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AN ANALYSIS OF GLOBAL COUNTRIES IN TERMS OF TOURISM INDICATORS USING MULTIVARIATE ANALYSIS

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Abstract: Tourism performance is commonly evaluated using outcome indicators such as tourist arrivals and tourism receipts; however, these indicators alone are insufficient to capture its multidimensional nature. This study aims to rank and classify 45 countries from different world regions according to tourism performance using seven indicators derived from 2024 data. It also examines the effect of data standardization on country rankings and cluster structures. Data on tourist arrivals, tourism receipts, number of rooms, number of bed-places, occupancy rate, average length of stay, and the share of tourism receipts in gross domestic product were compiled primarily from the World Tourism Organization and national statistical sources. Principal component analysis was applied to both non-standardized (original) and standardized (z-score) data to construct a tourism development index, followed by cluster analysis to classify countries. Based on the non-standardized data, the top five countries were the United States, Spain, the United Kingdom, France, and Japan, whereas under standardized data this ranking changed to the United States, Spain, France, China, and Japan. A three-cluster solution offered the most consistent classification for both datasets. Non-standardized clusters largely reflected differences in tourism volume, whereas standardized clusters revealed more detailed differences in occupancy rate, length of stay, and economic dependence on tourism, with countries such as Greece, Jamaica, and Jordan showing the strongest tourism-GDP dependence. These findings demonstrate that country rankings and classifications are highly sensitive to data standardization, suggesting that tourism performance should be evaluated within a multidimensional framework rather than relying solely on absolute indicators.

Keywords: tourism indicators, tourism performance, data standardization, principal component analysis, cluster analysis

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INTRODUCTION

Tourism, despite ongoing debates over its definition, is generally regarded as a human activity that determines the supply and demand for tourism products, involves the use of resources, and can generate positive or negative socio-economic outcomes at both national and international levels (Song et al., 2012).

As a dynamic and rapidly expanding service sector, tourism plays a crucial role in fostering economic growth, creating employment, and supporting regional development. In recent years, the increasing strategic importance attributed to tourism has led many countries to actively promote tourism development by leveraging their unique resource endowments, resulting in an unprecedented expansion of the global tourism market (Zhao et al., 2025). At the same time, processes such as globalization, advancements in transportation infrastructure, and rising living standards have significantly increased international tourism mobility and intensified competition among countries and destinations. In light of the rapid transformations brought about by economic, environmental, and technological changes, understanding these dynamics is essential for sustainable tourism planning and destination management (Szőllős-Tóth et al., 2025).

Despite its economic significance, the tourism sector is characterized by a highly vulnerable structure due to the flexibility of its demand and its strong dependence on external factors. Terrorist attacks, pandemics, natural disasters, and economic crises can directly influence tourists' travel decisions and lead to sudden fluctuations in international tourism movements. Although events such as the September 11 attacks, the SARS outbreak, the global financial crisis, and the MERS epidemic between 2000 and 2015 negatively affected tourism, they did not result in a long-term global decline (Gössling et al., 2021). However, the COVID-19 pandemic that emerged in 2019 caused an unprecedented contraction in the tourism sector. Nevertheless, following the severe disruptions experienced in 2020, international tourism largely recovered by 2023 and once again assumed an important role in promoting economic growth and employment (World Tourism Organization, 2024).

An examination of global and regional tourism statistics for 2024 indicates that international tourist arrivals reached 1.468 billion worldwide, while total tourism receipts amounted to USD 1,738.2 billion. At the regional level, Europe accounted for the highest share of tourist arrivals, followed by Asia and the Pacific, the Americas, the Middle East, and

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Africa (Figure 1). At the country level, France, Spain, and the United States ranked among the leading destinations in terms of tourist arrivals, whereas the United States, Spain, and the United Kingdom led in tourism receipts.

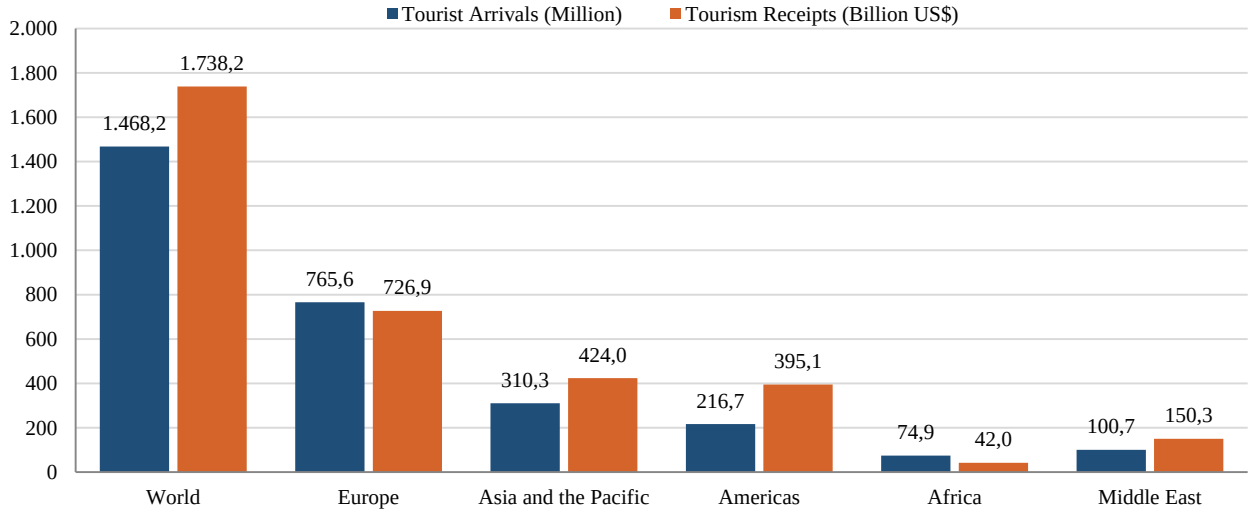


Figure 1. Tourist arrivals and tourism receipts, world and by region (Source: World Tourism Organization, 2025)

Although tourist arrivals and tourism receipts are widely accepted as primary indicators for evaluating the tourism performance of countries, relying on these indicators alone may be insufficient to reveal the structural differences and similarities among countries. The tourism performance and destination competitiveness literature shows that a destination's success cannot be determined solely by outcome indicators such as visitor numbers or tourism receipts. Approaches to destination competitiveness emphasize the interrelationships among tourism demand, inherited and created resources, supporting factors, tourism infrastructure, and destination management (Ritchie & Crouch, 2003; Dwyer & Kim, 2003). Accordingly, tourism performance can be regarded as a multidimensional construct that reflects the extent to which a country converts its tourism resources and infrastructure into visitor flows and economic value.

Therefore, evaluating countries' tourism performance requires consideration not only of the tourism volume achieved, but also of the supply capacity that sustains this volume, the utilization level of existing capacity, the length of visitors' stay at the destination, and the structural importance of tourism within the national economy. In this context, tourist arrivals, tourism receipts, number of rooms, number of bed-places, occupancy rate, average length of stay, and the share of tourism receipts in gross domestic product (GDP) are treated as indicators reflecting different, interrelated dimensions of tourism performance. Among these indicators, average length of stay is of particular importance owing to its effect on visitor expenditure and destination revenues (Emir & Kılıç, 2014; Martinez-Garcia & Raya, 2008). Furthermore, the multidimensional nature of tourism indicators requires not only the evaluation of current performance, but also the consideration of future trends in the context of tourism demand forecasting and strategic planning (Chang & Liao, 2010).

Each of the tourism indicators represents a different dimension of tourism performance. In line with recent integrative theoretical frameworks on tourism economic indicators, tourist arrivals and tourism receipts primarily reflect tourism demand and the overall economic value generated by the destination, whereas the number of rooms and bed-places represent the tourism supply and infrastructure capacity available to meet this demand (da Costa et al., 2026).

Occupancy rate is a central indicator in the tourism sector, serving as a key measure of both a destination's attractiveness and its broader economic performance (Sürekçi Yamaçlı, 2025). Tourists' length of stay is shaped by a combination of factors such as socio-demographic characteristics, travel motivations, and the mode of trip organization, and this in turn has a direct effect on destination-level tourism revenue (Oklevik et al., 2021). The share of tourism receipts in GDP is an important indicator reflecting a country's degree of economic dependence on the tourism sector (Seraj et al., 2025). This share also has a consistent and significant effect that reinforces tourism performance. Similarly, the relationship between economic growth and tourism receipts exhibits a strong and nearly proportional structure (Heryana et al., 2026). These indicators are considered together in this study to evaluate tourism performance within a multidimensional framework. In addition, these indicators are regarded as key components associated with destination competitiveness. The destination competitiveness literature shows that this competitiveness cannot be explained by a single determinant, but rather by a combination of numerous determinant attributes (Crouch, 2011).

Studies in the literature indicate that tourism performance cannot be adequately explained by a single indicator and should be examined through multidimensional approaches (Kozak & Rimmington, 1999; Cracolici & Nijkamp, 2009; Font et al., 2023; Matijová et al., 2023). In this regard, multivariate statistical techniques such as factor analysis, principal component analysis, and cluster analysis have been widely employed to identify similarities and differences among countries and destinations. These methods enable the comparative assessment of the quantitative dimensions of tourism performance and the structural differences among countries (Pulido-Fernández & Rodríguez-Díaz, 2016).

Furthermore, recent studies demonstrate that multi-indicator performance rankings can be applied at both national and international levels (Bayramoğlu, 2025; Pantović et al., 2024).

Despite these developments, a significant proportion of existing studies rely on pre-pandemic data or focus on specific regions, thereby limiting their ability to reflect the structural transformations that have occurred in the global tourism system during the post-COVID-19 period. As a result, the extent to which methodological choices influence country rankings and the classification of tourism performance remains insufficiently explored. In this context, the present study aims to comparatively evaluate the tourism performance of 45 countries using seven key indicators and multivariate statistical methods based on 2024 data. By adopting an up-to-date and multidimensional approach focused on the post-pandemic period, this study seeks to provide both methodological and empirical contributions to the literature on global tourism performance assessment. Accordingly, this study addresses the following research questions:

RQ1: To what extent does data standardization influence country rankings in tourism performance?

RQ2: How does the use of standardized versus non-standardized data affect the clustering structure of countries?

This study contributes to the literature in two important ways. First, it provides an up-to-date comparative analysis of tourism performance across 45 countries using post-pandemic (2024) data. Second, it demonstrates that country rankings and classifications of tourism performance can differ substantially depending on the statistical approach employed, highlighting the importance of considering underlying structural characteristics when interpreting the results.

METHODOLOGY

Data Collection

Tourism activity is inherently complex and can be measured using a wide range of indicators. However, to ensure meaningful cross-country comparisons, it is necessary to rely on variables that are both commonly available and comparable across different national contexts. In this study, a dataset was compiled using the 2024 tourism indicators of 45 countries from different regions of the world. In constructing the data set, 56 countries with a certain level of tourism potential were initially considered, and tourism statistics for these countries across seven indicators were sought primarily from the World Tourism Organization. In addition, missing data were sought to be obtained through the respective countries' ministries of tourism and other national statistical institutions. Within this framework, countries lacking complete and reliable data for all seven indicators were excluded from the analysis. Missing data were identified when at least one of the seven indicators for a given country was not available in official sources for the year 2024; countries with such missing or inconsistent data were accordingly excluded from the sample. As a result of this process, a final sample of 45 countries, geographically diverse and representative of different tourism structures, was obtained.

The variables used in the study include: (i) number of tourist arrivals, (ii) tourism receipts (USD), (iii) number of rooms, (iv) number of bed-places, (v) occupancy rate (%), (vi) average length of stay (days), and (vii) the share of tourism receipts in gross domestic product (GDP). These variables capture both the scale and structural characteristics of tourism performance. The countries examined within the scope of these seven indicators are presented in Figure 2.

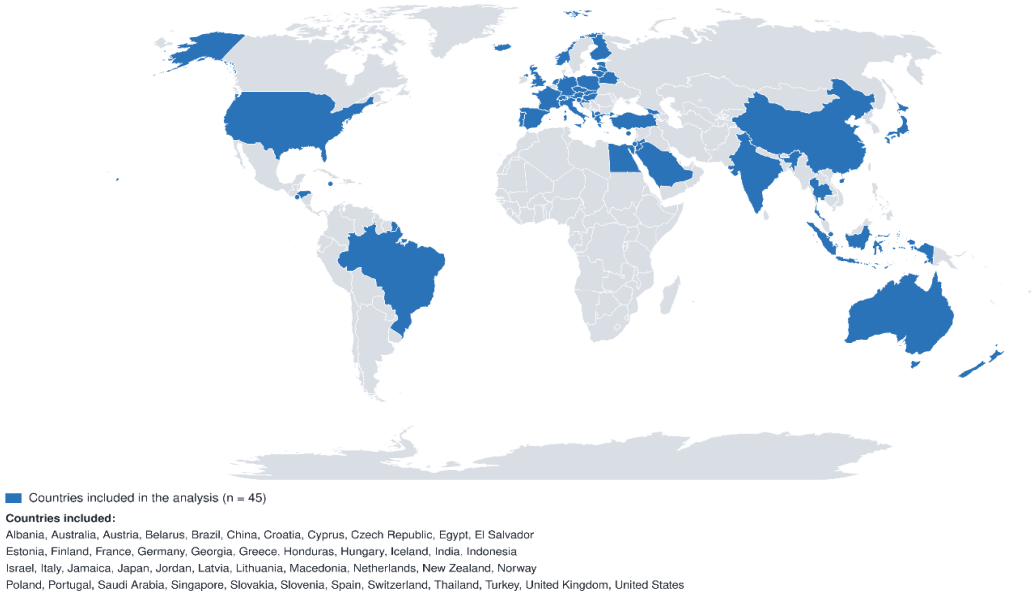


Figure 2. Countries included in the analysis

The data were obtained primarily from the World Tourism Organization (UNWTO, 2024), supplemented by official national sources such as ministries of tourism and national statistical institutions where necessary. Since the variables are expressed in different measurement units (e.g., counts, monetary values, ratio and days) and exhibit substantial variation in magnitude, two types of datasets were constructed for the analysis: non-standardized (original) data and standardized data. The use of both datasets enables a comparative assessment of how differences in data structure influence the outcomes of multivariate analyses, which is central to the methodological focus of this study.

Since the indicators used in this study differ in their units of measurement (count, monetary value, ratio, days) and magnitude, indicators with larger values (such as tourism receipts or the number of rooms) carry the risk of exerting a

dominant influence on the results when analyses are conducted on non-standardized (original) data. This can cause countries' tourism performance rankings to be shaped more by the magnitude of the units of measurement than by the actual structural importance of the indicators. The main purpose of analyzing standardized and non-standardized data together in this study is to examine this potentially bias-inducing effect in terms of country rankings and the cluster structures in which they are grouped. In this respect, the comparative examination of the effect of standardization on the results allows the study to go beyond a merely descriptive application and offer a methodological contribution demonstrating how the data structure used in measuring tourism performance shapes the results.

Statistical Methods

The data were analyzed using IBM SPSS Statistics 26. To evaluate and compare tourism performance across countries, multivariate statistical techniques were employed, including principal component analysis (PCA) and hierarchical cluster analysis. Multivariate analysis is a widely used approach in studies where multiple interrelated variables are examined simultaneously for the same observational units (Morrison, 1990). In this study, both non-standardized (original) data and standardized data were analyzed. Standardization was performed using z-score transformation, whereby the mean of each variable was subtracted from its values and the resulting differences were divided by the corresponding standard deviation. The overall analytical procedure followed in this study, from data compilation to the construction of the tourism development index and the classification of countries, is summarized in Figure 3.

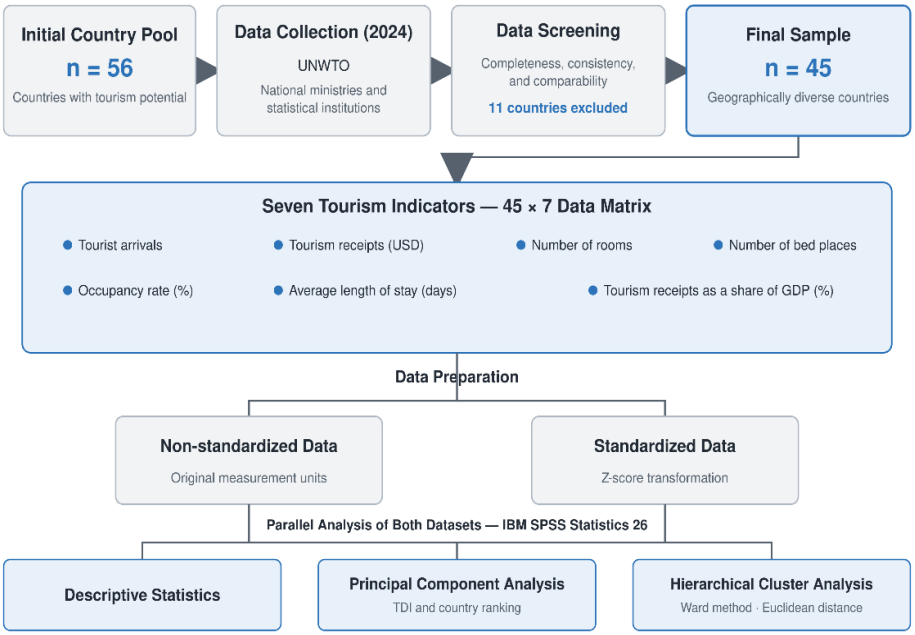


Figure 3. Flowchart of the research methodology

This procedure was necessary due to differences in measurement units (e.g., counts, monetary values, percentages, and days) and variations in magnitude across variables. The use of both standardized and non-standardized datasets allows for a comparative evaluation of how differences in data structure influence the results of the analyses. The dataset used in the analysis consists of 45 countries and seven tourism indicators. Accordingly, the dataset can be represented as a 45 × 7 data matrix, where rows correspond to countries and columns represent tourism indicators, as shown in Figure 4.

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} \ldots\ldots X_{1,45} \\ X_{2,1} & X_{2,2} \ldots\ldots X_{2,45} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ X_{7,1} & X_{7,2} \ldots\ldots X_{7,45} \end{bmatrix}$$

Figure 4. Structure of the 45 × 7 data matrix used in the multivariate analysis

In this study, factor analysis was applied using the principal components method in order to construct a development index and rank countries in terms of the seven indicators. Principal component analysis (PCA) was employed to reduce the dimensionality of the dataset and to construct a composite measure of tourism performance. PCA is a multivariate statistical technique that transforms a set of correlated variables into a smaller number of uncorrelated components while preserving most of the total variance in the data (Greenacre et al., 2022). In this study, beyond its core purposes such as determining the factor structure, KMO, Bartlett's test, the eigenvalues associated with each factor, and the proportion of variance explained, the PCA procedure was applied solely to determine the factor (component) loadings needed to construct a tourism development index and rank countries accordingly. The literature includes studies in different fields that have used PCA for this same purpose (Krishnan, 2010; Nuralina et al., 2023; Aydemir Dev, 2023; Abedin et al., 2025). Accordingly, the first principal

component, which explains the largest share of the total variance, was taken as the basis for ranking countries according to their tourism performance. Countries' Tourism Development Index (TDI) was obtained by multiplying each Tourism Indicator (TI) by its Factor Loading (FL) derived from PCA and summing the results. This is expressed in the following formula.

$TDI=TI_1*FL_1+ TI_2*FL_2+ TI_3*FL_3+ TI_4*FL_4+ TI_5*FL_5+ TI_6*FL_6+ TI_7*FL_7$

$$TDI = \sum_{k=1}^{7} TI_k * FL_k \qquad (k=1,2,3.....7)$$

In addition to PCA, hierarchical cluster analysis was conducted to classify countries into homogeneous groups based on their tourism characteristics. Cluster analysis enables the simultaneous evaluation of multiple variables and facilitates the identification of similarities and differences among observational units (Garcia-Dias et al., 2020). In this study, Ward's method was employed as the clustering algorithm, and Euclidean distance was used as the measure of dissimilarity between countries. This approach minimizes within-cluster variance and produces relatively homogeneous and balanced cluster structures. The results of the clustering procedure were visualized using a dendrogram, which illustrates the hierarchical relationships among countries. The optimal number of clusters was determined by examining the dendrogram and identifying substantial increases in agglomeration distance. Accordingly, based on the magnitude of increase in merging distances, the 2- and 3-cluster solutions for the non-standardized data, and the 2-, 3-, and 5-cluster solutions for the standardized data, constitute the most distinct groupings, and the findings are interpreted based on these solutions. The evaluation of alternative cluster numbers that may emerge at different distance thresholds beyond these solutions is left to the reader.

RESULTS

Descriptive statistics for the tourism indicators of the 45 countries are presented in Table 1. The results indicate substantial variation across countries in terms of tourism indicators. On average, countries received 23.447 million tourists and generated USD 26,771.28 million in tourism receipts in 2024. The average accommodation capacity was 826.478 thousand rooms and 1,732.134 thousand bed-places. The mean occupancy rate was 54.17%, while the average length of stay was 4.91 days. The average share of tourism receipts in GDP was 5.06%, and tourism revenue per capita was USD 1,337.75. The relatively high standard deviation values observed across most variables indicate significant disparities among countries, particularly in terms of accommodation capacity and tourism receipts. This suggests that tourism performance is unevenly distributed and reinforces the need for a multidimensional analytical approach.

Table 1. Descriptive statistics of tourism indicators (Source: Calculated by the authors based on UNWTO (2024) and national data sources)

	Mean (Per Country)	**Standard Deviation**
Number of Tourist Arrivals (Million)	23.447	29.089
Tourism Receipts (Million $)	26,771.28	3,784.777
Number of Rooms (Thousands)	826.478	2,716.276
Number of Bed-Places (Thousands)	1,732.134	5,677.682
Occupancy Rate (%)	54.17	14.58
Average Length of Stay (Day)	4.91	3.25
The Share of Tourism Receipts in GDP Rate (%)	5.06	5.24
Tourism revenue per capita ($)	1,337.75	1,471.127

The results of the principal component analysis indicate that all tourism indicators were grouped under a single factor, explaining 64.863% of the total variance. The tourism performance rankings based on both non-standardized (original) data and standardized data are presented in Table 2. Based on the non-standardized data, the top five countries are the United States, Spain, the United Kingdom, France, and Japan, while the bottom five countries are Macedonia, Honduras, Belarus, Latvia, and Estonia. In contrast, the rankings derived from standardized data show that the top five countries are the United States, Spain, France, China, and Japan, whereas the bottom five countries are Slovakia, Belarus, Finland, Lithuania, and Estonia. A comparison of the two ranking structures reveals that the United States and Spain consistently maintain their leading positions in both datasets, indicating stable tourism performance regardless of data scaling. However, notable differences emerge for several countries, particularly within the middle and lower segments of the rankings, highlighting the influence of data standardization on country positioning.

The most pronounced changes are observed in countries such as Jamaica (from 33rd to 16th), Macedonia (from 45th to 35th), Switzerland (from 19th to 32nd), and Finland (from 32nd to 43rd), indicating that countries with low absolute tourism volume but strong performance on scale-independent indicators move up in the ranking after standardization, while the opposite holds for countries in the reverse situation.

Table 2. The sorting of countries according to tourism indicators

Rank (Non-Standardized)	**Country**	**Index (Non-Standardized)**	**Rank (Standardized)**	**Index (Standardized)**	**Rank Differences**
1	United States	157,317.68	1	7.730	0
2	Spain	74,605.26	2	4.010	0
3	United Kingdom	56,772.80	7	1.580	-4
4	France	52,995.29	3	2.840	+1

Rank (Non-Standardized)	Country	Index (Non-Standardized)	Rank (Standardized)	Index (Standardized)	Rank Differences
5	Japan	42,160.39	5	1.850	0
6	Italy	42,035.83	8	1.510	-2
7	Turkey	39,197.72	6	1.680	+1
8	China	38,914.39	4	2.690	+4
9	Australia	35,415.73	18	-0.360	-9
10	Thailand	30,291.05	9	1.130	+1
11	Germany	29,361.06	11	0.260	0
12	Saudi Arabia	28,597.96	12	0.240	0
13	India	23,757.51	19	-0.440	-6
14	Portugal	20,573.45	13	0.030	+1
15	Austria	18,301.22	17	-0.270	-2
16	Netherlands	16,929.39	15	-0.190	+1
17	Greece	16,760.95	10	0.400	+7
18	Singapore	16,044.85	22	-0.680	-4
19	Switzerland	15,203.72	32	-1.300	-13
20	Indonesia	13,138.43	23	-0.870	-3
21	Croatia	11,031.38	14	0.020	+7
22	Egypt	10,797.56	20	-0.540	+2
23	Poland	10,523.51	31	-1.210	-8
24	Czech Republic	6,781.69	28	-1.180	-4
25	New Zealand	6,734.40	26	-0.950	-1
26	Brazil	6,447.82	27	-0.970	-1
27	Hungary	5,602.22	34	-1.510	-7
28	Norway	5,328.59	38	-1.870	-10
29	Jordan	4,889.24	33	-1.360	-4
30	Albania	3,753.41	21	-0.580	+9
31	Georgia	3,117.12	24	-0.910	+7
32	Finland	3,002.59	43	-2.060	-11
33	Jamaica	2,952.08	16	-0.220	+17
34	Cyprus	2,782.80	25	-0.920	+9
35	Slovenia	2,491.70	36	-1.620	-1
36	El Salvador	2,337.93	29	-1.200	+7
37	Iceland	2,224.57	30	-1.210	+7
38	Israel	1,668.62	37	-1.660	+1
39	Lithuania	1,361.55	42	-2.020	-3
40	Slovakia	1,273.62	45	-2.080	-5
41	Estonia	1,173.54	41	-1.950	0
42	Latvia	960.02	39	-1.890	+3
43	Belarus	793.28	44	-2.070	-1
44	Honduras	620.60	40	-1.910	+4
45	Macedonia	462.91	35	-1.530	+10

A similar tendency is observed among countries ranked at the top in the non-standardized (original) data: the United Kingdom, ranked 3rd in the non-standardized data, falls to 7th after standardization, and Australia, ranked 9th, falls to 18th, while China, ranked 8th, rises to 4th and enters the top five (Figure 5).

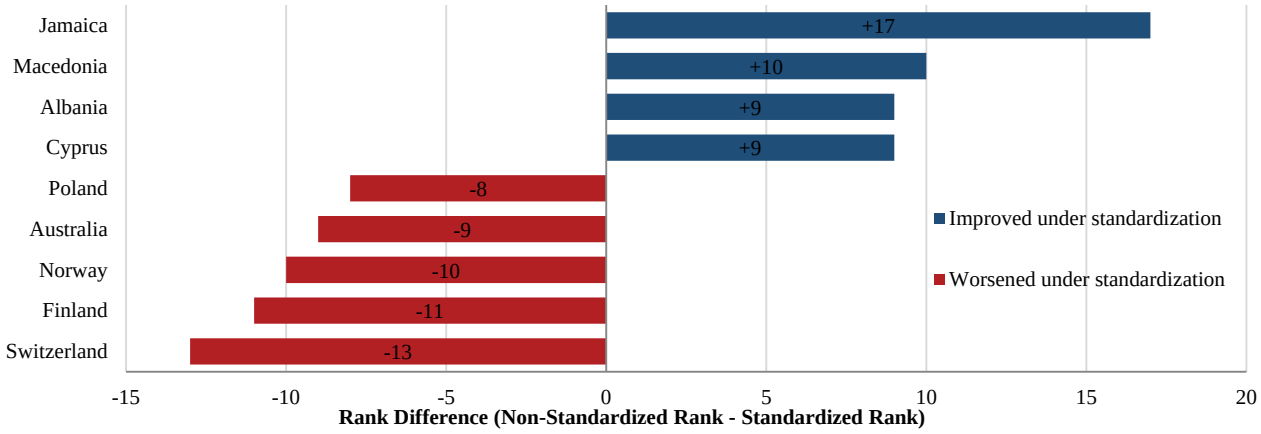


Figure 5. Effects of standardization on country rankings

A dendrogram graph was created for the non-standardized (original) data (Figure 6). An examination of the dendrogram reveals that, at the distance threshold of 20, the observations are grouped into two primary clusters. When the distance

threshold is reduced to 10, the clustering structure becomes more detailed, resulting in the formation of three distinct clusters. A dendrogram graph was created for standardized data (Figure 7). When Figure 7 is examined, it can be observed that the data are divided into two clusters at the distance value of 20. At the distance value of 10, the structure separates into three clusters, while at the distance value of 5, it is possible to identify five clusters.

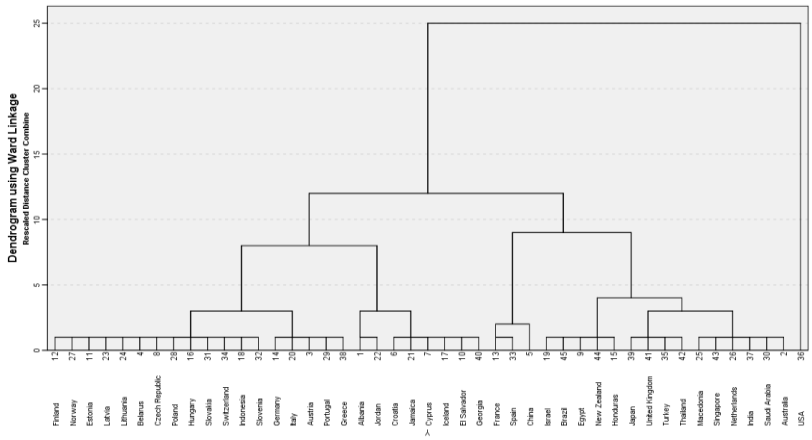


Figure 6. Dendrogram related to clustering of countries for non-standardized (original) data

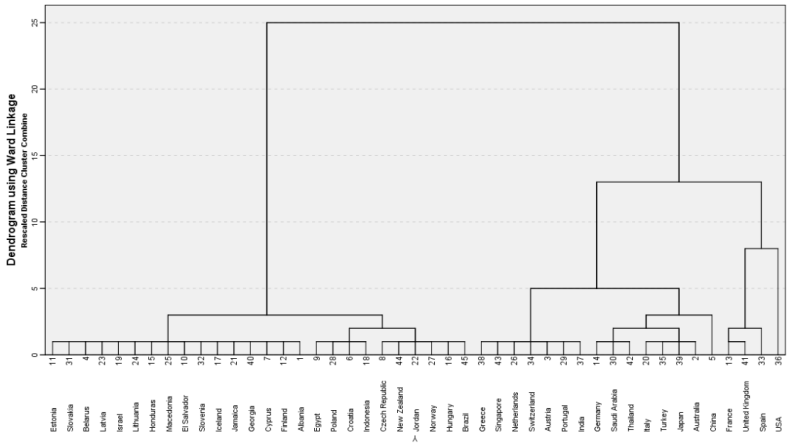


Figure 7. Dendrogram related to clustering of countries for standardized data

The clustering results obtained using the Ward method are presented in Table 3. Based on the non-standardized (original) data, both two-cluster and three-cluster solutions were identified. In the two-cluster solution, countries with relatively high tourism indicator values—including the United States, Spain, France, the United Kingdom, and China—are grouped together, while countries with comparatively lower tourism volumes form a separate cluster.

Table 3. Clustering of countries according to tourism indicators by Ward Method

	c	Countries
Non-Standardized Data	2	**Cluster 1:** Australia, Austria, China, France, Germany, Greece, India, Italy, Japan, Netherlands, Portugal, Saudi Arabia, Singapore, Spain, Switzerland, Thailand, Turkey, United Kingdom, United States; **Cluster 2:** Albania, Belarus, Brazil, Croatia, Cyprus, Czech Republic, Egypt, El Salvador, Estonia, Finland, Georgia, Honduras, Hungary, Iceland, Indonesia, Israel, Jamaica, Jordan, Latvia, Lithuania, Macedonia, New Zealand, Norway, Poland, Slovakia, Slovenia.
	3	**Cluster 1:** France, Spain, United Kingdom, United States; **Cluster 2:** Australia, Austria, China, Germany, Greece, India, Italy, Japan, Netherlands, Portugal, Saudi Arabia, Singapore, Switzerland, Thailand, Turkey; **Cluster 3:** Albania, Belarus, Brazil, Croatia, Cyprus, Czech Republic, Egypt, El Salvador, Estonia, Finland, Georgia, Honduras, Hungary, Iceland, Indonesia, Israel, Jamaica, Jordan, Latvia, Lithuania, Macedonia, New Zealand, Norway, Poland, Slovakia, Slovenia.
Standardized Data	2	**Cluster 1:** United States; **Cluster 2:** Albania, Australia, Austria, Belarus, Brazil, China, Croatia, Cyprus, Czech Republic, Egypt, El Salvador, Estonia, Finland, France, Georgia, Germany, Greece, Honduras, Hungary, Iceland, India, Indonesia, Israel, Italy, Jamaica, Japan, Jordan, Latvia, Lithuania, Macedonia, Netherlands, New Zealand, Norway, Poland, Portugal, Saudi Arabia, Singapore, Slovakia, Slovenia, Spain, Switzerland, Thailand, Turkey, United Kingdom.
	3	**Cluster 1:** United States; **Cluster 2:** Australia, Brazil, China, Egypt, France, Honduras, India, Israel, Japan, Macedonia, Netherlands, New Zealand, Saudi Arabia, Singapore, Spain, Thailand, Turkey, United Kingdom; **Cluster 3:** Albania, Austria, Belarus, Croatia, Cyprus, Czech Republic, El Salvador, Estonia, Finland, Georgia, Germany, Greece, Hungary, Iceland, Indonesia, Italy, Jamaica, Jordan, Latvia, Lithuania, Norway, Poland, Portugal, Slovakia, Slovenia, Switzerland.
	5	**Cluster 1:** United States; **Cluster 2:** China, France, Spain; **Cluster 3:** Australia, Brazil, Egypt, Honduras, India, Israel, Japan, Macedonia, Netherlands, New Zealand, Saudi Arabia, Singapore, Thailand, Turkey, United Kingdom; **Cluster 4:** Austria, Belarus, Czech Republic, Estonia, Finland, Germany, Greece, Hungary, Indonesia, Italy, Latvia, Lithuania, Norway, Poland, Portugal, Slovakia, Slovenia, Switzerland; C**luster 5:** Albania, Croatia, Cyprus, El Salvador, Georgia, Iceland, Jamaica, Jordan.

In the three-cluster solution, a more hierarchical structure emerges. Countries with the highest tourism volumes (France, Spain, the United Kingdom, and the United States) form a distinct cluster. Countries with moderately high tourism indicators are grouped in the second cluster, whereas countries with lower tourism performance levels are included in the third cluster.

For the standardized data, two, three and five cluster solutions were obtained. In the two-cluster solution, the United States forms a cluster on its own, while all other countries are grouped in the second cluster. In the three-cluster solution, the United States again remains as a separate cluster, whereas the remaining countries are distributed into two clusters according to differences in their overall tourism performance profiles. In the five-cluster solution, a more detailed clustering structure emerges. The United States continues to appear as a single country cluster, while China, France and Spain are grouped together in a cluster consisting of countries with high tourism performance. Countries with moderate tourism performance form another cluster, several countries with relatively balanced indicators constitute a separate group and smaller destinations or those with lower tourism volumes are classified under another cluster. Overall, the clustering results demonstrate that the use of standardized data leads to a more nuanced and differentiated classification structure, particularly by isolating extreme values and revealing group patterns that are less apparent in the non-standardized data.

Table 4. Cluster means obtained by complete linkage clustering method (*: 0.05; **: 0.01; ***: 0.001)

Non-standardized (Original) data					**Standardized data**			
Variables	**Cluster 1 (n=4)**	**Cluster 2 (n=15)**	**Cluster 3 (n=26)**	**p**	**Cluster 1 (n=1)**	**Cluster 2 (n=18)**	**Cluster 3 (n=26)**	**p**
	Mean	**Mean**	**Mean**		**Mean**	**Mean**	**Mean**	
Number of Tourist Arrivals	77.47	37.32	7.52	0.000***	72.39	34.57	14.26	0.014*
Tourism Receipts	119.94	37.90	6.01	0.000***	213.80	37.21	12.35	0.000***
Number of Rooms	2,091.33	1,721.03	115.79	0.000***	5,700.00	479.28	199.95	0.000***
Number of Bed-Places	4,333.15	3,650.99	228.172	0.000**	11,400.00	1,309.88	730.32	0.000***
Occupancy Rate	62.02	59.88	49.67	0.048*	63.01	67.90	46.47	0.000***
Average Length of Stay	4.32	5.05	4.91	0.800	4.50	7.11	3.40	0.000***
The Share of Tourism Receipts in GDP Rate	2.90	3.78	6.13	0.571	0.73	2.91	6.72	0.039*

The results of the discriminant analysis based on cluster membership are presented in Table 4 and indicate that a three-cluster solution provides the most appropriate classification for both standardized and non-standardized datasets. For the non-standardized (original) data, Cluster 1 (n=4) is characterized by the highest mean values in terms of key tourism scale indicators, including number of tourist arrivals (M=77.47), tourism receipts (M=119.94), number of rooms (M=2,091.33), number of bed-places (M=4,333.15), and occupancy rate (M=62.02). This cluster represents countries with high tourism volume and capacity. Cluster 2 (n=15) exhibits the highest mean for average length of stay (M=5.05), indicating a relatively longer duration of tourist visits, while Cluster 3 (n=26) shows the highest mean value for the share of tourism receipts in GDP (M=6.13), suggesting a greater economic dependence on tourism despite lower absolute tourism volumes.

For the standardized data, Cluster 1 (n=1), consisting solely of the United States, displays exceptionally high mean values across core tourism indicators, including number of tourist arrivals (M=72.39), tourism receipts (M=213.80), number of rooms (M=5,700.00), and number of bed-places (M=11,400.00), confirming its dominant position. Cluster 2 (n=18) is distinguished by higher mean values in occupancy rate (M=67.90) and average length of stay (M=7.11), reflecting relatively efficient utilization of tourism capacity and longer visitor stays. Cluster 3 (n=26), on the other hand, has the highest mean value for the share of tourism receipts in GDP (M=6.72), indicating a stronger reliance on tourism as a source of national income. The discriminant analysis supports the clustering results and highlights clear structural differences among country groups. While non-standardized data primarily capture differences in tourism scale, standardized data reveal more nuanced distinctions related to efficiency, intensity, and economic dependence on tourism.

DISCUSSION

This study presents a comparative assessment of countries worldwide in terms of key tourism indicators. The findings show that the average number of tourist arrivals per country exceeds 23 million, while average tourism receipts approach USD 27 billion. In addition, the average accommodation capacity per country reaches approximately 826,000 rooms and 1.73 million beds. The results also show that the average occupancy rate is 54.17%, the average length of stay is 4.91 days, and the average share of tourism in GDP is 5.06%. When compared with earlier findings reported by Emir and Kılıç (2014), the results clearly demonstrate a substantial expansion of the tourism sector. Both the average number of tourist arrivals and average tourism receipts have more than doubled, indicating a strong upward trend in global tourism mobility and a growing contribution of tourism to the global economy.

The results of the cluster analysis conducted in this study reveal that countries are mainly grouped into three clusters based on both non-standardized (original) and standardized data. These clusters are relatively homogeneous within clusters and more heterogeneous between clusters. Based on the non-standardized (original) data, France, Spain, the United Kingdom and the United States are grouped in Cluster 1. Countries in this cluster have higher values in terms of tourism indicators such as number of tourist arrivals, tourism receipts, number of rooms, number of bed-places and occupancy rates compared with the countries in other clusters. The prominence of these countries can be explained by their status as mature destinations with well-developed transport infrastructure, access to large source markets, and established tourism brands. Indeed, accessibility and infrastructure have been emphasized as key determinants of tourism competitiveness among the

most visited countries (Salinas Fernández et al., 2020). Cluster 2 which include countries like Australia, Austria, Germany, Greece, Italy, Japan and Turkey have higher average lengths of stay compared with countries in the other clusters.

This finding can be explained by the attractiveness of the natural and cultural resources possessed by these countries. The attractiveness of a destination's natural and cultural environment has an increasing effect on tourists' length of stay (Gokovali et al., 2007). Similarly, tourists have been found to stay longer at destinations with cultural attributes (Atsız et al., 2022). In addition, the prevalence of package tour organizations in these countries also contributes to longer stays, as tourists traveling within package tours have been found to stay longer (Oklevik et al., 2021). In Cluster 3, which includes countries such as Albania, Cyprus, Egypt, El Salvador, Georgia and Indonesia, the share of tourism in gross domestic product is higher compared with the other clusters. This finding indicates that the economic structures of these countries are relatively more dependent on the tourism sector. The literature notes that when the share of tourism in GDP exceeds a certain threshold (20%), countries are classified as highly tourism-dependent economies, and small, developing economies tend to fall above this threshold (Ortega & Ribeiro, 2025). Such economies exhibit a more fragile structure against fluctuations in tourism demand and external crises due to the limited diversity of their income sources. Furthermore, it has been shown that increasing tourism dependence in developing countries raises, rather than reduces, economic vulnerability (Wang et al., 2022).

The findings obtained from the study indicate that countries exhibit different levels of tourism development as reflected by key tourism indicators. The higher values observed for countries in Cluster 1 in key tourism indicators, such as tourist arrivals, tourism receipts, the number of rooms, and the number of bed-places, demonstrate that these countries are more developed and stronger destinations in the global tourism market. The higher average length of stay observed in Cluster 2 suggests that these countries provide destinations where tourists tend to stay for longer periods. In Cluster 3, the higher share of tourism in gross domestic product indicates that tourism plays a more dominant role in the economic structures of these countries. These findings demonstrate that the level of tourism development cannot be explained solely by indicators such as tourist arrivals or tourism receipts. Instead, additional factors such as tourists' spending profiles, length of stay, and the level of integration of tourism activities into the local economy should also be considered.

Indeed, the literature emphasizes that tourism flows alone are not sufficient indicators for evaluating the contribution of tourism to economic growth. Rather, tourism revenues and tourist expenditure per capita should be considered to obtain more meaningful results (Sanchez-Rivero & Pulido-Fernández, 2020).

When standardized data are examined, it is observed that the United States, which is in Cluster 1, has higher values in terms of tourist arrivals, tourism receipts, number of rooms, and number of bed-places. This is consistent with the country's high ranking in global competitiveness indices in terms of infrastructure and tourism resources, as well as the long-run, strong co-movement between the accommodation sector and economic growth (Aratuo & Etienne, 2019). In Cluster 2, countries such as Brazil, China, France, India, Saudi Arabia, Singapore, and Turkey have higher occupancy rates and longer average lengths of stay compared with countries in the other clusters. The high level of tourism specialization in these countries can be regarded as a factor that may raise occupancy rates in the accommodation sector through increased tourism demand (Zhang et al., 2020). In destinations where tourism represents a larger share of the national economy, accommodation supply tends to expand in parallel with tourism demand, contributing to higher occupancy rates. In Cluster 3, which includes countries such as Greece, Jamaica, Jordan, Norway, and Poland, the share of tourism in gross domestic product is higher than that of the other clusters. The high share of tourism in GDP in countries such as Greece, Jamaica, and Jordan indicates that these countries' economies are relatively more dependent on the tourism sector. In small and island economies with a limited industrial base and few alternative sources of foreign exchange, a high level of tourism specialization, reflected in tourism's large share of GDP, suggests that this dependence may not generate the expected economic growth benefits over time and may instead be associated with diminishing returns (Croes et al., 2018).

The dominance of large economies in the rankings under non-standardized data stems from the fact that the indicators used largely consist of absolute values related to countries' population and economic size. Indicators such as the number of tourist arrivals, tourism receipts, and the number of rooms tend to reflect a country's overall economic and demographic scale rather than its relative tourism performance. As a result, large economies such as the United States, Spain, and France naturally rank at the top when rankings are based on the absolute values of the indicators. In the standardized data, however, each indicator is rescaled according to the cross-country mean and standard deviation, so that the ranking reflects countries' relative performance independent of their absolute size. This explains why countries such as Jamaica and Cyprus, which lag behind in absolute indicators but show strong tourism performance relative to their own scale, rise markedly in the standardized ranking. The literature likewise emphasizes that the normalization step in constructing indicators is a critical prerequisite for making variables with different units and magnitudes comparable (Freudenberg, 2003; Mazziotta & Pareto, 2013). In this respect, the ranking based on standardized data offers a fairer comparison of tourism performance across countries, regardless of differences in scale. Overall, the findings clearly demonstrate that tourism performance is inherently multidimensional and cannot be adequately captured through single-indicator approaches.

A comprehensive evaluation of tourism performance requires simultaneous consideration of scale, efficiency, and economic dependence. These results are consistent with previous studies emphasizing that tourism flows alone are insufficient for assessing the economic contribution of tourism, and that indicators such as tourism receipts and expenditure per capita should also be considered (Sanchez-Rivero & Pulido-Fernández, 2020).

Finally, the study underscores that differences in tourism performance across countries are closely linked to structural factors such as tourism infrastructure, destination attractiveness, accessibility, and investment levels. In this regard, the findings support the argument that tourism competitiveness is shaped not only by demand volume but also by the quality and efficiency of tourism systems (Crouch & Ritchie, 1999; Dwyer & Kim, 2003).

CONCLUSIONS

This study aims to rank and classify 45 countries on the basis of tourism indicators using multivariate statistical techniques. The results show that the seven tourism indicators are largely explained by a single principal component. Based on the non-standardized (original) data, the United States, Spain, the United Kingdom, France, and Japan were ranked as the top five countries. However, when the standardized data are considered, the ranking changes to the United States, Spain, France, China, and Japan. This study addresses selected quantitative indicators such as the number of tourist arrivals, tourism receipts, number of rooms, number of bed-places, occupancy rate, average length of stay, and the share of tourism receipts in GDP. Tourism performance extends beyond these indicators to include dimensions such as sustainability, destination quality, service competitiveness, governance, digital readiness, seasonality, and visitor satisfaction. Since the indicators used in this study do not cover these dimensions, the resulting ranking should be regarded not as a complete measure of tourism competitiveness, but as a limited comparison based on the selected quantitative indicators. This constitutes one of the limitations of the study.

The findings of this study contribute to the tourism literature by providing a comparative framework for evaluating tourism performance across countries using multiple indicators rather than relying solely on absolute tourism figures. Accordingly, the assessment of a country's tourism performance and related indicators, as well as cross-country comparisons, should be conducted with due consideration to demographic characteristics, economic scale and territorial size.

Based on the findings of this study, several recommendations can be made for the tourism sector and for researchers who will conduct future studies. First, tourism performance should not be evaluated solely based on indicators such as tourist arrivals or tourism receipts. Instead, tourism performance should be assessed more comprehensively by also considering indicators such as accommodation capacity, average length of stay, and the share of tourism in gross domestic product. Second, countries aiming to improve their tourism competitiveness should focus on strengthening tourism infrastructure, increasing accommodation capacity, and developing strategies that encourage tourists to stay longer at destinations. Lastly, researchers could conduct comparative studies across different country groups, such as developed and developing economies, to better understand regional variations in tourism performance. Such strategies may contribute to increasing tourism revenues and enhancing the economic impact of tourism activities. Future researchers may conduct studies that include a greater number of tourism indicators and a larger number of countries. In addition, examining changes in tourism indicators over time through comparative analyses may provide important contributions to the literature.

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