ICEMIT BLACE
The Second International Scientific Conference on Economics, Management and Information Technologies – ICEMIT 2025
CONFERENCE PROCEEDINGS

Context aware model for sentiment analysis in tourism

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Article info

Original scientific paper

DOI:
https://doi.org/10.71159/icemit2506A

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Acknowledgement: This research is part of the scientific research project "Application of predictive analytics and artificial intelligence for the advancement of tourism in North Macedonia," funded by the Ministry of Education and Science of the Republic of North Macedonia, under number 15-6171/19 dated August 7, 2025.

Abstract

The latest methods for natural language analysis allow for contextual analysis of the text and examination of the type of emotions that can be detected. Emotions such as anger, joy, sadness, optimism can show us which emotions prevailed among visitors during their stay in a certain destination. These emotions, through the written reviews, can influence future potential tourists who plan to visit the same destination. In this paper, a combined sentiment analysis of reviews taken from online travel agencies was performed, analyzing the polarity of the sentences, but additionally analyzing the emotions in their context, while also monitoring their change over time. More than 2,000 reviews from visitors who visited the same destination and were accommodated in different accommodation facilities were analyzed.

Keywords: *sentiment, analysis, context, model, review*

1. Introduction

The development of natural language analysis models, especially the transformer neural network model, has significantly contributed to better analysis of the context of the entered text. These networks allow the analysis of complete sentences, unlike previous models based on recurrent networks that analyzed the text word by word. Additionally, according to their architecture for parallel data processing, the time required for text analysis is significantly shorter compared to previous models for natural language analysis. Sentiment analysis in its original form analyzes the polarity of the text (sentences or paragraphs) whether it is positive, negative or neutral, as well as the intensity of it. Aspect-based sentiment analysis allows the detection of keywords, significant for the context of the text and their further analysis. Wilson et al., (2009) explore the challenge of context-sensitive polarity and develops feature-rich methods to detect sentiment at the phrase level.

This is important for analyzing the attitudes of the respondents and their opinion about different products and services that were the subject of the review. After the keywords for the corresponding product or service are detected, an appropriate sentiment analysis should be performed. The combination of the two methods for sentiment analysis, polarity and keyword detection, provides excellent results in the analysis of consumer reviews and provides good guidelines for improving the reviewed products or services. The latest methods for emotion-based sentiment analysis provide additional opportunities for determining not only the polarity of sentences and their intensity, but also the type of emotion present in the reviews. Ji et al., (2025) analyze tourists' emotions using LSTM networks in combination with a fuzzy process responsible for extracting the type of emotion. Payal (2023) recommends destination managers to consider managing tourist emotions to strategically manage the post-travel behavior of tourists on social media.

Online travel agencies (OTAs) have significantly altered the processes of reservation, travel planning, and accommodation selection. Tourists are creators of their own itinerary in destinations they have never visited before. The choice of accommodation is most often made based on its position in the tourist destination, but also on the basis given information and the rating given by previous visitors. These ratings have quantitative values for certain rating categories

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such as: location, cleanliness, facilities, host, etc., but also written text about the positive and negative aspects of the accommodation. Very often, the rating and written reviews from previous visitors are key to choose the right accommodation.

Guest reviews are critical for accommodation providers. They serve as a feedback loop, enabling providers to identify and correct deficiencies in their service, thereby enhancing their market competitiveness. While providers with a small capacity can easily analyze tourist reviews to pinpoint shortcomings, larger hotels or chains face greater difficulty in performing a simple analysis of these deficiencies.

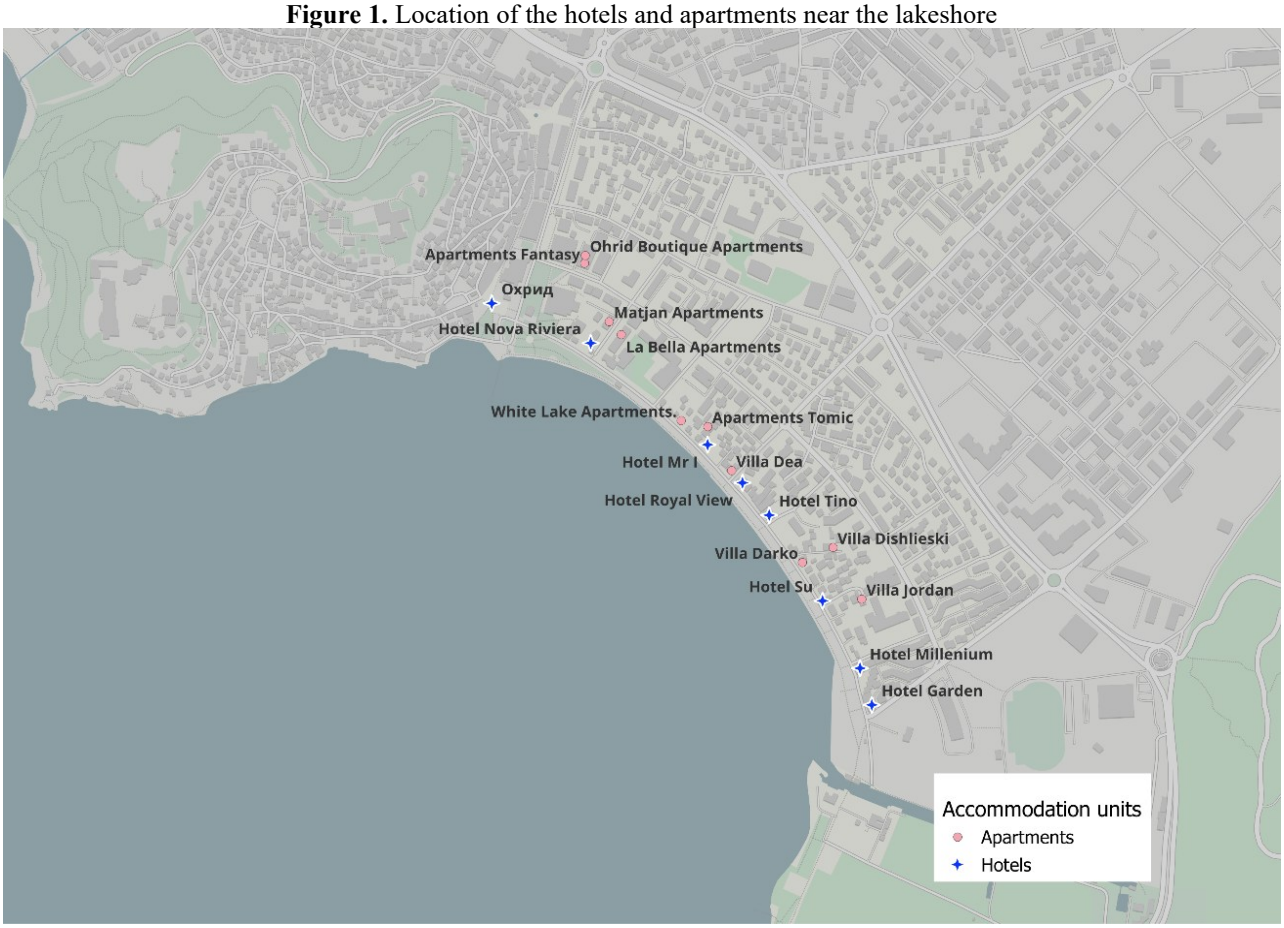
Sentiment analysis – SA (also called *opinion mining*) is a field of natural language processing (NLP)**,** computational linguistics, and text analytics that focuses on identifying, extracting, and classifying opinions or emotions expressed in text, speech, or other data (Liu, 2012). We can get valuable information from Mehraliyev et al., (2022). In this paper qualitative thematic review and quantitative systematic review were performed on 70 papers obtained from hospitality and tourism categories of two databases, namely, Web of Science and Scopus. Raees et al., (2024) use a lexicon-based method to perform sentiment analysis and shows an evaluation of classification models trained over textual data. Wankhade et al., (2022) give us tutorial on applications of sentiment analysis, advantages and disadvantages of different methods of SA. More on the comprehensive analysis of the opportunities, methods, and applications of sentiment analysis in tourist reviews can be found in Jain et al., (2021) and Manosso et al., (2021).

SA tries to answer questions about the expressed opinion, is it positive, negative or neutral. What is the intensity of the sentiment: very positive, positive or mildly negative. Are there some aspects or entity being discussed like service, quality, location, cleanliness etc., and what emotion is conveyed: joy, anger, sadness, optimism.

2. Data analysis and results

The analysis includes seven hotels and ten private accommodation facilities located in the central part of Ohrid, in attractive locations. All facilities are no more than 100 meters from the lakeside in the urban part of the city. The selection of hotels was simple, because there are not many hotels on the city's waterfront that would be subject to analysis. The selection of apartments is based on their proximity to the waterfront in the urban part of the city and the number of reviews they have. These apartments are the most visited in the urban part of the city and are therefore considered in the analysis of reviews. Figure 1 shows the geographical locations of the hotels and apartments that were included in the analysis.

Figure 1. Location of the hotels and apartments near the lakeshore



For all accommodation facilities, the texts of the reviews were downloaded. The texts were written over a period of three years, from September 2022 to the end of August 2025. Both positive and negative reviews were collected. This is important in the further analysis. After the texts were downloaded, they were organized for each accommodation facility individually according to the date of writing in order to maintain the chronology. Special characters, emoticons and stop signs were removed from the texts, and finally the text was normalized. Also, repetitive characters were removed, and words that were not written correctly were corrected. This was done in order to be able to perform an appropriate sentiment analysis for polarity and to determine the intensity of polarity for each review. Pre-processing of the text is very important to get better results from sentiment and context analysis of the review (Haddi et al., 2013; Kosala et al., 2025). All downloaded reviews are from the online travel agency booking.com, because this agency offers the largest selection of hotels and apartments in Ohrid, and the number of posted reviews meets the criterion for statistical significance of the sample.

Sentiment analysis of the data was done in the Google Colab platform, which offers access to online sentiment analysis functions. The data analyzed for the analysis were uploaded to Google Drive and referenced in Colab. Table 1 provides basic information on the number of analyzed accommodation facilities in the city of Ohrid, the number of reviews per group of facilities, the average value of the ratings from the reviews, and the standard deviation.

Table 1. Basic information about the number of analyzed objects and tourist reviews

Accommodation	Number of objects	Number of reviews	Average grade	σ
Hotels	7	1059	7.6	1.56
Apartments	10	970	9.3	0.61

Source: Authors according to reviews given on booking.com

Table 1 shows that the average score for hotels is significantly lower than the average score for apartments. Analysis of the data reveals distinct differences between hotel and apartment reviews.

For hotels, the average score is significantly affected by outliers, such as the Millennium Hotel, which recorded a low average of 3.9, though two other hotels achieved a high average of 7.9. The overall score range for hotels is 3.9 to 9.0. A total of 1,059 reviews were collected for hotels, averaging 151 reviews per establishment.

In contrast, apartment scores demonstrate less variance and higher overall satisfaction. The apartment scores range from 7.9 to 9.8, yielding an average score of 9.3, which is significantly higher than the hotel average. This difference in consistency is quantified by the standard deviation (σ). The standard deviation for hotels (σ=1.56) is substantially higher than that for apartments (σ=0.61), indicating that apartment scores are more tightly clustered and exhibit greater consensus among reviewers.

The reasons for the differences in ratings can be found in several aspects. Prices for accommodation in apartments are lower than prices in hotels. This is expected, because the costs of operating apartments are lower than the costs of hotel accommodation. The maintenance of apartments is more up to date than the maintenance of hotels. A significantly smaller number of deficiencies are reported for apartment accommodation compared to hotel accommodation. Some of the apartments do not offer food, but only accommodation. This is another reason for receiving better ratings, because tourists cannot express their opinion about this aspect of the offer in apartments compared to hotel accommodation.

Tourists submitting reviews have the option to provide numerical ratings for predefined aspects of their stay, or to include descriptive text covering both positive and negative experiences. Our analysis suggests that approximately half of all reviewers provide ratings only, while the remaining half supplement their ratings with textual comments. Satisfied guests typically elaborate on the positive aspects of their stay, whereas dissatisfied guests focus on the negative aspects or general comments regarding the accommodation facility.

In the following text we provide the results of the sentiment analysis for polarity, intensity, and quantitative analysis of certain emotions of tourists. We should mention that intensity of sentiment is represented on a continuous scale ranging from –1 to +1, where –1 denotes a highly negative sentiment, 0 indicates a neutral sentiment, and +1 corresponds to a highly positive sentiment. However, in our analysis, we consider the actual numerical values of sentiment intensity in order to get conclusive results. The average values of SA intensity are presented in Chart 1 and they are calculated by their real values, they are not clustered in groups.

Table 2 shows the number of positive and negative ratings from reviews for the analyzed hotels, as well as the average number of positive and negative ratings for each hotel and apartment.

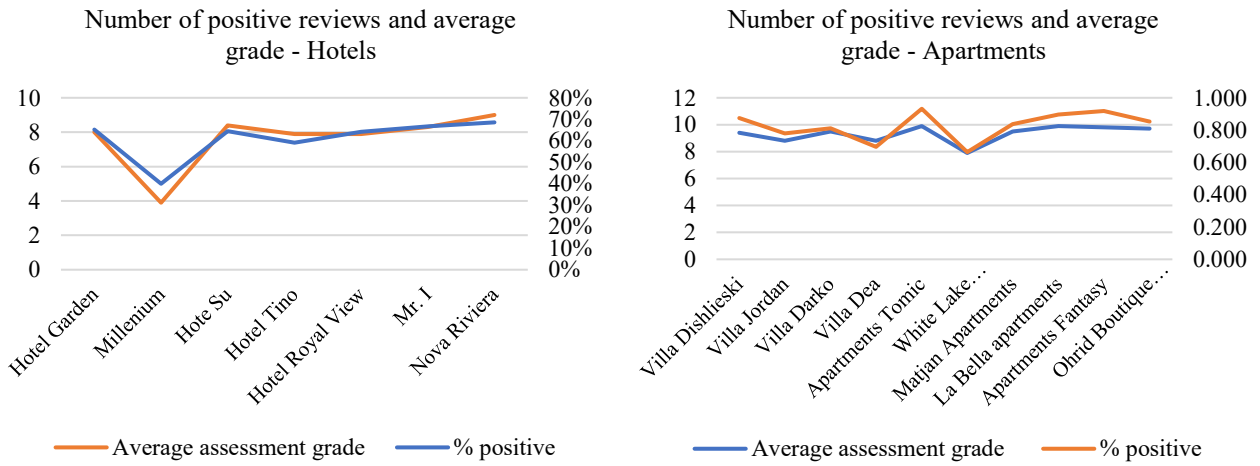
Table 2. Number of positive and negative ratings for the analyzed hotels and apartments

	POSITIVE	NEGATIVE	% positive	% negative	Average assessment grade
Hotels					
Hotel Garden	58	31	65%	35%	8.0
Hotel Millenium	4	6	40%	60%	3.9
Hotel Su	271	149	65%	35%	8.4
Hotel Tino	100	69	59%	41%	7.9
Hotel Royal View	97	54	64%	36%	7.9
Hotel Mr. I	100	50	67%	33%	8.3
Hotel Nova Riviera	48	22	69%	31%	9.0
Total	678	381			
Apartments					
Villa Dishlieski	49	7	0.875	0.125	9.4
Villa Jordan	67	19	0.779	0.221	8.8
Villa Darko	69	16	0.812	0.188	9.5
Villa Dea	105	46	0.695	0.305	8.8
Apartments Tomic	96	7	0.932	0.068	9.9
White Lake Apartments	75	38	0.664	0.336	7.9
Matjan Apartments	72	14	0.837	0.163	9.5
La Bella apartments	70	8	0.897	0.103	9.9
Apartments Fantasy	101	9	0.918	0.082	9.8
Ohrid Boutique Apartments	87	15	0.853	0.147	9.7
Total	791	179			

Source: Authors

The percentage values of positive reviews for hotels largely coincide with the average rating given by tourists. The correlation coefficient between these two columns is 0.98. This can best be seen from the graphic display of these two series shown in Chart 1. For apartments, the overlap of these two columns is smaller, and the correlation coefficient is 0.93. Here too, we are talking about a positive and high correlation between the values in the two columns.

Chart 1. Graphical display of columns for percentage of positive reviews and average rating for hotels and apartments



Source: Authors

For better comparison, the two columns are displayed on different Y axes, since the interval of their values is significantly different. From the analysis, it can be concluded that the average rating of the reviews can be obtained with high accuracy through sentiment intensity analysis.

Below is an analysis of the sentiment of the reviews, chronologically for the analyzed period. Average values were calculated for two-month periods, so that it is easier to notice differences in values in different periods.

The RoBERTa method was used for emotion analysis. RoBERTa (Robustly Optimized BERT Pretraining Approach) has been widely adopted for emotion analysis tasks due to its ability to generate rich contextualized embeddings that capture both semantic and affective nuances of language. We have chosen RoBERTa approach for its advantages on other similar methods. More on comparative analysis on pre-trained transformer models is discussed by Adoma et al., (2020). As a transformer-based model pre-trained on large-scale corpora with optimized hyperparameters, RoBERTa provides substantial improvements over earlier architectures such as LSTMs, CNNs, and lexicon-based approaches (Adoma et al.,

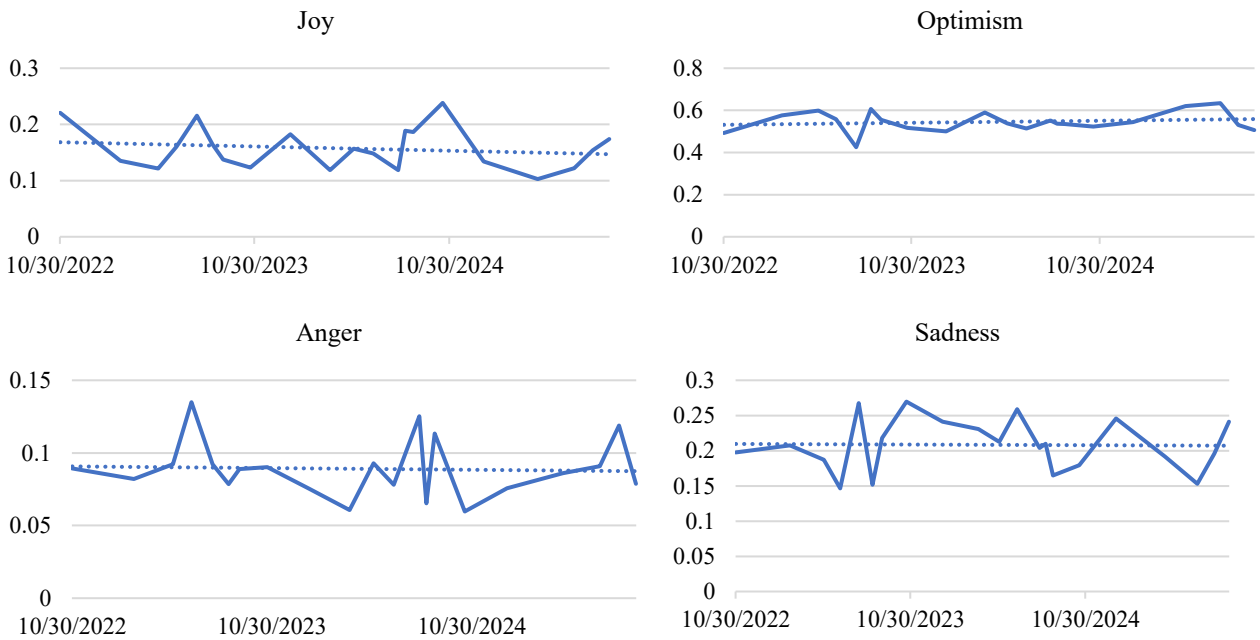
2020). When fine-tuned on annotated emotion datasets (e.g., GoEmotions, EmoBank, or SemEval benchmarks), RoBERTa effectively classifies text into discrete emotional categories (e.g., joy, anger, fear, sadness) or maps them onto dimensional affective spaces such as valence, arousal, and dominance. Empirical studies consistently demonstrate its state-of-the-art performance in emotion recognition, particularly in domains such as social media analysis, mental health monitoring, and dialogue systems (Maazallahi et al., 2025). However, challenges remain in terms of domain adaptation, interpretability, and mitigating biases inherited from pretraining data, which continue to be central concerns in advancing RoBERTa-based emotion analysis. Zakarija et al. (2024) applied the RoBERTa approach to the sentiment analysis of guest reviews, but their analysis was limited to paragraph-level polarity detection.

Four emotions were taken for analysis: joy, optimism, anger and sadness. Graph 2 shows the values of these emotions chronologically for all hotels in general. The analysis provides an overview of the intensity of the values, possible changes over time, i.e. the dynamics of change, as well as the direction of the trend if it exists.

The values for the emotion "joy" are at a very low level, the average value is only 0.157, out of a possible maximum value of 1. The values of this emotion gain higher values during the months of July in the analyzed years, and outside the main tourist season their value decreases. This emotion has a decreasing trend over the years, which should be a signal for hoteliers that they need to make certain changes in their operations in order to increase this emotion among tourists.

The emotion "optimism" has the highest values of all four analyzed emotions. There is no seasonal increase or decrease in its values. They move around the mean value of 0.545.

Graph 2. Timeline of emotion values for hotels

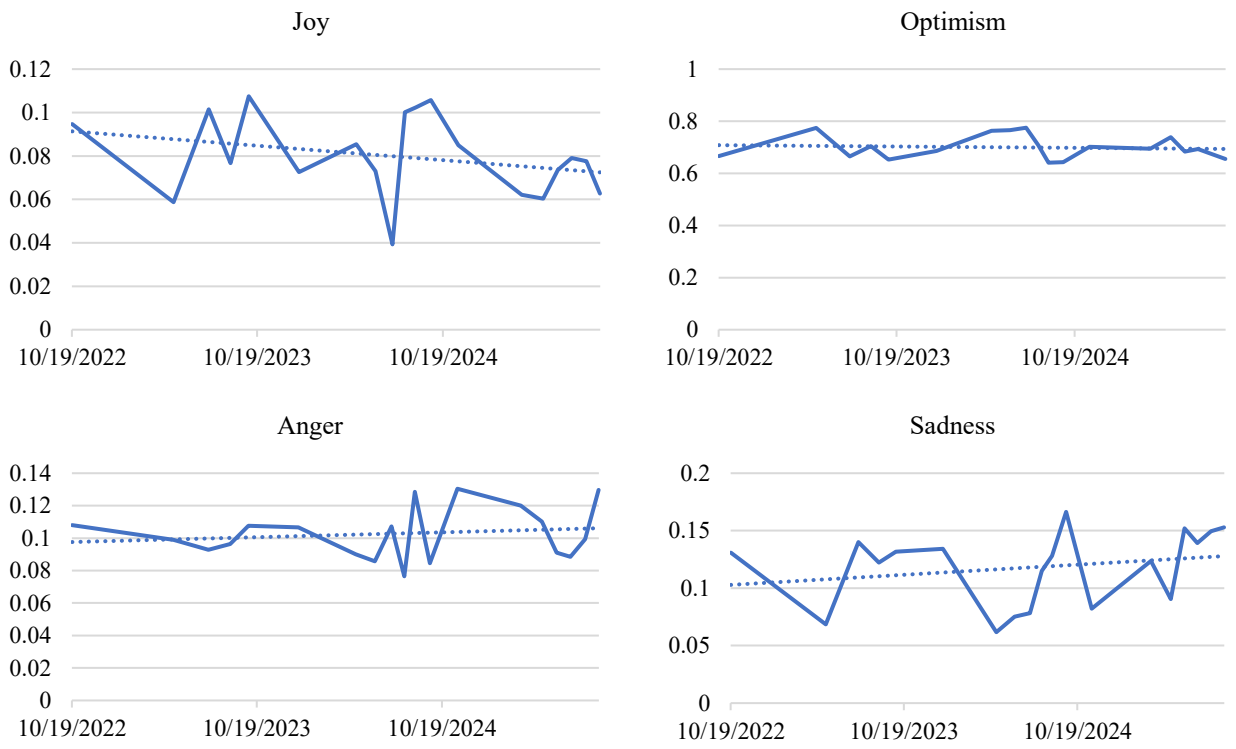


Source: Authors

The emotion "anger" has the lowest values of all analyzed. Its mean value is 0.089. This means that there are not a large number of negative reviews in which this emotion is presented. There is no significant increase or decrease in the emotion during the analyzed period, there is no pattern for repeating the values. There are a certain number of spikes, but they do not affect the overall mean value of the emotion.

The last analyzed emotion is "sadness". According to the mean value (0.208), this emotion is in second place in intensity. There is no trend of increasing or decreasing intensity over the years and there is no pattern of increasing or decreasing. Chart 3 shows the chronological values of emotions for the analyzed apartments. The analysis period is identical to the period for hotels. The methodology used is identical and the period for calculating the average values is the same as for hotels, every two months.

Graph 3. Timeline of emotion values for apartments



Source: Authors

The emotion "joy" for apartments has the lowest values compared to all other analyzed emotions. Its average value is 0.08. What is evident is the pronounced downward trend over time. There are no pronounced seasonal values, as is the case with hotels. The coefficient of decrease is $-2 \cdot 10^{-5}$. Although its value is small, the decrease is evident considering that the analysis was done for a period of three years.

The emotion "optimism" has the highest values compared to the others. There is a slight downward trend, but not significant. The values do not deviate significantly from the mean value. The mean value is 0.699, significantly higher than the same value for hotels, which had a value of 0.545. Interestingly, this emotion shows its peaks before the start of the summer season, in May. Apartment owners will have to try to maintain the values for positive emotions, especially for the emotion “Joy”.

The emotion "anger" has an upward trend in the analyzed period. In 2024 and 2025, the variation of the series has higher values compared to 2022 and 2023. The average value for this emotion is 0.103 and is higher than the same for hotels, which has a value of 0.089.

The last emotion analyzed is "sadness", which, like anger, is showing a positive trend. Tourists' expectations are higher than what they actually receive, and over the years, disappointment with the offer has increased. This is also correlated with the decline of the emotion Joy.

3. Conclusions

Sentiment analysis is a good tool for analyzing accommodation reviews. Through intensity analysis, the average rating of an accommodation facility can be determined with high precision, regardless of whether it is a hotel or a private apartment. In the case of hotels, the ratings demonstrate a stronger correlation with the percentage of positive intensity values. This conclusion is novelty in application of sentiment analysis. SA can give us information for polarity intensity and average values of reviews only by making analysis on written reviews. We don’t need to take additional analysis on quantitative data of the reviews. We can automate this process and calculate all needed information only by analyzing written reviews. We were unable to identify other studies that examine the relationship between tourists’ average ratings and the average values of sentiment intensity. We should make more and additional analysis to prove this conclusion, but the initial results give a good basis for this conclusion.

Sentiment analysis is a particularly good solution for accommodation facilities with large capacity and for hotel chains, since a large amount of data needs to be analyzed to reach conclusions about the comments of visitors. Big data analysis is a great advantage of sentiment analysis models.

The models for contextual analysis of reviews and emotion analysis provide additional analysis of the degree of positive and negative emotions when writing reviews, as well as determining the trends of the expressed emotions. Transformer-based models that are trained on large amounts of data provide excellent results in the contextual analysis of emotions. In hotels, although the average ratings are lower, the change in emotions during the analyzed period does not show significant changes. In apartments, the decrease in the emotion joy and the increase in the negative emotions anger and sadness are evident. This is a good indicator that apartments should monitor tourist reviews and improve their offer based on visitors' expectations. Given that the ratings for their accommodation are very high, it is not easy to maintain the ratings over a long period. However, if the comments and emotions of the guests are responded to appropriately, it is expected that the high ratings can be maintained in the future.

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