Events and Tourism Review

December 2025 Volume 8 No. 1

Aggregating Travel Destination Sustainability Rankings Using Principal Component Analysis (PCA)

Yen-Soon Kim
Natalie Hudson
Rhonda Montgomery
Ashok Singh
Soyeon Jung

University of Nevada, Las Vegas
Correspondence: yen-soon.kim@unlv.edu *(Y. Kim)*

Recommended Citation
Kim, Y., Hudson, N., Montgomery, R., Singh, A., and Jung, S. (2025). Aggregating Travel Destination Sustainability Rankings Using Principal Component Analysis (PCA). *Events and Tourism Review*, *8*(1), 15-35.

Events and Tourism Review Vol. 8 No. 1 (2025), 15-35, DOI: 10.18060/28905

Abstract

Tourism destinations are ranked by multiple sustainability indices that differ in scope and weighting, producing inconsistent standings that hinder benchmarking and management. We propose a transparent aggregation of Travel Destination Sustainability Indices (TDSIs) using principal component analysis (PCA). Using six published indices for 136 destinations, we standardize ranks and apply PCA to the correlation matrix. The first two components explain 91% of total variance: PC1 captures a common efficiency/competitiveness dimension, whereas PC2 reflects methodological emphases, clarifying why prior rankings diverge. We construct a variance-weighted composite from the retained components to yield a reproducible meta-ranking with interpretable loadings. Results identify stable leaders and reveal meaningful re-orderings where sub-dimensions differ. Practically, the composite enables managers to prioritize interventions, allocate resources toward high-leverage indicators, and communicate performance with a single auditable score that can be recalibrated as benchmarks evolve. The approach is software-light, scalable, and readily updated with new indicators and years.

Keywords: Principal Component Analysis (PCA); Travel Destination Sustainability; Tourism Benchmarking; Composite Index; Sustainable Tourism Management

Introduction

The onset of the First Industrial Revolution in 1765 marked a transformative era characterized by significant developments such as the extensive extraction of coal, the advent of the steam engine, and mechanization of various industries. The Second Industrial Revolution, commencing in 1870, introduced new sources of energy including electricity, gas, and oil, and was notable for the emergence of groundbreaking technologies, particularly automobiles and airplanes. Subsequently, the Third Industrial Revolution in 1969 ushered in the era of nuclear energy. Currently, we are witnessing the Fourth Industrial Revolution, which is distinguished by the pervasive influence of the Internet and large web-based corporations (iED Team, 2019). To clarify the research gap, we explicitly define the study's problem as the lack of a transparent, endogenously weighted method to synthesize heterogeneous destination sustainability rankings into a reproducible meta-ranking suitable for policy and management.

Amidst these technological advancements, the concept of sustainability emerged during the Second Industrial Revolution (Popular Mechanics, 1912). This period, now recognized as a pivotal juncture in history, gave rise to growing concerns about global warming and its profound implications for the planet. The concept of sustainability evolved as a response to the increasing awareness of the finite nature of natural resources and the environmental impact of industrial activities. We emphasize the study's significance by arguing that a common, auditable signal extracted from multiple indices reduces noise for decision makers and enables defensible prioritization, progress tracking, and cross-destination communication.

Early popular media explicitly linked fossil-fuel combustion to greenhouse warming. A widely circulated 1912 caption explained that burning ~2 billion tons of coal annually would add ~7 billion tons of CO_2, "making the air a more effective blanket for the earth," with effects "considerable in a few centuries" (Popular Mechanics, 1912). The same text appeared as "Coal Consumption Affecting Climate" in Australian and New Zealand newspapers weeks later, indicating transnational diffusion of this understanding (Coal Consumption Affecting Climate, 1912a, 1912b)

As the discourse on sustainability has matured, it has expanded to encompass a holistic approach that integrates environmental, economic, and social dimensions (Scoones, 2016). This tripartite approach aims to achieve a balance between development and the health of our planetary ecosystems. The challenges posed by global warming and environmental degradation have intensified the urgency for sustainable practices and have catalyzed a global movement towards more responsible stewardship of the Earth's resources.

Tourism destinations are increasingly evaluated by multiple sustainability indices that differ in scope, indicator selection, and weighting logic. As a result, the same destination can occupy markedly different positions across indices, obscuring performance signals for managers and policymakers. This methodological fragmentation complicates benchmarking, impedes longitudinal monitoring, and can undermine stakeholder trust in sustainability claims. The research problem addressed here is the lack of a transparent, data-driven method to synthesize heterogeneous destination sustainability rankings into a single, interpretable composite that preserves information contained across indices.

Prior studies have advanced destination sustainability measurement using composite indicators, efficiency-based approaches, or index-specific frameworks; however, limited work has focused on aggregating multiple published rankings into a coherent, reproducible meta-ranking that explicitly accounts for the shared variance among indices. In particular, the field lacks an open, endogenously weighted method that (i) reduces dimensionality, (ii) avoids purely subjective weighting, and (iii) is easy to implement with standard statistical software.

We introduce and illustrate a principal component analysis (PCA) aggregation procedure that treats published sustainability rankings as observed manifestations of an underlying latent construct—destination sustainability. The proposed method yields a composite ranking by forming a weighted sum of the first principal components, where weights equal the proportion of variance explained by each retained component. Contributions are threefold: (1) a transparent and replicable aggregation procedure; (2) an empirical meta-ranking of 136 destinations based on six widely cited indices; and (3) managerial guidance on how such a composite can inform benchmarking and resource allocation.

Literature Review

Sustainability and Destination Measurement

Extending prior evidence that composite rankings are highly sensitive to indicator selection and weights, we frame sustainability as a latent construct only partially observed by existing indices; accordingly, we apply PCA to recover their common signal and reduce reliance on subjective weighting.

Sustainability research emphasizes balancing environmental, economic, and social dimensions and has motivated destination-level indicators and benchmarking frameworks (Torres-Delgado & Saarinen, 2014; Punzo et al., 2022). Within tourism, scholars have proposed holistic measurement systems and composite indices to support policy and management decisions (Pérez et al., 2013; Giambona et al., 2024). Several studies deploy data-reduction or weighting strategies—PCA, regression-based scoring, and entropy or non-compensatory schemes—to consolidate multidimensional information (Pérez et al., 2013; Lozano-Oyola et al., 2019; Punzo et al., 2022), while others critique the sensitivity of composite rankings to indicator selection and weighting rules and call for transparent, auditable methodology (Greco et al., 2019; Kelemen et al., 2024; Kármán-Tamus & Gárdos, 2025). We further explain how the cited works guided our objectives: dimensionality reduction without ad-hoc weights, retention of shared information across indices, and generation of a reproducible meta-ranking that can be audited and updated as methodologies evolve.

Work linking sustainability to destination competitiveness highlights both conceptual alignment and empirical challenges: sustainability indicators covary with broader competitiveness measures, and methodological choices (e.g., efficiency-frontier models vs. composite indices) can change destination standings (Cracolici & Nijkamp, 2009; Rodríguez-Díaz et al., 2020; Assaf & Josiassen, 2016; González-Rodríguez et al., 2023). Recent critiques of market-oriented benchmarking urge careful interpretation of rankings and triangulation across measures when communicating results to stakeholders (Miller & Crabolu, 2023).

Building on this body of work, we treat six published indices as correlated indicators of a single latent sustainability construct and use PCA to extract the dominant common signal. Unlike equal-weight averaging or judgement-based multi-criteria methods, PCA endogenously determines weights from the covariance structure, facilitating reproducibility and reducing

Origins and Evolution of Sustainability Research

The word sustainability, nachhaltigkeit in German, appeared in 1713 in Europe in a book written by German scientist and forester Hans Carl von Carlowitz, after which the practice of planting trees became a path to “sustained-yield forestry” among French and British foresters (Heinberg, 2010). In January 1972, a series of articles called “Blueprint for Survival,” laying out the facts of the global situation at the time regarding world population, resources, and environmental problems, were published in The Ecologist; the articles were contributed by more than 30 scientists. These articles later appeared as a British book Blueprint for Survival, and over 750,000 copies of this book were sold (Goldsmith et al., 1972). The ideas presented in Blueprint for Survival were not supported by all researchers at the time, as can be inferred from two letters which appeared in the Correspondence section of the magazine Nature (Nature, 1972). The term “sustainability” later appeared (Kidd, 1992) in the United States in 1974, in a United Nations document in 1978, and in a Meeting of G7 countries held in 1989 in Paris, France (G7 Summit, 1989).

Principal Components Analysis and Tourism

Corral, Hernández, Navarro Ibáñez, and Ceballos collaborated with Spanish authorities and tourism related businesses and organizations to develop a strategy for renovating mature tourist destinations (Corral et al., 2016). Muresan, Oroian, Harun, Arion, Porutiu, Chiciudean, Todea, and Lile (Muresan et al., 2016) used 22 measures of residents’ perceptions toward tourism, and eight measures of support for tourism; data was collected from the Nord-Vest region in Romania and Principal Components Analysis (PCA) of data yielded four perception components and two support components. Harun, Chiciudean, Sirwan, Arion, and Muresan (Harun et al., 2018) collected 320 responses from a survey of residents of Sulaimani and Halabja Governorates in the northern region of Iraq and used PCA for data analysis; increase in local pollution emerged as a negative aspect of tourism, but strong support for the development of tourism was also found.

Garrigos-Simon, Narangajavana-Kaosiri, and Lengua-Lengua (Garrigos-Simon et al., 2018) conducted a bibliometric investigation of research in Tourism and Sustainability (TS) to identify research patterns in TS and presented results visually. Pulido-Fernández and López-Sánchez used the method of logistic regression on data collected from 1,118 responses of Western Costa del Sol (Andalusia, Spain) visitors and determined that the tourists with knowledge of sustainability were willing to pay to visit destinations that were sustainable but were not willing to pay for the increased cost of sustainable tourism (Pulido-Fernández & López-Sánchez, 2016). Sun, Wandelt and Zhang (2022) considered the impact of Covid-19 on global air traffic based on approximately 200 research publications on this topic (Sun et al., 2022). Palacios-Florencio, Santos-Roldán, Berbel-Pineda and Castillo-Canalejo (2021) show that one way to maintain the tourism industry in challenging times such as Covid-19 is the development of sustainable tourism (Palacios-Florencio et al., 2021).

Deri, Chiti, and Ciuffoletti (Deri et al., 2023) called for understanding a cultural tourism destination well and argued for promoting slow tourism in order to preserve the distinguishing features of an inland tourist destination. Lyon (Lyon, 2023) suggested that approaches and perspectives must be integrated when developing the science of sustainability. Mastria, Vezzil, and De Cesarei (Mastria et al., 2023), after reviewing results from 40 publications, suggested that tourists' preferences and sustainable choices were impacted by perceived value of green products and services. The emergence of sustainable wine tourism in the post COVID-19 years was considered by Santorinaios, Kosma, and Skalkos (Santorinaios et al., 2023); a statistical analysis of 595 survey responses revealed that wine consumption and winery visitations had increased after COVID-19. Jiang, Cai, Chen, Zhang, Wang, Xie, and Yu (Jiang et al., 2022) applied spatiotemporal methods for assessment of sustainability of Shandong Province's cultural heritage.

Tourism Destination Sustainability Indices

Cracolici, Cuffaro & Nijkamp (Cracolici et al., 2009) developed a statistical method for evaluating tourism sustainability. Castellani and Sala (Castellani & Sala, 2010) proposed a holistic method for evaluating sustainability by defining measures for evaluating effects of policies.

The initial idea for the Scandinavian Destination Sustainability Index was born in 2010 in Gothenburg in a joint meeting of ICCA's Scandinavian Chapter and MCI, leading to the first Scandinavian benchmark (Global Destination Sustainability Movement, 2017). The Global Destination Sustainability Index (GDS-Index) was subsequently created through an MoU among the ICCA Scandinavian Chapter, ICCA, IMEX, and MCI in 2015 (Global Destination Sustainability Movement, 2023, 2025). The GDS-Index reached 50 destinations by 2019 (Global Destination Sustainability Movement, 2023) and now covers around/over 100 audited destinations worldwide (Bordeaux Tourism & Conventions, 2024). In parallel, the GDS-Academy launched in June 2021, offering an open-enrolment GDS-ICCA-CityDNA Certificate in Regenerative Destination Management (ICCA, 2021; Global Destination Sustainability Movement, 2025; City Destinations Alliance, 2025). Tourism destinations increasingly use such destination sustainability indices to attract visitors and communicate their sustainability performance (Global Destination Sustainability Movement, 2025).

Crouch (Crouch, 2011) used an online survey of tourism researchers and tourism destination managers to evaluate 36 competitiveness attributes to develop determinance measures, statistically analyzing these measures. A total of 10 of the 36 attributes had statistically significant measures. Angelkova, Koteski, Jakovleva, and Mitrevska (Angelkova et al., 2013) discussed the importance of cooperation among various stakeholders such as national and regional authorities, tourism companies and destinations for achieving true sustainability. Pérez, Guerrero, González, Pérez, and Caballero (Pérez et al., 2013) developed a Principal Component Analysis (PCA)-based composite tourism destination index. Mikulić, Kožić, and Krešić (Mikulić et al., 2015) pointed out potential issues with commonly used methods for combining sustainability indices. Carrillo and Jorge

(Carrillo & Jorge, 2017) developed a composite index for tourism sustainability of Spanish regions via weighting of simple indicators. Martin and Assenov discussed the importance of developing tourism sustainability indices for surf sites and developed a Surf Resource Sustainability Index (SRSI) for surfing-based tourism destinations (Martin & Assenov, 2015)

Rodríguez-Díaz and Pulido-Fernández (Rodríguez-Díaz & Pulido-Fernández, 2020) investigated the relationship between sustainability and tourism competitiveness for various regions and developed a synthetic sustainability index at global and regional levels. A systematic literature review of sustainability is provided by Streimikiene, Svagzdiene, Jasinskas, and Simanavicius (Streimikiene et al., 2021). Wang, Nie, Jeronen, Xu, and Chen (Wang et al., 2023) combined value belief-norm theory with environmental awareness on a dataset of 301 students from a university in eastern China; their results point to an important role university can play in promoting sustainable tourism. Nguyen, Kuo, Lu, and Nhan (Nguyen et al., 2024) developed a two-stage network to benchmark 111 global tourist destinations; their empirical results show that inefficiency in sustainability primarily comes from technology gaps among the tourist destinations.

Companies such as Mabrian (Mabrian, n.d.) and S & P Global (S & P Global, n.d.) provide a range of sustainability indices. Jørgensen (Jørgensen, 2023) argues for a deep investigation into various sustainability indices and destination rankings obtained from these indices. Asmelash and Kumar (Asmelash & Kumar, 2019) used Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM) on data collected from a three-round Delphi Method involving evaluation of indicators using 6 well-accepted indicator selection criteria in order to obtain an alternative travel sustainability index.

Gómez-Vega and Picazo-Tadeo (Gómez-Vega & Picazo-Tadeo, 2019) used data from the 2017 Travel & Tourism Competitiveness Report of the World Economic Forum (WEF) and determined weights to rank 136 tourist destinations; the weighted indicator rankings were found to be quite similar to the unweighted WEF rankings.

Methodology

PCA is a statistical method which is typically used for reducing the number of variables in a correlated dataset. PCA uses eigen analysis of the covariance matrix or the correlation matrix and yields uncorrelated principal component scores (PC scores) and PC loadings of each variable of the PCs. PC scores are used as inputs to further statistical analyses such as Multiple Linear Regression (MLR). In this article, we will develop an aggregating method for several TDSI rankings into a single ranking via the dimensionality reduction method of Principal Components Analysis (PCA) (Jolliffe, 2002) and will illustrate the proposed method using the TDSI rankings data given in Appendix 2 of Gómez-Vega and Picazo-Tadeo (Gómez-Vega & Picazo-Tadeo, 2019). We compiled six published index variables for each of 136 destinations (see Table 1), verified directionality so that lower ranks denote better performance, and standardized variables (z-scores) to ensure commensurability before PCA.

We compiled rankings for 136 destinations across six sustainability-related indices reported in the tourism competitiveness literature: four index variants (A–D), a Data Envelopment Analysis-based composite (DEA), and the World Economic Forum's Travel & Tourism Competitiveness components (WEF). All six are available for the same set of destinations, yielding a balanced 136×6 matrix (see Table 1).

For transparency and reproducibility, we detail the pipeline: data screening for completeness, z-standardization, PCA on the correlation matrix, component retention via scree and cumulative-variance criteria, and construction of the composite as a variance-weighted sum of retained components; software and parameters are listed in the online appendix.

Rankings were encoded such that lower numeric values denote better performance in all six indices. To place indices on a common scale, variables were standardized to zero mean and unit variance prior to PCA (z-scores). Because variables represent ordinal ranks, we verified results using the correlation matrix (equivalent to PCA on standardized variables). No imputation was required because the dataset is complete for the 136 destinations.

We applied PCA to the 6 standardized variables using the correlation matrix and extracted component scores and loadings with the prcomp routine in R. Component retention followed the scree-plot and cumulative variance criteria: the first two components explained 91% of total variance. We constructed a composite sustainability score S as a weighted sum of the first two component scores: $S = w_1 \cdot PC1 + w_2 \cdot PC2$, where weights equal the proportion of variance explained ($w_1 = 0.79$, $w_2 = 0.12$, normalized to sum to 0.91). Destinations were ranked by S (descending sustainability).

Code was executed in R (version current at analysis time). We provide figure descriptions (scree plot; biplots of scores/loadings; correlation heatmaps) to support interpretation. Figures and the full ranking table remain unchanged in substance but are referenced in the revised narrative for clarity.

All computations in this article were done in the statistical software environment R (R Core Team, 2023). The function "prcomp" of R was used to run PCA on the data file with 136 rows and 6 columns shown in Table 1.

Results and Discussion

Figure 1 (Scree Plot) shows the percent variance explained by the six PCs, with the first two cumulatively explaining 91%, and first three cumulatively explaining almost all (98%) of the total variation in the data. The first principal component captures the dominant common variance across indices, consistent with an overarching efficiency/competitiveness construct for destinations, whereas the second component loads on methodological emphases specific to individual indices. Together, these dimensions clarify why prior rankings sometimes diverge and provide a coherent basis for reconciling results across benchmarking systems.

Figure 2 is a plot showing the correlations among the PCs and the original variables. It can be seen from this plot that the TDSI rankings WEF and DEA load very heavily on PC1, followed by the rankings C, A, B, and then D. The rankings D and A load heavily on PC2, and the third PC is just the ranking B. Figure 3, which is a plot of the PC scores and PC loadings, confirms the conclusions drawn from Figure 2. We will next show how the results of the PCA can be used to average the six TDSI rankings into a single ranking via the results of PCA. Practically, managers can apply the PCA-informed ranking to identify leverage points (e.g., indicators with high loadings), allocate resources toward dimensions with outsized influence, and benchmark progress as input indices update; we also contrast our results with equal-weight, entropy-weighted, and efficiency-frontier approaches to highlight when each may be preferred.

Figure 1. Percentage of Variation Explained by the PC's (Scree Plot)

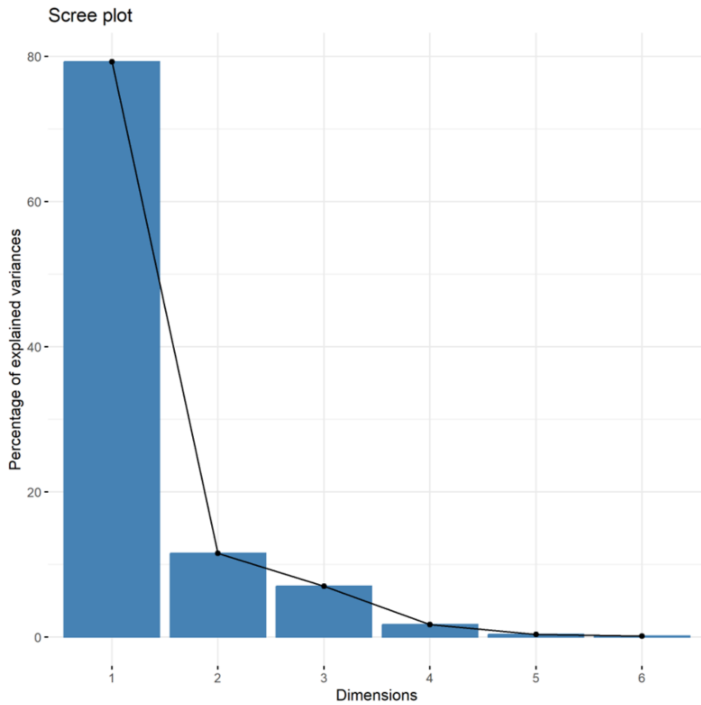

Figure 2. Correlation Plot of the PC's and Raw Variables

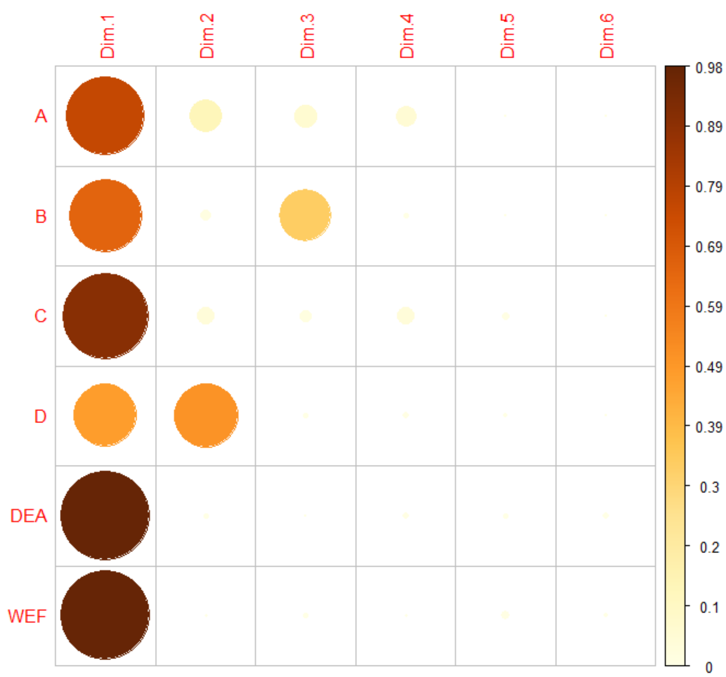

Figure 3. Plot of PC Scores and Loadings for the First Two PC's

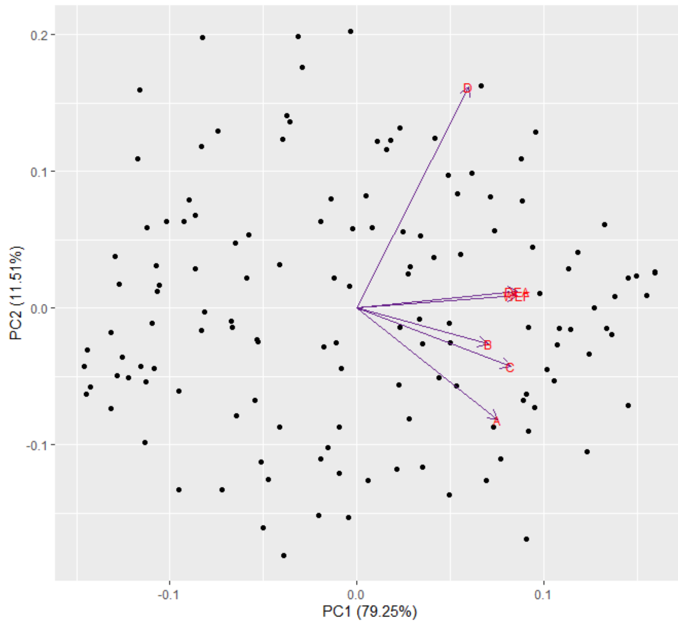

Figure 3 displays the Principal Component (PC) scores and loadings for the first two components derived from the PCA of TDSI rankings. Each data point represents a country or region, plotted in relation to its position along the PC1 and PC2 axes, which together explain a significant portion of variance. The loadings indicate the contribution of each original variable to the components, allowing for visual interpretation of how strongly each ranking index influences the new composite dimensions.

Figure 4. Correlation Plot of the 6 Rankings and the PCA-based Ranking

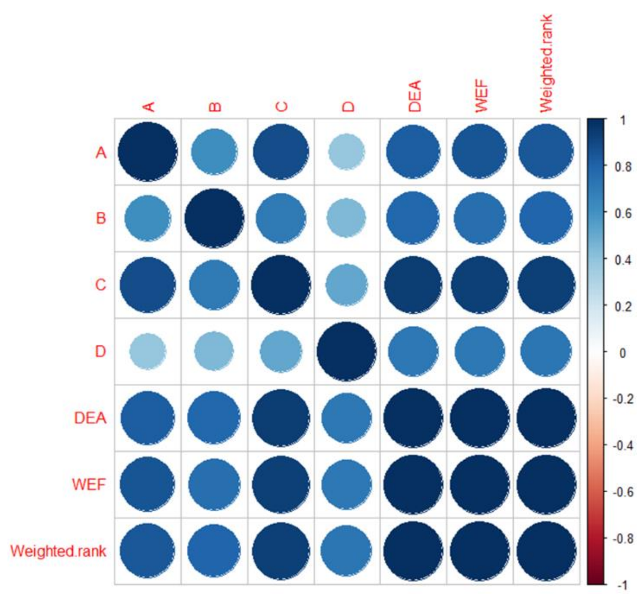

Figure 4 is the correlation plot of the six original rankings given in brackets along with the proposed PCA loadings weighted rankings. It can be seen that the ranking obtained by the proposed method is highly correlated with the rankings C, DEA, and WEF.

Table 1 shows the original ranking data and the ranking obtained by the proposed method of computing the weighted average of the first two PC scores using the PCA loadings of 0.79 for PC1 and 0.12 for PC2 (see Figure 3).

Table 1. Rankings of Tourist Destinations –
Last Column is Ranking by the Proposed Method

Country/ region	A	B	C	D	DEA	WEF	Weighted Rank
Spain	27	9	10	3	3	1	1
Germany	16	19	3	6	5	3	2
France	23	20	7	4	4	2	3
Japan	4	22	12	8	6	4	4
United States	21	61	1	1	1	6	5
Austria	22	15	9	20	10	12	6
United Kingdom	15	60	4	9	7	5	7
Portugal	32	3	21	18	13	14	8
Hong Kong	2	14	16	36	16	11	9
Switzerland	1	41	8	29	14	10	10
Australia	19	45	20	12	9	7	11
Italy	48	47	17	5	8	8	12
Republic of Korea	14	51	19	13	11	19	13
Canada	25	74	5	14	12	9	14
Greece	46	10	23	22	17	24	15
Iceland	10	12	2	67	15	25	16
Belgium	20	42	15	27	19	21	17
Netherlands	12	25	14	51	22	17	18
Singapore	7	1	11	89	18	13	19
Norway	5	46	26	33	23	18	20
New Zealand	13	17	32	42	28	16	21
Sweden	6	35	31	35	25	20	22
China	60	83	18	2	2	15	23
Croatia	40	31	33	17	21	32	24
Ireland	24	11	22	58	27	23	25
Denmark	8	34	29	55	31	31	26
Finland	3	30	35	60	33	33	27

Czech Republic	30	29	24	48	30	39	28
Malaysia	39	26	41	37	36	26	29
United Arab Emirates	18	68	6	62	26	29	30
Taiwan	28	38	40	39	35	30	31
Mexico	73	55	51	11	20	22	32
Malta	29	4	27	84	34	36	33
Luxembourg	9	32	13	111	32	28	34
Thailand	66	48	39	25	38	34	35
Panama	65	23	34	50	40	35	36
Bulgaria	41	28	49	40	41	45	37
Estonia	17	8	45	88	39	37	38
Slovenia	35	24	46	63	44	41	39
Brazil	72	92	64	7	24	27	40
Costa Rica	59	36	62	30	47	38	41
Turkey	68	73	44	16	37	44	42
Hungary	49	16	47	57	46	49	43
Indonesia	94	7	77	21	43	42	44
Chile	55	13	65	44	49	48	45
Poland	52	27	60	43	48	46	46
Cyprus	51	21	36	70	42	52	47
India	109	62	61	10	29	40	48
Russian Federation	54	100	43	24	45	43	49
Slovak Republic	37	44	55	61	52	59	50
Mauritius	57	5	48	104	51	55	51
Peru	84	72	81	15	50	51	52
Latvia	36	18	56	105	56	54	53
Lithuania	31	33	53	102	55	56	54
South Africa	85	86	52	28	57	53	55
Ecuador	87	67	63	32	61	57	56
Romania	58	57	68	49	62	68	57
Qatar	11	90	28	123	54	47	58
Barbados	44	52	25	122	53	58	59
Argentina	69	102	74	23	65	50	60
Jamaica	82	6	57	91	60	69	61
Morocco	74	78	67	34	64	65	62
Colombia	91	66	93	19	58	62	63
Oman	42	104	58	47	66	66	64
Sri Lanka	80	49	73	53	67	64	65

Dominican Republic	102	2	59	82	59	76	66
Israel	33	108	37	85	63	61	67
Azerbaijan	43	80	71	65	70	71	68
Vietnam	77	81	96	26	69	67	69
Saudi Arabia	34	110	54	80	71	63	70
Bahrain	26	96	38	134	68	60	71
Georgia	50	71	69	96	72	70	72
Uruguay	38	76	82	83	76	77	73
Kenya	116	54	86	41	77	80	74
Jordan	53	58	70	113	75	75	75
Guatemala	99	43	91	59	79	86	76
Namibia	86	82	66	71	80	82	77
Montenegro	63	84	50	114	78	72	78
Philippines	97	64	97	52	82	79	79
Trinidad & Tobago	70	105	30	119	74	73	80
Tanzania	123	37	104	46	83	91	81
Tunisia	75	59	76	95	81	87	82
Bhutan	76	53	98	87	84	78	83
Kazakhstan	47	97	89	79	87	81	84
Cape Verde	90	63	42	129	73	83	85
Egypt	95	70	85	81	88	74	86
Honduras	113	40	87	77	85	90	87
Armenia	61	93	80	93	86	84	88
Cambodia	105	39	106	66	91	101	89
Iran	89	115	101	31	92	93	90
Ukraine	83	89	72	94	89	88	91
Botswana	88	98	88	74	98	85	92
Nicaragua	112	50	94	86	94	92	93
Macedonia	56	91	75	120	90	89	94
Mongolia	64	103	112	54	96	102	95
Lebanon	71	77	83	115	93	96	96
Lao PDR	98	65	92	103	95	94	97
Serbia	62	107	79	108	97	95	98
Bolivia	108	116	103	45	101	99	99
Albania	79	87	84	121	99	98	100
Nepal	114	69	127	64	102	103	101
Uganda	119	88	116	56	103	106	102
El Salvador	103	56	100	124	100	105	103
Kuwait	45	122	78	136	104	100	104

Rwanda	81	94	107	110	105	97	105
Venezuela	125	129	113	38	113	104	106
Zambia	115	99	118	75	107	108	107
Zimbabwe	126	101	110	68	109	114	108
Senegal	107	128	99	72	112	111	109
Ethiopia	117	106	114	73	111	116	110
Cote d'Ivoire	111	120	90	92	114	109	111
Paraguay	101	75	111	127	106	110	112
Bosnia-Herzegovina	78	109	95	130	108	113	113
Gambia	110	85	108	117	110	112	114
Tajikistan	93	117	115	100	118	107	115
Kyrgyz Republic	92	118	129	78	120	115	116
Algeria	96	132	120	76	121	118	117
Moldova	67	114	102	135	116	117	118
Madagascar	131	79	124	98	115	121	119
Mozambique	120	95	119	99	117	122	120
Pakistan	127	113	105	101	119	124	121
Ghana	104	123	109	112	122	120	122
Mali	130	127	123	69	124	130	123
Gabon	100	126	117	118	123	119	124
Malawi	122	112	131	97	125	123	125
Bangladesh	118	121	122	109	126	125	126
Nigeria	128	124	121	107	127	129	127
Cameroon	124	133	126	106	129	126	128
Lesotho	106	111	133	131	128	128	129
Benin	121	131	125	116	130	127	130
Democratic Republic of Congo	134	136	135	90	133	133	131
Mauritania	132	119	128	126	131	132	132
Sierra Leone	129	125	134	128	132	131	133
Chad	136	130	132	125	134	135	134
Yemen	135	135	130	132	136	136	135
Burundi	133	134	136	133	135	134	136

Table 1 compiles the rankings of 136 tourist destinations across six sustainability indices (A, B, C, D, DEA, WEF) and presents the final weighted ranking derived via a PCA-based aggregation method. Notably, top destinations such as Spain, Germany, and France rank high across multiple indices and likewise lead the aggregated PCA ranking. The table underscores how PCA effectively consolidates diverse sustainability metrics into a single composite rank, supporting the article's methodology and validating its conclusions

The scree plot indicates steep decline after the first component and an elbow after the second, with PC1 and PC2 jointly capturing 91% of variation. Biplots show that WEF and DEA load most strongly on PC1, with additional contribution from indices C and A, while index D contributes more prominently to PC2. This pattern suggests a dominant common dimension aligned with broad competitiveness and efficiency, and a secondary dimension capturing index-specific emphases.

The PCA-weighted score consolidates the six indices into a single ordering. Consistent top performers include Spain, Germany, and France; large, diversified destinations such as the United States and Japan also rank highly. The composite is highly correlated with several source indices, yet notable re-ordering occurs where individual indices emphasize distinct sub-dimensions of sustainability. See Table 1 for the complete list of destinations and the final composite rank.

Recent discourse surrounding the Fourth Industrial Revolution (4IR) has further emphasized the role of digital transformation in sustainability. Technological convergence, including artificial intelligence, big data, and the Internet of Things (IoT), is now increasingly viewed as both a challenge and a solution in managing sustainable tourism (Gretzel et al., 2015; Li et al., 2018). As urbanization and mobility grow, there is a renewed focus on balancing economic growth with ecological and social responsibilities (UNWTO, 2020). Consequently, the urgency of incorporating sustainability into tourism planning has intensified, leading to a greater reliance on analytical methods that can consolidate multidimensional sustainability metrics into meaningful insights.

More recently, studies have highlighted the role of digital ecosystems and governance frameworks in managing sustainable destinations. For example, Baggio and Sainaghi (2016) applied network theory to tourism systems, revealing structural imbalances in how sustainability efforts are distributed. Similarly, Becken and Scott (2020) emphasized the importance of climate resilience in tourism infrastructure and its influence on long-term sustainability. Researchers have argued for integrating ESG (Environmental, Social, and Governance) principles into tourism sustainability indices, signaling a convergence with corporate sustainability reporting standards. This shift reflects the increasingly complex, ESG-driven data environment in which TDSI evaluations now operate (Guix et al., 2025; Bonilla-Priego et al., 2014; UN Tourism ESG Framework, 2024)

To enhance robustness, researchers are combining PCA with other dimensionality-reduction and weighting techniques such as factor analysis and entropy weighting (Liang, 2018; Wu et al., 2022). For example, hybrid PCA–entropy models reduce indicator subjectivity (Liang, 2018; Wu et al., 2022). These integrative approaches offer greater reliability and are gaining traction in sustainability benchmarking across sectors, including tourism (Palacios-Florencio et al., 2021)

Furthermore, widely used R and Python ecosystems—exemplified by FactoMineR for multivariate analysis and scikit-learn for machine learning—enable researchers to implement and compare multiple dimensionality-reduction strategies within reproducible workflows, and large-scale benchmarks now guide method selection across contexts (Lê et al., 2008; Pedregosa et al., 2011; Cantini et al., 2021). In this context, our use of PCA remains a foundational and reproducible choice, especially for benchmarking exercises like TDSI.

PCA loadings indicate that indices such as DEA and WEF contribute most strongly to the first component, while regional discrepancies likely reflect differences in how each index defines and weights sustainability. This interpretation aligns with Nguyen et al. (2024), whose benchmarking of 111 global destinations showed that environmental metrics can diverge substantially from economic or social indicators

This nuance is important when designing unified indices, as shown in Table 1, which presents notable rank shifts. Additionally, temporal shifts in sustainability-related destination rankings are evident in leading benchmarking systems: the World Economic Forum's TTDI 2024 updated its indicator set and methodology—recalculating components and limiting direct comparability with earlier editions—while the GDS-Index 2024 introduced new and refined criteria that produced measurable rank and score changes. These ongoing methodology updates and data refreshes underscore the need for periodic recalibration of TDSI tools to reflect current trends. Therefore, our PCA-based averaging approach offers a statistically grounded and adaptive solution for monitoring tourism sustainability.

Our findings suggest that PCA is not only effective in aggregating multidimensional sustainability rankings but also adaptable for real-world policy use. As tourism destinations increasingly adopt regenerative and climate-smart strategies (Becken & Kaur, 2021; Becken, Whittlesea, Loehr, & Scott, 2020), the need for integrated indices becomes critical. Policymakers and destination managers can utilize PCA-informed rankings to prioritize interventions, allocate resources more efficiently, and communicate performance to stakeholders. Future work could explore dynamic TDSI modeling through machine learning and predictive analytics to anticipate performance trajectories and policy trade-offs (Font et al., 2023). As global sustainability frameworks continue to evolve, maintaining methodological transparency and flexibility will be essential to ensure the relevance and credibility of destination rankings.

Theoretical and Practical Implications

Treating multiple published indices as noisy indicators of a latent sustainability construct provides a conceptual bridge between measurement and theory. The strong first component suggests substantial shared variance across indices, supporting the use of a common composite for benchmarking. The presence of a meaningful second component cautions that destinations can differ along secondary dimensions (e.g., policy/regulation vs. environmental efficiency), reinforcing the value of examining loadings and score plots alongside ranks.

For destination management organizations, the PCA-based composite offers a transparent yardstick for (i) prioritizing interventions, (ii) tracking progress over time, and (iii) communicating outcomes to stakeholders who face multiple, sometimes conflicting rankings. Because weights arise from the data, the approach reduces the perception of arbitrariness associated with judgment-based weighting and can be re-estimated annually as new indices or indicators become available.

Equal-weight averaging ignores covariance among indices and can dilute salient signals. Multi-criteria methods such as AHP depend on expert judgments and can be difficult to audit at scale. Entropy weighting exploits indicator dispersion but may overweight noisy measures. Efficiency-frontier techniques (e.g., DEA) identify relative best practice but can be sensitive to outliers and model specification. PCA balances parsimony and transparency by extracting the common structure and producing orthogonal components with clear variance-explained diagnostics. In contexts with many correlated indices, this offers a replicable baseline against which more complex models can be compared.

In this article, we proposed a novel method of averaging TDSI rankings via PCA, wherein PC-scores and PC-loadings are computed from a dataset of tourist destination rankings. The PC-scores are then averaged using PC-loadings as weights to obtain a consolidated ranking for all destinations in the dataset. This method was illustrated using a dataset from the tourism literature.

This PCA-based approach offers a robust solution for synthesizing multidimensional sustainability data into a single, interpretable index. Unlike simple averaging or unweighted aggregation methods, PCA accounts for inherent correlations among indicators and objectively identifies the most influential components driving destination performance. Our analysis revealed that high loadings on the first principal components reflect dominant sustainability metrics—particularly those related to economic performance and environmental efficiency—validating the value of weighting dimensions through principal components rather than subjective judgment.

The implications for policymakers and destination management organizations are significant. By applying PCA in this manner, decision-makers can benchmark destinations more equitably, detect underlying structural patterns, and prioritize interventions based on data-driven insights. This method is adaptable to incorporate new indicators such as resilience, climate risk, or local stakeholder participation. Moreover, our model supports longitudinal comparisons, enabling institutions to monitor sustainability improvements or regressions over time and evaluate the impact of strategic initiatives.

Recent studies have further emphasized the importance of integrating renewable energy sources into tourism infrastructure to enhance sustainability. For instance, Guo and Chai (2025) investigated BIMSTEC countries and found that renewable energy consumption improves environmental quality as measured by the load capacity factor (LCF), and can moderate tourism's environmental pressures. This underscores the potential for destinations to improve their sustainability rankings by investing in renewable energy solutions.

Additionally, the role of environmental policies as attractors for tourists has been explored in recent research. Serio et al. (2024) examined international tourism flows across Italian provinces using a gravity framework and found a positive association between tourism demand and sustainable labels, suggesting that eco-certifications can influence destination choice. This is consistent with Capacci, Scorcu, and Vici (2015), who showed that Blue Flag eco-labels significantly increase future foreign tourist inflows to Italian coastal destinations. Incorporating such policy-driven indicators into PCA can therefore provide a more comprehensive assessment of destination sustainability.

Furthermore, the integration of advanced technologies into tourism planning has gained attention. Banerjee et al. (2025) introduced a composite sustainability indicator for tourism recommender systems, combining CO_2 emissions, destination popularity, and seasonality. Their work demonstrates the feasibility of using complex, multidimensional data to guide sustainable travel decisions, reinforcing the applicability of PCA in processing and interpreting such data for destination ranking purposes.

In conclusion, our findings suggest that PCA is not only effective in aggregating multidimensional sustainability rankings but also adaptable for real-world policy applications. As tourism destinations increasingly adopt regenerative and climate-smart strategies, the need for integrated indices becomes critical. Policymakers and destination managers can utilize PCA-informed rankings to prioritize interventions, allocate resources more efficiently, and communicate performance to stakeholders. Future research could explore dynamic TDSI modeling through machine learning and predictive analytics. As global sustainability frameworks continue to evolve, maintaining methodological transparency and flexibility will be essential in ensuring the relevance and credibility of destination rankings.

Limitations and Future Research

PCA assumes linear relationships and focuses on variance rather than causality; future work could combine PCA with confirmatory factor analysis, explore dynamic updates as new indicators emerge, or test robustness to alternative standardizations (e.g., rank-based normal scores). Extending the framework to include resilience, climate risk, or stakeholder participation metrics would further enhance decision relevance.

References

Angelkova, T., Koteski, C., Jakovleva, Z., & Mitrevska, E. (2013). Sustainability and competitiveness of tourism. Procedia – Social and Behavioral Sciences, 44, 221–227.

Asmelash, A. G., & Kumar, S. (2019). Assessing progress of tourism sustainability: Developing and validating sustainability indicators. Tourism Management, 71, 67–83.

Assaf, A. G., & Josiassen, A. (2016). Frontier analysis: A review of frontier studies in tourism. Journal of Travel Research, 55(5), 612–627. https://doi.org/10.1177/0047287515569776

Baggio, R., & Sainaghi, R. (2016). Mapping time series into networks as a tool to assess the complex dynamics of tourism systems. Tourism Management, 54, 23–33. https://doi.org/10.1016/j.tourman.2015.10.008

Banerjee, A., Mahmudov, T., Adler, E., Aisyah, F. N., & Wörndl, W. (2025). Modeling sustainable city trips: Integrating CO_2e emissions, popularity, and seasonality into tourism recommender systems. Information Technology & Tourism, 27, 189–226. https://doi.org/10.1007/s40558-024-00303-1

Becken, S., & Kaur, J. (2021). Anchoring “tourism value” within a regenerative tourism paradigm—A government perspective. Journal of Sustainable Tourism, 30(1), 52–68. https://doi.org/10.1080/09669582.2021.1990305

Becken, S., & Scott, D. (2024). Tourism and climate change stocktake: A call to action. Journal of Sustainable Tourism, 32(9), 2018–2038. https://doi.org/10.1080/09669582.2024.2390577

Becken, S., Whittlesea, E., Loehr, J., & Scott, D. (2020). Tourism and climate change: Evaluating the extent of policy integration. Journal of Sustainable Tourism, 28(10), 1603–1624. https://doi.org/10.1080/09669582.2020.1745217

Bonilla-Priego, M. J., Font, X., & Pacheco-Olivares, M. R. (2014). Corporate sustainability reporting index and baseline data for the cruise industry. Tourism Management, 44, 149–160. https://doi.org/10.1016/j.tourman.2014.03.004

Bordeaux Tourism & Conventions. (2024, October 16). Press release: Bordeaux ranks 6th in the Global Destination Sustainability Index 2024 (out of 100 audited global destinations)

Cantini, L., Zakeri, P., Hernandez, C., Naldi, A., Thieffry, D., Remy, E., & Baudot, A. (2021). Benchmarking joint multi-omics dimensionality reduction approaches for the study of cancer. Nature Communications, 12, 124. https://doi.org/10.1038/s41467-020-20430-7

Capacci, S., Scorcu, A. E., & Vici, L. (2015). Seaside tourism and eco-labels: The economic impact of Blue Flags. Tourism Management, 47, 88–96. https://doi.org/10.1016/j.tourman.2014.09.003

Carrillo, M., & Jorge, J. M. (2017). Multidimensional analysis of regional tourism sustainability in Spain. Ecological Economics, 140, 89–98. https://doi.org/10.1016/j.ecolecon.2017.05.004

Castellani, V., & Sala, S. (2010). Sustainable performance index for tourism policy development. Tourism Management, 31(6), 871–880. https://doi.org/10.1016/j.tourman.2009.10.001

City Destinations Alliance. (2025). Regenerative tourism: The GDS-Academy. (Open-enrolment GDS-ICCA-CityDNA Certificate in Regenerative Destination Management).

Coal consumption affecting climate. (1912a, July 17). The Braidwood Dispatch and Mining Journal, p. 4. Trove, National Library of Australia.

Coal consumption affecting climate. (1912b, August 14). Rodney and Otamatea Times, Waitemata and Kaipara Gazette, p. 7. Papers Past, National Library of New Zealand.

Corral, S., Hernández, J., Navarro Ibáñez, M., & Rivero Ceballos, J. L. (2016). Transforming mature tourism resorts into sustainable tourism destinations through participatory integrated approaches: The case of Puerto de la Cruz. Sustainability, 8, 680. https://doi.org/10.3390/su8070680

Cracolici, M. F., & Nijkamp, P. (2009). The attractiveness and competitiveness of tourist destinations: A study of Southern Italian regions. Tourism Management, 30(3), 336–344. https://doi.org/10.1016/j.tourman.2008.07.006

Crouch, G. I. (2011). Destination competitiveness: An analysis of determinant attributes. Journal of Travel Research, 50(1), 27–45. https://doi.org/10.1177/0047287510362776

Deri, M. G., Chiti, L., & Ciuffoletti, A. (2023). A sustainable approach to tourist signage on heritage trails. Sustainability, 15, 16251. https://doi.org/10.3390/su152316251

Font, X., Torres-Delgado, A., Crabolu, G., Palomo Martínez, J., Kantenbacher, J., & Miller, G. (2023). The impact of sustainable tourism indicators on destination competitiveness: The European Tourism Indicator System. Journal of Sustainable Tourism, 31(7), 1608–1630. https://doi.org/10.1080/09669582.2021.1910281

G7 Summit. (1989). Summit of the Arch: Official documents (G7 Paris Meeting). https://www.g7.utoronto.ca/summit/1989paris/index.html

Garrigós-Simón, F. J., Narangajavana-Kaosiri, Y., & Lengua-Lengua, I. (2018). Tourism and sustainability: A bibliometric and visualization analysis. Sustainability, 10, 1976. https://doi.org/10.3390/su10061976

Giambona, F., Lagravinese, R., & Sarra, A. (2024). Assessing tourism sustainability in European Union countries: A composite indicator approach. Socio-Economic Planning Sciences, 95, 101849. https://doi.org/10.1016/j.seps.2024.101849

Global Destination Sustainability Movement. (2017, July 21). World Tourism Organization publishes report featuring the Scandinavian Sustainability Index. (Notes the SSI's 2010 origin in Scandinavia/Gothenburg).

Global Destination Sustainability Movement. (2023, June 5). GDS-Movement's journey. (2015 MoU establishing the GDS-Index; 2019 milestone of 50 destinations).

Global Destination Sustainability Movement. (2025, June 12). About the Global Destination Sustainability Movement. (History and partners; creation of the GDS-Index).

Global Destination Sustainability Movement. (2025). GDS-Academy. (Certificate overview and details)

Global Destination Sustainability Movement. (2023). GDS-Movement's journey. https://www.gds.earth/gds-movements-journey/

Goldsmith, E., & The Ecologist. (1972). A blueprint for survival. Penguin.

Gómez-Vega, M., & Picazo-Tadeo, A. J. (2019). Ranking world tourist destinations with a composite indicator of competitiveness: To weigh or not to weigh? Tourism Management, 72, 281–291.

González-Rodríguez, M. R., Martín-Santana, J. D., & Suárez-Velázquez, M. R. (2023). Tourist destination competitiveness: An international comparison. Tourism Economics, 29(5), 1177–1202. https://doi.org/10.1177/13548166231168665

Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. Social Indicators Research, 141(1), 61–94. https://doi.org/10.1007/s11205-017-1832-9

Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: Foundations and developments. Electronic Markets, 25(3), 179–188. https://doi.org/10.1007/s12525-015-0196-8

Guix, M., Nájera Sánchez, J. J., Bonilla-Priego, M. J., & Font, X. (2025). The changing institutional logics behind sustainability reports from the largest hotel groups in the world in 2014, 2018 and 2021. Tourism Management, 106, 105031. https://doi.org/10.1016/j.tourman.2024.105031

Guo, Y., & Chai, Y. (2025). Toward green tourism: The role of renewable energy for sustainable development in developing nations. Frontiers in Sustainable Tourism, 4, 1512922. https://doi.org/10.3389/frsut.2025.1512922

Harun, R., Chiciudean, G. O., Sirwan, K., Arion, F. H., & Muresan, I. C. (2018). Attitudes and perceptions of the local community towards sustainable tourism development in Kurdistan Regional Government, Iraq. Sustainability, 10, 2991. https://doi.org/10.3390/su10092991

Heinberg, R. (2010). What is sustainability? In The Post Carbon Reader Series: Foundation concepts. Post Carbon Institute. https://cdn.auckland.ac.nz/assets/arts/documents/What%20is%20Sustainability.pdf

iED Team. (2019, June 30). A brief history of the 4 industrial revolutions that shaped the world. Institute of Entrepreneurship Development. https://ied.eu/project-updates/the-4-industrial-revolutions/

International Congress and Convention Association (ICCA). (2021, June 18). ICCA partners with GDS to develop sustainability training (launch of GDS-Academy on 9 June 2021 and the GDS-ICCA Certificate)

Jiang, A., Cai, J., Chen, F., Zhang, B., Wang, Z., Xie, Q., & Yu, S. (2022). Sustainability assessment of cultural heritage in Shandong province. Sustainability, 14, 13961. https://doi.org/10.3390/su142113961

Jolliffe, I. T. (2002). Principal component analysis (2nd ed.). Springer.

Jørgensen, M. T. (2023). The fallout of market-oriented sustainability measures: Tourism destination sustainability benchmarking and ranking. Journal of Travel Research. https://doi.org/10.1177/00472875231204844

Kármán-Tamus, É., & Gárdos, S. (2025). Sensitivity and uncertainty analyses of a composite index: Lessons for transparent indicator construction. Regional Statistics, 15(1), 8–26. https://www.ksh.hu/statszemle_archive/regstat/2025/2025_01/rs150108.pdf

Kelemen, A., Kovács, E., & Molnár, S. (2024). A sensitivity analysis of composite indicators: Min/max weights and beyond. Heliyon, 10(9), e30123. https://doi.org/10.1016/j.heliyon.2024.e30123

Kidd, C. V. (1992). The evolution of sustainability. Journal of Agricultural and Environmental Ethics, 5(1), 1–26.

Lê, S., Josse, J., & Husson, F. (2008). FactoMineR: An R package for multivariate analysis. *Journal of Statistical Software*, *25*(1), 1–18. https://doi.org/10.18637/jss.v025.i01

Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. Tourism Management, 68, 301–323. https://doi.org/10.1016/j.tourman.2018.03.009

Liang, X. (2018). Measurement of scenic spots' sustainable capacity based on PCA–Entropy–TOPSIS (tourism context). International Journal of Environmental Research and Public Health, 15(1), 10. https://doi.org/10.3390/ijerph15010010

Lozano-Oyola, M., Contreras, I., & Blancas, F. J. (2019). An operational non-compensatory composite indicator: Measuring sustainable tourism in Andalusian urban destinations. Ecological Economics, 159, 1–10. https://doi.org/10.1016/j.ecolecon.2019.01.008

Lyon, S. W. (2023). A cross-disciplinary approach needs to be at the core of sustainability. Sustainability, 15, 15954. https://doi.org/10.3390/su152215954

Mabrian. (n.d.). Sustainable tourism insights. https://mabrian.com/solutions/sustainable/
Martin, S. A., & Assenov, I. (2012). The genesis of a new body of sport tourism literature: A systematic review of surf tourism research (1997–2011). Journal of Sport & Tourism, 17(4), 257–287. https://doi.org/10.1080/14775085.2013.766528
Martin, S. A., & Assenov, I. (2015). Measuring the conservation aptitude of surf beaches in Phuket, Thailand: An application of the surf resource sustainability index. International Journal of Tourism Research, 17, 105–117. https://doi.org/10.1002/jtr.1961
Mastria, S., Vezzoli, A., & De Cesarei, A. (2023). Going green: A review on the role of motivation in sustainable behavior. Sustainability, 15, 15429. https://doi.org/10.3390/su152115429
Mikulić, J., Kožić, I., & Krešić, D. (2015). Weighting indicators of tourism sustainability: A critical note. Ecological Indicators, 48, 312–314. https://doi.org/10.1016/j.ecolind.2014.08.026
Miller, G., & Crabolu, G. (2023). A state-of-the-art review of sustainable tourism indicators. Journal of Sustainable Tourism, 31(10), 1483–1503. https://doi.org/10.1080/09669582.2023.2213859
Muresan, I. C., Oroian, C. F., Harun, R., Arion, F. H., Porutiu, A., Chiciudean, G. O., Todea, A., & Lile, R. (2016). Local residents' attitude toward sustainable rural tourism development. Sustainability, 8, 100. https://doi.org/10.3390/su8010100
Nature. (1972, January 21). Correspondence: Blueprint for survival. Nature, 235, 179.
Nguyen, D. T., Kuo, K.-C., Lu, W.-M., & Nhan, D. T. (2024). How sustainable are tourist destinations worldwide? An environmental, economic, and social analysis. Journal of Hospitality & Tourism Research, 48(4), 698–711. https://doi.org/10.1177/10963480231168286
Palacios-Florencio, B., Santos-Roldán, L., Berbel-Pineda, J. M., & Castillo-Canalejo, A. M. (2021). Sustainable tourism as a driving force of the tourism industry in a post-COVID-19 scenario. Social Indicators Research, 158(3), 991–1011. https://doi.org/10.1007/s11205-021-02735-2
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., VanderPlas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825–2830. https://jmlr.org/papers/v12/pedregosa11a.html
Pérez, V., Guerrero, F., González, M., Pérez, F., & Caballero, R. (2013). Composite indicator for the assessment of sustainability: The case of Cuban nature-based tourism destinations. Ecological Indicators, 29, 316–324. https://doi.org/10.1016/j.ecolind.2012.12.027
Popular Mechanics. (1912, March). Remarkable weather of 1911: The effect of the combustion of coal on the climate—What scientists predict for the future (p. 341). Popular Mechanics, 17(3).
Pulido-Fernández, J. I., & López-Sánchez, Y. (2016). Are tourists really willing to pay more for sustainable destinations? Sustainability, 8(12), 1240. https://doi.org/10.3390/su8121240
Punzo, G., Trucco, G., & Toccaceli, D. (2022). A multi-modelling approach for assessing sustainable tourism: Building and validating the SusTour-Index. International Journal of Environmental Research and Public Health, 19(11), 6733. https://doi.org/10.3390/ijerph19116733
R Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/

Rodríguez-Díaz, B., & Pulido-Fernández, J. I. (2020). Sustainability as a key factor in tourism competitiveness: A global analysis. Sustainability, 12, 51. https://doi.org/10.3390/su12010051

Santorinaios, A., Kosma, I. S., & Skalkos, D. (2023). Consumers' motives on wine tourism in Greece in the post-COVID-19 era. Sustainability, 15, 16225. https://doi.org/10.3390/su152316225

Scoones, I. (2016). The politics of sustainability and development. Annual Review of Environment and Resources, 41, 293–319. https://doi.org/10.1146/annurev-environ-110615-090039

Serio, R. G., Dickson, M. M., de Graaff, T., & Pels, E. H. (2024). Environmental policies as a pull factor for tourists? Insights from Italy. Preprint. https://arxiv.org/abs/2404.08696

S&P Global. (n.d.). Sustainability indices. https://www.spglobal.com/esg/solutions/indices

Streimikiene, D., Svagzdiene, B., Jasinskas, E., & Simanavicius, A. (2021). Sustainable tourism development and competitiveness: The systematic literature review. Sustainable Development, 29(1), 259–271. https://doi.org/10.1002/sd.2133

Sun, X., Wandelt, S., & Zhang, A. (2022). COVID-19 pandemic and air transportation: Summary of recent research, policy consideration and future research directions. Transportation Research Interdisciplinary Perspectives, 16, 100718. https://doi.org/10.1016/j.trip.2022.100718

Torres-Delgado, A., & Saarinen, J. (2014). Using indicators to assess sustainable tourism development: A review. *Tourism Geographies, 16*(1), 31–47. https://doi.org/10.1080/14616688.2013.867530

UN Tourism, & University of Oxford SDG Impact Lab. (2024). ESG framework for tourism businesses: Project brochure. UN Tourism. https://pre-webunwto.s3.eu-west-1.amazonaws.com/s3fs-public/2024-09/UN%20Tourism-Oxford_ESG%20Project%20Brochure%204.pdf

Wang, Z., Nie, L., Jeronen, E., Xu, L., & Chen, M. (2023). Understanding the environmentally sustainable behavior of Chinese university students as tourists: An integrative framework. International Journal of Environmental Research and Public Health, 20(4), 3317. https://doi.org/10.3390/ijerph20043317

World Economic Forum. (2024, May 21). Travel & Tourism Development Index 2024. World Economic Forum.

World Economic Forum. (2024, May 21). Travel & Tourism Development Index 2024: Appendix A—Methodology changes. World Economic Forum.

World Tourism Organization (UNWTO). (2020, May 28). UNWTO global guidelines to restart tourism. https://webunwto.s3.eu-west-1.amazonaws.com/s3fs-public/2020-05/UNWTO-Global-Guidelines-to-Restart-Tourism.pdf

World Tourism Organization (UNWTO). (2020, June). One Planet Vision for a Responsible Recovery of the Tourism Sector. https://webunwto.s3.eu-west-1.amazonaws.com/s3fs-public/2020-06/one-planet-vision-responsible-recovery-of-the-tourism-sector.pdf

Wu, R. M. X., Zhang, Z., Yan, W., Fan, J., Gou, J., & Liu, B. (2022). A comparative analysis of the principal component analysis and entropy weight methods to establish the indexing measurement. PLOS ONE, 17(1), e0262261. https://doi.org/10.1371/journal.pone.0262261