

THESES OF THE DOCTORAL (PhD) DISSERTATION

THE DYNAMICS OF TOURISM AT THE GLOBAL LEVEL AND THE CONNECTIONS BETWEEN EUROPEAN TOURISM: BASED ON THE EXAMINATION OF SELECTED EUROPEAN CITIES

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1. INTRODUCTION OF THE TOPICS AND OBJECTIVE

In the years preceding the pandemic, excessive tourism became perhaps the most critical challenge facing global tourism, resulting in significant economic, social, and environmental impacts. Beyond my personal and academic interest in the topic, several factors motivated my choice of research subject, including the international nature of the phenomenon, the relevance of sustainability issues, the opportunity to monitor changes caused by the pandemic, and changes in travel habits. In addition, during my previous studies (BSc in Tourism and Catering and MSc in International Economics and Business), I focused on the interrelationships between tourism management and international processes, so my doctoral research provides me with an opportunity to examine the phenomenon of overtourism in a complex way by linking these areas.

Excessive tourism or overtourism became a problem that preoccupied many tourism professionals in the years leading up to the COVID-19 pandemic. Although the pandemic seemed to temporarily eliminate the source of the problem, thousands of tourists rushed back to popular attractions after restrictions were removed. This places a huge pressure on the natural environment (e.g. flora and fauna, water and air pollution), built heritage (e.g. vandalism, destructive activities) and also has many disadvantages for the local population (e.g. overcrowded transport, crowds, light and noise pollution).

The main objectives

My doctoral dissertation focused on the global examination of tourism in urban destinations with the aim of determining which settlements are most affected by overtourism. This part of the research involved the comprehensive ranking of 255 cities, which was analyzed using cluster analysis (VARCLUS), principal component analysis (PCA), and factor analysis of mixed data (FAMD).

The rankings and the temporal evolution of the individual sub-indicators were examined using cluster analysis (VARCLUS) and principal component analysis (PCA). The application of factor analysis of mixed data (FAMD) made it possible to create a map that represents the locations together with continuous and categorical data. The analysis also reveals notable regional and typological patterns, highlighting the dominance of international indicators in European coastal and heritage locations and the dominance of

domestic indicators in North American and Asian urban locations. The analysis thus provides a basis for deriving direct regulatory and economic policy recommendations.

It is relatively rare in academic circles for economists to conduct comprehensive statistical analyses of overtourism in urban areas around the world. Most research in this field has focused on individual countries or continents. The COVID-19 pandemic has fundamentally changed the dynamics of tourism, with tourists shifting their focus to other destinations, which justifies the need for a time series analysis of tourism at the global level. Overtourism can be identified as a significant global problem with numerous negative externalities. The other main research question of the dissertation was the following: To what extent are the European cities examined affected by overtourism, and how has this changed since the emergence of the COVID-19 pandemic? One of the main objectives of the doctoral thesis was to develop a criterion that objectively shows the extent of tourism, thus establishing a dynamic ranking of the selected European cities. This is because there is a lack of studies that use sophisticated statistical methods to analyze secondary data on overtourism. In the final stage of the analysis, the focus of the study was narrowed down to European overtourism destinations. This reduction allows the study to analyze the development of excessive tourism in a more targeted context. The 28 European settlements, which were selected based on their exposure to excessive tourism, were ranked using multi-criteria decision-making methods for the period 2014-2023. The rankings were calculated using the VIKOR, TOPSIS, and MMOORA methods, and a composite ranking was also produced using Cross-Entropy optimization. In addition, the annual changes in the rankings were presented graphically using Principal Component Analysis in a two-dimensional space. Finally, the locations were classified into three different clusters based on their level of overtourism using the K-means algorithm.

2. MATERIAL AND METHODS

In accordance with the chapter entitled " Results and evaluation of research," I have divided the chapter entitled "Materials and methods" into three main sections.

2.1. Trends in overtourism

The presentation and analysis of current issues related to the phenomenon of overtourism was mainly carried out using data obtained from online databases (e.g., EUROSTAT, UNWTO or UN Tourism, Knoema, UNESCO, Statista, INE), using publicly available data banks, professional compilations, and interactive maps. When processing the data, I endeavored to place the collected and systematized information in context, thereby providing a deeper understanding of the current issues surrounding overtourism. This chapter presents the most commonly used derived indicators for measuring overtourism: tourism density and tourism intensity.

2.2. Global trends in the scale of urban tourism in the 21st century

To ensure the reliability of the statistical analyses used in the research, the data used for the study were obtained from a major international database that is widely accepted and recognized in professional circles. The Oxford Economics (2024) database collects data at global and regional levels, with information obtained from multiple sources, including government statistics, industry surveys, and reports from international organizations. I further narrowed down and systematized the information provided by the database during my research to ensure that it accurately matched the requirements of the statistical models. As a result, the statistical analyses were carried out using 255 destinations, mainly urban locations.

A comprehensive study focusing on overtourism was published in 2018, examining tourist destinations around the world. A study by experts from the European Parliament's Committee on Transport and Tourism (TRAN) (Peeters et al., 2018) analyzed indicators of overtourism by analyzing secondary data and focusing on case studies. They concluded that, due to the complex causes and effects of overtourism, it is not possible to define common indicators in their case.

In their study, they compiled a list of locations at the global level that are exposed to the negative effects of overtourism, specifically referred to as "overtourism destinations." TRAN used a variety of statistical analysis methods to examine the sites mentioned, but after a few years and using other statistical methods, new results can be obtained.

Measuring overtourism is a challenging task, but there are indicators that can help experts in this regard. Buitrago and Yñiguez (2021) used relative indicators (tourism indicators/general indicators) to measure tourism intensity (e.g., tourists/residents, visitors/residents, overnight stays/residents, overnight stays/1,000 residents, cruise ship passengers/residents) and tourism density (e.g., tourists/km², overnight stays/km², guest beds/km²). Tourism density is usually measured by the number of visitors per square meter, the number of overnight stays, or the number of tourists. Tourism intensity is typically measured by the number of visitors, overnight stays, or tourists per resident (WTTC, 2017).

The results of a study of hundreds of settlements around the world over the past decades were compiled using data such as the area of the settlement, population and GDP, the number of guest nights spent in domestic and international paid accommodation, the number of domestic and international tourist arrivals, and the total tourism expenditure of domestic and international tourists in the settlement.

In the first stage of the analysis, variable clustering (VARCLUS) (Vigneau – Qannari, 2003) was performed to eliminate redundant dimensions and represent the data in a lower-dimensional space. The method is closely related to both principal component analysis (PCA) and cluster analysis. The algorithm identifies groups of variables that show the highest possible correlation with each other and the lowest possible correlation with variables in other clusters. The aim of the procedure is to create latent components (optimal representations) for each correlated group of variables as a linear combination of the given variables. The procedure first uses K-means (agglomerative) cluster analysis for the initial grouping, then assigns the latent components to each cluster. In the final stage, new clusters are formed based on the Pearson's correlation coefficient between the variables and the latent components.

The process is iterative and ends when the cluster structure has reached a stable state. Variables separated within a cluster must be correlated with other variables in their own cluster and must not be correlated with other clusters. Thus, variables clustered into one class are identical or very similar and do not resemble variables in other classes (Khattaba et al., 2019). The aggregation strategy is based on the observed variances, and the merging of two clusters depends on the minimum reduction in the total explained variance after the merger. One of the main advantages of VARCLUS over simple principal component analysis is that the resulting structure is clearer and easier to interpret. In addition, a Kruskal-Wallis analysis was performed on the latent components generated by VARCLUS to reveal differences in the scores of the latent components in terms of region, location, and type of overtourism.

The aim of principal component analysis is to transform a series of interrelated variables into unrelated, linear variables using linear transformation (Ghauri – Grønhaug, 2016). The method reduces the number of variables while preserving as much information as possible about the original variables, so that information about the original system can be extracted from the factor model (Jánosa, 2023). In the study of cities around the world, a simple PCA was ultimately used to form a single principal component from all the overtourism indices used in the research, with the aim of developing a uniform, general index to measure overtourism.

Factor analysis of mixed data (Factor Analysis of Mixed Data – FAMD) is a statistical method that can combine and analyze different types of data (e.g., continuous and categorical data), making it ideal for mixed data sets where the variables are of different types but all contribute to revealing the structure of the data set. Factor analysis is a so-called exploratory method, meaning that it is used to reveal the underlying structure of the data (Molnár, 2017). In the second stage of the analysis, factor analysis of mixed data (FAMD) (Pagès – Pagès, 2014) was used to create a map depicting the locations, together with continuous and categorical data. Continuous data are characterized by the fact that they can take any value within a given interval (Füzesiné, 2018). Continuous data included international and domestic tourist arrivals, international and domestic guest nights in paid accommodation, and international and domestic tourism spending. Categorical variables cannot be described by numerical values, but by categories or groups. Categorical data

included the region (Africa, Asia, Australia, Europe, North and South America) and types of overtourism, such as coastal and island, heritage, urban, rural, and the category of settlements that are not exposed to overtourism according to a global study published in 2018 (Peeters et al., 2018).

2.3. The extent of overtourism in European destinations

Data was collected from online sources, the most important of which are Oxford Economics, an independent economic consulting firm (Oxford Economics, 2024), and Eurostat, the statistical office of the European Union (Eurostat, 2023).

The aim of this study is to present new findings using statistical and analytical methods for locations previously identified as "overtourism destinations" by the European Parliament's Committee on Transport and Tourism (TRAN). In addition to the indicators used by the Committee on Transport and Tourism, other metrics are also considered in the research, which make the combined effects of natural conditions and socio-economic processes in areas affected by overtourism even more transparent. The 67 European destinations identified by TRAN include several small villages, rural settlements, unique attractions, and smaller units (e.g., the Geiranger Fjord area, Plitvice Lakes, Vesuvius, the Ring of Kerry, Stonehenge). The tourism indicators to be examined are not really comparable between categories in the case of some smaller destinations (as in many cases they do not have population figures or do not measure the size of tourism for such small units), so the research mainly focuses on urban locations. Data were available for a total of 28 destinations, which allowed for a larger sample analysis than in other studies with similar themes and objectives, such as the research by Amore et al. (2020). It is important to note that in cases where the location listed by TRAN was a special part of the settlement or a historic city center, the data for the entire settlement was examined, as tourism data for smaller units was not available (e.g., Dubrovnik Old Town, Athens - Acropolis, Florence historic center).

Since 2020 – since the COVID-19 pandemic – density indicators have become increasingly important, as tourists are increasingly mindful of avoiding the risk of infection and the inconvenience of restrictions.

The following indicators were used for the results presented in the chapter of the doctoral thesis dealing with European urban tourism: number of air passengers per capita, number of guest nights in paid accommodation per capita, number of guest nights per capita, number of guest nights per km² per km, and total tourism expenditure as a percentage of GDP. The reliability of the variables on the scale was checked using McDonald's omega, which is an alternative to the traditional Cronbach's alpha and is most suitable for scales based on multidimensional and factor analysis. The McDonald omega value can range from 0 to 1: a value above 0.7 is acceptable, while a value above 0.8 is considered excellent for assessing the reliability of latent variables (Kocsel, 2019).

To measure the extent of tourism, this study used the same or similar indicators as Popescu et al. (2023), Maggi and Fredella (2010), and Manera and Valle (2018). However, other tourism experts also acknowledge that the difference between absolute tourism indicators and derived indicators can be significant, and therefore the use of concentrated indicators and derived indicators may be justified (Tóth, 2016).

Using MCDM (Multiple-Criteria Decision-Making) (Gyarmati – Szalai, 2018; Rideg et al., 2009), researchers are able to compare different alternatives based on complex criteria systems (Gyarmati – Szalai, 2018). The first phase of the research on European destinations was based on the application of multi-criteria decision-making methods (MCDM) to rank 28 overtourism sites according to 7 criteria (indicators) and 10 years (between 2014 and 2023). To increase reliability (Kocsi, 2020), three different ranking methods were used:

- TOPSIS (Behzadian et al., 2012) with vector normalization (Hwang – Yoon, 1981). The TOPSIS method summarizes performance as the distance between each decision alternative and the best and worst performances (Kovács, 2019).
- The VIKOR method (Opricovic, 1998) focuses on ranking alternatives and selecting compromises between them in the case of conflicting criteria (Gyarmati – Szalai, 2018).
- The MMOORA (Brauers – Zavadskas, 2006) method ranks the available alternatives based on ratio systems in which the performance of each alternative is compared to a denominator that represents all alternatives in relation to a given criterion (Singh et al., 2024).

These methods are often used successfully in other research areas, but some authors have also applied them in various areas of tourism, for example Önder et al. (2013) and Göksu and Kaya (2014). Based on several different rankings, a composite ranking was created using Cross-Entropy, a fairly robust optimization algorithm developed by Rubinstein (1999) and Kroese et al. (2006). The algorithm minimizes the following objective function (Pihur et al., 2009):

$$\Phi(\delta) = \sum_{i=1}^m w_i \cdot d(\delta, L_i), \quad (1)$$

where δ is the general ranking,

m is the number of criteria,

L_i is the i -th ranking ($1 < i < m$),

d notes the distance metric used, which in this case is the Euclidean distance,

w_i denotes the criterion weights.

After applying several other weighting methods, the final result was obtained by applying equal weights, which gave the most interpretable result.

The next step was to graphically represent the rankings of the locations and their annual changes using PCA (Principal Component Analysis) in a two-dimensional space, the so-called biplot graph (double scatter plot). PCA is a dimension reduction technique that helps to display information in complex data sets in fewer dimensions while retaining the most important information. This method helps to analyze the main directions (main components) along which the greatest variance in the data set can be explained. The biplot graph visualizes the results of PCA along two principal components. This graph displays points and vectors at the same time. The points represent the settlements under investigation based on their position along the two principal components. The distance between the points shows how similar the settlements are to each other in terms of the ranking under investigation. The vectors represent the directions representing the criteria and indicators. The length of the vectors shows the explanatory power of the principal components, while their direction shows the direction in which the given factor has an effect (Podani, 1997).

Based on the rankings of the locations, a cluster analysis was also performed using K-means (Bock, 2007; Jauhari et al., 2022) and hierarchical clustering (Murtagh – Contreras, 2012) to form 2-6 groups. In the K-means method, the researcher is responsible for selecting the optimal number of clusters, and then each element is assigned to the cluster closest to its center. In the hierarchical method, a hierarchical structure of the data is built, in which case no predefined number of clusters is required. Finally, based on the so-called Silhouette coefficient (Sekula et al., 2017), the 3-group solution was selected using K-means clustering.

Following the cluster analysis, the data set divided into three sets was subjected to ANOVA (Analysis of Variance) in order to determine whether the clusters are significantly different from each other along one or more variables, or whether the differences are merely due to chance.

3. MAIN FINDINGS OF THE DISSERTATION

3.1. Trends in overtourism

The 21st century has been marked by a number of global events, one of the most significant of which is the outbreak of the novel coronavirus (SARS-CoV-2) at the end of 2019. The global pandemic has had a major impact on the tourism industry, with visitor numbers to previously popular destinations falling dramatically. The phenomenon of overtourism has temporarily ceased due to flight cancellations, border closures, and quarantine measures.

Koh (2020) showed that the outbreak of the COVID-19 pandemic had a serious impact on the phenomenon of overtourism, but at the same time created new opportunities for a more sustainable and responsible future for tourism.

Seasonality is a regularly occurring, predictable phenomenon that is not unique to tourism (Szöllös-Tóth, 2022c). Based on data from the World Tourism Organization, four different levels of seasonality can be distinguished. Level 1 is typical in countries where tourist traffic is significant throughout the year, i.e., where the traffic in the three most popular months does not exceed 35% of the total annual traffic based on visitor numbers. Examples include the United States (29%), Fiji (30%), Spain (35%) and Hungary (34%). The strongest seasonality – level 4 – is found in countries where tourist arrivals in the three most popular months account for at least 55% of the total annual arrivals. There are few such countries, all of which are located in Europe: Norway (61%), Croatia (64%) and Greece (56%). These countries are most exposed to seasonality due to the nature of tourism and, therefore, to the resulting inequality (UNWTO, 2022).

Among the negative effects of seasonality, we can also mention overtourism, as in many cases the problems caused by tourism are exacerbated by its seasonal nature. An excessive increase in visitor numbers leads to overcrowding in areas where residents suffer from the consequences of seasonal tourist peaks (Milano et al. 2019). Although Gonda (2016) states that seasonality, temporal and spatial concentration are fundamental characteristics of tourist demand, stimulating demand outside the tourist season is one of the central tasks of tourism development. There is also a notable trend towards off-peak vacationing becoming more ingrained in travelers' consciousness. A survey of residents in six countries (the United Kingdom, the Netherlands, Germany, Italy, France, and Spain) about their travel plans for

2025 found that almost a third (31%) of the nearly 8,000 respondents said they would definitely not travel during peak season to avoid overcrowding (Accor, 2024).

The global pandemic, which has had such a profound impact on tourism in recent years, has further reinforced seasonal patterns in many countries.

Another study of mine published in 2022 (Szöllős-Tóth, 2022d) focuses on the fact that the spatial distribution of attractions is uneven. Some areas have several times more attractions than other regions of similar size. Thus, areas with more tourist attractions usually have higher tourist traffic, and these destinations are particularly vulnerable to the dangers of overtourism.

One reason for the emergence and existence of overtourism may be the concentrated location of the attractions considered most popular by tourists. It can be demonstrated that the spatial distribution of tourist attractions does not follow a regular pattern, so the share of tourism revenues is also highly differentiated between countries around the world and within individual countries.

Most of the world heritage sites listed by UNESCO, the United Nations Educational, Scientific and Cultural Organization, are located in Europe. In 2022, there were a total of 1,154 World Heritage Sites, of which 897 were cultural, 218 were natural, and 39 were both cultural and natural World Heritage Sites. Italy has the most World Heritage Sites (58), followed by China (56) and Germany (51). They are followed by Spain and France (both with 49 sites), India (41 sites) and Mexico (35 sites) (UNESCO, 2022).

An excellent example of the irregular spatial distribution of attractions is the appeal of coastlines, which is a kind of natural resource for countries. Countries without access to the sea cannot reap the benefits of popular 3S (sun, sea and sand) tourism as host countries. The success of coastal tourist destinations is unparalleled worldwide; these destinations typically receive the most tourists and benefit the most from tourism revenues.

It can be observed that countries where tourism is the sector that contributes most to GDP are mainly smaller coastal countries that take full advantage of the benefits of 3S tourism (Knoema, 2022).

Just as the location of natural attractions shows no pattern whatsoever, the location of man-made attractions is also rather irregular, typically concentrated in certain areas. In many countries, the most popular attractions are clustered around global cities. Within these cities, concentration is also common, as there is often an old town or historic city center that is crowded with tourist attractions.

The most visited country in Europe – and in the world – in 2023 was France with 100 million tourist arrivals, followed by Spain with more than 85 million tourist arrivals, which was also enough for second place in the world rankings (UN Tourism, 2025). Looking at the number of guest nights spent in tourist accommodation in European Union countries, the Mediterranean coast – mainly Spain, France, and Italy – and the Atlantic coast – Spain, France, and Ireland – stand out (Eurostat Nights, 2025).

Based on tourism intensity, the most overburdened areas are located in northern Italy, Croatia, Iceland, and, among the European islands, Cyprus, Crete, the Aegean islands, Malta, Corsica, Sardinia, the Balearic Islands, the Canary Islands and Madeira (Eurostat Population, 2025). The density of tourism also indicates the overburdening of coastal areas by tourism. Among the European islands, the Aegean islands, the Ionian islands, Cyprus, Malta, Corsica, the Balearic Islands, the Canary Islands and Madeira are particularly affected (Eurostat Area, 2025).

Some of the results of my research on urban locations were published in 2022 (Szöllős-Tóth, 2022b). In the years before the pandemic, tourism was one of the fastest growing economic sectors. Looking at European cities, London was the most popular in 2019 in terms of the number of overnight stays (City Destinations Alliance, 2024). It is worth examining the ratio of international and domestic tourists in European urban locations. In this respect, Dubrovnik is truly international, with 94% of its tourists coming from abroad. The number of international tourists is also significant in the Palma de Mallorca – Calvià area of the Balearic Islands (88%) and in Venice (86%). The proportion of international tourist traffic is similarly high compared to domestic traffic in Budapest (83%), Lisbon (81%) and Barcelona (81%). In contrast, among the European cities surveyed, Madrid (54%), Paris (53%) and Berlin (35%) have a much lower proportion of international tourists than the former (Statista Distribution, 2024).

According to the results of primary research conducted among nearly 8,000 European travelers (Accor, 2024), the effects of overtourism are no longer unknown to tourists. 11% say they have had their vacation ruined by choosing an overcrowded destination. Eight percent of respondents have felt guilty about staying in a vacation spot affected by overtourism. That's why the vast majority of travelers (90%) believe that problems caused by overtourism will influence where and how they travel in 2025. Some (31%) plan to avoid traveling during peak season, others (27%) will avoid destinations that suffer from overtourism, and many (19%) will avoid destinations where locals protest against tourism. A significant proportion of respondents (22%) will consciously choose lesser-known destinations in 2025 to avoid contributing to the negative effects of tourism. A quarter of participants understand the hostile and protesting attitude of the host community, the problems they raise, and sympathize with the protesting residents.

The measures introduced or planned at the sites concerned are diverse, but most of them focus on protecting the natural environment and built heritage and maintaining the standard of living of the local population, which is discussed in more detail in the doctoral thesis.

Airbnb, an online platform where private individuals can rent out their properties (either the entire property or part of it) for short periods, appeared on the accommodation market in 2008, allowing interested parties to rent properties, thus connecting supply and demand. Short-term rental (STR) refers to accommodation rented out for a short period of time, typically from one night to a few weeks, usually by private individuals or property owners. They are managed by individuals (rather than large hotel chains or campsites) and include various types of accommodation, such as apartments, houses, and rooms in private homes. Airbnb has gained enormous popularity in just a few years, and by the summer of 2024, it offered more than 8 million active accommodation options in more than 100,000 locations worldwide (Airbnb, 2025). Its entry into the European market has also been very successful (Eurostat Guests, 2025): in 2023, for example, more than 159 million guest nights were realized in France through the use of Airbnb and other platforms for renting short-term accommodation (e.g., Booking.com). While initially it seemed like an excellent opportunity for private individuals to use their empty guest rooms or apartments for tourism, providing a good source of income for hosts, a number of problems later arose in connection with this

form of the sharing economy. As more and more owners opted for more lucrative short-term tourist rentals instead of long-term subletting, this led to a drastic increase in local rental prices. As a result, some local residents were forced to move out of the town or its center because they could no longer afford the increased prices. Celata and Romano (2020) noted that online short-term rental platforms such as Airbnb not only increase the accommodation capacity of urban areas, but also affect the relationships between residents and visitors. The conversion of homes into tourist accommodation through short-term rentals contributes to the displacement of residents from city centers. This has also had an impact on property purchase prices, which have also started to rise rapidly.

3.2. Global trends in the scale of urban tourism in the 21st century

The research results presented in the subchapter discussing the dynamics of urban tourism were published in a study in 2025 (Szöllős-Tóth et al., 2025).

It is relatively rare in academic circles for experts to conduct comprehensive statistical analyses of tourism in urban destinations around the world. Most research on overtourism focuses on individual countries or, at most, continents. The doctoral research applied a methodology analogous to tourism intensity and density indices using population- and area-based indices.

When interpreting the results presented, I considered whether individual settlements were affected by overtourism based on the work of Peeters et al. (2018). A detailed examination of the classification methodology and criteria is beyond the scope of my research, so I used the categorization established by TRAN as a starting point for further analysis. Overtourism status is a determining factor in my calculations and statistical analyses. In my research, I treated this classification as an exogenous variable, which was defined in advance and did not change during the study, but played a key role in the data analysis process and the interpretation of the results.

The VARCLUS method was used to determine the clusters of the tourism indicators examined and to form latent components for each cluster in order to reduce the dimensionality of the data. The VARCLUS method is a more practical approach to clustering overtourism indicators, as it allows the selection of the most correlated measures and the creation of subgroups and latent components from them. The initial cluster was

divided into five different clusters, each consisting of one, two, or three indicators (Figure 1).

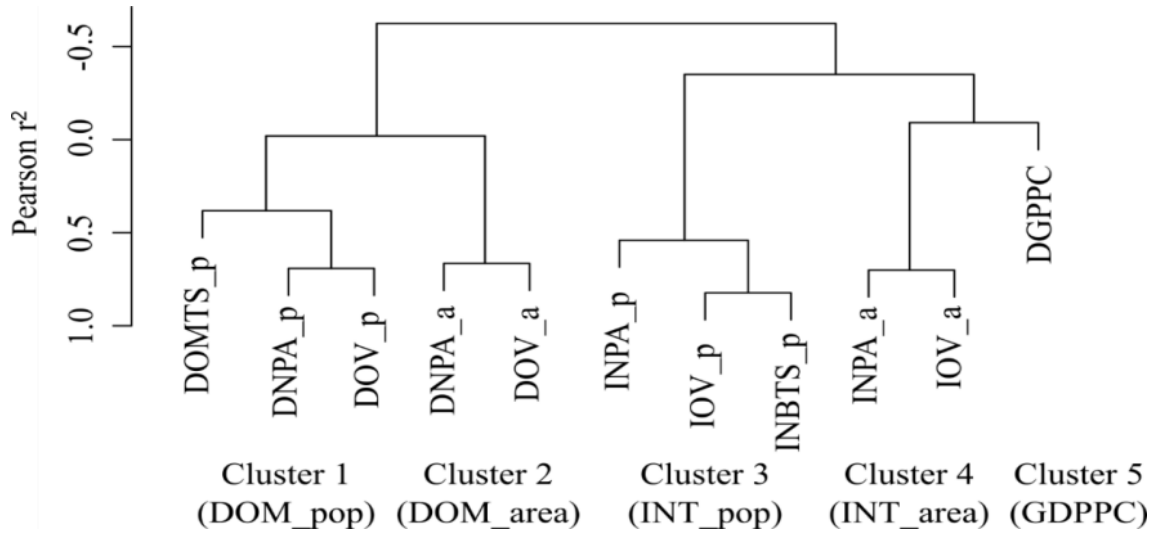


Figure 1: Cluster and correlation structure of overtourism indicators

Source: own compilation (2025)

The Pearson r-squared indicator shows how much the indicators within a cluster are related to the underlying latent component of the cluster. Table 1 shows the five clusters and how much each indicator is related to the latent component of the cluster. This method is used to identify the variables assigned to each cluster. Furthermore, the indicators are selected for a given cluster so that they show the highest correlation with their own cluster ($r^2_{(OWN)}$) and the lowest correlation with the closest clusters ($r^2_{(CLOSEST)}$).

The $1-r^2$ ratio is calculated as follows (SAS Institute Inc., 2013):

$$1 - r^2 \text{ ratio} = \frac{1 - \text{Pearson } r^2_{(OWN)}}{1 - \text{Pearson } r^2_{(CLOSEST)}} \quad (1)$$

A given indicator strongly correlates with its own cluster ($r^2_{(OWN)} \rightarrow 1$) and does not correlate with the nearest cluster ($r^2_{(CLOSEST)} \rightarrow 0$), so the $1-r^2$ ratio is close to 0 (Sanche – Lonergan, 2006). Therefore, the indicator with the lowest $1-r^2$ value is likely to be the most representative of the cluster.

Table 1. Correlations of indicators with their own and next closest clusters, and general component weights

Cluster (explained variance%)*	Type of claculation	Indicators	Abbreviation	$r^2_{(OWN)}$	$r^2_{(CLOSEST)}$	1- r^2 ratio*	General compo-nent weights**
DOM_pop (82%)	Population based	domestic guest nights in paid accommodation	DNPA_p	0.897	0.304	0.149	0.741
		domestic tourist arrivals	DOV_p	0.820	0.364	0.284	0.674
		domestic tourism expenditure	DOMTS_p	0.731	0.212	0.341	0.729
DOM_area (91%)	Area based	Domestic guest nights in paid accommodation	DNPA_a	0.908	0.318	0.135	0.679
		domestic tourist arrivals	DOV_a	0.908	0.330	0.138	0.671
INT_pop (88%)	Population based	international guest nights in paid accommodation	INPA_p	0.810	0.035	0.197	0.516
		international tourist arrivals	IOV_p	0.915	0.199	0.106	0.629
		international tourism expenditure	INBTS_p	0.908	0.097	0.102	0.546
INT_area (92%)	Area based	international guest nights in paid accommodation	INPA_a	0.919	0.156	0.097	0.567
		international tourist arrivals	IOV_a	0.919	0.133	0.094	0.570
GDPPC (100%)		GDP / capita	GDPPC	1.000	0.047	0.000	0.262

Note:

*: Total explained variance= 89%

**: 1- r^2 ratio calculated according to formula (1)

***: weight of general components calculated using PCA analysis

Source: own compilation (2025)

The explanatory power of the clusters is quite significant. Area-based clusters explain a relatively large proportion of the variance, 91% for domestic indicators and 92% for international indicators. In the case of population-based clusters, the proportion of explained variance is relatively lower, at 82% for domestic indicators and 88% for international indicators. Overall, latent components explain 89% of the variance. The correlation coefficients of the individual indicators exceed 0.7, indicating a stronger correlation with the corresponding latent component. Domestic indicators are relatively more strongly linked to the general overtourism indicator. Domestic paid guest nights based on population and domestic travel expenditure have the highest weights, with correlation coefficients of 0.741

and 0.729, respectively. The lowest weight (0.262) is attributable to GDP per capita in the general component. The results of the VARCLUS clustering yielded five synthetic components, which were created according to the given indicator clusters. Thus, each VARCLUS component represents a separate cluster of indicators with a single score. These components are more distinct and easier to interpret than the rotated principal components, which is the primary advantage of the VARCLUS method.

Figure 2 examines the pattern of overtourism in different types of locations by calculating the average score of the VARCLUS components for each group. In coastal areas and on islands, international population-based indicators are high, as is the general overtourism component. However, the other indicators show lower values. In urban areas, GDP per capita is higher, and the general overtourism component and international area-based indicators are the highest. In the case of heritage sites, international indicators are relatively modest, while domestic indicators are the lowest. The Kruskal-Wallis analysis showed statistically significant differences at a 5% significance level for all indicators examined.

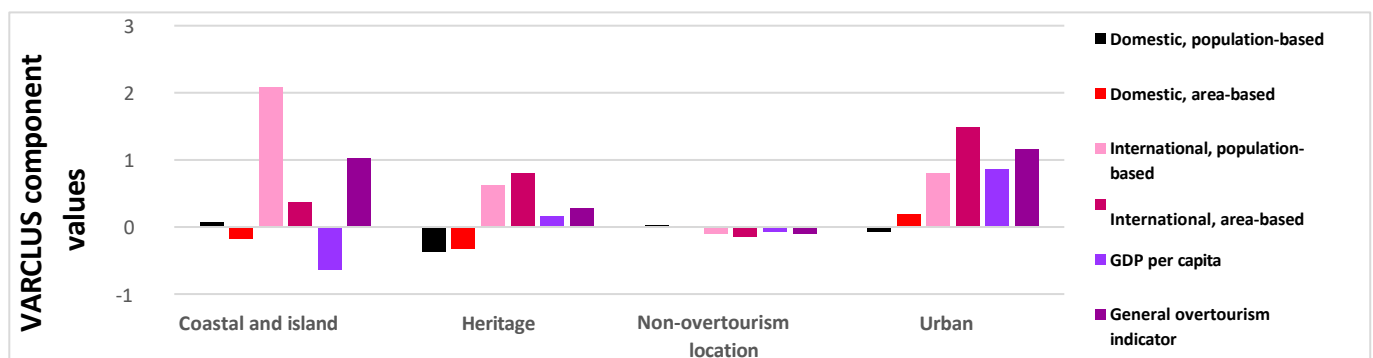


Figure 2: Differences between VARCLUS components by type of overtourism

Source: own compilation (2025)

Figure 3 shows the average scores of the VARCLUS components for each region. South American locations have particularly low scores, as do Africa and Asia. In the case of Australia, although GDP per capita is higher, the scores for the other indicators are very low. Higher scores are mainly observed in North America and Europe for domestic and international indicators, as well as for indicators based on population and territory. North America in particular has relatively high domestic indicators, including area and population-based measures and GDP per capita. However, other indicators are lower. European locations with higher GDP per capita show the highest international population-based indicators and an outstanding overall component, largely due to coastal and heritage locations. The

Kruskal-Wallis analysis showed statistically significant differences for all indicators examined at a 5% significance level.

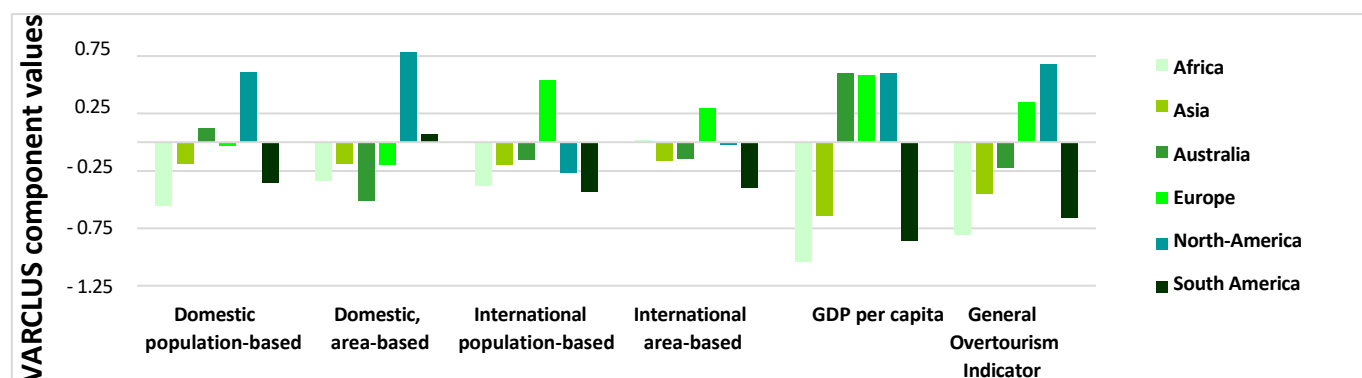


Figure 3: Differences between VARCLUS components by region

Source: own compilation (2025)

Figure 4 shows a consistent upward trend in all groups of VARCLUS components between 2000 and 2019. The growth becomes particularly steep after 2010, indicating that the factors examined showed significant improvement in the areas concerned. Among the components, the general tourism indicator stands out, showing the most dynamic growth of all the components. The growth continues until 2019, followed by a dramatic decline in 2020, which affects all indicators and clearly reflects the impact of the global pandemic.

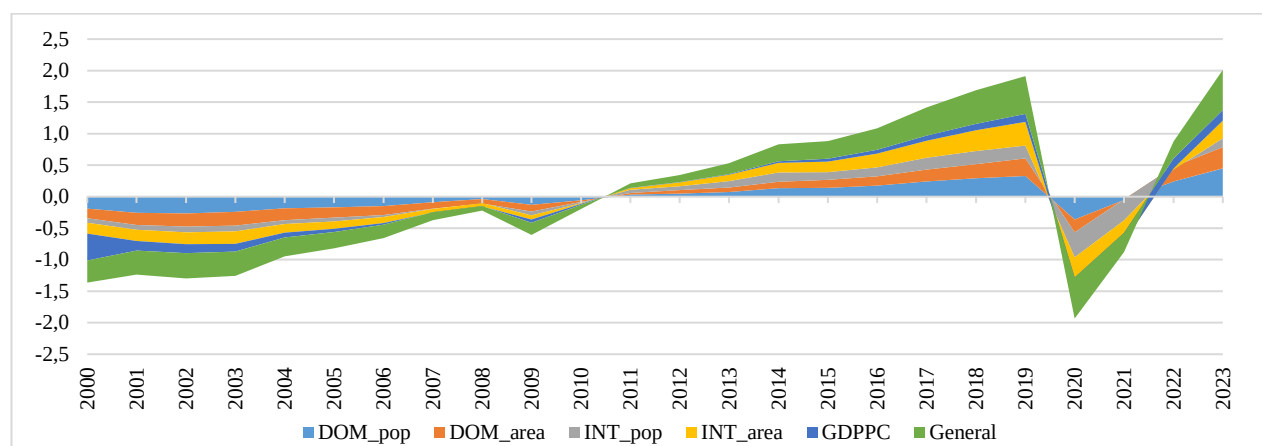


Figure 4: Development of VARCLUS components by year

Source: own compilation (2025)

Starting in 2021, a strong recovery can be observed, indicating that international tourism and economic performance are approaching pre-pandemic levels. Growth dynamics will become steeper again in 2022–2023, signaling the post-pandemic recovery of tourism and the economy.

Figures 5 and 6 present the results of factor analysis of mixed data (FAMD) and highlight the main correlations within the data set from different perspectives. The scatter plot on the left side of the figure provides information about the regions, while the graph on the right shows the types of overtourism. The axes (dimensions 1 and 2) attempt to capture the relationships between the data variables. Dimensions 1 and 2, which are illustrated in the graph, are the principal components explaining 26.27% and 16.91% of the total variance. The spatial pattern of the two upper graphs shows that the regions and the different types of tourism can be clearly distinguished in the scatter plots, as there are significant differences between the regions and the types of overtourism along the dimensions.

The correlation circle in the lower half of the figure helps to understand how the different variables relate to each other. Within the circle, the arrows of the variables show which variables correlate with each other and to what extent. The direction and length of each vector indicate the extent to which the variable contributes to the factors and how it correlates with other variables. GDP per capita is a shorter vector, indicating that this variable has less impact on the dimensions and/or is influenced by other factors. If two vectors point in the same direction, it means that the two variables are positively correlated with each other (e.g., domestic overnight stays in paid accommodation / area and domestic tourist arrivals / population). The results of the principal component analysis, presented in two-dimensional correlation circles, clearly show that components located closer to each other are more closely related.

The first two dimensions accounted for 43.2% of the total variance. The first dimension accounts for the largest part of the variance (26.27%) and can be interpreted as an index of tourism intensity. This is due to its relationship with international and domestic indicators based on area and population data. The second dimension separates international indicators (located in the first quadrant) from domestic indicators (located in the fourth quadrant). The factor map clearly shows that the first quadrant contains a significant number of European destinations, including Mallorca, Lanzarote, Fuerteventura, Dubrovnik, Paris, and Ibiza. It also includes several Asian destinations, such as Macau, Denpasar, and Shanghai. These are primarily coastal and island, heritage and urban types of overtourism destinations, which are most affected by high international interest. The fourth quadrant includes North and South American destinations (e.g., Acapulco, Cancún, Guadalajara, Las Vegas) and some

Asian destinations (e.g., Kuala Lumpur, Sanya, Okinawa), which are of greater domestic interest.

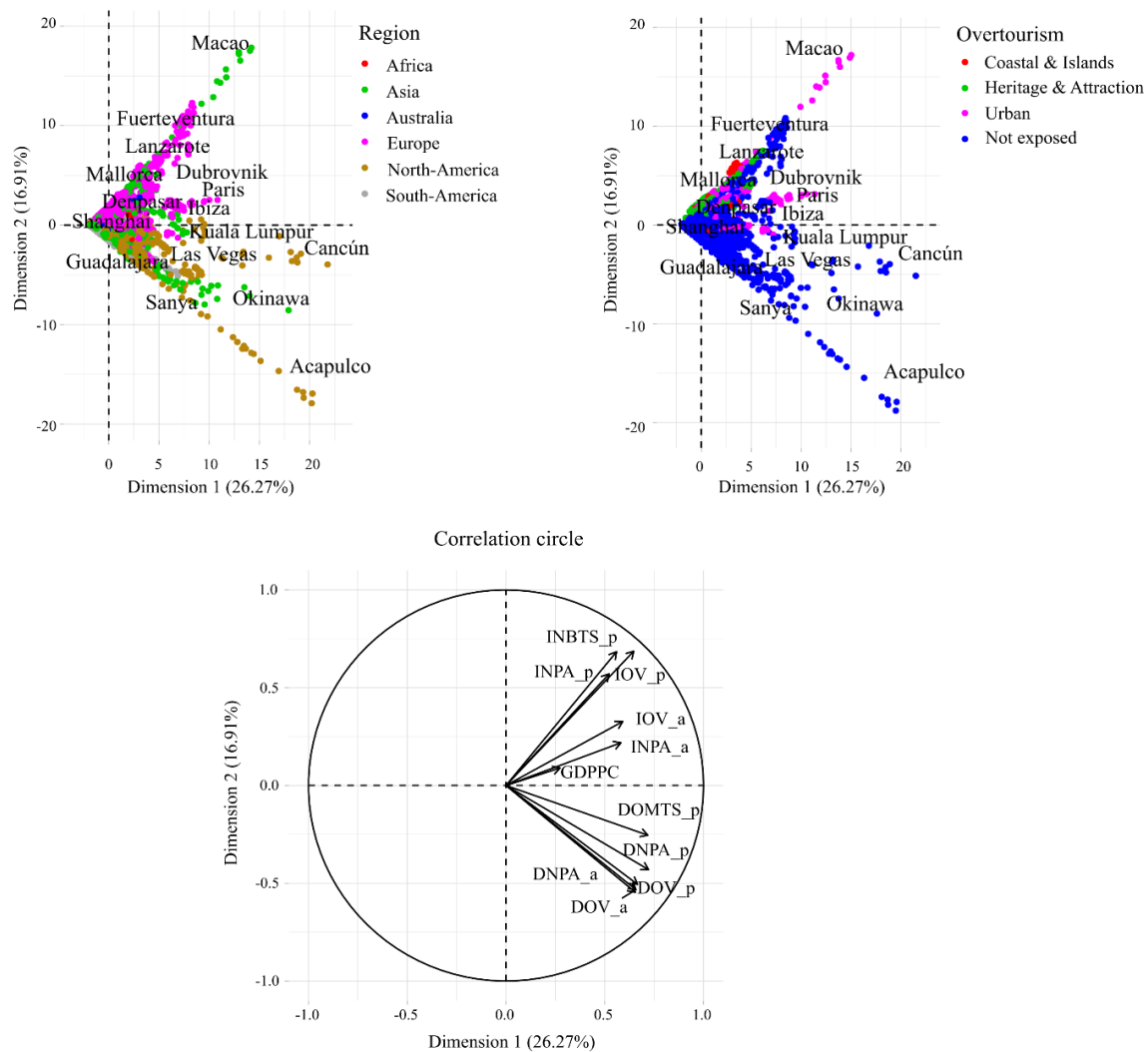


Figure 5: Correlation circle and factor map (dimension 1 and 2) of the locations by region and type of overtourism

Source: own compilation (2025)

The third dimension is also presented, which explains 10.83% of the variance. The first three dimensions together explain 54% of the variance. It is important to present the second and third dimensions on a factor map as well, as this allows for a clear distinction between the components of VARCLUS (Figure 5).

In Figure 6, the first quadrant contains area-based international indicators, while the second quadrant contains population-based international indicators. The third cluster shows population-based domestic indicators, while the fourth quadrant relates to area-based domestic indicators.

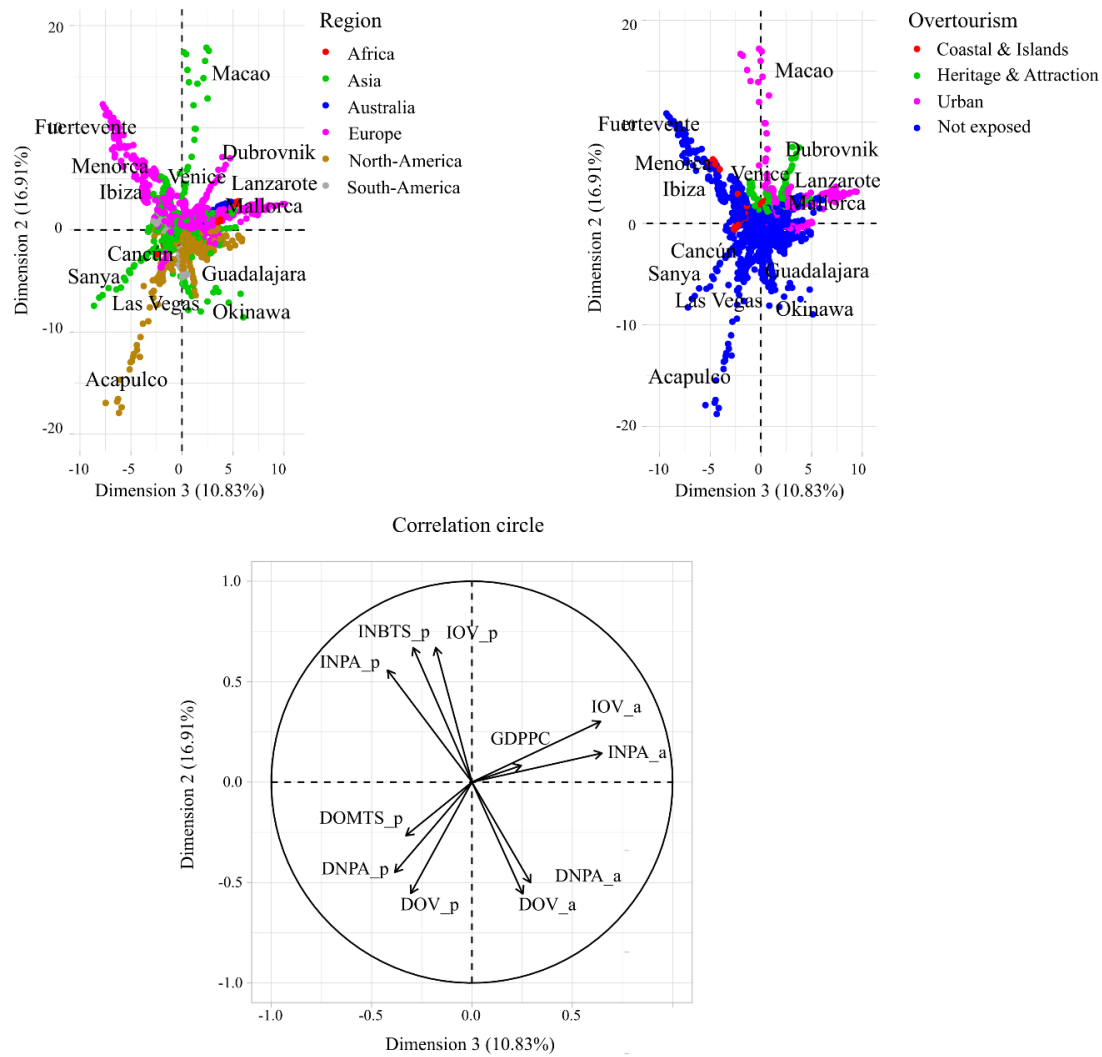


Figure 6: Correlation circle and factor map (dimension 2 and 3) of the locations by region and type of overtourism

Source: own compilation (2025)

The second dimension allows for the separation of international and domestic indicators. The third dimension allows for further differentiation between area-based and population-based indicators. It is clear that European coastal locations and islands (e.g., Mallorca) are characterized by relatively high international interest compared to their population. It is also noteworthy that Asian urban locations (e.g., Macau) attract relatively more international interest in relation to both their area and population. Domestic area-based indicators are highest for North American urban destinations (e.g., Guadalajara) and some Asian destinations not exposed to overtourism (e.g., Okinawa). In contrast, domestic indicators based on population are highest for North American (e.g., Las Vegas, Acapulco, Cancún) and Asian (e.g., Sanya) destinations that are not exposed to overtourism.

Table 2 shows the best and worst places in terms of the given VARCLUS component (the ten cities with the highest and lowest scores for each indicator).

Table 2. The 10 locations with the highest and lowest VARCLUS component scores (Source: Authors)

Location	General indicator	Location	DOM_pop	Location	DOM_area	Location	INT_pop	Location	INT_area
Macao (MO)	7.91	Las Vegas (US)	8.12	Okinawa (JP)	10.13	Fuerteventura (ES)	13.14	Paris (FR)	9.91
Las Vegas (US)	7.87	Acapulco (MX)	7.44	Guadalajara (MX)	5.74	Lanzarote (ES)	12.16	Macao (MO)	6.67
Okinawa (JP)	7.65	Cancún (MX)	4.78	Acapulco (MX)	4.91	Macao (MO)	11.48	Geneva (CH)	6.64
Paris (FR)	7.52	Adelaide (AU)	4.35	Las Vegas (US)	4.50	Ibiza-Formentera (ES)	8.11	Miami (US)	3.89
Lanzarote (ES)	7.06	Okinawa (JP)	3.87	Miami (US)	4.05	Mallorca (ES)	6.37	Dubrovnik (HR)	3.52
Fuerteventura (ES)	6.71	Orlando	3.21	Paris (FR)	3.82	Menorca (ES)	5.44	Kuala Lumpur (MY)	3.37
Acapulco (MX)	6.56	Edinburgh (UK)	3.17	Mexico City (MX)	3.45	Dubai (AE)	4.21	Dublin (IE)	3.07
Cancún (MX)	6.16	Kuala Lumpur (MY)	2.69	Orlando (US)	2.85	Mecca (SA)	3.84	Lisbon (PT)	3.00
Kuala Lumpur (MY)	4.96	Lanzarote (ES)	2.67	Osaka (JP)	2.76	Gran Canaria (ES)	2.82	Bucharest (RO)	2.97
Ibiza-Formentera (ES)	4.51	Honolulu (US)	2.35	Cancún (MX)	2.40	Dubrovnik (HR)	2.73	Nice-Cannes (FR)	2.94
Malacca (MY)	-1.65	Malacca (MY)	-1.11	Malacca (MY)	-0.74	Dhaka (BD)	-0.59	Ehime (JP)	-0.61
Nairobi (KE)	-1.61	Luanda (AO)	-1.11	Manaus (BR)	-0.74	Karachi (PK)	-0.58	Miyagi (JP)	-0.61
Izmir (TR)	-1.58	Kolkata (IN)	-1.08	Izmir (TR)	-0.74	Kolkata (IN)	-0.58	El Hierro (ES)	-0.61
Daegu (KR)	-1.58	Dakar (SN)	-1.07	El Hierro (ES)	-0.74	Nairobi (KE)	-0.58	Izmir (TR)	-0.61
Dar Es Salaam (TZ)	-1.58	Ljubljana (SI)	-1.07	Ljubljana (SI)	-0.73	Lagos (NG)	-0.58	Manaus (BR)	-0.61
Manaus (BR)	-1.56	Lille (FR)	-1.07	La Palma (ES)	-0.73	Daegu (KR)	-0.58	Chengdu (CN)	-0.61
La Paz (BO)	-1.54	Daegu (KR)	-1.06	La Gomera (ES)	-0.73	Lahore (PK)	-0.58	Jinan (CN)	-0.61
Luanda (AO)	-1.53	Kuwait City (KW)	-1.05	Fuerteventura (ES)	-0.73	Curitiba (BR)	-0.57	Daegu (KR)	-0.60
Hyderabad (IN)	-1.52	Manila (PH)	-1.05	Panama City (PA)	-0.72	Malacca (MY)	-0.57	Oklahoma City (US)	-0.60
Belgrade (RS)	-1.48	Colombo (LK)	-1.04	Daegu (KR)	-0.72	Niigata (JP)	-0.57	Brasília (BR)	-0.60

Source: own compilation (2025)

Macau achieved the highest score in the overall overtourism index, while Melaka in Malaysia received the lowest score (-1.65). The results show that the cities with the highest scores, including Las Vegas, Okinawa, and Paris, are typically tourist hubs that attract visitors from both domestic and international markets.

visitors. In contrast, cities such as Nairobi in Kenya and Hyderabad in India received lower scores and are considered less attractive tourist destinations.

In terms of domestic indicators per local resident, Las Vegas performs best (8.12), while Malacca and Luanda score lowest (1.11). This indicates that Las Vegas, Acapulco, and Cancún are particularly attractive to domestic tourists, while cities with lower scores lag behind in terms of domestic visitor appeal.

In terms of international indicators per local resident, Fuerteventura received the highest score (13.14) and Dhaka the lowest (-0.59), suggesting that destinations with high scores (e.g., Canary Islands, Macau, the Balearic Islands, Dubai, Mecca, and Dubrovnik) are particularly popular with international tourists, while destinations at the other end of the list (e.g., Dhaka, Karachi, Kolkata, and Nairobi) attract fewer foreign visitors.

In terms of area-based international indicators, Paris leads the field (9.91), while Ehime is at the bottom of the list (-0.61). This finding confirms the outstanding international tourist appeal of global cities such as Paris, Macau, Geneva, and Dubrovnik, while demonstrating the relatively minor global tourist significance of cities such as Ehime and Miyagi.

The comprehensive analysis highlights the economic development and international popularity of high-scoring cities such as Honolulu, Paris, London, Acapulco, Las Vegas, and Okinawa. This is consistent with other international findings, such as the comprehensive research conducted by the WTTC (2022) (World Travel and Tourism Council), which examined the tourism readiness of 63 cities and classified them into five clusters. The group of cities with the most dynamic growth and leading role includes Amsterdam, Barcelona, Honolulu, Las Vegas, London, New York, Paris, San Francisco, Singapore and Tokyo. Meanwhile, the cities with the lowest level of tourism readiness

"emerging" cities with the lowest level of tourism readiness were Antalya, Bogotá, Cairo, Durban, Ho Chi Minh City, Jakarta, Lagos, Lima, Manila, Mumbai, and Riyadh. Cities with lower levels of development and less international renown are less competitive in the global tourism market.

3.3. The extent of overtourism in European locations

The results of the global study provided grounds for research with a narrower geographical focus. It also seemed justified to analyze tourist destinations that are specifically considered to be affected by overtourism (Nádasi et al., 2024). Qualitative research methods are frequently used to study the phenomenon of overtourism, and quantitative analyses on this topic are rare. In contrast to the qualitative methods often cited in the literature, which usually focus on the relationship between residents and visitors, Amore et al. (2020) published a study using a novel approach that applied quantitative analysis of the most significant tourism indicators. Amore et al. examined 15 European urban locations using a composite index, which was then used to rank the cities, with Venice in first place, followed by Florence, Seville, Lisbon, and Amsterdam.

The European Parliament's Committee on Transport and Tourism (TRAN) identified 67 destinations in Europe as places affected by overtourism (Peeters et al., 2018). The TRAN categorization distinguished between urban, coastal and island, heritage, and rural destinations. However, this classification is not a disjunctive resolution, and it is not possible to categorize individual settlements unambiguously in such a way that each settlement belongs to only one of the defined groups. Several urban sites have significant heritage, and several coastal sites are also rural, so these destinations could be classified in two categories. For these reasons, the rest of the statistical analysis focuses only on urban areas. One reason for narrowing the research focus to European locations is that, according to international literature, the problem of overtourism seems to be particularly relevant in European cities, as the continent's major tourist destinations have long been struggling with the negative effects of tourism. On the other hand, in terms of data availability and comparability, the European context provides a more uniform framework, which allows for a more in-depth analysis of the phenomenon. In addition, the results of the global analysis presented also support the prominent position of European settlements.

Furthermore, it is important to note that, for the sake of consistency, I have only considered European destinations that have been classified as overtourism sites by TRAN experts.

The first step was to check the internal reliability of the scale and to identify the correlation structure between the indicators used in the ranking. This revealed whether the results

obtained were reliable, whether the indicators used were consistent with each other, i.e. whether the internal reliability of the scale was adequate. This makes it possible to check whether the ranking results are consistent and interpretable. The analysis of the correlation structure between the tourism indicators used in the ranking made it possible to identify which indicators measure the same phenomenon. Indicators that were found to correlate with each other were omitted and not included in the analysis.

For the indicators that were ultimately used, Pearson's correlation coefficients and McDonald's omega were also determined for each pair. McDonald's omega is used to measure the reliability of the scale; it shows how coherent the selected indicators are and how well they explain the common latent factor (Kocsel, 2019). Based on the results, the overall reliability of the scale is excellent, as the omega value is 0.807. This indicates that the indicators selected for the analysis measure the same latent structure, namely overtourism. The two most influential elements are the number of nights spent in paid accommodation per capita and the number of tourist arrivals per capita, as reliability decreased to 0.665 and 0.698, respectively, after deleting these items individually. In addition, the highest correlation between these two factors can be found, as the correlation coefficient is 0.899 ($p < 0.001$). All correlation coefficients are significant at the 1% level, except for the value of -0.11 ($p = 0.065$) between total tourism expenditure as a percentage of GDP and the number of guest nights spent in paid accommodation by area. The ratio of total tourism expenditure to GDP also correlates strongly with the number of guest nights spent in paid accommodation ($r = 0.762$; $p < 0.001$) and the number of tourist arrivals ($r = 0.526$; $p < 0.001$). The number of air passengers per capita is moderately correlated with the number of tourist arrivals ($r = 0.464$; $p < 0.001$) and total tourism expenditure as a percentage of GDP ($r = 0.456$; $p < 0.001$).

For the period between 2014 and 2023, the 28 locations affected by overtourism were ranked for each year using the VIKOR, MMOORA, and TOPSIS methods, based on the indicators presented. The consensus-based ranking was then performed for each year using Cross-Entropy optimization. The rankings were averaged and then divided into four different periods between 2014 and 2023 (Figure 7). Thus, I separated the pre-COVID-19 period into two periods (2014-2016 and 2017-2019), followed by the years covering the pandemic (2020-2021), and finally the recovery and regeneration period (2022-2023).

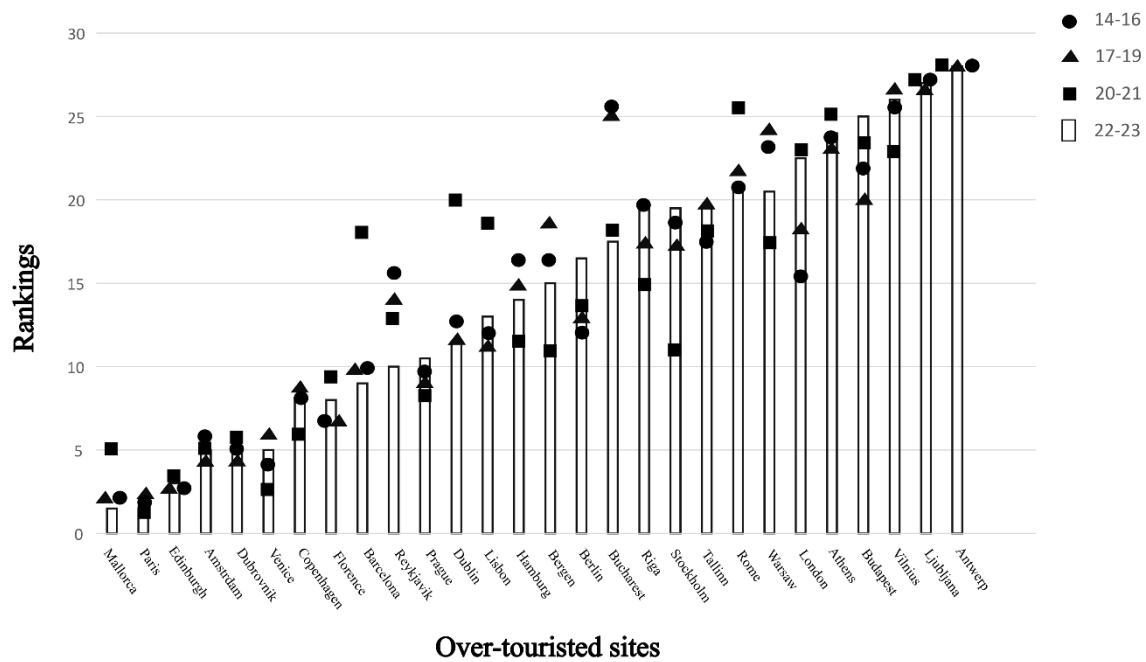


Figure 7: Average rankings of the sites affected by overtourism in the studied periods

Source: own compilation (2024)

The horizontal axis shows the geographical units, while the vertical axis shows their position in the ranking. The locations are listed from left to right according to their average ranking in the period 2022-23. Lower values in the ranking indicate higher levels of overtourism, while higher values indicate lower levels of overtourism. Among the most overtouristed locations, Amsterdam, Antwerp, Dubrovnik, Edinburgh, Ljubljana, Paris, and Prague have remained stable in the rankings over the various periods. Bergen, Bucharest, Copenhagen, Hamburg, Riga, Stockholm, Venice, Vilnius, and Warsaw showed fluctuations in the 2020-21 period and achieved higher rankings, meaning that the level of overtourism increased in these locations. Barcelona, Dublin, Florence, Lisbon, and Mallorca also showed greater fluctuations in the 2020-21 period and achieved lower rankings, meaning that, according to the indicators examined, the level of overtourism decreased compared to other cities. The biggest shifts in the ranking were observed in Barcelona, Bucharest, and Lisbon, which fell significantly in the ranking in 2020-21, while Riga, Stockholm, and Vilnius moved up between 2020 and 2021. The most visited destinations were Mallorca, Paris, Edinburgh, Amsterdam, Dubrovnik and Venice. There are cities that moved up in the ranking in each period, suggesting that the level of overtourism has increased steadily over time (e.g., Bucharest, Reykjavík), and there are also cities that have consistently fallen behind in the

list, meaning that, based on the indicators examined, the level of overtourism has decreased compared to other locations (e.g., Berlin). Apart from fluctuations, Northern European cities such as Riga, Stockholm, Tallinn, and Vilnius were among the less overtouristed locations, as confirmed by the biplot graph in Figure 8. The figure graphically shows the changes in the rankings from year to year and the groups of locations examined. In terms of basic performance indicators, the PCA proved to be appropriate for the analysis, and the data are suitable for analysis, as the KMO index (Kaiser-Meyer-Olkin criterion) of 0.89 is very good and the Bartlett test is also significant ($\chi^2 = 840$; $p < 0.001$) (Csallner, 2015).

The variance explained by the two principal components (PC) was 98% (greater than the required 70%), and the first principal component was the most significant, contributing to more than 50% of the explained variance. The vectors show the relationship between each year and the given PC. The length of the vector indicates the strength of the correlation between each component and each year. The direction of the vector indicates the sign of the correlation.

The second component mainly separated the years 2020 and 2021 from the period before the COVID-19 crisis (between 2015 and 2019). The upper region includes locations that showed improvement (improvement in ranking) in overtourism immediately after COVID-19. The bottom of the list includes locations that became even more overtouristed after COVID-19, thus achieving a better ranking.

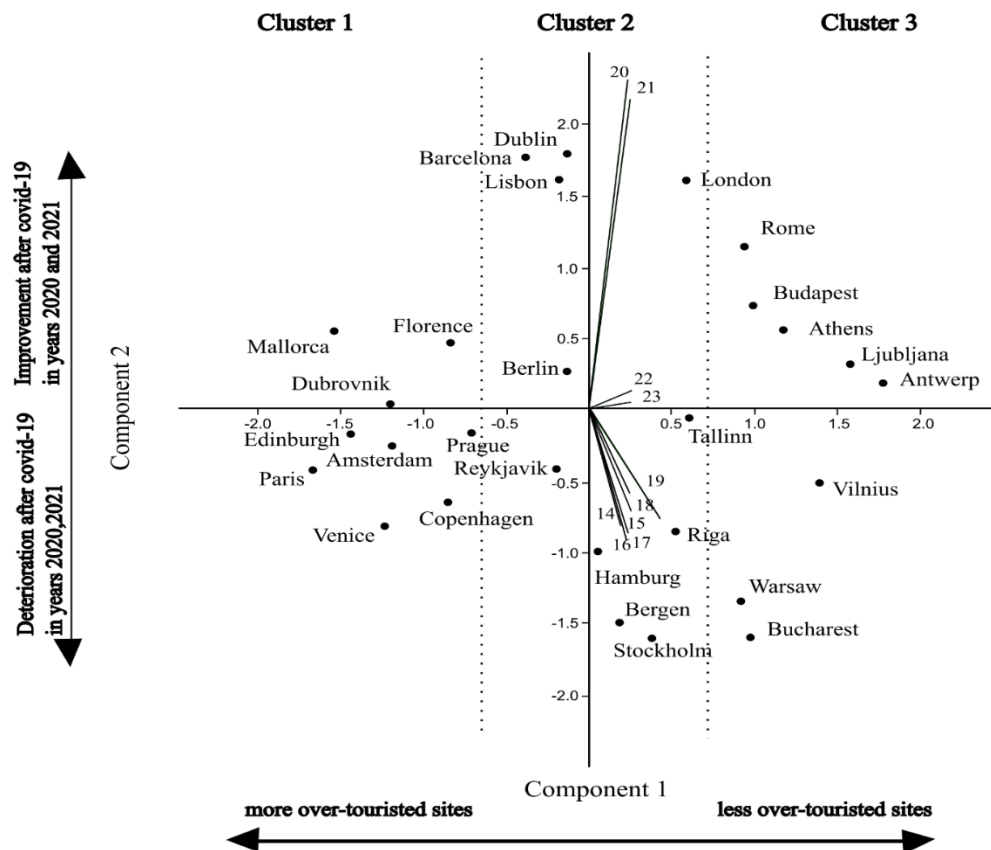


Figure 8: PCA biplot graph of overtouristed site rankings from 2014 to 2023

Source: own compilation (2024)

Component 1 mainly refers to the years 2014, 2022, and 2023. The less overtouristed locations were on the right side of component 1, while the locations more affected by overtourism were on the left side of the axis. Locations closer to the horizontal axis had more stable rankings, such as Dubrovnik, Edinburgh, Reykjavik, and Tallinn.

Although cluster analysis is a different statistical method, PCA was also able to capture the cluster structures of the data. Clusters 1, 2, and 3 can be interpreted as groups with high, medium, or low levels of overtourism. The K-means clustering algorithm was used to develop the final cluster structure, which showed a higher Silhouette index (0.519) than hierarchical clustering (0.445).

Table 3 shows the cluster profiles and the averages of the indicators for the periods examined.

Table 3: Description of clusters by research indicators for each period

Cluster	Indicator	Unit	Average of 2014-2023	Period			
				2014-2016	2017-2019	2020-2021	2022-2023
Cluster 1	air passengers/population	passenger/resident	20.86	25.38	30.56	9.91	10.47
	nights in paid accommodation/area	night/1000 m2	101.00	99.08	119.22	55.15	122.41
	nights in paid accommodation/population	night/resident	22.88	23.76	27.69	10.76	26.44
	overnight visits/population	visit/resident	6.63	6.81	8.15	3.07	7.61
	total travel spends/GDP	1000 US\$/GDP	119.32	130.89	139.38	54.97	136.23
	Short-stay accommodation via online platforms*	nights spent (million)	4.26	-	5.52	1.84	5.43
Cluster 2	air passengers/population	passenger/resident	7.53	9.53	10.91	3.46	3.50
	nights in paid accommodation/area	night/1000 m2	60.43	64.69	74.04	22.39	71.67
	nights in paid accommodation/population	night/resident	6.71	7.23	8.13	2.96	7.55
	overnight visits/population	visit/resident	2.89	3.10	3.50	1.33	3.26
	total travel spends/GDP	1000 US\$/GDP	48.79	53.10	53.44	26.23	57.89
	Short-stay accommodation via online platforms*	nights spent	2.58	-	3.45	1.21	3.06
Cluster 3	air passengers/population	(million)	4.51	5.14	6.76	2.31	2.40
	nights in paid accommodation/area	passenger/resident	27.35	27.52	33.27	12.07	33.51
	nights in paid accommodation/population	night/1000 m2	3.17	3.15	3.89	1.41	3.89
	overnight visits/population	night/resident	1.57	1.59	1.94	0.70	1.86
	total travel spends/GDP	visit/resident	48.65	48.40	54.16	27.69	61.71
	short-stay accommodation via online platforms	1000 US\$/GDP	2.04	-	2.56	0.88	2.68

Note: Data on short-term stays are sourced from Eurostat and are available for 2018-2023. However, due to compatibility issues, they are only used for illustrative purposes and have not been used in the ranking, as they are not available for Dubrovnik, Edinburgh, Mallorca, and London.

Source: own compilation (2024)

One of the reasons for the growth of urban tourism before the outbreak of the COVID-19 pandemic was the emergence of Airbnb and other online accommodation booking platforms. Airbnb capacity is very high in some European cultural cities (Christensen, 2020), so for comparison purposes, another factor, short-term accommodation through online accommodation booking platforms (e.g., Airbnb), was also taken into account. This indicator only covered the period between 2018 and 2023, and data was only available for 24 of the 28 locations examined. Although it provided additional information, it was not

used in the ranking as data was not available for four key locations (Dubrovnik, Edinburgh, Mallorca, and London), but removing these locations from the ranking would not have been appropriate. However, the index correlated somewhat with the ranking of the locations, as the Pearson correlation coefficient was -0.306 ($p < 0.001$). This suggests that the higher the number of nights spent in short-term accommodation in a given location, the more likely that location is to be heavily affected by overtourism.

According to the ANOVA test, the clusters show significant differences in the indicator of tourist arrivals per capita, with an F-statistic of 137.19 ($p < 0.001$). In addition, the number of guest nights spent in paid accommodation per local resident proved to be the second most significant variable with an F-statistic of 130.55 ($p < 0.001$), followed by the number of air passengers per local resident with an F-statistic of 57.15 ($p < 0.001$). Based on the results, it can be concluded that the strongest correlation with overtourism is observed in the number of guest nights spent in paid accommodation per capita, followed by the number of tourist arrivals per capita, and the third most significant indicator is the number of air passengers per local resident. It can also be observed that, regardless of the level of overtourism, all indicators decreased between 2020 and 2021, then regained or exceeded their pre-pandemic levels between 2022 and 2023.

Table 4 shows the results of rank aggregation using randomization tests. During the randomization test, 1,000 random rankings were generated, and then the sum of absolute differences (SAD) between the aggregated (optimal) rankings was calculated for each method for the entire test period. The mean and standard deviation of these values were also calculated, as well as the probability of obtaining a certain SAD value or less. If the value of p is very low, this indicates that the SAD value could not have been achieved by chance and that it was fairly low and did not differ significantly from the optimal ranking.

Table 4: Sum of Absolute ranking Difference (SAD) values and randomization test results (2014-2023)

Year	SAD values of each method				Randomization test results	
	VIKOR	MOORA	TOPSIS	Sum	Mean/st.dev.	p-values per method Vikor/Moora/Topsis
2014	180**	144***	174**	498	260.6/30.0	0.003/0.001/0.002
2015	208*	156***	210*	574	261.5/31.7	0.045/0.001/0.049
2016	262	186*	202*	650	262.1/32.5	0.482/0.014/0.038
2017	210*	248	230	668	261.1/31.5	0.045/0.337/0.153
2018	246	194*	226	666	262.6/32.1	0.279/0.019/0.115
2019	228	236	222	686	260.6/30.4	0.139/0.210/0.102
2020	228	150***	200*	578	259.8/31.2	0.155/0.001/0.028
2021	246	150***	200*	596	261.7/32.6	0.306/0.001/0.033
2022	250	126***	146***	522	262.4/32.1	0.344/0.001/0.001
2023	268	214	206*	688	260.1/31.2	0.584/0.074/0.044
Sum	2326	1804	2016			

Note: ' : $p<0.10$; *: $p<0.05$; **: $p<0.01$; ***: $p<0.001$

Source: own compilation (2024)

Table 4 shows the SAD values and the results of the randomization test for three different methods (VIKOR, MMOORA, TOPSIS) for each year between 2014 and 2023. The SAD value shows how much the ranking of a given method deviates from the aggregate ranking. The lower the SAD value, the closer the result of the given method is to the overall ranking. The SAD values of the MMOORA method are generally lower than those of VIKOR and TOPSIS, indicating that MMOORA is more stable and closer to the aggregate ranking. The sum of the SAD values for each method is shown in the row for all years examined. This indicates the extent to which each method deviated from the aggregate values over the entire period. The sum for MMOORA (1804) is the lowest, making it the most stable, while VIKOR (2326) shows the most deviation.

The next column of the table shows the average and standard deviation of the SAD values obtained from the randomization test for each year. The average value of the test was approximately 261, with a standard deviation of 32.

These values serve as a reference for comparing how much the results of a given method deviate from random values.

The p-values shown on the right side of Table 4 indicate whether the ranking of a given method differs significantly from random values ($p < 0.10$: weakly significant; $p < 0.05$: significant; $p < 0.01$: highly significant). If the SAD value of a method is significantly lower than the average of the randomized values, then the method is reliable and stable. The low SAD values and significantly different p-values of the MMOORA method indicate that this method was better able to model the aggregate ranking than the other two methods in most of the years examined.

In terms of periods and p-values, the analysis shows that at the beginning of the COVID-19 pandemic, the rankings did not differ significantly from random rankings, indicating that there was greater uncertainty in the rankings during this period. This may be due to the fact that in the early stages of the pandemic, the data were characterized by greater volatility and unpredictability, which meant that the methods produced less stable results.

4. NEW AND NOVEL RESULTS OF THE DISSERTATION

4.1. Global research

Within the framework of a global analysis, I carried out a complex ranking of 255 tourist destinations, which was achieved by including the most relevant indicators in terms of tourist overload.

I used the VARCLUS method to cluster the composite indicators used to analyze overtourism. In the five clusters thus formed, the area-based indicators proved to be the strongest in explaining the variance of the individual indicators, with all components explaining 89% of the variance. The new results of my research were presented by calculating the average score of the VARCLUS components of each cluster, examining the patterns of overtourism in different types of locations, in each region and over time. The most notable of these is the dominance of international indicators in the European coastal-island and heritage overtourism sites examined, and the dominance of domestic indicators in North American and Asian urban overtourism sites. The settlements that achieved high scores in the complex, multidimensional ranking using the VARCLUS method are also outstanding in terms of international and domestic tourism. The ranking, which takes into account demographic, geographical, economic, and tourism indicators, uses a unique and innovative methodological approach.

Although some authors mention the different perceptions of international and domestic tourists and the fact that the presence of international tourist groups contributes significantly to the feeling of overcrowding (Koens et al., 2018), it seems that the link between overtourism and an excessively high proportion of international tourists has not been proven before. However, the analysis I have presented has made it possible to distinguish between the overload caused by domestic and foreign visitors, identifying key locations where the balance between international and domestic tourism is severely disrupted.

Principal component analysis (PCA) helped us back up other authors' views that overtourism mainly affects European destinations, with some Asian places getting hit harder and North American areas getting hit moderately, but it's not really a big deal in most of the Australian and African locations examined, which can be considered a novel finding of the research,

since although it is not a new finding, the results of an analysis examining fresh data and focusing on a wide geographical area have not yet been published by other authors.

4.2. European research

In a quantitative analysis of 28 European tourist destinations, mainly urban, data from before and after the COVID-19 pandemic were compared, which distinguishes this research from the existing literature.

In the doctoral thesis, I presented a composite index for the objective ranking of the European overtourism sites examined and for monitoring changes over different periods. To this end, indicators with an excellent reliability scale were used. The 28 European destinations affected by overtourism were ranked using the VIKOR, MMOORA, and TOPSIS methods for each year between 2014 and 2023, and then four periods were defined. One of the new scientific results of my doctoral thesis is that I conducted a temporal comparative analysis of the 28 European destinations affected by overtourism in terms of the most important tourism indicators, separating the pre-COVID-19 period, the pandemic period, and the subsequent recovery period.

My dissertation provides valuable new results with a Cross-Entropy-based ranking aggregation for the period before the COVID-19 pandemic, which proved to be stable between 2014 and 2019. I consider the presentation of the ranking during the pandemic period to be a particularly new result, which, contrary to previous years, shows a temporary strengthening of cities in northern Europe based on the composite indicators examined. I would also like to highlight the finding that, among the derived indicators included in the study, tourism density and tourism intensity had a greater impact than other variables. A randomization test was also performed for the ranking summary, which showed that MMOORA performed best among the three multi-criteria decision-making methods used.

Using principal component analysis (PCA), I classified the 28 destinations examined into three clusters according to high, medium, or low levels of overtourism, and presented the cluster profiles.

5. PRACTICAL APPLICABILITY OF THE RESULTS

5.1. Trends in overtourism

Considering the tourism trends of the past decades, it seems like a good idea to encourage the use of digital solutions in tourism, like contactless payment, online booking systems and online ticket purchasing for attractions, or the use of real-time visitor monitoring systems (e.g., Google Popular Times). Such smart tourism analytics tools can also help manage excessive tourist traffic through the use of dynamic pricing, an algorithm based on comparing current demand with expected demand based on historical data or forecasts. In dynamic pricing, prices change dynamically during regular reviews based on the relationship between supply and demand, taking into account changes in the market environment and consumer behavior (Danyi, 2020). In the case of city centers, seaside resorts, and natural attractions most affected by overtourism, pricing based on weather conditions, time of day, and tourist seasonality may also be justified.

It may be worth considering extending the opening hours of the most popular museums and cultural institutions and introducing night-time visits. Combined with dynamic pricing, this can improve the visitor experience by reducing long waiting times before entry and avoiding large crowds during peak periods. Other benefits of nighttime opening include attracting new visitor groups, for example through special guided tours for younger generations.

In places where human presence causes excessive damage, it may be necessary to tighten environmental regulations (e.g., to reduce excessive pressure on coastal regions) or introduce visitor restrictions. Differentiating tourist taxes between popular and less visited sites can also be effective. In the case of overvisited cultural, historical, and natural attractions, an effective strategy may be to bundle them with lesser-known attractions.

By applying this strategy, overcrowded attractions could be partially relieved by encouraging tourists to visit less frequented sites during their stay in the area, which would receive more attention. This could be encouraged by offering discounted combined tickets, free tickets, and themed packages.

In the long term, in addition to implementing creative ideas, it is essential to introduce regulations and restrictions. Regulations that focus on tourist behavior are becoming

increasingly necessary. Some of these have been formulated for the safety of visitors (e.g., a ban on hiking in flip-flops in the Cinque Terre area (Street, 2019)), but there are also those designed to ensure the peace and quiet of the local population (e.g., a ban on drinking alcohol at night) or to protect heritage (e.g., restrictions on the use of drones near fragile ecosystems or historical monuments). Such regulations help visitors to behave in line with the principles of sustainable tourism, but further education, training and awareness-raising campaigns could further strengthen responsible behavior among tourists.

In my doctoral dissertation, I not only presented the range of measures and restrictions that have been introduced or planned, but also sought to strengthen the practical applicability of my doctoral thesis with other innovative ideas and good practices.

5.1.1. *Global trends*

The application of the VARCLUS method effectively identified five different clusters of overtourism indicators, each represented by latent components that facilitate the interpretation of the data. These components showed strong explanatory power, accounting for 89% of the variance, with high correlations between the indicators and the corresponding clusters. The analysis revealed notable regional and typological patterns, highlighting the dominance of international indicators in European coastal-island and heritage sites and the dominance of domestic indicators in North American and Asian urban sites. In addition, the results emphasized the impact of area- and population-based metrics in distinguishing the dynamics of overtourism. The VARCLUS ranking shows that cities with high scores, including Paris, Las Vegas, and Okinawa, are prominent tourist destinations both domestically and internationally. These cities show significant strength in terms of both the number of overnight stays per capita and area-based indicators. In contrast, cities with low scores which are typically characterized by less developed economies, play a smaller role in tourism. The results provided a robust framework for analyzing overtourism patterns and suggest that the VARCLUS method offers a practical and interpretable alternative to traditional approaches to clustering complex tourism data.

The use of a time series approach made it possible to identify trends, focusing on dynamic processes as opposed to cross-sectional analysis. The present analysis also made it possible to distinguish between congestion caused by domestic and foreign visitors. This phenomenon has economic policy implications, highlighting the need for different regulatory mechanisms for domestic and inbound tourism. In European coastal and heritage destinations such as Mallorca, Dubrovnik, or Venice, where the balance between international and domestic tourism has been severely disrupted, third-degree price discrimination may be applied to foreign visitors. In the context of such destinations, it may be worth

considering the introduction of a "sustainability tax" or "heritage fee" for visitors, with the revenue being used for site maintenance and infrastructure development. In order to protect fragile resources and ensure sustainability, the emphasis should be on visitor regulation, conservation, and dynamic pricing. In North American and Asian urban locations, the focus should be on urban planning, infrastructure regulation, and congestion management to support growing domestic tourism while maintaining the quality of life for local residents. A balance must also be struck between tourism growth and improving urban standard of living. There is a need to strengthen infrastructure and support sustainable domestic tourism.

5.1.2. European destinations

The significance of the research lies in its approach and the novelty of its perspectives, as well as the large number of destinations included in the study: the sample comprises 28 European destinations, predominantly cities, but also enriched by geographical diversity such as entire islands. The value of my findings is further enhanced by the opportunity to analyze tourism trends during the COVID-19 pandemic and the recovery period following the pandemic. This dual perspective not only allows for a unique interpretation of the phenomenon of overtourism, but also provides a deeper understanding of the tourism sector's responses to the crisis and its regeneration processes.

When analyzing tourism indicators for European destinations, the ranking for the years prior to 2020 appears very stable, with Paris, Mallorca, Edinburgh, Dubrovnik, and Amsterdam occupying the top spots in almost every year between 2014 and 2019. However, the first year affected by COVID-19 disrupted the ranking. In the year affected by the COVID-19 pandemic, destinations in northern Europe took center stage: Amsterdam, Copenhagen, Dublin, Stockholm, Berlin, Hamburg, Bergen, Riga, and Tallinn all moved up in the rankings of places affected by overtourism. However, the impact of the pandemic appeared to be temporary, as in most cases the situation returned to pre-pandemic levels or very similar ones.

The results also confirm that there is a need to promote sustainable tourism practices in relation to overtourism. This can be achieved, for example, by developing city-level sustainable tourism strategies that can serve as models for smaller towns. In cities experiencing overtourism, these strategies often include restrictions on tourists (e.g., limiting the number of tourists, controlling visitor behavior), entrance fees, special permits for certain sensitive heritage sites, and the introduction or increase of tourism taxes. It is undeniable that observing and monitoring the phenomenon, collecting data and subsequent analysis can help identify early signs of overtourism based on existing tourism trends.

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7. LIST OF PUBLICATIONS RELATED TO THE DISSERTATION



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Subject: PhD Publication List

Candidate: Andrea Szöllős-Tóth
Doctoral School: Doctoral School of Management and Business
MTMT ID: 10071384

List of publications related to the dissertation

Articles, studies (6)

1. **Szöllős-Tóth, A.**, Kovács, S., Müller, A. É., Nádas, L.: Global trends in tourism scale change in the 21st century.
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Total IF of journals (all publications): 2,8

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The Candidate's publication data submitted to the Tudóstér have been validated by DEENK on the basis of Web of Science, Scopus and Journal Citation Report (Impact Factor) databases.

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