

Research article

Sentiment Analysis: a Comparative Study of Online Booking Platforms Used for Spa Tourism in Northern Oltenia, Romania

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Abstract: Purchasing a tourist package for a specific tourist destination has become extremely easy and transparent through the diversity and continuously upgraded online booking platforms. Their content provides information through the reviews among tourists and hospitality managers, being, at the same time, opened Big Data for researchers or policymakers. Mining the reviews of two global platforms (Booking and TripAdvisor) and a national one (Turistinfo) the study aims to analyze the tourists' sentiments and emotions experienced in a balneary destination such as Northern Oltenia, Romania. The research addresses the overarching question of whether positive sentiments dominate in destinations led by spa tourism, and consequently, which emotions are definers? For this purpose, 10,945 online reviews, from 2018 to 2020 for 248 accommodation units of the studied area were collected and processed in Statistical Package for the Social Sciences (SPSS 17.0) and Geographical Information System (GIS). The key findings indicate that most travelers are satisfied with tourist destinations, sustained by the dominance of positive sentiments (82%) associated with a high rating score (8.9) and 'joy' and 'trust' emotions. Mostly positive sentiments are linked to the quality of five- and four-star accommodation units, but also to the intimacy of the small family's business, the spatial framing in the landscape, and the friendship of the hosts. At the same time, the repulsive aspects draw attention to some problems of the state of the indoor or outdoor environment and the price-quality ratio. The research demonstrates the effectiveness of leveraging electronic word of mouth as a valuable resource for stakeholders in the tourism industry. This approach enables a swift and sustainable assessment of tourist satisfaction, providing valuable insights for accommodation service providers to make informed decisions.

Keywords: sentiment analysis; reviews; booking platforms; balneary tourism; Big Data; spatial analysis

1. Introduction

Recent progress in online and mobile technologies has expanded significantly in the hotel industry [1]. Thus, online and mobile services offer information about the hotel and booking possibilities, with spatial and temporal easiness [2] moving from the initial approach, for website promotion, to interactive booking and sale services [3]. Their content is in an unprecedented dynamic process, implicitly their role in the development of marketing and post-purchase policies [4] in the context of increasing consumer demands, sustainable development, and competitiveness in the tourism market [5]. Thus, the traditional way of collecting personal opinions and views through surveys [6] - time and resource-consuming and often irrelevant because negative opinions are more difficult to express or accept and can be taken out of context or even deleted [7] - has been replaced by online applications, where the respondent can express his/her opinions openly. Thus, the widespread use and application of online booking systems have improved the quality

of tourism services, as many of them contain elements to ensure consumer feedback towards tourism industry managers [8].

Together with the development of blogs, social media, and tourist unit websites, they allow easy sharing of information, freely and transparently, to create a significant and free database, accessible for tourists who want to know others' opinions to choose the best destination or hotel [9].

In this regard, there are numerous systems on the market that operate globally, regionally, or nationally, with certain features and tools to facilitate translation into different languages, according to diverse customer' categories, online payment systems, etc. Romania, the country with one of the best online navigation systems in the world [10] has experienced a rapid alignment of the tourism industry to online promotion and particularly to external booking systems such as Booking.com, Tripadvisor.com, Agoda.com or national ones (Turistinfo.ro).

Booking.com, a platform founded in 1996 in Europe with 24/7 customer support in 43 languages for 28 million accommodation listings [11] ranks first place in search engines based on tourism keywords, 1,050,000,000 results in 0.58 seconds [12], with 230.5 million visitors in January 2021 [13].

The Tripadvisor.com platform set up in 2000 in the US displays 465,000,000 results in 0.62 seconds [12] and registered in January 2021, 101.5 million visits to its web page [13].

Turistinfo.ro (appeared in 2006) is the first booking accommodation site in Romania and is considered the largest tourism portal in the country [14]. It has about 179,000 results in 0.48 seconds [12], with 720,000 visits in January 2021 [13].

Many of these platforms make pools for Big Data analysis and marketing managers for further research through the possibility of studying different aspects that allow understanding of the qualitative aspects of the tourism industry [15] such as spatial aspects of tourist feedback [16] through sentiment analysis (SA).

SA is one of the recent research topics in the field of information processing [17] which analyzes large amounts of data of natural language (NLP-Natural Language Processing), based on machine learning techniques. SA is a concept that encompasses several tasks, mainly processing, mining, or extracting information from various textual sources and classifying feelings. Opinions, feelings, appreciations, attitudes, and emotions are the core elements of the analysis of feelings [18, 19] to obtain the characteristics of an action, product, service, problem, or subject [7] and represent elements with qualitative value.

SA, widely used in various fields, has gained widespread popularity in tourism studies [20, 21], from hotel management to the spatial assessment of tourist destinations in different geographical areas such as Indonesia [22, 23], USA [24, 25], Turkey [7], South Italy [16], Canada [26], Hong Kong or Singapore [27]. Thus, within this frame of reference, the addition of a new study that approaches temporally and spatially the analysis of the online environment's feelings of a tourist destination mainly focused on spa tourism can bring added value to such type of research in the field.

The central question guiding this research is 'does sentiment analysis reveal that positive emotions characterize a destination focused on health tourism cures?' To address this question, the study has outlined several clear objectives. Firstly, to evaluate the sentiments of tourists by carefully analyzing online reviews as feedback regarding their experiences in tourism facilities. The second objective aims to identify key factors influencing the formation of these positive sentiments, providing a detailed perspective on emotions contributing to the construction of a positive tourist experience. Lastly, to identify the role of resorts in the destination by spatial clustering of tourists' sentiments and ratings for accommodation units.

2. Literature review

Over the last decades, most of the debates and research on the sustainable development of tourism have been focused on finding indicators, but, perhaps, the most important element is the feedback given by consumers, which returns, recommends, or not a destination. It is argued mainly that the tourists' choice to visit a destination or buy a tourist product is influenced by friends' and relatives' opinions, travel agencies' consulting services, or marketing policy [28], but, in recent times of rapid digitalization, the final decision on the holiday destination is influenced by social media implicitly the assessment of online reviews [22, 29, 30].

Tourists' online reviews have become a novel information source for researchers in the field of tourism [31, 32]. The evaluation by tourists serves as the primary method for assessing the company's performance [33]. In the service industry, reviews represent a potent means of gauging customers' perceptions regarding the quality of services or products [34, 35, 36]. They are also a helpful way to improve competitiveness and determine future strategies [31] and market trends.

Many review sites and social networks have launched their application programming interfaces (APIs), facilitating researchers' and developers' data collection and analysis [37].

SA offers many opportunities to understand consumer behavior, mainly due to the massive increase in user-generated content on review websites and social networks [17], also, due to advanced technology, which has led to social media, blogs, and review sites, products or events power increase [38]. Websites, such as travel booking platforms, store information from these sources to summarize or compose a general opinion and generate a positive, negative, or neutral feeling towards a hotel, a stay, an area, etc. Considering this, small and large companies, as well as other organizations, such as governments use these tools to find out what people say about their brands, products, or members [39, 40, 41].

SA operates with social media data, considered as tools that encourage the community to contribute with ideas and knowledge by participating in debates or by providing feedback and reviews [1, 22, 42, 43], being one of the primary sources of information for tourism and hospitality customers [44, 45]. The importance of these analyses with online data is also given by their transformation into essential channels of promotion [8, 46, 47] and sales with a potential market of over 4.38 billion Internet users [43].

There are, however, approaches that draw attention to some limitations of online data that can hinder the process of analyzing feelings: the quality of opinions, forum spammers, irrelevant opinions, and false opinions [9]. The issue of credibility has been brought to discussion by many researchers. Some researchers believe that sources are relatively reliable [45, 48, 49], while others have concluded that online sources are less credible [50, 51]. Other studies highlight various analysis software that cannot capture context-related issues [16].

However, the benefits resulting from SA related to the understanding and analysis of the emotions or satisfaction of tourists are essential to attract new customers, gain their loyalty, or provide better services [28]. Tourist experiences and satisfaction, subjects encapsulated within reviews, are directly and empirically perceived by consumers [52], playing a crucial role in the selection of a destination or the decision to revisit it [53, 54, 55].

SA highlights tourists' satisfaction/dissatisfaction, measured through the difference between the quality of a product or service and pre-purchase expectations [56, 57, 58]. SA is high when expectations related to services or products are met or exceeded [57]. Customer satisfaction plays a vital role in motivating tourist loyalty, leading to positive reviews and recommending one product or service to others [56, 57, 59]. Customer dissatisfaction may influence future tourist services or product acquisitions [60,61], reorientation to other companies, or negative reviews that can impact the company's reputation and image [61, 62].

Post-purchase satisfaction with a tourist product is a revisiting factor because a tourist's intention to revisit a particular destination can be mainly affected by the quality and/or satisfaction of the visit [63, 64].

The satisfaction-intention paradigm is based on previous performances and satisfactions, which determine the intention to repurchase [65]. Numerous studies have indicated that the intention to visit is closely linked to past visits, demonstrating that previous visits are among the key motivators [66, 67, 68]. Tourists demonstrated a higher inclination to revisit a hotel when it evoked a sense of joy [69].

SA of text data on Tripadvisor platforms and/or Booking.com was approached through various methods: word list-based method [70], Leximancer [71], Polarity Aggregation Model [72], transformed sentiment analysis into a multi-classification problem based on machine learning methods [21], etc., demonstrating the advantages and limitations of such approaches.

The application of SA in spa tourism research has not received widespread attention. Studies have shown its effectiveness in customer segmentation within China's spa tourism industry [73], while in Portugal, it has aided in identifying and addressing negative aspects that require resolution [74].

That's why, in an era characterized by the growth of the aged population mostly tied to health tourism, such qualitative research could be considered very important for all stakeholders. The paper is organized as follows: the overview of research based on sentiment analysis and tourism the introduction of the case study, the description of the research flow, results, discussions, and finally conclusions and future works.

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3. Setting scene of studied area

The tourist region of North Oltenia includes the Subcarpathians of Oltenia between the Motru River Valley in the West and the Topolog River Valley in the East, being in connection to the north, with the western half of the Southern Carpathians and bordered in the south with a predominantly agricultural piedmont plateau. It stretches over an area of 2,395 km², which represents 1% of Romania's surface, concentrating about 3% of the country's population, according to the National Institute of Statistics (NIS) [75], with an average density population of 293 per km² (Figure 1).

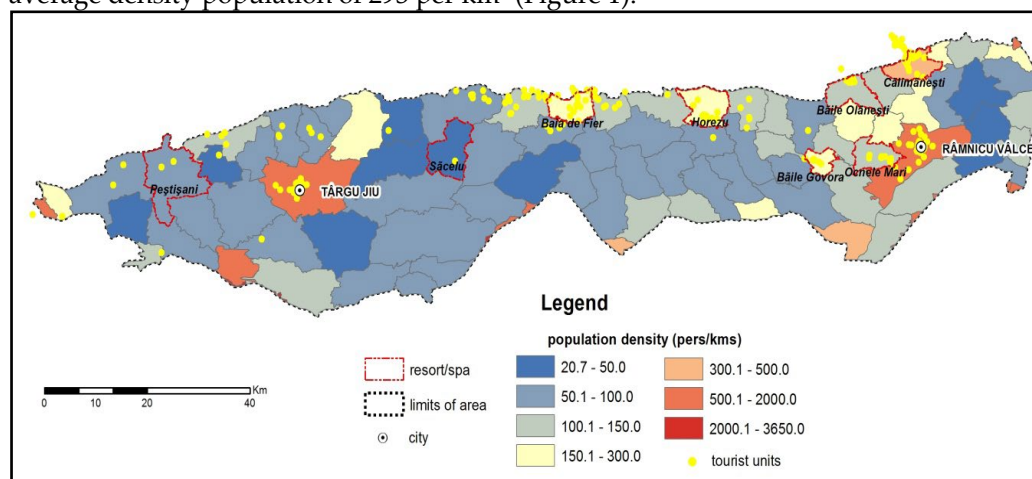


Figure 1. Population density and tourist establishments in 2019. Processed in ArcMap after NIS data, 2021.

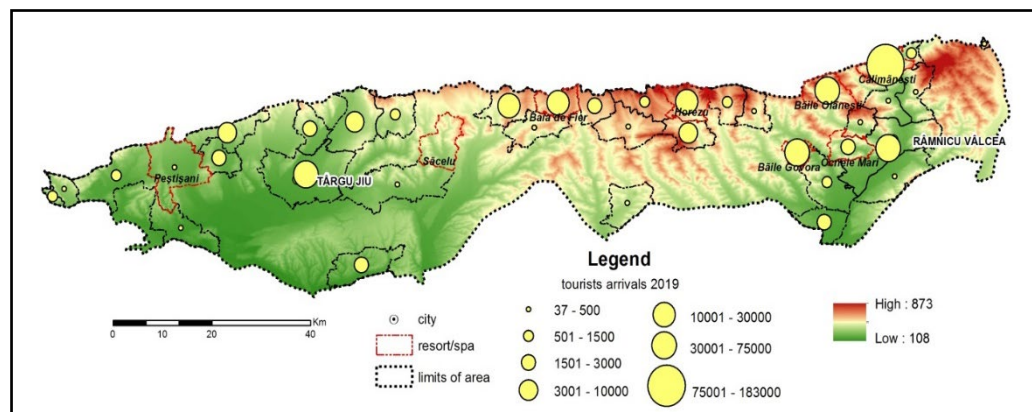


Figure 2. Number of tourist arrivals in resorts/spas and other settlements. Processed in ArcMap after NIS data, 2021.

There are 273 tourist accommodation units established and stimulated by both national and local importance spa resorts, which have developed due to the presence of mineral and hot water springs. They capitalize on the bioclimate with soothing, calming effects on the nervous system upon contact with the mountains, as well as on agrotourism resources [76].

The tourist flow in 2019 was 487,279 arrivals, respectively 3.6% of the country's total, gathering as main poles of attraction the national importance tourist resorts Călimănești-Căciulata (37.4%), Băile Olănești (13%) and Băile Govora (7%), and the municipalities of Râmnicu Vâlcea and Târgu Jiu (over 10% each) (Figure 2).

4. Research methodology

The research on opinion mining through the SA method on tourist destinations in Romania, particularly on spa resorts, is a novelty. The study started with bibliographical sources, followed by a description of the studied area, providing general geographical and tourist primary data about the region to help better understand the analyzed topics. SA has been applied to research tourist satisfaction.

Thus, the data mining method has been applied to reviews from global booking platforms Booking.com and Tripadvisor.com, recognized as two of the most important and used digital tourism global companies, with tourist and related services, and social platforms, where consumers can freely share their tourist experiences [77]. Turistinfo.ro is a Romanian booking platform where tourists can both purchase travel packages and share opinions about their journeys.

The problem of the credibility of information about tours and trips on these platforms [50, 51] is avoided because the collected data are secured. These online systems allow only those who have purchased to express their opinions, which can further help others to easily understand issues. For the current case study, we gathered a total of 10,945 reviews spanning from June 2018 to August 2020, sourced from 248 systematically classified and unclassified tourist accommodation facilities. The selection of this time frame was influenced by the policy of the Booking.com platform, which retains reviews for a maximum of two years compared to other platforms with a much longer review history. The size of the reviews ranges from a minimum of one word across all platforms to a maximum of 895 words on Booking.com (Table 1). All reviews without word content or one meaningless word (such as 'and' or 'by') have been deleted. This period, starting from June 2018 to August 2020, was chosen because, within the context of the COVID-19 pandemic, it encapsulates a significant transition in the tourism industry, particularly starting from 2019 when the pandemic began to have a global impact. By including these years, there is an opportunity to assess how events related to COVID-19 have influenced reviews and travelers' perceptions of accommodation services.

Table 1. Statistics of the Reviews' length. Source: Statistics extracted by Rvest

No words	No	
	reviews	%
1-9	2256	20.6
10-19	2605	23.8
20-29	1587	14.8
30-39	1168	10.8
>40	3329	30
Total	10945	100

Exploring the intricacies of web scraping, a pivotal methodology in contemporary data acquisition involves the systematic extraction of targeted information from online sources. Within the purview of this study, the R language, operating seamlessly within the RStudio environment, is fortified by the Rvest package—a robust tool designed for effective navigation of intricate web structures and the extraction of pertinent data [78].

The intricacies of web scraping become palpable when examining the process through a practical lens. Consider the following code snippet, which encapsulates the extraction of review text from Booking.com [79]:

```
install.packages('rvest')
library(rvest)
url_booking <- 'https://www.booking.com/hotel/example.html'
booking_reviews <- url_booking %>%
  read_html() %>%
  html_nodes('.review-text') %>%
  html_text()
```

In this succinct script, `url\_booking` represents the designated URL. Leveraging the Rvest package, the code reads the HTML structure, targets specific nodes containing review text (identified by the class `review-text`), and subsequently extracts the textual content. This methodological step ensures a selective and focused retrieval of data essential for the study.

To provide a comprehensive overview of the data processing workflow, it is essential to highlight that, in a subsequent stage, the tm package in the R programming language was employed. This package played a crucial role in conducting a meticulous data cleaning process, ensuring that the extracted set of reviews is optimized for subsequent analyses.

Having harvested the reviews, the subsequent phase involved their preservation and structuring. To accomplish this, the R language's `write.csv` function was employed, encapsulating the acquired data in a CSV (Comma-Separated Values) format. This procedure serves a twofold purpose: it enhances data organization and facilitates subsequent analytical endeavors [80, 81].

The code snippet for exporting the reviews is exemplified as follows:

```
write.csv(booking_reviews, file = 'booking_reviews.csv', row.names = FALSE)
```

In this script, `booking\_reviews` denotes the dataset, `booking\_reviews.csv` represents the desired filename, and `row.names = FALSE` ensures the exclusion of row names in the exported file. The utilization of this function ensures a systematic and structured cataloging of the acquired reviews, priming them for further analyses and insights.

The overarching goal of this comprehensive process is to equip researchers with a refined dataset, systematically curated and structured, laying the foundation for nuanced

sentiment analysis and contributing to the substantive understanding of tourist perceptions in the chosen domain.

SA has been processed through R Software, namely the Syuzhet package. Data analysis followed a scheme of research flow as shown in Figure 3. The Syuzhet package, renowned for its effectiveness in linguistic sentiment analysis, has established itself as a preferred choice in tourism studies [82]. Its versatile features, such as 'get_sentiment' for sentiment scoring and 'get_nrc_sentiment' for more nuanced emotion analysis, allowed us to delve into the emotional nuances of tourist sentiments. Specifically, the 'get_nrc_sentiment' function enabled the extraction of emotions based on the NRC Emotion Lexicon, offering a detailed understanding of sentiments such as joy, sadness, anger, and more [83]. The application of R and the Syuzhet package not only provided a nuanced understanding of emotional aspects within our dataset but also emphasized the tool's significance in tourism research. Its efficiency and versatility make it an invaluable resource for researchers and practitioners, enhancing sentiment analysis in a way that contributes both to academic excellence and the practical improvement of tourism services.

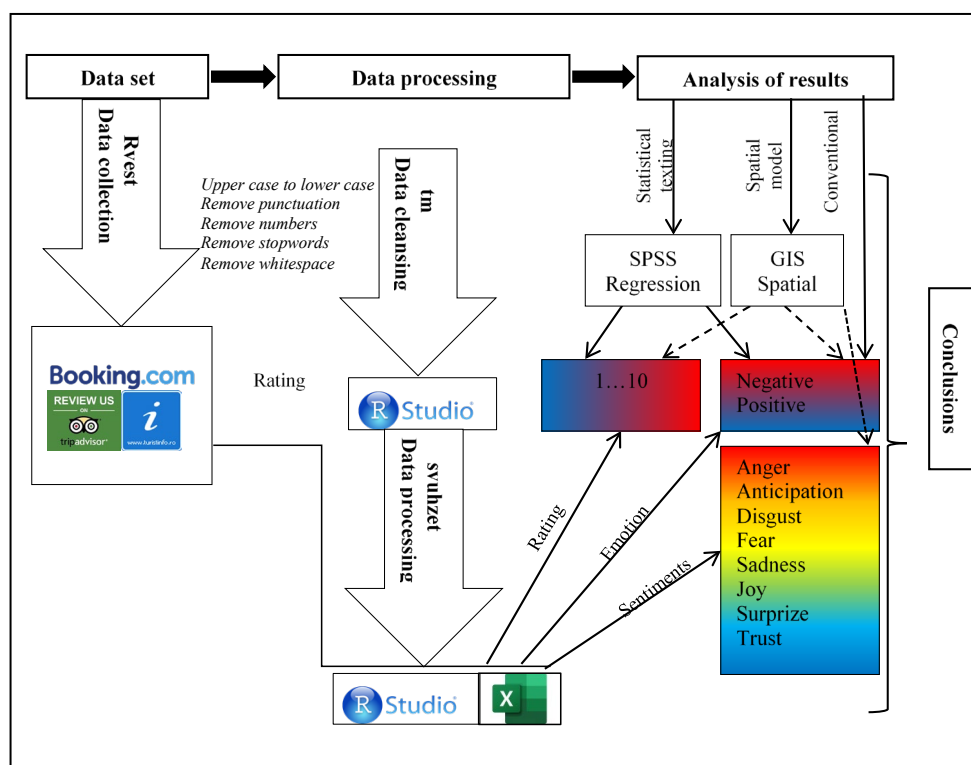


Figure 3. Scheme of research flow

In the first stage, an empirical analysis of the SA results was performed according to the extracted elements: tourists' opinions (feelings and emotions), review score or rating (Rs), distance from the hotel to the center (d), period the consumer was accommodated (T), staying (t), preferred room type (s), information about types of tourists (tt), gender (G), nationality (N). The next stage analyzed the type of preferred booking platform: Booking.com (B), Tripadvisor.com (A), Turistinfo.ro (I), and also the positive (L) and negative (D) feelings selected through the RStudio program. The graphs have been generated by processing data in Microsoft Excel 2015.

The SPSS 17.0 program was used to test emotions and feelings correlated with the tourists' ratings through the Regressive Equation. The dependent variables were encoded such as: (a) 1 stands for L and D, whether positive or negative feelings extracted from the program R, and (b) 0 stands for missing variable. In addition to that, the Rs (rating score) given by the tourist for each hotel structure was normalized on a scale from 1 (very little) to 10 (excellent) for all booking platforms.

Spatial representation has been obtained in ArcMap, 10.3.1 Esri ArcGIS package, Symbology Level, and Hot Spot Analysis. To analyze the spatial clustering of the topics, we used the score obtained in R, followed by the Getis-Ord G_i^* statistic program [84, 85]. This statistical instrument by z-scores and p-values provides the high or the low values, which may coincide, indicating whether or not to reject the following null hypothesis [71].

5. Results and discussions

5.1. Demographic particularities of the tourists' reviews

The reviews on the Booking.com platform are predominant, but they differ over the three years, being fewer in 2020, a year affected by the pandemic with periods of closure or limitation of tourism activity. Although 10% of respondents did not provide their gender, 49.6% represent the male respondents. By writing a review, tourists have the opportunity to evaluate their stays and give a score. The majority of reviews evaluate tourists' stays, attributing scores exceeding 8.1 (76.6%) (Table 2).

In the Oltenia Subcarpathians, national interest resorts, the county municipalities, followed by local interest resorts clustered 81.9% of the total reviews. Regarding types of tourists, one can notice that most of them are families with children and couples (77.9%).

Although the destination includes resorts focused on spa treatment that requires a longer stay, the duration of most of the stays is between 1 and 3 days (84.1%).

Tourists' favorite seasons are summer (51.9%) and autumn (22.8%), and 3 stars (56%) and 4 stars (20.4%) accommodation structures located at a distance of less than 1 km from the center (47%) with a capacity between 11 and 50 beds (58%). Furthermore, the majority of tourists are domestic residents (80.6%) (Table 2).

Table 2. Variable characteristics and rating of the sample. Source: Statistics extracted by Rvest

Variable	Characteristics	(%)	Variable	Characteristics	(%)	Variable	Characteristics	(%)
Platform	Booking	83.1	Time spent	1-3 days	84.1	Distance from center	< 1 km	47
	Tripadvisor	5.7		4-7 days	15.1		1.1-2 km	19.5
	Turistinfo	11.2		8 days or over	0.8		> 2.1 km	33.5
Year	2018	32.6	Season	Winter	13.5	Number of beds places	< 10 beds	17.6
	2019	57.9		Spring	11.8		11-50 beds	58.1
	2020	9.5		Summer	51.9		51-100 beds	7.8
				Autumn	22.8		> 100	16.5
Gender	Male	49.6	Stars classification	Unclassified	17.9	Country of origin	Romania	80.6
	Female	40.4		2 stars	4.8		International	19.4
	Anonymous	10		3 stars	56.7	View rooms	Yes	4.7
Rating	>5	6.5		4 stars	20.4		Usually	95.3
	5.1-8	16.9		5 stars	0.2			
	8.1-10	76.6	Type of tourist	Others	18.1			
Location	Băile Olănești	8.2		Families with children	43.2			
	Băile Govora	4.6		Couples	34.7			
	Călimănești-Căciulata	27.5		Groups of friends	11.9			
	Râmnicu Valcea	18.5		Solitaire	8.1			
	Târgu Jiu	12.5		Business travelers	2.1			
	Horezu	3.9						
	Baia de Fier	6.1						
	Săcelu	0.6						

5.2. Sentiment Analysis

Exploring tourists’ perception of a specific tourist product reveals both positive and negative remarks expressed as likes and dislikes in the form of terms and expressions connected to different aspects: accommodation, access transport, destination attractions, facilities, etc. [86].

Feelings and emotions expressed in reviews of the Oltenia Subcarpathians on all three booking platforms are mostly (over 80%) positive, defined as the following categories: trust, joy, anticipation, and less negative such as anger, disgust, fear, and sadness. The analysis shows that the reviews from Turistinfo.ro, the positive emotions and feelings are slightly higher than those on the other two international platforms, as shown in Figure 4.

Regarding the association of words, there is a difference among the three platforms in terms of the most used words. The differences consist of terms belonging to the positive range such as ‘welcoming’ and ‘quiet’ for Turistinfo.ro and ‘friendly’, ‘nice’, and ‘good’ for the international platforms. The negative range of words resides in expressions like ‘noise’ and ‘pool’ for Booking.com and Tripadvisor.com, as well as ‘parking’ and ‘kitchen’ for Turistinfo.ro (Figure 4). The explanation for these differences lies in the types of tourists, namely Romanians on the national platform and foreigners, as well as Romanians, on the international ones.

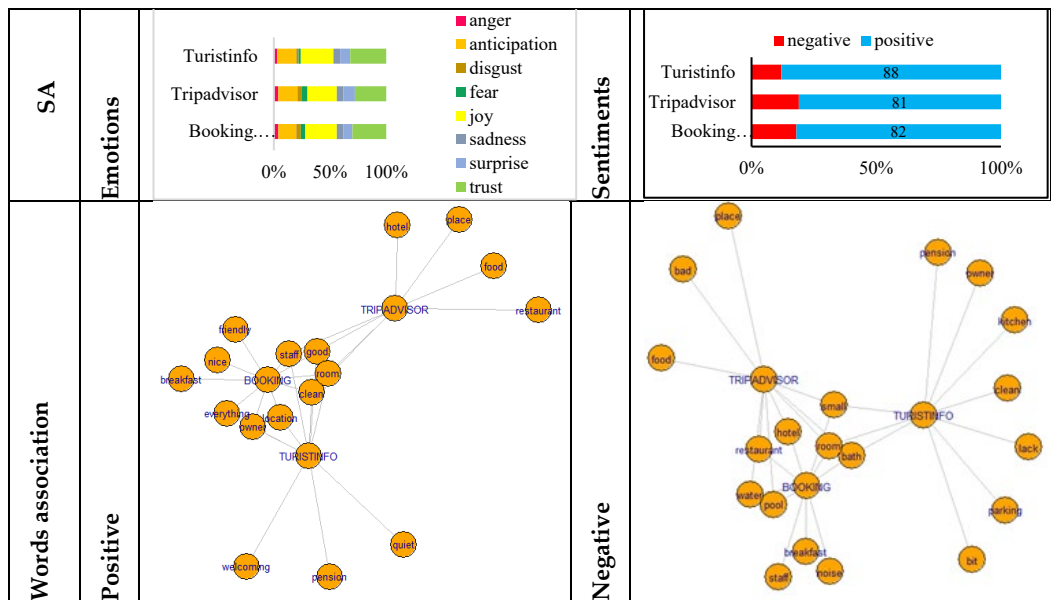


Figure 4. Sentiment analysis results and differences in word association on the three platforms

Emotions analysis by years shows that ‘anger’ and ‘disgust’ feelings were higher in 2020, while ‘joy’ and ‘confidence’ were higher in 2019 and 2018, probably as a consequence related to the SARS-CoV-2 pandemic situation.

Examining the evolution over the years in detail, there is a notable focus on room quality, with ‘cleanliness’ emerging as a positive aspect. However, the increased usage of the word ‘pool’ in 2020 is associated with negative sentiments, as illustrated in Figure 5. The other words remain constant.

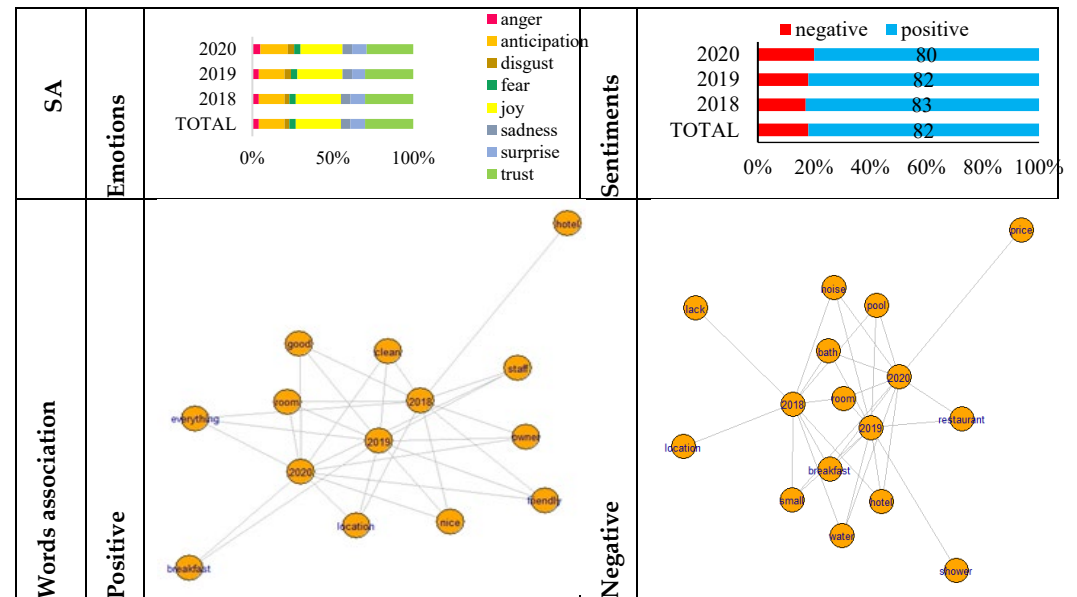


Figure 5. Sentiment analysis results and difference in word association by years

The reviews for stays meet the values of positive or negative emotions and feelings, such as in low ratings, the values of negative emotions and feelings are higher than the values of positive and almost positive ratings.

Tourists who gave higher ratings repeated the word 'clean' both in the positive word range and as a negative term in low ratings within the negative word range. Also, within the negative words range in the low ratings, 'location' appears as a new word, as shown in Figure 6.

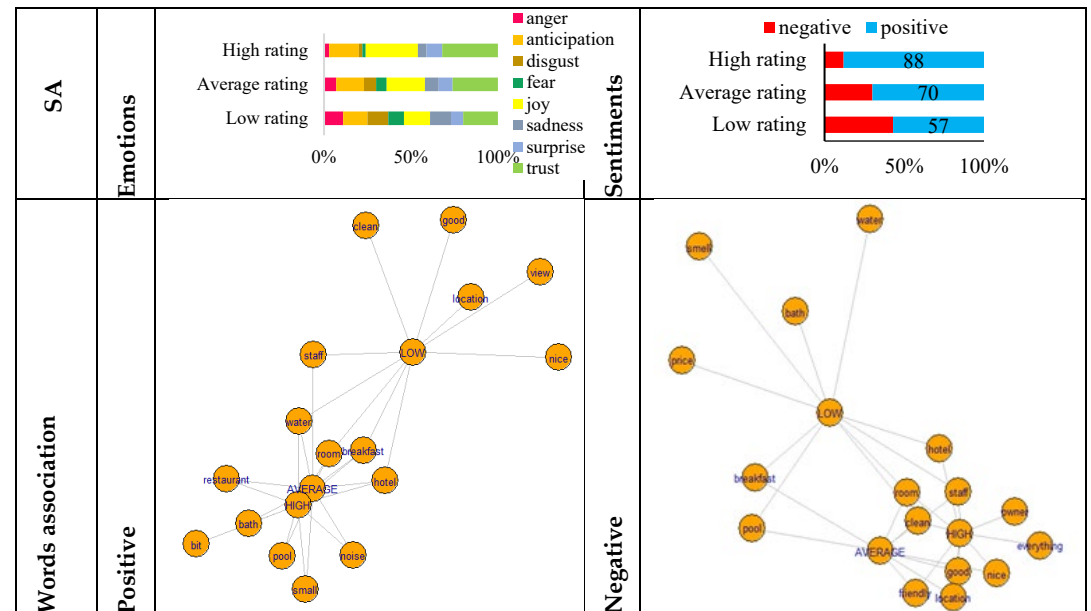


Figure 6. Sentiment analysis results and difference in words association in rating hotels

Tourists' gender in tourism is an important aspect, and we observed that female customers tend to assess with more positive feelings [10] compared to their male or anonymous counterparts, as illustrated in Figure 7.

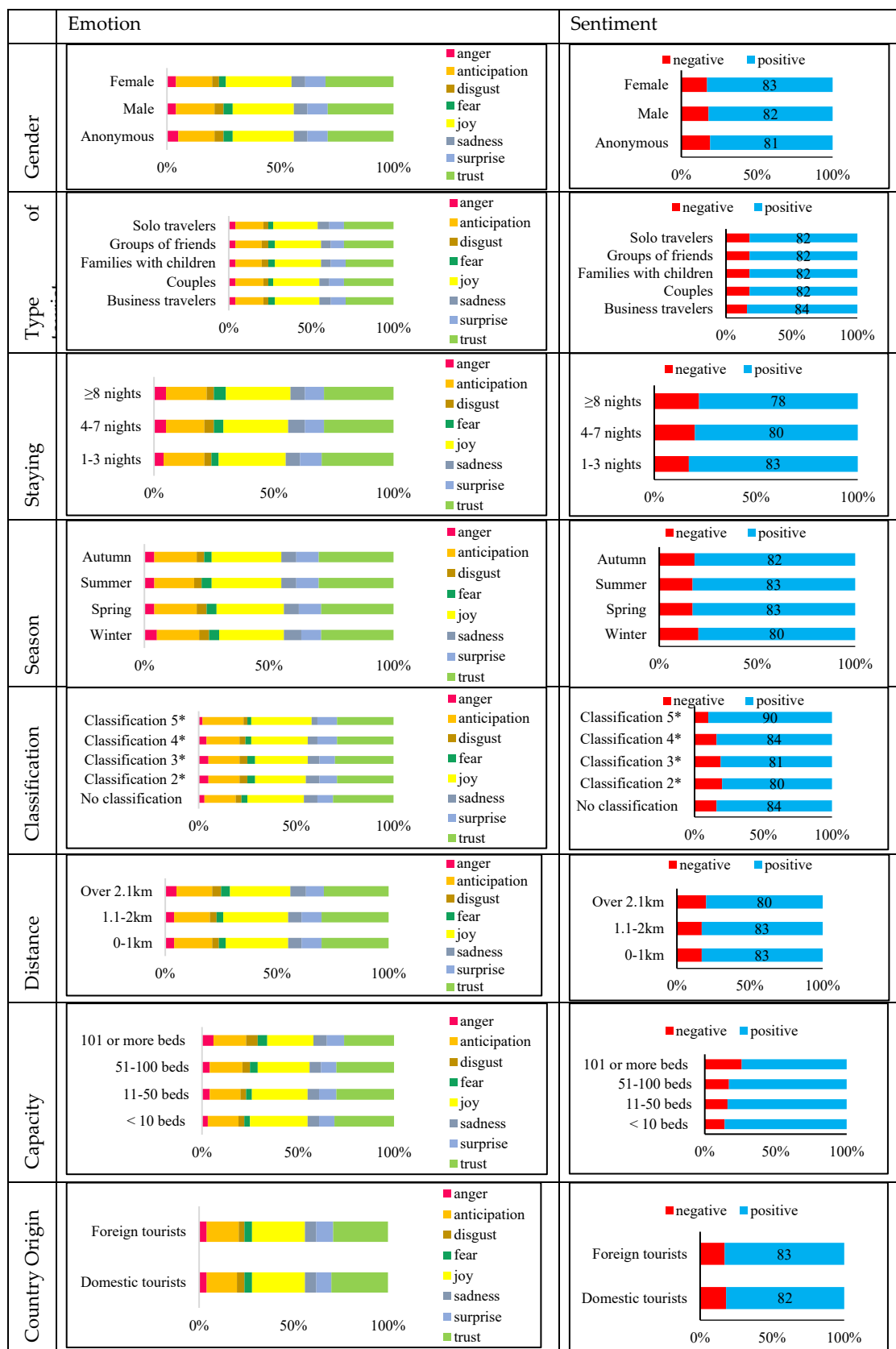


Figure 7. Sentiment analysis results by tourists' demographic and hotel characteristics

There are insignificant differences in the values of the emotions and feelings by types of tourists. Within the negative words range, the 'business travelers' used 'parking' as well as 'groups of friends' used 'work' which are different from other types of tourists.

The duration of the trip is a key element of a tourist package, having an important role in expressing emotions and feelings, so one can notice that positive feelings are higher for

1-3 days stays, compared with longer stays. By season, there are lower values of positive emotions and feelings in winter. The words 'beautiful' appear in summer reviews as part of the positive word range, and 'price' comes in winter reviews as a dominant term of the negative word range. In the category of this variable, the frequency shows a repetition of the words 'bed' and 'stay' in ratings for stays longer than 8 nights and increased use of the word 'pool' for stays of 4-7 nights within the negative words range.

The higher the standards of hotel and boarding houses classified from 2 to 5 stars/flowers (or unclassified accommodation units such as rooms/apartments for rent) the more positive feelings. On the other side, when the accommodation unit has a lower capacity, it tends to create a cozier atmosphere, evoking a greater sense of satisfaction and positive emotions among tourists.

Regarding the tourist structures' classification, there is a greater frequency of the words 'beautiful' and 'welcoming' for the unclassified accommodation units, and 'view' for the 5-star structures, which comes as part of the positive category of words. The negative category of words is dominated by the term 'kitchen' for the unclassified accommodation units.

Tourists feel better if accommodation is closer to the center of the town/city. Negative expressions include the word 'parking' for the closest to the center structures, and 'noise', 'bed', and 'price' for the farthest ones.

Also, tourist structures with a larger capacity generate more significant emotions of anger, disgust, and fear, unlike those with less accommodation capacity. 'Beautiful' and 'quiet' as negative terms stand for accommodation units with less than ten beds, while 'parking', 'pool', and 'price' stand for accommodation units with more than 51 beds. Another category is made by tourist structures with less than 51 beds which is described with words like 'noise' and 'shower' as negative words.

There isn't so much difference between the feelings and emotions of Romanian tourists and foreigners. Regarding the origin of tourists, foreigners repeated 'breakfast' several times, while the domestic ones uttered 'quiet' in the category of positive words. In the category of negative words, the foreign tourists constantly wrote 'bed', 'night', and 'shower', while the domestic ones wrote 'lack', 'noise', and 'pool'.

5.3. Rating score and sentiments correlation

The overall rating value is 8.9, which is linked somewhat with the positive sentiment percent (82%). To test the correlation between Rs and sentiments synthesized as negative (like - L) and negative (dislike-D), regressive analysis was applied, where the Rs was considered as a dependent variable, and positive and negative sentiments as independent variables to test their role in the classification process. In the resulting model, the adjusted R-square explains 19.1% of the variance in the data. The F-test is highly significant (1295.00), so it can be assumed that the model explains a significant amount of variance for Rs as shown in Table 3.

Table 3. Model of regressive equation between Rs and sentiments

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	5.626	0.065		86.845	0.000		
Positive	3.325	0.065	0.438	50.887	0.000	1.000	1.000
Negative	-0.045	0.031	-0.012	-1.446	0.148	1.000	1.000

Dependent Variable: Rating. Source: Extras from SPSS v.17 output

Thus, in the 'enter' linear regression Rs have a significant predictor in 'L', respectively positive sentiments. The higher the standardized coefficients (beta) are, the bigger the

impact revealed. The multicollinearity in this linear regression model has a tolerance > 0.1 for it.

5.4. Spatial analysis

The spatial configuration of the accommodation units shows a concentration in Călimănești Resort (26%) and the municipalities of Râmnicu Vâlcea and Târgu Jiu (12%). About 30% are not classified, there is one 5-star hotel (Băile Olănești), 7% are classified with 2 stars, about half of all are 3 stars classified, and the rest are 4 stars classified and they are located mainly in Râmnicu Vâlcea City.

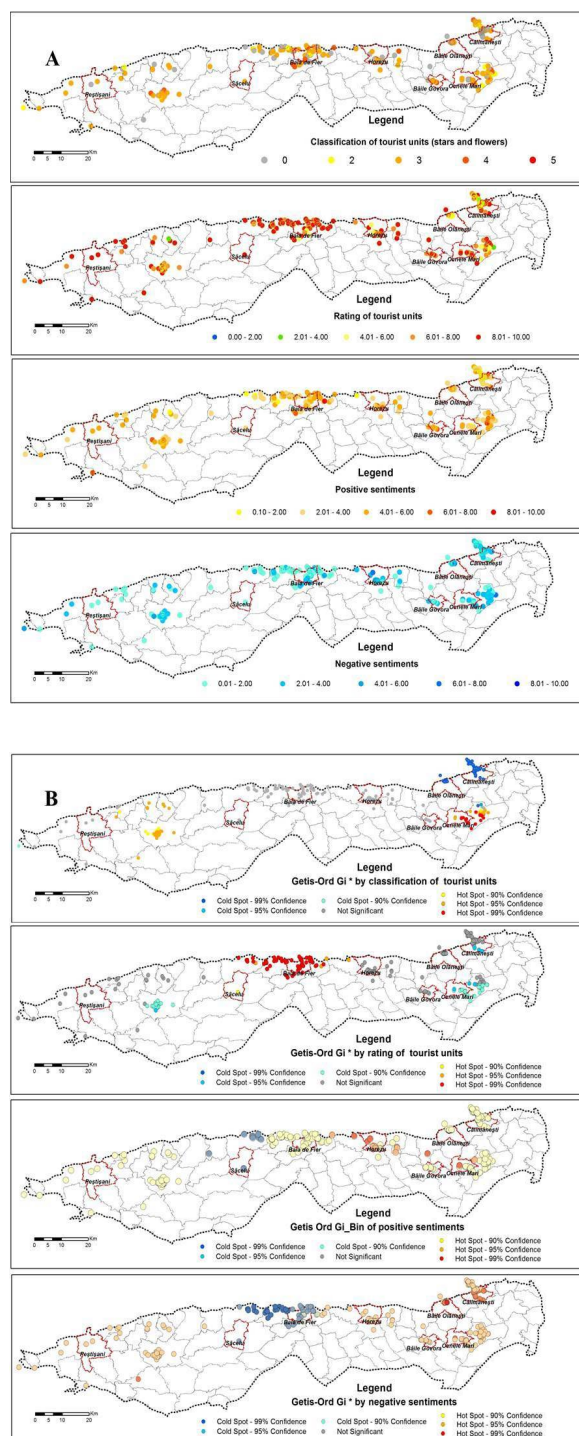


Figure 8. Hotels' classification, rating, negative and positive sentiments maps (A) and their clustering by Getis-Ord Gi* (B)

The average Rs is 8.9, and about 75% have a value over 9, mostly located in the resorts and large cities. Figure 8 shows that negative sentiments have low values under the threshold of gap 5, with the most unlikely structures in Horezu resort or other towns or cities in the area, while positive values at the top of the ranking are concentrated in the central parts of resorts and towns.

The spatial distribution patterns of classification Rs, and positive and negative sentiments used the Getis-Ord G_i^* statistic to measure their spatial autocorrelation to identify the clustering models. According to the Getis-Ord G_i^* statistic, divisions are cold spots of 99%, 95%, and 90%, then hot spots of 90%, 95%, and 99% (Table 4).

Table 4. Statistics of hot spot and cold spot hotels in the studied area

	Confidence	Classification	Rating	Positive	Negative
Hot Spots	99%	21	59	0	0
	95%	41	4	5	3
	90%	8	1	13	34
Cold spots	99%	98	48	0	28
	95%	1	7	8	27
	90%	0	0	1	6
Total	100%	159	121	31	98

Considering the confidence levels of 99%, 95%, and then 90%, the highest clustering is observed for hotel ratings, while the positive sentiments reveal the lowest clustering.

The classification clustering was applied to observe any relation between the three topics of analysis. Lower clusters appear in Călimănești Resort and higher in the eastern part of the area (Râmnicu Vâlcea City and Ocnele Mari Resort). A second trend of high clustering is in the western part of the region around Târgu Jiu City and its surroundings.

Rs clustering is specific in the northern part, where new hotels and boarding houses were built in an area recently declared as a resort, near the Carpathian Mountains. A low cluster trend is observed in the previous eastern resorts, defined by higher clustering of classification. This space is also a subject of low clusters of negative sentiments and to some extent positive sentiments.

5.5. Discussions and Practical Implications

The practical implications of our findings extend beyond academia, offering actionable insights for tourism managers and policymakers. The practical implications of the findings for tourism managers and policymakers are significant and can guide strategic decision-making within the tourism industry. Firstly, the insights derived from SA offer a valuable tool for tourism managers to assess the overall satisfaction levels of tourists visiting critical destinations in Romania. Understanding the sentiment dynamics allows managers to identify areas of strength and weakness in their services, enabling them to tailor improvements that align with tourists' preferences and expectations.

Furthermore, tourism managers can utilize the sentiment data to refine marketing strategies and promotional efforts. Positive sentiments can be leveraged in advertising campaigns to enhance the destination's image, attract more visitors, and foster a positive reputation. Conversely, addressing negative sentiments promptly can help mitigate potential reputational damage and improve overall visitor satisfaction.

For policymakers, the findings contribute to evidence-based decision-making in the development and enhancement of tourism policies. By understanding the factors influencing tourist satisfaction, policymakers can implement measures that promote a positive experience for visitors. This may involve infrastructure improvements, cultural preservation initiatives, or the development of new attractions aligned with the preferences expressed in sentiment analyses.

Overall, the practical implications extend to the strategic planning of both tourism managers and policymakers, providing actionable insights to enhance the overall quality of tourism experiences and strengthen the competitiveness of Romania's critical destinations in the global tourism market.

6. Conclusions

It is vital to quantify the feedback and to analyze how consumers think and react during their tourist experiences. Such an approach brings new inputs to the tourism industry, helping in the continuous improvement of the quality of products and services to meet tourists' demands, needs, and expectations.

SA has recently received special attention in the research field, but also from practitioners. The study used a data mining system that allowed the analysis and research of a large amount of data, figuring out the qualitative elements that may make a difference in tourism.

This study delved into the dynamics of tourist reviews across three platforms, with a primary focus on Booking.com, within the Oltenia Subcarpathians region. Despite a consistent prevalence of reviews on Booking.com, the year 2020 witnessed a decline due to pandemic disruptions. The demographic profile revealed a significant representation of male respondents (49.6%) and a diverse range of tourists, predominantly families and couples favoring shorter stays. Seasonal preferences leaned towards summer (51.9%) and autumn (22.8%), while 3-star (56%) and 4-star (20.4%) accommodations garnered popularity.

Emotion analysis uncovered fluctuations, notably higher levels of 'anger' and 'disgust' in 2020, potentially linked to the SARS-CoV-2 pandemic. Positive aspects included a spotlight on room quality and cleanliness. However, the increased use of the term 'pool' in 2020 correlated with negative sentiments.

The implications of this study extend to both tourism managers and policymakers. For managers, a nuanced understanding of tourist sentiments guides service improvements, tailored marketing strategies, and effective reputation management. Policymakers can leverage these insights for evidence-based decision-making, influencing policies related to infrastructure, cultural preservation, and attraction development.

This study contributes valuable insights into the intricacies of tourist satisfaction, laying the groundwork for future research and strategic planning within the tourism sector of the Oltenia Subcarpathians region.

7. Study limitations

The study exhibits certain limitations that warrant consideration. Firstly, the accuracy of the results could be further enhanced by extending the analysis to encompass additional national platforms and diverse data sources, such as online hotel databases and evaluations from Google reviews. The exclusive reliance on the three selected platforms and the narrow scope of three years might introduce potential biases in the findings. To address this, future studies could adopt a more comprehensive approach, considering a broader array of platforms and an extended timeframe. Additionally, it is crucial to acknowledge the inherent biases in online reviews, recognizing that user-generated content may not fully represent the entire spectrum of traveler experiences. This limitation underscores the need for caution when generalizing findings from online reviews to the broader context of tourist satisfaction and preferences.

8. Further Research:

This study marks a crucial step in evaluating satisfaction through SA by examining vital destinations in Romania. To shape future research endeavors, a notable avenue involves extending the application of SA to diverse tourism sectors beyond the spa tourism focus. Investigating sentiment dynamics across contexts like cultural tourism, adventure tourism, and ecotourism presents a captivating opportunity to comprehend the distinct factors influencing tourist satisfaction.

To deepen future research, a more comprehensive integration of managers' opinions within the SA framework is recommended. Integrating tourism managers' perspectives can yield a holistic understanding of the industry, exploring the alignment or divergence with guest sentiments for valuable insights into refining strategies. Additionally, expanding the study of social media texts through SA methodologies to encompass a broader range of tourism experiences promises a comprehensive view of tourists' opinions. Analyzing sentiments expressed on various online platforms, beyond conventional booking websites, enriches the dataset, offering a nuanced understanding for researchers and industry professionals alike.

Authors Contributions

Conceptualization, M.N.T., and D.N.; methodology and data collection, M.N.T.; analysis and writing, M.N.T., and D.N.; review and editing, M.N.T. and D.N.; supervision, M.N.T.; funding acquisition, M.N.T. All authors have equal contributions, and they read and agreed to the published version of the manuscript.

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