FACTOR ANALYSIS OF THE TOURISM SECTOR IN THE ADRIATIC-IONIAN INITIATIVE COUNTRIES

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ARTICLE INFO

Original Scientific Paper
Received: 14.04.2025
Revised: 23.05.2025
Accepted: 27.05.2025
doi:10.63356/ace.2025.001
UDK
338.486.1.02-053.6(497.5)

Keywords: *factor analysis, Adriatic-Ionian Initiative, tourism, economic growth*

JEL Classification: C38, O52, R11, Z32.

ABSTRACT

Tourism represents a key segment of economic development in the countries of the Adriatic-Ionian Initiative (AII), contributing to the gross domestic product (GDP) and influencing employment, investments, and the trade balance of the region. This analysis examines the trends of tourism creation and diversion in eight AII countries-Albania, Bosnia and Herzegovina, Croatia, Greece, Italy, Montenegro, Serbia and Slovenia-over the period from 1995 to 2024.

This paper employs a multivariate approach to identify key factors that shape the competitiveness of destinations and contribute to the stability of the tourism sector. The study considers the impact of infrastructure investments, political stability, macroeconomic indicators, government policies on tourism subsidies, as well as the effects of pandemics and global economic crises on tourism flows.

The results indicate that Croatia, Greece and Montenegro are the leaders in the tourism industry, with tourism accounting for more than 10% of GDP. Albania and Slovenia show stable growth, whereas Italy, despite being an economic powerhouse, has a lower tourism share compared to its industrial and technological sectors. Bosnia and Herzegovina and Serbia face challenges in attracting foreign tourists due to infrastructural constraints and insufficient promotion.

The study's conclusions emphasise the importance of sustainable tourism development strategies, increased investments and regional cooperation to mitigate the effects of seasonality and enhance the sector's resilience to global economic changes.

1. INTRODUCTION

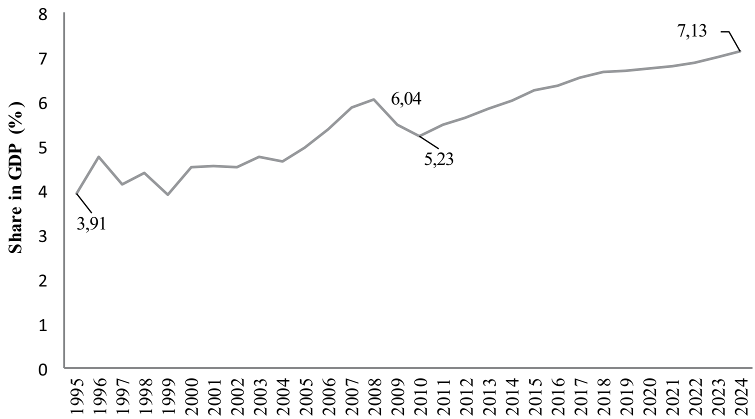
Tourism in the Adriatic-Ionian Initiative region represents one of the key segments of economic development, but its importance and contribution to the economy vary among countries (Ritchie & Crouch, 2003). While some countries, such as Croatia and Montenegro, heavily rely on revenue generated through tourism. Others, such as Serbia and Bosnia and Herzegovina, view tourism as an addition to overall economic activity.

The development of tourism in the region is shaped by various factors, including natural and cultural resources, investments in infrastructure, tourism support policies, as well as global trends and economic crises (Gössling et al, 2020; Blake & Sinclair, 2003). Historically, tourism in the region has grown gradually, with occasional fluctuations caused by economic crises, pandemics and changes in the political landscape (Hall & Williams, 2008; Sharpley & Telfer, 2014; Papatheodorou, 2004).

Given the different economic models and priorities of each country, the level of tourism's share in GDP varies significantly (Earl & Hall, 2021; Page & Connell, 2020). Albania, Montenegro and Croatia record high tourism growth rates, whereas Italy, despite being economically strong, has a diversified economic structure in which tourism is not the dominant sector (UNWTO, 2025; WTTC, 2023). On the other hand, Serbia and Bosnia and Herzegovina face challenges in attracting international tourists due to a lack of investment in promotion and infrastructure capacity.

Through an analysis of tourism trends in the region over the past thirty years, this paper examines the economic and political factors shaping the tourism industry and provides recommendations for its further stabilisation and growth (World Bank, 2022; OECD, 2024). The key research objectives include identifying the main drivers of tourism growth, assessing the factors contributing to the creation and diversion of tourism flows, and defining strategies for enhancing the region's competitiveness in the global tourism market.

The graph illustrates the movement of tourism's share in the gross domestic product (GDP) of the AII countries over the period from 1995 to 2024, analysing trends, year-on-year fluctuations and long-term projections (UNWTO, 2025; WTTC, 2023). The data show significant differences depending on the country and period, with some countries recording stable tourism growth, while others have experienced more pronounced oscillations. Descriptive statistics indicate variations in the average share of tourism in GDP, with the standard deviation reflecting the sector's volatility.



*Note: Data for 2023 and 2024 represent projections.

Figure 1. Share of the Tourism Sector in AII Countries, 1995-2024*
Source: UNWTO, 2025; WTTC, 2023

In Albania, the share of tourism in GDP increased from 3.56% in 1995 to 8.61% in 2024. Significant growth has been recorded since 2010, indicating increased investments in tourism and the development of tourism infrastructure. Given Albania's smaller overall economic strength, tourism plays a crucial role in its growth and development.

Bosnia and Herzegovina experienced slow growth, from an initial 1.09% in 1995 to 3.04% in 2024. Stabilisation and mild growth in recent years suggest the potential for sector development, but also highlight challenges in attracting investments due to slower economic growth and structural issues.

In Croatia, where tourism is a key economic sector, the share grew from 7.48% in 1995 to 12.64% in 2024, with continuous growth and only short-term declines during global economic crises. As a country whose economy significantly depends on tourism, Croatia invests in infrastructure projects and destination promotion to maintain its leading position in the region.

Greece has maintained a relatively stable share of tourism in GDP, ranging from 4.75% in 1995 to 8.62% in 2024. Although the pandemic caused a decline, the sector quickly recovered and continued to grow. Greece, as a more developed economy, uses tourism as an important part of its economy but also relies on other sectors, contributing to its resilience.

Italy has maintained a stable tourism share in GDP between 4.34% and 5.79%, with a slight increase in recent years. As one of the world's leading economies, Italy does not rely solely on tourism, but rather uses it as an additional economic driver, alongside a strong industrial and technological sector.

Montenegro has experienced a sharp rise in tourism since 2000, increasing from 2.15% to over 12% in 2024, demonstrating sector expansion in recent decades. Given its less developed economy, tourism has become a key factor in economic growth and development.

Table 1. Share of Tourism in GDP (1995-2024), AII Countries

Year	Albania	BiH	Croatia	Greece	Italy	Montenegro	Serbia	Slovenia
1995	3.56	1.09	7.48	4.75	4.34	4.12	1.28	4.66
1996	2.81	0.93	9.54	4.33	4.55	10.71	0.54	4.68
1997	3.20	0.62	6.34	3.77	4.65	9.29	0.54	4.53
1998	2.99	2.64	6.89	4.18	4.78	8.77	0.81	4.12
1999	4.31	2.33	6.77	5.35	4.87	3.32	0.75	3.54
2000	5.70	2.15	6.71	6.17	5.31	4.10	2.07	3.93
2001	5.77	2.28	7.59	6.15	5.14	4.48	1.16	3.86
2002	6.47	2.66	7.24	6.06	4.78	4.54	0.86	3.61
2003	5.72	2.66	10.23	5.54	4.48	5.19	0.89	3.31
2004	5.54	2.79	9.44	5.56	4.46	5.23	0.92	3.26
2005	6.30	2.90	9.71	5.80	4.30	6.35	1.04	3.30
2006	6.86	2.98	9.62	5.59	4.33	9.21	1.01	3.27
2007	7.72	2.96	9.59	5.38	4.24	12.29	1.66	3.14
2008	7.60	2.80	10.05	5.46	4.00	13.43	1.77	3.18
2009	8.35	2.65	9.16	5.62	3.86	9.10	1.79	3.32
2010	7.71	2.42	8.39	5.47	3.85	8.87	1.79	3.30
2011	7.52	2.40	9.12	5.96	4.27	9.23	1.83	3.37
2012	8.19	2.16	8.80	6.08	4.52	9.96	1.91	3.37
2013	7.64	2.25	9.44	6.98	4.81	10.30	1.90	3.42
2014	8.13	2.22	9.81	7.45	5.05	10.17	2.03	3.34
2015	8.05	2.37	10.13	7.74	5.32	10.91	2.24	3.30
2016	8.55	2.55	10.44	7.60	5.37	10.72	2.35	3.29
2017	8.47	2.61	10.93	8.05	5.49	11.01	2.33	3.29
2018	8.49	2.67	11.00	8.28	5.51	11.67	2.32	3.38
2019	8.46	2.73	11.28	8.23	5.53	11.60	2.36	3.37
2020	8.44	2.80	11.55	8.31	5.55	11.43	2.39	3.44
2021	8.46	2.86	11.73	8.39	5.59	11.43	2.45	3.49
2022	8.46	2.91	11.97	8.45	5.65	11.54	2.50	3.54
2023*	8.53	2.97	12.30	8.53	5.72	11.82	2.56	3.59
2024*	8.61	3.04	12.64	8.62	5.79	12.04	2.63	3.64

*Note: Data for 2023 and 2024 represent projections.

Source: UNWTO, 2025; WTTC, 2023

Serbia had a lower initial share of tourism in GDP, but in the last decade, the sector has grown significantly, reaching approximately 5.5% in 2024. Although Serbia's economy relies on industry and agriculture, the growth of tourism reflects its increasing role in economic diversification.

Overall, the average share of tourism in GDP in the region has significantly increased, reaching 8% in 2024. Projections indicate continued growth, driven by investments, tourism promotion and post-pandemic recovery. The Adriatic-Ionian Initiative countries are seeing an increasing importance of tourism in GDP, with Croatia, Montenegro and Greece emerging as regional leaders. Further growth will depend on market stability, infrastructure investments, and the sustainability of tourism offerings, while each country's economic strength will shape its tourism development capacity.

The importance of tourism to the overall economy can be analysed through the indicator of total tourism contribution (Dwyer, 2022; Gladstone, & Fainstein, 2001). The total contribution of tourism consists of three main components, as shown in the following table (Hall, 2024).

Table 2. Structure of Tourism Contribution to the Economy

Name	Description
Direct Contribution of Tourism	Revenue directly related to the tourism sector: hotels and accommodation capacities, restaurants and hospitality services, transport and travel agencies, airlines and other means of transport in tourism
Indirect Contribution of Tourism	Activities related to tourism but not forming the core of the tourism industry: supply, food and beverages for hotels, government tax revenues from tourism, investment in marketing and tourism promotion, government incentives and sector support
Induced Contribution of Tourism	Spending by employees in the tourism sector: salaries of hotel employees, housekeeping and tourism, household consumption dependent on the tourism industry, multiplier effects on other economic sectors.

2. MATERIALS AND METHODS

Principal Component Analysis (PCA) is a statistical technique used for reducing the dimensionality of large datasets (Abdi & Williams, 2010). This method allows the transformation of a set of highly correlated variables into a new set of mutually uncorrelated variables, known as principal components. PCA is widely applied in the fields of machine learning, statistics, economics, biology and other scientific disciplines focused on data analysis. By using PCA, complex data can be simplified while retaining the maximum amount of information, which facilitates interpretation and visualisation (Jolliffe, 2002). This technique includes several iterations, which will be explained in the following text (Günter et al, 2007).

Data Normalisation. Before applying PCA, data are often standardised to avoid the dominance of variables with larger scales. Standardisation is performed using the formula:

$$Z_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j} \qquad (1)$$

Where:

a) x_{ij} - value of the j-th variable for the i-th sample,
b) $\bar{x}_j$ - mean value of the j-th variable,
c) s_j - standard deviation of the j-th variable.

Calculation of the Covariance Matrix

For standardised data, the covariance matrix is calculated as follows:

$$C = \frac{1}{n-1} X^T X \qquad (2)$$

Where:

a) X - data matrix of dimensions n×p (n samples, p variables),
b) C - covariance matrix of dimensions p×p.

Eigenvalue and Eigenvector Calculation. A key part of PCA is finding the eigenvalues and eigenvectors of the covariance matrix.

a) Eigenvalues λ_j measure variance along the new axis.

b) Eigenvectors v_j define the directions of the new coordinate systems:

$$Cv_j = \lambda_j v_j \qquad (3)$$

Eigenvalues are sorted from highest to lowest, with the first components carrying the most information about the data.

Projection of Data onto New Axes

Once the eigenvectors are found, the original data are projected onto new axes. The data are transformed into a new space using the eigenvector matrix:

$$Z = XV \qquad (4)$$

Where:

- Z - Transformed data matrix expressed in principal component coordinates.

This step enables dimensionality reduction while retaining only the first few components that carry the highest variance.

Interpretation of PCA

- Variance of Principal Components – The total percentage of variance explained by the first k components is calculated as follows:

$$\text{Percentage of variance} = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i} \times 100\% \qquad (5)$$

This procedure helps in selecting the number of components to retain. Typically, the minimum number of components explaining a high percentage of variance (e.g., 85-95%) is chosen.

- Interpretation of Principal Components – The coefficients in eigenvectors ($\mathbf{v}_j$) provide information on the influence of each original variable on the principal components. High absolute values suggest a strong relationship between original variables and principal components.

Application of PCA

- Dimensionality reduction – Retaining only principal components that explain the highest variance.
- Data visualisation – Projecting data into 2D or 3D space for better analysis of data structure.
- Decorrelation of data – Originally correlated variables are transformed into a mutually uncorrelated set of variables.
- Preprocessing data for regression and classification models – PCA can improve the efficiency of machine learning models.

PCA is a powerful technique for analysing large and complex datasets. It reduces dimensionality while preserving essential information, making it easier to interpret and analyse data. By leveraging linear algebra and eigenvalues, PCA identifies the most significant patterns in the data. In comparison, Factor Analysis (FA) is another dimensionality reduction technique, but it focuses on modeling the underlying relationships between observed variables and latent factors.

PCA aims to maximise the variance captured in the data by transforming it into a set of orthogonal (uncorrelated) components. It uses eigenvalues and eigenvectors to identify principal components, which are linear combinations of the original variables. PCA does not assume any underlying structure in the data. The principal components are ordered by the amount of variance they explain, making it easier to identify the most important patterns. PCA is widely used in fields like image processing, finance and neuroscience for tasks such as noise reduction, data visualisation and feature extraction.

FA aims to identify latent factors that explain the correlations among observed variables. It models the data as a combination of common factors and unique variances, using techniques like maximum likelihood estimation. FA assumes that the observed variables are influenced by a smaller number of unobserved latent factors. The factors are interpreted based on their loadings which represent the strength of the relationship between observed variables and latent factors. FA is commonly used in psychology, social sciences and market research to identify underlying constructs, validate questionnaires and explore data structures.

While PCA components are orthogonal and independent, FA factors can be correlated. PCA focuses on capturing maximum variance, whereas FA focuses on explaining covariances among variables. PCA is often used for data compression and visualisation, while FA is used for identifying underlying constructs and validating measurement models. Both techniques are valuable for dimensionality reduction, but the choice between PCA and FA depends on the specific goals and assumptions of the analysis.

The following table presents explanations of tourism sector indicators, which will serve as the basis for PCA analysis in the AII region countries.

The original data used in this analysis were retrieved from reputable international databases, primarily UNWTO and WTTC. However, due to occasional gaps in time series and differing reporting standards, certain preprocessing steps were necessary. First, the dataset was reviewed for missing values, which were addressed through linear interpolation for intermediate years and forward-filling for recent gaps. Secondly, all variables were standardised using z-score normalisation to ensure comparability and avoid dominance of variables measured on larger scales.

Table 3. Selection and Explanation of Variables

O. nr	Variable Name	Model abbreviation	Explanation
1.	Capital Investment in Tourism (CIT)	CIT	Total value of investments directed towards the development of tourism infrastructure and facilities. This includes investments in hotels, accommodation, economic and service infrastructure, recreational parks and other key facilities in the tourism industry. Capital investment is crucial for long-term sustainability and competitiveness of the tourism sector and the national economy.
2.	Visitor Export (Foreign Expenditure) (VEFE)	VEFE	Revenues that the domestic economy generates from foreign tourists. This includes all spending made by foreign tourists in a country, including accommodation, shopping and services. This indicator measures the impact of tourism on the national economy.
3.	Business Tourism Spending (BTS)	BTS	Total business travel expenses in the country. This includes costs related to conferences, seminars, business meetings and travel for corporate purposes. This indicator shows the level of attractiveness of a destination for business tourism.
4.	Direct Contribution of Travel & Tourism (DCTT)	DCTT	Direct contribution of hotels, restaurants, transport and related businesses to the tourism industry. This includes revenue generated directly from tourism-related services. This indicator measures the direct GDP impact of tourism, excluding indirect effects.
5.	Domestic Tourism Spending (DTS)	DTS	Spending by domestic residents on tourism-related travel within their own country. This includes accommodation, transport and leisure activities. This indicator assesses the strength of domestic tourism demand.
6.	Government Tourism Spending (GTS)	GTS	Public expenditures directed toward tourism development and promotion. This includes funding for tourism campaigns, subsidies for tourism businesses and investment in local and national tourism infrastructure.
7.	Internal Travel & Tourism Contribution (ITTC)	ITTC	Total revenue generated from domestic and international tourism. This indicator includes both direct and indirect contributions of tourism to GDP, reflecting the broader economic impact of the sector.
8.	Leisure Travel & Tourism Spending (LTTS)	LTTS	Total spending on leisure tourism, including domestic and international travelers. This indicator measures tourism demand for leisure activities such as vacations, cultural visits and recreational travel.
9.	Outbound Travel & Tourism Expenditure (OTTE)	OTTE	Spending by residents of a country on travel and tourism abroad. This indicator reflects the economic impact of outbound tourism and measures the purchasing power of residents for travel and tourism services.
10.	Travel Total Tourism Contribution (TTTC)	TTTC	Indicator that measures the total economic impact of tourism on the national economy. This variable is key to assessing tourism's contribution to overall economic performance.

Source: UNWTO, 2025; WTTC, 2023

To assess the adequacy of the dataset for Principal Component Analysis, two standard diagnostics were applied. The **Kaiser-Meyer-Olkin (KMO) measure** of sampling adequacy reached a value of **0.814**, which indicates a very good degree of common variance and supports the use of PCA. Furthermore, **Bartlett's test of sphericity** was statistically significant (**χ^2 = 12004.689**, **df = 45**, **$p < 0.001$**), confirming that the correlation matrix is not an identity matrix and that sufficient intercorrelation exists among variables.

The **correlation matrix** revealed very high pairwise correlations among most indicators, with the majority of coefficients exceeding **0.90** and all significant at the **0.001 level**. This suggests strong multicollinearity, which justifies dimensionality reduction via PCA. However, the **determinant of the correlation matrix was extremely low (6.29×10^{-23})**, indicating near-singularity and suggesting a high level of redundancy among variables. This explains the empirical result where the first principal component captures over **99.7%** of the total variance in the dataset.

Although both Factor Analysis (FA) and PCA are widely used for multivariate data exploration, PCA was chosen for this study due to its focus on maximising explained variance rather than modeling latent constructs. Given the objective of reducing multicollinearity and simplifying the complex structure of interrelated tourism indicators across countries, PCA provides a more straightforward and interpretable framework. Unlike FA, PCA does not assume an underlying factor model or error terms, which aligns well with the exploratory nature of this research.

To contextualise the factor structure, descriptive statistics for all variables were computed prior to analysis. These include means, standard deviations and pairwise correlations. This step supported the interpretation of principal components and provided insight into the variability and distribution of each indicator across the observed time period and countries.

3. RESULTS

The following section presents the results of the Principal Component Analysis (PCA) through tables, based on which discussions can be made, appropriate conclusions can be drawn, and recommendations for further development policies in the tourism sector, as well as projections for further research, can be given. The authors used the SPSS software package, version 25, for the analyses.

The variables TTTC and ITTC, with their substantial covariance values of 5747.392 and 3221.785 respectively, underscore their pivotal role in contributing to the total variance within the dataset. These pronounced covariance figures indicate that these variables are paramount in elucidating the overall variability, thereby making them indispensable for comprehending the underlying patterns inherent in the data.

A fundamental component of Principal Component Analysis (PCA) is the computation of eigenvalues and eigenvectors derived from the covariance matrix. Eigenvalues quantify the variance encapsulated along each newly defined axis, while eigenvectors delineate the orientations of these axes within the transformed coordinate framework. The eigenvalues are instrumental in pinpointing the principal components that encapsulate the maximum variance, thus facilitating dimensionality reduction while preserving critical information.

In light of these findings, the elevated covariance values associated with TTTC and ITTC accentuate their significance within the dataset. This suggests that any developmental policies or subsequent research endeavors within the tourism sector should prioritise these variables. The insights gleaned from PCA can serve as a strategic compass for policymakers, enabling them to concentrate on key areas that drive variability in tourism data. This targeted focus can lead to more nuanced and effective strategies.

Covariance Matrix. The covariance matrix presents the overall variability of the data among the variables. In this case, the determinant of the matrix amounts to 52.902, indicating the presence of multicollinearity among the variables.

It is particularly important to note that variables such as TTTC and ITTC have high covariance values (5747.392 and 3221.785), which means that they dominate in explaining the total variance in the data. A key part of PCA is finding the eigenvalues and eigenvectors of the covariance matrix. Eigenvalues measure variance along the new axis, while eigenvectors define the directions of the new coordinate system.

The table 'Total Variance Explained' elucidates the contribution of each principal component to the overall variability of the dataset. Remarkably, the first principal component accounts for an overwhelming 99.69% of the total variance. This indicates that nearly all the information within the dataset is encapsulated within a single dimension, underscoring the dominance of this component in capturing the essence of the data.

Such a high percentage of explained variance by the first component suggests that the dataset is highly structured, with most of the variability being driven by a single underlying factor. This simplification is advantageous as it allows for a significant reduction in dimensionality without substantial loss of information, facilitating more efficient data analysis and interpretation.

Table 4. Communalities and covariance matrix

	Initial	Extraction
BTS	137.72	137.72
CIT	20.98	20.98
DTS	1875.88	1875.88
GTS	.24	.24
ITTC	3221.78	3221.78
LTTS	2038.44	2038.44
OTTE	87.73	87.73
TTTC	5747.39	5747.39
DCTT	956.89	956.89
VEFE	199.72	199.72

*Extraction Method: Principal Component Analysis

Source: Author's own calculations in SPSS 25

In scientific terms, the ability of the first component to capture almost the entirety of the variance implies that subsequent components contribute minimally to the overall variability. This highlights the effectiveness of PCA in distilling complex datasets into their most informative elements, thereby streamlining the analytical process.

Explained Variance and Number of Components. The table 'Total Variance Explained' shows how much each component contributes to the total variability of the data. The first component accounts for 99.69% of the total variance, meaning that practically all the information is contained within a single dimension.

This suggests that it would be sufficient to use only one component to summarise the data, as the remaining components contribute negligibly to the total variability.

Table 5. Total Variance Explained

Component	Initial Eigenvalues[a]			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	14243	99.69	99.69	14243	99.69
2	30.79	.22	99.91	30.79	.22
3	9.76	.068	99.98	9.76	.068
4	1.16	.008	99.99	1.16	.008
5	.79	.006	99.99	.79	.006
6	.74	.005	99.99	.74	.005
7	.35	.002	99.99	.35	.002
8	.13	.001	100.00	.13	.001

Source: Author's own calculations in SPSS 25.

The factor loading matrix reveals the strength of the relationship between each original variable and the newly derived components. Notably, all variables demonstrate high loadings on the first component, exceeding 0.9. This confirms that the first component is the primary factor in explaining tourism data. Such high loadings suggest that the dominant dimension in the dataset is closely linked to the overall economic significance of tourism. The factor loadings underscore the importance of the first component in capturing the essence of the data. The strong association between the original variables and this component indicates that the economic impact of tourism is a central theme driving the variability in the dataset. This insight is crucial for understanding the key factors influencing tourism and can guide policymakers in developing strategies that focus on the economic aspects of tourism.

The high loadings on the first component also highlight the effectiveness of PCA in identifying the most informative dimensions of the data.

Factor Loading Matrix. The factor loadings indicate how strongly each original variable is related to the new components. All variables exhibit high loadings on the first component (above 0.9), confirming that it is the key factor in explaining tourism. This suggests that the dominant dimension in the data is associated with the overall economic significance of tourism.

Table 6. Factor Loading Matrix

Indicators	Component			
	1	2	3	4
BTS	.993	-.097	.038	.038
CIT	.923	.207	.304	-.028
DTS	.997	-.080	-.012	-.002
GTS	.923	-.112	.086	.151
ITTC	1.000	.005	-.014	.003
LTTS	.999	.022	-.035	-.005
OTTE	.992	-.038	.062	.085
TTTC	1.000	.008	.025	-.004
DCTT	1.000	-.001	-.014	.009
VEFE	.961	.273	-.032	.018

*Extraction Method: Principal Component Analysis. a. Four components extracted.

Source: Author’s own calculations in SPSS 25.

The rotation of principal components (Varimax rotation) enables a better interpretation of factor structures. The results are presented in the following table and through this rotation, several key factors have been identified:

a) Factor 1 (Economic Contribution of Tourism)
This factor includes high loadings for BTS (Business Tourism Spending), DTS (Domestic Tourism Spending) and ITTC (Internal Travel & Tourism Contribution). This indicates that tourism is predominantly linked to the economic performance of the countries.

b) Factor 2 (Investments and Government Support). CIT (Capital Investment in Tourism) and GTS (Government Tourism Spending) show strong influence on this factor. This suggests that investments and government support are key elements in sustaining tourism.

c) Factor 3 (Tourism Flows). The variables VEFE (Visitor Export - Foreign Expenditure) and OTTE (Outbound Travel & Tourism Expenditure) are more pronounced in this factor. This highlights the importance of foreign exchange earnings and tourism flows for the region.

Table 7. Rotated Factor Loading Matrix

	Rescaled									
	Component									
	1	2	3	4	5	6	7	8	9	10
BTS	.704	.465	.516	.135	.008	-.053	-.001	.000	.000	.000
CIT	.440	.788	.408	.134	.005	.000	.000	.000	.000	.000
DTS	.717	.453	.501	.170	-.003	.015	-.004	-.003	.000	-.003
GTS	.461	.391	.777	.177	-.001	.003	.000	.000	.000	.000
ITTC	.689	.499	.472	.230	.001	.013	-.004	-.006	.009	.001
LTTS	.689	.493	.464	.255	-.002	.022	-.006	.001	-.007	.004
OTTE	.649	.503	.536	.172	.095	-.002	.000	.000	.000	.000
TTTC	.674	.522	.478	.210	.002	.008	.001	.015	-.001	.000
DCTT	.687	.491	.483	.232	-.004	.006	.018	.001	.000	.000
VEFE	.572	.607	.360	.418	.011	-.005	.000	.000	.000	.000

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation. a. Rotation converged in 11 iterations

Source: Author's own calculations in SPSS 25.

Hence, the Varimax rotation of principal components has facilitated a clearer interpretation of the factor structures, revealing several key dimensions within the tourism data. Factor 1, labeled as the Economic Contribution of Tourism, encompasses high loadings for BTS, DTS and ITTC, underscoring the strong link between tourism and the economic performance of countries. Factor 2, identified as Investments and Government Support, is characterised by significant loadings for CIT and GTS, highlighting the critical role of investments and governmental support in sustaining the tourism sector. Lastly, Factor 3, termed Tourism Flows, includes pronounced loadings for VEFE and OTTE, emphasising the importance of foreign exchange earnings and tourism flows for the region. These insights collectively underscore the multifaceted nature of tourism, driven by economic contributions, investment and support, and international tourism dynamics, providing a comprehensive framework for policy development and strategic planning in the tourism sector.

Dominance of the First Component. The first component is so dominant that, in practice, it can replace all variables, demonstrating that tourism in the region primarily depends on its economic contribution. Next, the PCA analysis results will be compared with the data on the share of tourism in GDP across AII countries, leading to certain conclusions.

Table 8. Heatmap of Factor Loadings

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10
BTS	.993	-.097	.038	.038	0	.049	.003	-.001	-.001	0
CIT	.923	.207	.304	-.028	.012	-.003	.001	.001	.001	0
DTS	.997	-.080	-.012	-.002	.019	-.015	.005	.001	.001	.003
GTS	.923	-.112	.086	.151	.011	.011	.001	.001	0	0
ITTC	1.000	.005	-.014	.003	.011	.008	.008	.005	.002	0
LTTS	.999	.022	-.035	-.005	.014	-.018	.005	-.005	-.006	-.002
OTTE	.992	-.038	.062	.085	-.08	-.012	-.001	-.001	-.001	0
TTTC	1.000	.008	.025	-.004	-.002	.008	.005	-.005	.002	0
DCTT	1.000	-.001	-.014	.009	.015	-.015	-.002	-.016	.007	.002
VEFE	.961	.273	-.032	.018	-.014	.017	.002	0	0	.001

* Dark grey shading indicates high positive loadings, meaning that the variable strongly contributes to a specific component. Underlined values indicate negative loadings, meaning that the variable has an opposite effect in relation to the component. Light grey cells denote a weaker or borderline association with the component, while white cells indicate a negligible or minimal relationship.

The factor analysis generated through the heatmap of factor loadings provides insight into the data structure and the way individual variables contribute to different factors. This matrix allows us to understand how key tourism variables relate to the principal components, i.e., the latent dimensions that shape tourism in the analysed countries.

At first glance, it becomes clear that the first component is dominant in the analysis. Almost all variables have high factor loadings in relation to it, which means that tourism, as a sector, exhibits a high degree of homogeneity among the variables. In other words, internal and direct tourism contributions, capital investments, domestic and foreign tourism expenditures, as well as government support, collectively form a strong dimension that can be interpreted as overall tourism activity and its economic significance. This component essentially integrates all the main factors that shape tourism and indicates that countries with high values in this component are largely dependent on tourism as an economic sector.

It is interesting to observe the role of the second and third component, which isolate certain aspects of tourism that are not as present in the first dimension. The second component shows significant correlation with capital investments in tourism, suggesting that some countries do not rely solely on natural resources and existing attractions but instead heavily invest in tourism development. This component may represent the difference between countries that actively invest in developing tourism infrastructure, hotels and transport networks and those that depend on already established capacities. The third component further enriches this picture by including government support and foreign tourism expenditures, indicating countries where the government actively subsidises tourism or where the sector largely depends on incoming foreign tourists.

Further examination of the remaining components reveals that a significant portion of the data variance is explained by the first three or four factors, while the remaining components do not show strong associations with key variables. These less pronounced components may indicate specific, less significant patterns of variability in the data that are not dominant in the overall tourism picture but may be useful for understanding minor nuances among countries or individual aspects of tourism that do not affect the entire industry to the same extent.

4. DISCUSSIONS

The analysis suggests that tourism is a highly integrated sector, where economic factors, investments, and tourism expenditures move together, creating a strong development dimension (Hall, 2024). However, it is also evident that there are countries investing in tourism in different ways while some rely on natural resources and existing attractions, others invest significant funds in infrastructure and marketing to attract tourists (Hall, 2024). This means that, although tourism may appear as a homogeneous industry at first glance, in reality, it is shaped by different factors that are key to understanding the specific differences between countries (Dwyer, 2022).

The conclusion that can be drawn from this analysis is that overall tourism activity is the most important dimension that distinguishes countries, but there are also additional nuances that set some countries apart depending on whether they rely more on private investments, government support or international tourism expenditures (Gladstone, & Fainstein, 2001). This type of analysis can help in formulating policies for the future development of tourism, as it clearly demonstrates which countries already have a stable tourism economy and which could benefit from additional investments or strategies to attract tourists.

The analysis of tourism's share in GDP in the AII region provides a clear economic context for understanding the results obtained through factor analysis and the heatmap of factor loadings. In both datasets, it is evident that tourism does not function in the same way in every country. While in some states it is a key pillar of the economy, in others, it remains a secondary economic activity.

One of the most important insights derived from this analysis is the stability of tourism in different economies over time. In some countries (such as Croatia and Montenegro), tourism has been and remains one of the fundamental pillars of the economy, while in others (such as Italy and Greece), it has maintained moderate growth without fundamental changes. Countries such as Serbia and Bosnia and Herzegovina show slight growth in tourism, but not in a way that would lead to major changes in their economic structures.

These trends are clearly recognised in the factor analysis. Countries that are most dependent on tourism are dominated by the first component, while others group around investments, government regulations and specific factors that do not play a crucial role in the overall economy. This difference could significantly impact tourism development policies, as it suggests that the tourism sector cannot be viewed as a universal economic model that operates under the same conditions in every country.

It is interesting to note that business tourism spending shows a slightly different pattern compared to other variables. Its connection with PC1 indicates that business tourism is part of the broader economic picture of tourism, but its strong correlation with higher-order components suggests that business tourism is not evenly distributed among countries. Some countries have a highly developed conference and business travel industry, while others do not play a significant role in this segment. This difference is clearly reflected in the factor loadings, where we see that business tourism partially deviates from the dominant tourism pattern.

When we look at the direct contribution of tourism to the economy, we see that this variable shows a negative correlation with one of the higher-order components. This may indicate that in some countries, although tourism has high economic significance, its direct monetary benefits may be distributed differently compared to other aspects of tourism. This phenomenon is particularly evident in countries where tourism has a strong multiplier effect and where tourism does not only generate direct revenues through hotels and restaurants but also creates additional economic effects in related sectors.

It is also interesting that outbound tourism expenditure does not have a strong connection with any of the first few components. This suggests that the amount citizens of a particular country spend on traveling abroad does not significantly differ between countries in a way that would affect key patterns of variability. In other words, while domestic tourism activity is one of the main factors shaping a country's tourism profile, outbound tourism does not play a significant role in the overall data structure.

5. CONCLUSIONS

When we compare the results of the PCA analysis with the data on the share of tourism in GDP in AII countries, we gain interesting insights into how tourism shapes the economies of these countries. The principal component analysis has shown which variables are key in defining tourism economies, while GDP data provide concrete evidence of the significance of tourism in each country.

Considering the overall structure of the heatmap, we can conclude that tourism is an extremely complex phenomenon, where economic effects are not evenly distributed among countries. While some states rely on mass tourism with a strong domestic contribution, others depend on large investments and business tourism, and some are heavily reliant on government funding and strategic support. This analysis enables the identification of key drivers of tourism development and the differentiation of essential factors that shape tourism economies worldwide.

While the factor analysis and heatmap of factor loadings provide valuable insights into the structure of tourism data and the relationships between key variables, there are several limitations to this reasoning that should be considered.

Firstly, the dominance of the first component in explaining the majority of the variance may oversimplify the complexity of tourism dynamics. Although PC1 captures the overall economic significance of tourism, it may mask important nuances and interactions between variables that are critical for a comprehensive understanding of the sector. This could lead to an overemphasis on certain variables while neglecting others that may also play significant roles.

Secondly, the reliance on high factor loadings to interpret the importance of variables assumes that these loadings are stable and consistent across different contexts and datasets. However, factor loadings can be influenced by sample size, data quality and the specific characteristics of the dataset being analysed. This variability can affect the robustness and generalisability of the conclusions drawn from the analysis.

Thirdly, the interpretation of components as distinct factors (e.g., economic contribution, investments, government support) may not fully capture the interconnectedness and interdependencies between these factors. Tourism is a multifaceted industry influenced by a wide range of economic, social, and environmental factors. Simplifying these influences into discrete components may overlook the complex interactions that drive tourism development and sustainability.

Additionally, the analysis assumes that the identified components are equally relevant and impactful across all countries in the dataset. This may not be the case, as different countries have unique tourism profiles, policies and economic conditions that shape their tourism sectors. The conclusions drawn from the factor analysis may therefore be more applicable to some countries than others, limiting the universality of the findings.

Lastly, the focus on quantitative data and statistical techniques may neglect qualitative aspects of tourism that are equally important for understanding the sector. Factors such as cultural significance, visitor experiences and community impacts are difficult to capture through quantitative measures alone but are crucial for a holistic understanding of tourism.

In conclusion, the PCA analysis and data on tourism's share in GDP demonstrate a high level of mutual consistency. Countries where tourism is a dominant economic factor are clearly recognised in the first principal component, while countries with specific tourism development models are linked to components that reflect state investments, business tourism and infrastructure projects. This analysis not only enables the understanding of current trends but also allows for predictions about the future development of tourism in the region, depending on how individual countries approach further investments and tourism strategies.

The factor loading analysis and data on the share of tourism in GDP clearly show that there is no universal model for tourism development. Countries traditionally reliant on tourism, such as Croatia and Montenegro, showed the highest association with the first principal component, while countries that develop tourism through investments and government regulation were more linked to the second and third components. These differences are not just theoretical, they are visible through real economic indicators and clearly demonstrate how different countries shape their tourism policies.

In the long run, such analyses can help define strategies for sustainable tourism development, as they help understand which countries have already utilised their tourism potential and which still need to invest resources in its expansion. Ultimately, understanding this data is not just statistical but can play a key role in making economic and political decisions that will determine the future of tourism in the AII region.

ACKNOWLEDGEMENTS

We express our gratitude to our colleagues from the Department of Quantitative Analysis and Informatics, Economic Theory, Analysis and Policy at the Faculty of Economics, University of Banja Luka, as well as to the reviewers for their valuable suggestions, which have undoubtedly contributed to the improvement of the quality of this paper.

Conflict of interests

The authors declare there is no conflict of interest.

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ФАКТОРСКА АНАЛИЗА ТУРИСТИЧКОГ СЕКТОРА У ЗЕМЉАМА ЈАДРАНСКО-ЈОНСКЕ ИНИЦИЈАТИВЕ

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САЖЕТАК

Туризам представља кључни сегмент економског развоја у земљама Јадранско-јонске иницијативе (АІІ), доприноси бруто домаћем производу (БДП) и утиче на запосленост, инвестиције и трговински биланс региона. Ова анализа испитује трендове настајања и преусмјеравања туризма у осам АІІ земаља: Албанији, Босни и Херцеговини, Хрватској, Грчкој, Италији, Црној Гори, Србији и Словенији, у периоду од 1995. до 2024. године.

Рад примјењује мултиваријациони приступ како би се идентификовали кључни фактори који обликују конкурентност дестинација и доприносе стабилности туристичког сектора. Студија разматра утицај инфраструктурних инвестиција, политичке стабилности, макроекономских показатеља, државних политика о субвенцијама у туризму, као и ефекте пандемија и глобалних економских криза на токове туризма.

Резултати показују да су Хрватска, Грчка и Црна Гора лидери у туристичкој индустрији, с тим да туризам чини више од 10% БДП-а. Албанија и Словенија биљеже стабилан раст, док Италија, иако економски развијенија од осталих анализираних земаља, има мањи удио туризма у односу на своје индустријске и технолошке секторе. Босна и Херцеговина и Србија суочавају се с изазовима у привлачењу страних туриста због инфраструктурних ограничења и недовољно развијене промоције.

Закључци студије наглашавају важност стратегија одрживог развоја туризма, повећаних инвестиција и регионалне сарадње у циљу ублажавања ефеката сезоналности и јачања отпорности сектора на глобалне економске промјене.

Кључне ријечи: *факторска анализа, јадранско-јонска иницијатива, туризам, економски раст.*