 2016; Kunst and Ivandić, 2021; Ritchie and Crouch, 2010; Rodríguez-Díaz and Pulido-Fernández, 2021; Uyar *et al.*, 2022). Nevertheless, the progress presented to date reveals, among other factors, certain limitations regarding the selection of evaluation variables and the calculation of their respective weights (Carayannis *et al.*, 2018), the methodology used to aggregate the information and the explanatory power of the results.

Amongst the diverse initiatives developed to measure destination competitiveness, there is the travel and tourism competitiveness index (TTCI) developed by the World Economic Forum (WEF) (WEF, 2015, 2017, 2019), which constitutes the most noteworthy contribution. This index has been launched biannually since 2007 and serves as a comprehensive strategic tool to measure the factors and policies that make the development of the tourism sector attractive in various countries, by enabling all stakeholders to work jointly to improve the competitiveness of the tourism industry in their national economies, thereby contributing towards growth and national prosperity (WEF, 2019).

The TTCI is composed of 14 “pillars” comprising a set of qualitative and quantitative variables. Each of the pillars is calculated as an unweighted average of the individual component variables. The sub-indices are then calculated as unweighted averages of the pillars included, and this process has remained invariable since its first publication (WEF, 2019).

This is one of the most commonly used and feasible indices, thanks to its credibility, data accuracy (Abreu-Novais *et al.*, 2016) and the desirable combination of hard and soft data, which is narrowly limited to a small number of initiatives. The index is a valuable comparability tool for the demonstration of destination strengths (Pérez León, *et al.*, 2021a) and support of their visibility. Consequently, following the findings of Uyar *et al.* (2022), diverse studies assess destination competitiveness using the TTCI in global analysis (Rodríguez-Díaz and Pulido-Fernández, 2021; Salinas *et al.*, 2022) and evaluate different destinations according to their general behaviour (Salinas *et al.*, 2020) or compare regional destinations, including the Mediterranean (Kunst and Ivandić, 2021), Middle Eastern destinations (Leung and Baloglu, 2013), European Union countries (Kayar and Kozak, 2010) and Caribbean destinations (Pérez León *et al.*, 2021a), among others.

This index is one of the most highly criticised initiatives in the measurement of destination competitiveness, due to its intense use. The criticism involves methodological issues (Croes and Kubickova, 2013), the arbitrary weighting of the variables (Pulido-Fernández and Rodríguez-Díaz, 2016; Salinas *et al.*, 2020), the number of indicators within each pillar (Gómez-Vega and Picazo-Tadeo, 2019), the components of the index that most influence destination competitiveness (Kubickova and Martin, 2020; Uyar *et al.*, 2022), its viability as a reliable measure of destination competitiveness (Kunst and Ivandić, 2021) and the amount of information required for its creation (Mendola and Volo, 2017), among other issues.

The latter consideration is the main reason why various countries have been omitted from certain editions, as is the case with several destinations in the Caribbean region. While most developed countries succeed in collecting reliable tourism data, less developed countries struggle to provide accurate and timely statistics (Mendola and Volo, 2017). Alternatives are therefore needed that allow tourism competitiveness to be measured with a smaller number of indicators, whose degree of reliability and understanding is at least as high as that of the TTCI.

Along these lines, this study aims to introduce various proposals for the measurement of tourism destination competitiveness (TDC) that serves as an alternative to the TTCI, which reduces negative aspects such as the amount of information needed for its creation, includes the possibility of introducing external information and provides ease in interpreting the results, thereby revealing the strengths and weaknesses of the destinations analysed, and identifying the contribution of the subindices to the global competitiveness measure. This research includes the achievement of a competitiveness ranking using different methods, such as the DP_2-distance, principal component analysis, goal programming and data envelopment analysis (DEA), and the study of their differences according to the weights and aggregation processes. Additionally, a meta-index is obtained by means of the Borda count method through allowing decision-makers to achieve a global ranking representative of the overall degree of competitiveness for compared destinations, starting from the results of different aggregation methods.

This is an innovative approach in the achievement of meta-indices as it enables the strengths of the composite indicators to be taken into account while striving to reduce their weaknesses. In contrast to other studies that use similar methods (Salinas *et al.*, 2020, 2022), the DP_2-distance proposes the identification of those indicators that measure tourism competitiveness without having to use all the information required in the TTCI and/or in the distance-principal component (DPC) indicator. Moreover, in contrast to Gómez-Vega and Picazo-Tadeo (2019), our proposal uses goal programming to create the dimensional indicators with all the information available, together with the consideration of both internal and external information. Furthermore, the use of DEA is proposed to obtain the global competitiveness index so that it could be possible to identify the contribution of each dimension to the global measure. Finally, the use of the Borda count method is proposed to merge the rankings obtained and to solve the problem of their differences. Additionally, the study includes the comparison of the rankings obtained with the rankings from the WEF, both for each sub-index and globally to validate the feasibility of the proposed approaches. Comparison to other indicators related to TDC is also made to evaluate their possibility of being representative of a certain degree of competitiveness.

This research involves the measurement of destination competitiveness in various destinations from Central America and the Caribbean region, using the country level. Notwithstanding, this topic has been addressed at different levels: resorts (Claver-Cortés *et al.*, 2007), tour operator and hotel companies (Assaf, 2012), cities (Enright and Newton, 2005), regions (Cracolici and Nijkamp, 2009) and countries (Salinas *et al.*, 2020). The approaches presented in this study are useful for all destination sizes and depend on the scope of the indicators and the information used.

The paper is structured as follows. First, after the presentation of the research gap and of the objectives in the introduction, the proposals for the measurement of destination competitiveness are described in detail. The region case study and the data used in the verification of the suitability of the proposed methods are then presented. The results are given, both per dimension and globally, and include their relationship to other non-previously used indicators. Lastly, the conclusion section reveals the implications and proposes further research.

2. Methods

2.1 The DP_2-distance indicator

The first method, called the DP_2-distance indicator, was initially developed to measure the evolution of social welfare (Pena, 1978; Zarzosa and Somarriba, 2013). This method is objective and eliminates the problems related to duplicity of information. It has also been used as an alternative in the measurement of TDC by Salinas *et al.* (2020, 2022) to solve the problems arising from the aggregation of variables with different measurements and the assignation of arbitrary weights.

The DP_2-distance for a destination is defined as:

$$DP_2 = \sum_{i=1}^{n} \frac{d_i}{\sigma_i} \left(1 - R^2_{i,i-1,i-2,\ldots,1}\right) \text{with } R^2_1 = 0$$

For $i = 1, \ldots,$ n, d_i is the distance between the observed unit and the reference situation for the ith indicator, and σ_i is the standard deviation of the ith indicator. The d_i dividing the standard deviation of each indicator eliminates the problems associated with the units of measure. $R^2_{i,\ i-1\ldots1}$ is the determination coefficient, and the term $1 - R^2_{i,\ i-1\ldots1}$ is the correction factor that represents the variability percentage of the ith indicator that is not lineally explained for the previous $i - 1$ indicators. In this way, the problem of information duplicity is solved because this coefficient eliminates the information contained in the ith indicator contributed in the $i - 1$ previously added indicators.

This procedure contains certain advantages, such as its objectivity, its independence from normalisation processes and the fact that its weights are determined endogenously; therefore, any duplicity of information is eliminated.

2.2 Distance-principal component indicator (DPC)

This indicator combines principal component analysis with the concept of distance to a reference point based on multi-criteria decision-making philosophy and is defined as follows:

$$DPC_i = \sum_{j=1}^{q} \left[VE_j \left(\sum_{k=1}^{p} IN_{ik} |Corr_{jk}| \right) \right]$$

for $i = 1, 2, \ldots, n$, where n is the number of observations, p is the number of original indicators, q is the number of components selected, VE_j is the variance explained by the jth component and $Corr_{jk}$ is the correlation between the jth component and the kth indicator. IN_{ik} is the normalised value of the ith observation in the kth indicator, which is needed for the normalisation of the data such that the measuring units used for each indicator exert no effect on the final result. This procedure involves dividing the distance to the anti-ideal point by the difference between the maximum and the minimum values:

$$IN_{ik} = \frac{I_{ik} - Min}{Max - Min}$$

where I_{ik} is the value of the ith observation in the kth indicator. The minimum value of each indicator is taken as the reference point while bearing in mind that higher values indicate that the destination is assumed to be more competitive. This approach enjoys certain advantages, such as the ease in interpreting the results, as the values of the initial indicators are defined according to their distance to a fixed reference value such that the synthetic indicator is a linear combination of these distances and not of the principal components. Moreover, weights are determined endogenously.

The DP_2 and the DPC are valid for those analyses in which the destinations have not gathered all the information requested by the WEF for the creation of the TTCI. In this way, the procedure may help to identify the indicators required to measure destination competitiveness. Hence, only the data concerning the indicators resulting from the initial selection process should be collected, i.e. those indicators that contribute with a higher level of information to the competitiveness measure (DP_2) or those obtained from the prior application of the principal component analysis (DPC). Furthermore, their use is proposed when there is no information regarding the level of importance of the indicators.

2.3 The goal programming synthetic index (GPSI)

The goal programming synthetic index (GPSI) is encouraged in the procedure of Blancas *et al.* (2010), whereby a set of m initial indicators (I_j with j = 1, 2, . . ., m) is considered, for n units (U_i, with i= 1, 2, . . ., n), where X_{ij} represents the value of the ith unit valued in the jth indicator with $1 \leq i \leq n$ and $1 \leq j \leq m$. Firstly, it is necessary to differentiate between positive (I_{ij}^{+}) and negative (I_{ik}^{-}) indicators, depending on the direction of improvement: "more is better" or "less is better", respectively. In this way, X_{ij}^{+} represents the value for the ith unit in the jth positive indicator, with $j \in J$, (J, positive indicators) and X_{ik}^{-} is the value of the ith unit in the kth negative indicator, with $k \in K$, (K, negative indicators). The achievement levels or the target for each indicator can therefore be determined: u_j^{+} for the positive and u_k^{-} for the negative. Subsequently, goals are created by introducing the deviation variables to measure the difference between the indicator value and the target:

For positive indicators: $I_{ij}^{+} + n_{ij}^{+} - p_{ij}^{+} = u_j^{+}$ with $n_{ij}^{+},\ p_{ij}^{+} \geq 0,\ n_{ij}^{+} \cdot p_{ij}^{+} = 0$

For negative indicators: $I_{ik}^{-} + n_{ik}^{-} - p_{ik}^{-} = u_k^{-}$ with $n_{ik}^{-},\ p_{ik}^{-} \geq 0,\quad n_{ik}^{-} \cdot p_{ik}^{-} = 0$

where n_{ij}^{+} is the undesirable variable for positive indicators, and p_{ik}^{-} is the undesirable variable for the negative indicators. Values higher than these variables reveal an absence of competitiveness. This procedure enables several indices to be obtained and the net GPSI, $GPSI^N$, is selected for its compensatory character between the strengths and weaknesses for each unit under evaluation. The $GPSI^N$ for a unit is defined as:

$$GPSI_i^N = \sum_{j \in J} \frac{w_j^{+}\left(p_{ij}^{+} - n_{ij}^{+}\right)}{u_j^{+}} + \sum_{k \in K} \frac{w_k^{-}\left(n_{ik}^{-} - p_{ik}^{-}\right)}{u_k^{-}},\ \forall i\ \in \{1,\ 2,\ \ldots, n\}$$

where w_j^{+} and w_k^{-} are the weights for positive and negative indicators, respectively. The first sum shows the difference between the strengths and weaknesses for positive indicators, and similarly, the second sum shows this difference for the negative indicators.

The contribution of this proposal in measuring TDC involves the possibility of establishing a lower bound for the indicators in such a way that a destination could be considered competitive with respect to this target value in comparison with its competitors. Moreover, there is the facility of interpreting the results through the identification of the strengths and weaknesses of the destinations under comparison in a more comprehensible way than when the TTCI is used.

This procedure can be used both for those destinations that hold all the information available and for those that lack some data. This enables the inclusion of weights obtained externally. Once the dimensional indicators are obtained through the proposed methods, the second stage then involves the use of DEA to generate a global index, as described below.

2.4 Data envelopment analysis (DEA)

DEA is a non-parametric technique used for the construction of composite indicators (Gómez-Vega and Picazo-Tadeo, 2019). DEA models possess the advantage of displaying unit invariance, which renders the normalisation stage redundant. For this stage, the initial information was previously obtained from the dimensional indicators for each destination. A single dummy input with value unity for each destination can be used. This model is formally equivalent to the original input-oriented, constant-returns-to-scale DEA model presented (Charnes *et al.*, 1978). The global synthetic index for the i_O observation is obtained by solving the following the linear programming problem:

$$DEA_{i_0} = Max_w \sum_{j=1}^{d} w_j^{i_0} DI_{i_0 j}$$

subject to:

$$\sum_{j=1}^{d} w_j^{i_0} DI_{ij} \leq 1 \quad \forall i = 1, \ldots, n \;\; (\text{normalisation} \quad \text{constraint})$$

$$w_j^{i_0} DI_{ij} \geq \boldsymbol{\omega} \; \forall i = 1, \ldots, n, \;\; \forall j = 1, \ldots, d \;\; (\text{virtual} \quad \text{output} \quad \text{constraint})$$

$$w_j^{i_0} \geq 0 \; \forall j = 1, \ldots, d \;\; (\text{non} - \text{negativity} \quad \text{constraint})$$

where $w_j^{i_0}$ are the weights for the observation i_O, DI represents the jth dimension indicator for the ith observation, which would be the DPC if the global index refers to DEA after distance-principal component (DEAPC) or the GPSI is used if the global measurement represents DEA after goal programming (DEAGP); d is the number of dimensions considered (the sub-indices held in the TTCI) and $\boldsymbol{\omega}$ is a real number that represents the minimum value allowed for the jth virtual output for the ith observation. The virtual output constraint involves the implication of all the dimensions in the global composite index.

The objective function chooses the weights that maximise the value of the composite index for observation i_O. In the best situation, the index takes a value of 1, which implies that the destination has a performance equal to its reference unit. The 0 value represents the worst situation. The [0,1] range is a characteristic of the input-oriented model, which numerically renders results more comprehensible and guarantees results with a higher explanatory power: this is a desirable characteristic of composite indicators.

The virtual output constraint has been introduced to guarantee the presence of all dimensions in the composite index with a minimum value of $\boldsymbol{\omega}$. Its use in the second phase of aggregation enables the identification of the contribution of each dimension towards the global index.

2.5 The Borda count method

The Borda count method uses mapping from a set of individual rankings to create a combined ranking that leads to the most relevant decision (Lumini and Nanni, 2006). In Borda count, a voter ranks all candidates in a strict order by assigning different points according to the ranking (Vainikainen *et al.*, 2008). This method assigns zero points to a voter's least preferred option, 1 point for the next option and (n – 1) points for the most preferred (where n is the number of alternatives). However, this way of assigning zero points to the least preferred candidate is unfavourable for the implementation of the analytical calculation (Lawrence *et al.*, 2012). The Borda ranking is therefore determined by placing the Borda scores in order. This approach is useful in those cases where the decision-makers have attained different rankings due to the use of diverse aggregation methods.

3. Geographical context and dataset

The study comprises 17 destinations from Central America and the Caribbean, which is the highest number of countries to have been included in an edition of the TTCI. These are underdeveloped countries in close geographical proximity, in the most tourism-dependent region worldwide, according to the World Travel & Tourism Council (WTTC) (2020, 2021). These destinations compete within the same tourist market, and they offer a similar tourist experience: predominantly sun-and-sand tourism, with emphasis on cruise tourism, which has become big business, with the Caribbean accounting for more than 35% of all such vacations globally (Caribbean Council, 2019). Moreover, while the number of countries included in the TTCI had been steadily rising, the number of Caribbean countries included has decreased in the latest editions, thereby passing from 17 to 13 destinations in the space of only four years. Their absence was caused due to difficulties in providing all the information required. Consequently, some of the proposed approaches serve as alternatives to these destinations, due to the possibility of using less information.

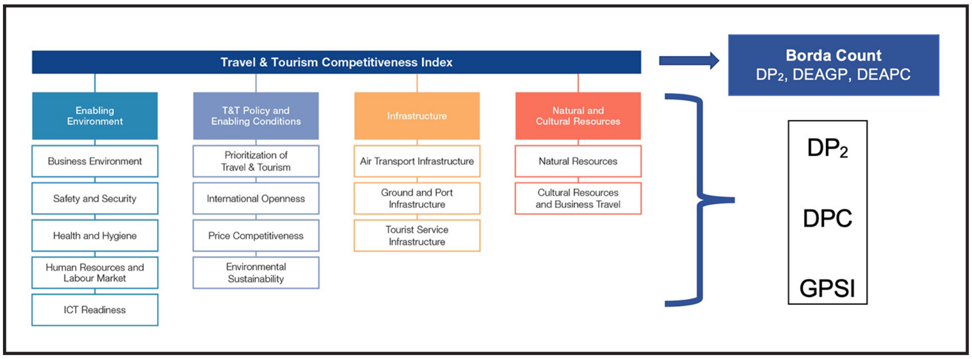
The data used correspond to the 2015 edition of the TTCI, which is the year that included the most destinations from the region. It comprises 90 indicators distributed into 14 pillars grouped into four sub-indices (WEF, 2015). Those indicators with more than three missing values are excluded. For those indicators with three or fewer missing values, their scores are substituted with the minimum. This substitution guarantees the presence of those indicators in the composite measure and, therefore, its representativeness. Moreover, the scores are not influenced, thanks to the proposed method. Consequently, the data set comprises 86 indicators: 40, 22, 14 and 10 for sub-indices A, B, C and D, respectively, of which 30 are subjective. In addition, all the pillars are presented in the study as follows: Pillar A.01 (12 indicators), A.02 (5), A.03 (6), A.04 (9), A.05 (8), B.06 (6), B.07 (3), B.08 (4), B.09 (10), C.10 (5), C.11 (4), C.12 (4), D.13 (5) and D.14 (5).

4. Results and discussion

The aggregation process is developed in the same way as that proposed by the WEF to create the TTCI (Figure 1). Firstly, the indicators are grouped into their pillars, and the pillars are then used to create the dimensional indicators. Lastly, a global index is built by grouping the sub-indices. The dimensional indicators are created through the DP_2, the DPC and the GPSI approaches. The global competitiveness index is subsequently built using the DP_2 and DEA methods. The latter is used for the two global indices proposed:

1. the DEAPC; and
2. the DEAGP methods.

Figure 1 Aggregation procedure



As a result, three alternative methods are presented for the creation of the dimensional and global indicators.

Despite the unfeasibility of the DPC and DP_2 indicators embracing more indicators than destinations, the proposed steps allow the inclusion of all the information. Moreover, to attain a process as close as possible to the WEF proposal, the aspiration level used for the GPSI is zero. In this regard, under this approach, all the destinations only evaluate their strengths. The denominators are omitted from the GPSI, and therefore, the weaknesses are not included.

The weights are achieved in a different way for each methodology. The DP_2 and the DPC methods calculate their weights endogenously. On average, the DP_2 assigns the highest weight to Sub-index B "T&T Policy and Enabling Conditions", and the DPC gives more weight to Sub-index C "Natural and Cultural Resources", while least importance is assigned to Sub-index A "Enabling Environment". These assignations are consistent with the conditions of the region, comprised of underdeveloped countries with lower scores on safety, health, information and communication technology (ICT) readiness (WEF, 2015, 2017) and the demonstrated efforts made by the governments towards the development of the tourism sector in the region (Pérez León *et al.*, 2021b), due to their dependence on this activity. For the GPSI, however, weights should be assigned. For the latter procedure (GPSI), the same importance is given to all the indicators contained in each pillar. For sub-dimensional indicators, the same importance is given to each pillar within the sub-indices. Lastly, all sub-indices receive the same importance in order to calculate the global indicator.

4.1 Dimensional results

The results for the pillars appear in Table A1, while the dimensional results are shown on Table 1. The dimensional results reveal great stability amongst the rankings, including the comparison with the results attained with those from the WEF. The five most and least competitive destinations coincide in all the rankings created. This is a great achievement because, despite the differences between the procedures, the results seem to present major similarity. The results from the GPSI approach are those more closely related to the other methods and, compared to those of the TTCI, the DP_2 and the GPSI are those closest to the WEF outputs. This is a great advantage for the DP_2 methodology because it reveals its capacity for englobing the relevant information under the statistical methods comprised in the procedure.

The similarities can be corroborated statistically. The Pearson correlation between scores demonstrates their similarity with all values higher than 0.871 and significant at the 0.01

Table 1 Dimensional results

Destinations	TTCI_A		DP_2_A		DPC_A		GPSI_A		TTCI_B		DP_2_B		DPC_B		GPSI_B	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Barbados	5.25	1	10.256	1	3.365	1	5.246	1	4.24	8	6.378	14	1.086	13	3.974	13
Colombia	4.08	13	5.588	11	1.919	14	4.152	13	4.24	9	7.795	8	1.517	8	4.269	8
Costa Rica	4.84	2	9.197	2	3.272	2	4.921	2	4.47	3	9.735	3	1.722	5	4.514	3
Dominican Republic	4.21	9	5.514	12	2.221	10	4.264	9	4.07	12	6.876	12	1.380	10	4.131	10
El Salvador	4.13	11	5.672	10	1.999	13	4.174	12	4.4	4	8.758	5	1.768	3	4.440	5
Guatemala	4.14	10	5.986	8	2.085	12	4.209	11	4.32	6	8.55	6	1.713	6	4.376	6
Guyana	4.11	12	4.734	14	2.276	8	4.22	10	4.3	7	7.103	10	1.186	12	3.986	12
Haiti	3.42	17	1.319	17	1.569	16	3.42	17	3.98	14	4.341	15	1.046	15	3.695	15
Honduras	3.92	15	4.688	15	1.851	15	3.998	15	4.5	2	10.039	2	1.820	2	4.548	2
Jamaica	4.26	8	5.924	9	2.092	11	4.339	8	4.23	10	7.964	7	1.437	9	4.254	9
Mexico	4.34	7	6.117	7	2.249	9	4.392	7	4.22	11	7.3	9	1.519	7	4.343	7
Nicaragua	4.06	14	5.275	13	2.328	7	4.085	14	4.36	5	8.812	4	1.757	4	4.461	4
Panama	4.7	4	8.239	4	2.893	4	4.766	4	4.69	1	10.956	1	1.854	1	4.729	1
Puerto Rico	4.73	3	8.459	3	2.951	3	4.794	3	4.06	13	6.556	13	1.070	14	3.749	14
Suriname	4.42	6	6.356	6	2.577	5	4.411	6	3.67	16	3.785	16	0.842	16	3.456	17
Trinidad and Tobago	4.53	5	7.062	5	2.358	6	4.584	5	3.96	15	7.025	11	1.338	11	4.021	11
Venezuela	3.58	16	3.088	16	1.252	17	3.643	16	3.4	17	2.99	17	0.756	17	3.479	16

Destinations	TTCI_C		DP_2_C		DPC_C		GPSI_C		TTCI_D		DP_2_D		DPC_D		GPSI_D	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Barbados	5.18	1	6.224	1	2.245	1	4.990	1	1.65	16	6.961	4	0.796	4	1.645	16
Colombia	2.92	13	2.25	11	1.017	10	3.121	10	3.67	2	6.608	6	0.742	6	3.666	2
Costa Rica	3.7	7	3.397	9	1.484	7	3.901	7	3.39	3	8.638	2	0.959	2	3.348	3
Dominican Republic	3.68	8	3.667	7	1.480	8	3.676	8	2.05	10	4.768	13	0.607	11	2.046	10
El Salvador	3.32	9	3.641	8	1.256	9	3.316	9	1.78	15	5.202	11	0.526	15	1.752	15
Guatemala	2.95	12	2.449	10	0.960	12	2.950	12	2.64	6	5.745	7	0.638	7	2.659	6
Guyana	2.84	14	1.974	14	0.897	13	2.840	13	1.78	14	3.824	14	0.553	13	1.770	13
Haiti	2.29	17	0.337	17	0.372	17	2.245	17	1.3	17	0.523	17	0.343	17	1.290	17
Honduras	3	11	2.22	12	0.965	11	2.998	11	2.24	8	5.375	9	0.542	14	2.215	8
Jamaica	3.93	5	4.051	6	1.530	6	3.927	6	1.95	12	5.362	10	0.57	12	1.928	12
Mexico	3.83	6	4.7	4	1.705	5	4.026	5	5.05	1	8.458	3	1	1	5.006	1
Nicaragua	2.8	15	1.904	15	0.779	15	2.741	15	2.28	7	5.076	12	0.631	8	2.301	7
Panama	4.72	2	5.43	3	2.229	2	4.742	2	3.02	5	8.753	1	0.876	3	2.963	5
Puerto Rico	4.64	3	5.882	2	2.051	3	4.645	3	2.22	9	6.684	5	0.777	5	2.171	9
Suriname	3.01	10	2.049	13	0.839	14	2.785	14	2.01	11	3.567	15	0.626	9	2.012	11
Trinidad and Tobago	4.57	4	4.682	5	1.942	4	4.566	4	1.8	13	5.42	8	0.613	10	1.767	14
Venezuela	2.43	16	0.727	16	0.5556	16	25.585	16	3.31	4	2.157	16	0.511	16	3.276	4

level in each comparison, as are Spearman's rho correlation coefficients, all higher than 0.850 for all the procedures. In general, the high correlation between each pair of scores and rankings in all the sub-indices demonstrates the feasibility of the proposals for reliable competitiveness measurements. An analysis can be made within each dimension, considering the sub-indices comprised, the indicators and their weights.

In the first sub-index, "Enabling Environment", the five most competitive destinations (first quartile) coincide for all the rankings: Barbados, Costa Rica, Panama, Puerto Rico and Trinidad and Tobago. Only Trinidad and Tobago leaves this group in the DPC ranking, where it worsens and occupies the sixth place, while Suriname shifts to the fifth position, due to the weighting method. Barbados occupies the first position in all the rankings attained. It presents the best scores in pillars A.02 "Safety and Security" and A.05 "ICT Readiness" and remains within the most competitive destinations in the other pillars. Its worst position is that of fifth in Pillar A.01 "Business Environment".

4.2 Global results

The global index is generated starting from the dimensional indicators. The DP_2 method is applied to the previous indices created with the same methodology. To determine the global DP_2-distance indicator, the first step involves obtaining the dimensional indicators and taking the maximum score for each indicator as the reference value. For the construction of a global index, a representative group of initial indicators is selected for each dimension. Initial indicators that show a correlation level greater than 0.5 with the dimensional measures are selected. Weights are represented by the variability percentage of the *i*th indicator, which is not lineally explained by the previous *i*-1 indicators. This constitutes the amount of new information added for each indicator included in the process.

To create the global competitiveness index with the DPC and the GPSI approaches, DEA is used to identify the contribution of each dimension to the global measure. As a result, the DEAPC and the indices are proposed. In the DEAPC and DEAPG procedures, the minimum admissible value for the virtual outputs that guarantees the feasibility of the linear problem is 0.015; therefore, this constitutes the lower bound established for this constraint $w_j^{i_0} DI_{ij} \geq \omega; \ \ \omega \geq 0.015$. The scores and rankings for all the global indices appear in Table 2.

The results enable a ranking for these methods to be established. By comparison with the TTCI ranking, the DEAGP is found to be the most similar to the WEF, with an average variation of 0.71 positions (less than one unit) and a variance of 0.471 in contrast to 0.809 for the DP_2 ranking and 4.375 for the DEAPC. A paired comparison of the rankings reveals that the most similar are the DP_2 and the DEAGP, and there is a minor average variation between them of 0.824. Although the DEAPC and DEAGP indices are calculated with the same method in the second stage, these are the indices that differ the most, and even present the greatest contribution to the global index, largely in Sub-indices A and B. The Pearson correlation and Spearman's rho correlation coefficients support the proximity between the rankings obtained. Both present values higher than 0.831 in all cases, significant at the 0.01 level.

The use of different aggregation processes and weighting methods may cause diverse rankings to be obtained. In the case that the decision-makers would like to use those different procedures, it would not be possible to establish an overall competitiveness ranking, despite the similarity of the indices. To this end, the Borda count approach is applied to the results of the DP_2, of the DEAPC and to those of the DEAGP. This is considered a suitable approach because it involves all the sub-indices and the outputs of the proposed methods. The final ranking is given in the "Borda Count" column of Table 2. This method is presented as an alternative for the decision-makers because it enables the results to be built as a single ranking. This is recommended when different aggregation methods are used, and unification of the results is desired for greater understanding and

Table 2 Global rankings

Destinations	TTCI Score	TTCI Rank	DP2 Score	DP2 Rank	DEAPC Score	DEAPC Rank	DEAGP Score	DEAGP Rank	Borda count Rank	GPSI Score	GPSI Rank
Barbados	4.08	4	6.96	4	0.75	4	0.89	4	4	3.96	4
Colombia	3.73	6	6.60	6	0.74	6	0.85	7	6	3.80	6
Costa Rica	4.10	3	8.63	2	0.93	2	0.93	3	2	4.17	3
Dominican Republic	3.50	10	4.76	13	0.67	12	0.82	12	12	3.52	10
El Salvador	3.41	12	5.20	11	0.70	10	0.82	11	13	3.42	12
Guatemala	3.51	9	5.74	7	0.73	7	0.83	9	7	3.54	9
Guyana	3.26	15	3.82	14	0.59	14	0.76	14	14	3.20	15
Haiti	2.75	17	0.52	17	0.43	17	0.65	17	17	2.66	17
Honduras	3.41	11	5.37	9	0.70	9	0.82	10	9	3.44	11
Jamaica	3.59	8	5.36	10	0.66	13	0.84	8	11	3.61	8
Mexico	4.36	1	8.45	3	0.88	3	0.94	2	3	4.44	1
Nicaragua	3.37	13	5.07	12	0.74	5	0.81	13	10	3.39	13
Panama	4.28	2	8.75	1	0.93	1	0.97	1	1	4.30	2
Puerto Rico	3.91	5	6.68	5	0.72	8	0.85	6	5	3.83	5
Suriname	3.28	14	3.56	15	0.55	15	0.72	15	15	3.16	16
Trinidad and Tobago	3.71	7	5.42	8	0.68	11	0.85	5	8	3.73	7
Venezuela	3.18	16	2.15	16	0.44	16	0.71	16	16	3.23	14

verification of their stability. However, it can be dispensed with in those cases where only one of the proposed methods is used.

4.3 Global programming synthetic index for global aggregation

The GPSI methodology is also used to calculate a global index. To determine the feasibility of the GPSI in replicating the WEF rank, a value of zero is conveniently assigned to all the aspiration levels, and the denominator is assigned a value of one to the GPSI function. This transformation is carried out due to the use of the normalised values provided by the WEF data set. The results are presented in last column of Table 2.

The main advantage involves the possibility of observing the amount by which a destination surpasses the established goals and the representative quantity of the improvement necessity for each indicator, pillar and sub-index. Additionally, it is possible to increase goal requirements for a more rigorous comparison by means of changing the target values.

4.4 Link to other indicators

The correlation between the scores obtained with the proposed approaches, the TTCI scores and other additional indicators is analysed (international tourist arrivals, income from international tourism, international tourist expenditure and travel and tourism contribution to the gross domestic product (GDP)) (Table 3). Except for international tourism expenditure, the remaining three variables could be used as approximations of tourism destination competitiveness rankings, depending on their relationship with the scores obtained with the TTCI and the proposed methods.

5. Conclusions

This study contributes towards demonstrating the feasibility of various aggregation methods in building composite indicators for the measurement of TDC and the ability of such indicators to propose rankings. These methods are proposed through the combination of a variety of algorithms, each with its own advantages and disadvantages. The procedures explained present differences, such as the variability of the results due to the order of entry of the initial indicators in the measure, the possibility of introducing subjective judgements,

Table 3 Spearman's rho correlations (ranking)

	TTCI	*DP_2*	*DEAPC*	*DEAGP*	*GPSI*	*Borda count*	*Int. tour. arrivals*	*Income from int. tourism*	*Int. tour. exp.*	*T&T GDP*
TTCI	1									
DP_2	0.961**	1								
DEAPC	0.831**	0.904**	1							
DEAGP	0.980**	0.971**	0.831**	1						
GPSI	0.990**	0.956**	0.826**	0.975**	1					
Borda	0.951**	0.988**	0.931**	0.951**	0.946**	1				
Int. tour. arrivals	0.630**	0.544*	0.522*	0.517*	0.650**	0.549*	1			
Income from int. tourism	0.725**	0.637**	0.566*	0.620**	0.740**	0.630**	0.934**	1		
Int. tourism expenditure	0.363	0.35	0.306	0.289	0.422	0.353	0.706**	0.699**	1	
TT_GDP	0.522*	0.456	0.395	0.444	0.591*	0.458	0.826**	0.804**	0.897**	1

Notes: *Correlation is significant at the 0.05 level (two-tailed). **Correlation is significant at the 0.01 level (two-tailed)

which enables not only the necessities of the stakeholders to be taken into consideration, but also the method used to calculate the weights. All these are practical implications that support the decision-making process.

The proposed methods complement each other and, together, contribute towards the decision-making process in measuring tourism competitiveness. They help reduce the weaknesses associated to the previous existent methods, mainly the TTCI, and therefore provide alternatives for the solution of key aspects, such as reducing the amount of information necessary, the weighting and the explanatory power of the results. The proposed methods can be applied separately, thereby taking advantage of each method to distribute information on the process of decision-making. Furthermore, they can be applied in a combined way, as explained in the study, thereby reaching the maximum of all of the positive aspects indicated.

The DP_2-distance and DPC do not allow all the indicators to be used, although the information selection process does permit the inclusion of a greater amount of information in a smaller set of indicators. This is a great finding for other destinations because it allows their inclusion in a competitiveness ranking with less information.

The GPSI permits the inclusion of all the indicators in the composite measure. This is the most flexible approach because it facilitates the inclusion of external information through the goals and the weights. It has greater explanatory power than the previous indices due to the possibility of directly revealing the strengths and weaknesses of each destination involved by means of the deviation variables. This method also allows various results to be obtained, and therefore, their combination enriches the analysis of the outputs. Furthermore, this methodology contributes towards solving several problems, such as that of the equitable weight distribution across the pillars, the facility to analyse the results, the influence of the size of destinations and the selection of the target values.

The use of DEA in the second step brings flexibility to the procedure and enables the contribution of each dimension to the overall competitiveness value to be identified. The introduction of the virtual output constraint guarantees the inclusion of all the sub-indices in the global measure. Additionally, it is possible that this method identifies those dimensions that represent a strength or a weakness for each destination.

The meta-index created offers the possibility for decision-makers to seek alternatives to obtain diverse competitiveness rankings and merge them into a single ordered list. This aggregation is presented as an alternative to corroborate the stability of the results when different methods are used on the same data set. Moreover, the stability of the results demonstrates the suitability of the proposed methods. The comparative analysis is supported, as it is possible to identify the dimensions, pillars and indicators that contributed the most regarding the competitiveness position of all the destinations analysed.

Furthermore, compared to the TTCI and to the results achieved, the correlation values indicate that the additional variables could be viewed as providing a good explanation of the rankings. Among these, the most representative is the income from international tourism, which is also significantly correlated to the meta-index results. Consequently, it is possible to affirm that these variables may be used to create indices with results almost identical to the outputs of the TTCI.

Future research should contemplate other possible analyses, such as the consideration of a common set of weights for DEA, the restrictive GPSI indicator and the use of participative methods to obtain the weights for the GPSI and/or DPC index. There is also the possibility of including a dynamic measure of the competitiveness with the consideration of information covering different time periods.

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Appendix

Table A1 Results for the pillars

Destinations/pillars		A.01			A.02			A.03			A.04			A.05	
	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI
Barbados	11.508	3.600	0.925	9.438	2.678	1.151	12.759	2.527	1.227	12.683	2.559	0.962	10.878	2.489	0.981
Colombia	7.639	2.644	0.845	2.418	0.708	0.564	10.131	1.990	1.021	10.088	2.272	0.875	7.923	1.998	0.847
Costa Rica	11.293	3.700	0.958	8.978	2.546	1.117	10.566	2.145	1.054	13.592	2.836	0.941	9.188	2.287	0.851
Dominican Republic	8.917	2.805	0.859	5.503	1.561	0.86	9.861	1.838	0.992	8.777	2.002	0.834	4.942	1.426	0.72
El Salvador	9.002	2.917	0.857	4.053	1.011	0.723	9.672	1.884	0.99	9.190	1.984	0.838	6.581	1.735	0.766
Guatemala	9.167	3.226	0.858	3.918	0.946	0.715	8.903	1.807	0.981	11.075	2.325	0.865	7.110	1.819	0.79
Guyana	10.346	3.398	0.914	6.145	1.784	0.914	4.923	1.259	0.964	8.864	2.069	0.79	3.580	0.985	0.638
Haiti	3.632	1.507	0.594	5.848	1.824	0.949	2.899	0.420	0.697	5.087	1.360	0.759	1.663	0.034	0.42
Honduras	7.728	2.586	0.834	4.186	1.014	0.727	8.284	1.694	0.944	9.816	2.058	0.833	4.667	1.270	0.66
Jamaica	9.919	3.168	0.92	4.78	1.146	0.77	7.323	1.496	0.973	10.753	2.301	0.911	6.629	1.591	0.764
Mexico	7.794	2.742	0.843	4.612	1.373	0.819	11.763	2.303	1.081	9.918	2.156	0.868	6.792	1.633	0.78
Nicaragua	7.265	2.219	0.725	7.926	2.270	1.028	7.446	1.503	0.871	7.870	1.791	0.807	4.409	0.894	0.655
Panama	12.221	4.107	1.016	7.674	2.138	1.005	10.142	2.007	1.04	9.562	1.892	0.827	8.424	2.293	0.879
Puerto Rico	12.23	3.853	0.971	7.51	1.952	0.963	13.32	2.565	1.189	12.387	2.590	0.878	7.152	2.132	0.792
Suriname	8.289	2.374	0.718	9.067	2.594	1.122	9.38	1.895	1.05	6.691	1.384	0.769	5.647	1.301	0.751
Trinidad and Tobago	11.365	3.788	0.937	4.853	1.325	0.82	9.404	1.855	1.069	9.964	1.997	0.863	8.646	2.058	0.895
Venezuela	2.932	0.715	0.502	3.238	0.774	0.672	10.856	2.114	1.057	4.452	0.860	0.709	4.486	1.245	0.704

Destinations/pillars		B.06			B.07			B.08			B.09	
	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI
Barbados	10.312	2.218	1.391	2.378	0.411	0.712	4.129	0.512	0.896	13.600	2.032	0.975
Colombia	7.138	1.422	1.095	5.279	1.012	1.075	4.733	1.121	1.119	12.899	2.047	0.981
Costa Rica	10.468	2.078	1.324	5.063	1.105	0.996	5.203	1.073	1.1	15.373	2.467	1.094
Dominican Republic	11.069	2.334	1.455	3.657	0.699	0.809	3.355	0.965	1.006	10.810	1.646	0.861
El Salvador	8.869	1.595	1.142	6.456	1.307	1.132	6.245	1.408	1.228	10.400	1.697	0.938
Guatemala	6.969	1.436	1.108	5.115	1.084	0.986	7.864	1.634	1.337	11.623	1.785	0.945
Guyana	6.123	1.076	0.921	3.893	0.611	0.914	7.677	0.972	1.051	13.331	2.102	1.101
Haiti	5.198	1.085	0.946	4.259	0.593	0.97	7.630	0.989	1.031	6.385	1.132	0.748
Honduras	8.794	1.718	1.201	5.444	1.148	1.012	7.537	1.528	1.286	14.293	2.222	1.05
Jamaica	10.130	2.173	1.382	4.449	0.782	0.899	5.991	1.029	1.073	11.161	1.737	0.901
Mexico	10.699	2.058	1.315	3.427	0.814	0.87	6.089	1.297	1.221	9.930	1.628	0.936
Nicaragua	6.761	1.481	1.135	5.311	1.119	0.991	7.877	1.624	1.314	12.543	1.929	1.019
Panama	10.908	2.088	1.323	5.000	1.114	1.025	7.225	1.481	1.287	15.667	2.280	1.094
Puerto Rico	9.907	1.873	1.217	2.960	0.244	0.461	7.287	1.161	1.204	17.358	2.254	0.979
Suriname	4.120	0.815	0.861	1.210	0.236	0.581	5.689	0.711	0.906	13.402	2.151	1.108
Trinidad and Tobago	3.997	0.830	0.877	4.063	0.715	0.875	8.456	1.497	1.336	10.854	1.686	0.932
Venezuela	5.531	0.835	0.852	0.763	0.112	0.56	7.456	1.003	1.158	7.436	1.257	0.908

Destinations/pillars		C.10			C.11			C.12			D.13			D.14	
	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI	DP_2	DPC	GPSI
Barbados	5.636	1.110	1.124	7.863	2.450	1.892	9.83	1.937	1.975	3.134	0.430	1.085	0.197	0.109	0.56
Colombia	3.824	0.729	0.887	1.960	0.710	1.039	5.29	0.949	1.195	5.393	1.387	2.066	4.249	2.288	1.6
Costa Rica	4.146	0.895	0.986	2.816	0.877	1.158	8.95	1.701	1.758	8.346	1.829	2.546	1.312	0.680	0.803
Dominican Republic	4.219	0.898	0.941	3.917	1.230	1.192	7.38	1.403	1.542	2.864	0.596	1.293	0.936	0.556	0.753
El Salvador	3.220	0.537	0.735	5.172	1.620	1.356	5.28	0.976	1.225	1.751	0.422	1.091	0.491	0.298	0.66
Guatemala	1.864	0.344	0.631	3.046	0.980	1.085	5.88	1.029	1.234	4.425	1.126	1.837	1.043	0.711	0.822
Guyana	3.766	0.943	1.077	2.674	0.877	1.034	1.94	0.299	0.728	2.514	0.569	1.218	0.064	0.060	0.553
Haiti	0.862	0.141	0.538	0.104	0.030	0.709	3.79	0.673	0.998	0.180	0.069	0.732	0.149	0.105	0.558
Honduras	2.031	0.428	0.698	2.697	0.928	1.067	5.37	0.990	1.233	3.544	0.808	1.487	0.630	0.445	0.728
Jamaica	3.436	0.675	0.815	5.164	1.714	1.582	7.19	1.376	1.531	3.280	0.572	1.249	0.524	0.365	0.68
Mexico	7.280	1.249	1.213	4.781	1.469	1.323	7.08	1.335	1.49	7.914	1.891	2.59	6.762	3.931	2.415
Nicaragua	1.694	0.237	0.577	2.311	0.670	0.955	5.57	0.984	1.208	3.546	0.899	1.605	0.518	0.418	0.697
Panama	8.419	1.739	1.515	5.094	1.750	1.406	9.06	1.764	1.821	6.549	1.473	2.169	1.471	0.622	0.795
Puerto Rico	5.318	0.976	1.015	7.419	2.296	1.829	9.28	1.766	1.801	4.268	0.768	1.444	1.104	0.529	0.726
Suriname	2.001	0.423	0.719	2.901	0.947	1.06	4.77	0.689	1.006	4.066	0.811	1.48	0.048	0.035	0.532
Trinidad and Tobago	6.494	1.475	1.392	4.898	1.521	1.456	7.85	1.585	1.717	2.399	0.469	1.139	0.381	0.223	0.629
Venezuela	1.450	0.419	0.712	0.907	0.253	0.821	2.62	0.604	1.025	5.140	1.518	2.243	1.214	0.989	1.032

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