Artuklu Tourism Studies

Makine Öğrenmesi ile Çevrimiçi Otel Yorumlarının Değerlendirilmesi: Duygu Analizi ve Konu Modelleme ile Derinlemesine Bakış*

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Öz

Turizm sektörü içerisinde bulunan seyahat platformlarına yapılan çevrimiçi kullanıcı değerlendirmeleri, otel işletmelerinin hizmet kalitesini ve sahip olduğu tüketici memnuniyetinin belirlenmesinde önemli bir faktör haline gelmiştir. Bu kapsamda ilgili turizm platformlarındaki bilgi birikiminin artması, otel yönetimlerinin büyük veri kapsamında kullanılan yöntemler ile çevrimiçi kullanıcıların yaptığı değerlendirmelerin net bir şekilde anlamasını sağlamaktadır. Bu değerlendirmelerin yapısal ve anlamsal özelliklerinin analiz edilmesi, otellerin misafir memnuniyet düzeyini etkileyen unsurları bulmalarına yardım etmektedir. Bu gelişmeler kapsamında bu çalışmada Türkiye'nin önemli bir turizm destinasyonu olan Alanya şehrinde bulunan otellerin çevrimiçi yorumları, makine öğrenmesi tabanlı doğal dil işleme ve metin madenciliği teknikleri kullanılarak analiz edilmiştir. Yorumların müşteri memnuniyeti durumunun analizi için duygu analizi, içermiş olduğu konuların ortaya çıkarılması için ise konu modelleme yöntemleri veri setine uygulanmıştır. Ayrıca çalışmada ortaya konan duygu sınıfları için hangi konuların bu sınıflara en fazla etkiye sahip olduğunu anlamaya yönelik ise lojistik regresyon analizi ek olarak yapılmıştır. Araştırma sonucunda otelin sahip olduğu olanaklar, animasyon ve personel konuları, misafirlerin memnuniyetine en fazla olumlu yansıyan konular olurken, önbüro ve oda konularının ise daha çok olumsuz duygularla ifade edildiği ortaya çıkmıştır.

Anahtar Kelimeler: Turizm İşletmeciliği, Otel, Makine Öğrenmesi, Konu Modelleme, Duygu Analizi, Alanya

Bu makale, Alanya Alaaddin Keykubat Üniversitesi'nde tamamlanan "Makine öğrenmesine dayalı çevrimiçi otel görüşlerinin duygu analizi ve konu modelleme yaklaşımlarıyla değerlendirilmesi" adlı doktora tezinden türetilmiştir.,

Evaluating Online Hotel Reviews with Machine Learning: Insights from Sentiment Analysis and Topic Modeling

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Abstract

User generated content platforms in tourism industry have become a significant factor according to determine customer satisfaction and service performance of hotel businesses. In this context, the increase in information on tourism platforms has enabled hotel managements to understand their shares more clearly by using several methods in the scope of big data management. Analyzing the structural and semantic features of online reviews helps hotel managements better find out the factors influencing guest satisfaction level. Taking into consideration of this fact, online reviews of hotels which located in Alanya, one of the Turkey's major tourism destinations, were analyzed using machine learning-based natural language and text mining techniques. Topic modeling and sentiment analysis were implemented into dataset to identify the most frequently mentioned topics and their impact on customer satisfaction level. Furthermore, logistic regression analysis was performed to achieve which topics have the most influence for the determined sentiment classes. The results show that amenities, animation and staff-related topics have the most positive influence on topics on satisfaction, whereas front desk and room-related topics are associated with negative sentiments.

Keywords: Tourism Management, Hotel, Machine Learning, Topic Modeling, Sentiment Analysis, Alanya

This article is derived from the doctoral thesis titled “Evaluation of online hotel reviews based on machine learning using sentiment analysis and topic modeling approaches” completed at Alanya Alaaddin Keykubat University.

Introduction

Technological developments in digital era have increased the participation of businesses and visitors in tourism industry. In this context, these developments have increased and improved the operational, marketing, and communication efficiency of firms and enable people to experience different tourism products and services (Bak et al., 2025; Ruan et al., 2025; Al Hakeem et al., 2024). Related technological innovations in tourism services, especially web-based technologies and B2B and B2c applications, have become one of the important key elements that allow business and destinations to get competitive advantage in international and domestic tourism markets (Buhalis, 2000; Aydınbaş, 2023; Kim et al., 2023). As a result of these developments, accommodation industry has benefited tremendously via related technologies to improve customer satisfaction, service quality and marketing strategies in the context of communicating more effectively with present and potential customers (De Pelsmacker et al., 2018; Kim & Kim, 2022).

In consequence of the extensive utilization of the internet, consumers have able to share their travel experiences. As a result of this, the concept of electronic word-of-mouth (eWOM) marketing has gained substantial importance (Cantallops & Salvi, 2014). Int his regard, customer-generated content is most prevalent today for the hotel industry which represents one of the core components of the tourism sector (Yang et al., 2018; Li et al., 2013). In travel behavior, visitors develop a habit of consulting online reviews and user experiences about hotels before booking process. These reviews consequently influence potential customers' decision-making processes. Negative experiences often lead customers to make more cautious travel decisions, both immediately and in the long term. It is known that dissatisfaction after purchasing accommodation services is typically difficult to compensate for. For that reason, online reviews shared by previous guests have become a reliable reference point for other potential consumers (Doğan et al., 2020; Roozen & Raedts, 2018).

Because of the rapid growth of Web 2.0 application, both users and businesses on digital platforms have significantly increased (Leung et al., 2013). User-generated content, especially online reviews of hotel businesses, has now reached such scale and diversity that it can be considered big data. (Zhong et al., 2023). To transform vast volume of data into meaningful insights, machine learning based analytical methods are being increasingly employed for the studies about tourism sector. By employing algorithms and methods such as sentiment analysis, topic modeling, classification, and clustering, hotel businesses can systematically identify the factors that influence customer satisfaction and make strategic decisions based on data-driven insights. (Ali et al., 2022; Calheiros et al., 2017; Hu et al., 2019). These methods not only facilitate the analysis of individual reviews but also provide significant advantages in assessing service quality, evaluating brand perception, and guiding marketing activities (Rosetti et al., 2016). The application of machine learning techniques offers hotel businesses a competitive advantage and allows for a deeper understanding and personalization of consumer experiences (Puh & Bahic Babac, 2023; Badouch & Boutaounte, 2023). Consequently, digital review analytics, underpinned by big data, play a crucial role in facilitating the customer-focused transformation of the accommodation sector (Zarezadeh et al., 2022).

Within the scope of the opportunities provided by big data analytics and machine learning methods, this study examines online reviews of hotels located in Alanya, one of Turkey's key destinations for the accommodation sector in Turkey. By employing natural language processing techniques particularly sentiment analysis and topic modeling, this study identifies the key themes through which consumers assess their hotel experiences and examines how these assessments are expressed emotionally.

1. Conceptual Framework

The development and widespread adoption of sharing platforms within the travel industry have led to a significant surge in the volume of consumer-generated reviews. Consequently, the visibility and service performance evaluation of businesses on these platforms have grown especially in last 10 years. The growing accessibility of the internet has substantially broadened both the volume and variety of data on these platforms and facilitating the multidimensional analysis of consumer reviews. (Roy, 2023; Cabi Bilge, 2024). Moreover, analyses of user-generated reviews on these platforms elucidate the relative significance of satisfaction-determining factors, the thematic groupings used to evaluate these factors, and the extent to which service similarities or discrepancies impact consumer satisfaction. (Ağca & Gündüz, 2023).

The tourism sector is one of the areas most affected by these developments. The tourism sector's structural characteristics and its status as a part of the service sector have increasingly increased the importance of online travel platforms and the reviews posted on them. One of the most important of these areas is the hotel industry. For this reason, analyzing online reviews related to hotel businesses plays a critical role in identifying the service components that influence customer satisfaction, as well as in enhancing financial performance and demand levels. Since guests' perceptions of elements such as rooms, food and beverage, pricing, or staff behavior may vary individually, these reviews need to be assessed through a comprehensive and multidimensional analytical approach (Sparks & Browning, 2011; Chittiprolu et al., 2021).

In light of these developments, the growing impact of eWOM has driven a substantial rise in the number of hotel visitors generating online reviews on digital travel platforms. In this context, the rising number of reviews, along with firms' efforts to engage with visitors and resolve service-related issues during their stay, has reinforced the significance of these online platforms in the hotel industry. This increment significantly makes high momentum to understand the context of digital reviews. For gain macro view in terms of big data, it is needed to transform written text into numeric data to understand by algorithms. In this way, machine learning based natural language processing and text mining techniques stand in the breach. In addition to being useful of the structured data forms like surveys, related machine learning based methods can provide more comprehensive information and multidimensional approaches in text analysis. In the context of the development in artificial intelligence, natural language processing methods allow scholars for the extraction of hidden topics, information and emotion laying in the texts with different perspectives (Xu & Lv, 2022; Li et al., 2018). Thus, comprehending information and topics generated by hotel visitors and their emotional tones empower critical and beneficial opinions and decisions into the service performance of hotels (Ameur et al., 2023).

Developments in the digital tourism landscape and the growing volume of data have led to the emergence of the concept of big data in the tourism industry. Within this framework, sentiment analysis has increasingly been applied to large datasets in recent years as a natural language processing method in the hotel sector. Sentiment analysis is a technique used to identify the emotional categories embedded in written documents and consumer reviews. Furthermore, it helps to classify reviews like negative, neutral or positive (Şeker, 2016). This method aids in figuring out which emotions people related to certain features of a business deliver notable findings in terms of marketing strategies, visitor satisfaction, service quality measurement (Borrajo et al., 2021).

One of the main reasons to implement sentiment analysis into text-based dataset is subjectivity matter and interpreting user reviews. For example, when a guest tries to evaluate their staying process at a hotel, this guest may use different criteria. This subjectivity naturally affects the scores he/she assigns at digital travel platform where most of them have 1-5 scale from worst to best respectively. This gives guests a standard scale to use to evaluate their accommodation according to previously determined scales. For instance, if a guest who has a negative experience with the hotel's room may give a rating of 2 out of 5, while another guest who had the same experience might rate it as 3. This may cause confusion in the evaluation in some cases. For this reason, sentiment analysis methods intend to modify the emotional expressions of guests in such reviews into more objective and structured perceptions (Hogenboom et al., 2014). Therefore, related studies that implemented sentiment analysis evaluate and figure out the content of reviews through a systematic approach (Palanisamy et al., 2013).

Moreover, along with sentiment analysis, another machine learning model that has been frequently used in text analysis in recent years is topic modeling techniques. This method has become widely used in recent years in natural language processing, text mining, and content analysis of digital reviews written by users. Topic modeling is an unsupervised machine learning approach used to uncover hidden themes especially for large datasets (Blei et al., 2003). The datasets used in relevant studies typically consist of thousands of user reviews. Rather than classifying texts into a single predefined category, topic modeling algorithms employ methods such as Bayesian approaches and matrix factorization to analyze word co-occurrences both within individual reviews and across the entire text corpus (Wang & Zhang, 2012; Momtazi & Naumann, 2013). Consumers often comment on multiple aspects of a hotel within a single review, including room quality, available facilities, food and beverage services, staff behavior, hygiene, and entertainment. Therefore, identifying the latent topics embedded in these reviews offers a macro-level perspective that is essential for interpreting online hotel feedback in a more holistic manner.

Considering these two NLP methods, studies combining sentiment analysis and topic modeling approaches on hotels evaluate the service elements affecting customer satisfaction, thematic trends, and emotional orientations based on customer reviews across different destinations and hotel types. When looking to the international studies which implemented these methods, they commonly notice that core services like room quality, hygiene and sanitation, food and beverage services, staff attitudes and behaviors, pricing strategies, and transportation opportunities play significant roles determining in customer satisfaction. Among these, a study conducts to examine online reviews from visitors of five-star hotels. According to findings, the most prominent factors were about rooms such as air conditioning, noise, and humidity level problems (Qi et al., 2017).

Furthermore, such different kind of factors also affect customer satisfaction in terms of hotel classification. In a study conducted according to hotel classes, the problems that the guests have are listed respectively that accommodation and infrastructure issues were stated for 1–2 star hotels; security and room quality issues were stated for 3-star hotels; accommodation conditions, waiting time, and customer interaction issues were stated for 4–5 star hotels (Nunkoo et al., 2020). Similarly, a related study was carried out at chain hotels which locations are near to airports. According to the findings, transfer capability was the most influential factor in terms of guest satisfaction. Furthermore, environmental factors also influence the accommodation experience (Moro et al., 2020).

In a study from Brazil, issues related to the situation of rooms, parking opportunities, and reservation issues stated as negative themes, whereas location, ambiance, staff, breakfast, and cost effectiveness were stated as positive themes (Paladini & Peres, 2021). A systematic review on sentiment analysis in tourism studies identified that main research concepts are predominantly focusing on market intelligence, customer satisfaction, reviewer behavior, and interaction (Mehraliyev et al., 2022). As can be seen, guests' hotel experiences vary depending on the destination and hotel structure.

The number of topic modeling and sentiment analysis studies conducted in Turkey also has increased in recent years, with diverse findings regarding hotel facilities. For example, a study analyzing Turkish reviews of 164 hotels in Antalya applied both sentiment analysis and topic modeling using the Zemberek library; the factors most influencing overall satisfaction were identified as service, room, sleep quality, and location satisfaction (Tuna, 2019). Another study in the Antalya region found that 80% of user reviews were positive and 20% were negative, with topics grouped as experience, value and entertainment, complaints, basic services, and activities (Büyükeke et al., 2020). A more recent study analyzing 2,743 user reviews from 20 hotels in Alanya identified five main themes: staff, rooms, food and beverage, hotel facilities, and transportation. The most positive evaluations were related to staff and food and beverage services, while transportation received the most negative comments (Sezgin & Duman, 2023). In this research, 180,478 online reviews of Antalya hotels were analyzed, revealing increased customer interest in environmentally sensitive services. The findings show that hotels emphasizing eco-friendly practices generally achieve higher customer satisfaction. Additionally, reviews related to environmental issues were more frequent and generally negative in low-rated hotels, whereas high-rated hotels showed a more balanced distribution of such comments.

2. Methodology

In this study, data from hotels located in Alanya were analyzed using machine learning methods applied within the scope of natural language processing on one of the world's most popular travel platforms, Tripadvisor. Hotels with 10 or more reviews were included in the study to ensure review reliability, and the Alanya region constituted the scope of the research. A total of 353 hotels meeting these criteria were included, and since the preprocessing methods employed in the study were designed for the English language, only reviews written in English were analyzed. Ultimately, 40691 data entries were collected using web scraping techniques. The study utilized the Orange Data Mining software, which is compatible with the Python programming language and integrates seamlessly with Python libraries (Demsar et al., 2013). Figure 1 illustrates the workflow of the methodology used in the study.

According to this workflow, after obtaining the raw dataset, the raw data was transformed into a corpus, and preprocessing steps were applied. During preprocessing, all letters were converted to lowercase, stopwords and numbers were removed. Following this process, word clouds were generated. Since words like "hotel" and "stay" frequently appeared and are naturally present in almost every review, such common words were eliminated from the corpus if they appeared in more than 95% or less than 5% of the reviews. At this stage, the Regexp Pattern: \w+ method was used to tokenize the text set into individual words.

After preprocessing, representing words in algorithms is a crucial step for computation, especially in the analysis of large texts. For this purpose, the study employed the Bag of Words (BOW) method. In this method, the frequency of words within each document is considered, and a vocabulary of unique words across all documents is created. Each document is then represented by a vector indicating how many times each word in the vocabulary appears in that document. Thus, texts are converted into fixed-length numerical data understandable by machine learning models. Within the BOW framework, the Term

Frequency-Inverse Document Frequency (TF-IDF) technique was used. TF calculation computes how often a word occurs in a particular document and thus shows the importance of this word in the relevant document. On the other hand, IDF calculation computes the logarithmic transformation of how often a word occurs in the entire text set and thus helps to reduce the importance of frequently occurring words. In TD-IDF calculation, computing is made by multiplying these two values, and in this way, high weight is given to the rare words of a word both in the relevant document and in the entire data set, and by doing so, the most meaningful words in the text set are expressed. (Zagar, 2022; Jain et al., 2024).

After the vectorization process using BOW and TF-IDF transformation, sentiment analysis was implemented. Valence Aware Dictionary and Sentiment Reasoner (VADER) method which is considerably used for studies is applied in this study. This method employs a lexicon of positive and negative words together to compute the sentiment score and assign and classify the documents sentiment type of each review in dataset. By doing this, this method computes the emotional category of each review as positive, negative, or neutral. Furthermore, this approach considers the co-occurrence of words within the text, as a result defining the compound score to reveal sentiment type (Hutto & Gilbert, 2014). Inside this algorithm, every sentence in a document is appointing a compound sentiment score based on the words it comprises and their structural principles. This score ranges between -1 and 1, where sentences scoring between -1 and -0.5 are classified as negative, between -0.5 and 0.5 as neutral, between 0.5 and 1 as positive sentiment. Moreover, if a document is closer the compound score is to -1 or 1, it has the stronger the sentiment magnitude.

In line with study's aim, topic modeling is implemented to dataset after preprocessing phase. Topic modeling helps obtain meaningful clusters and allows them to make classification of documents especially for larger datasets. Latent Dirichlet Allocation (LDA) model was implemented which is an unsupervised machine learning model helps to extract topic clusters. This method is beneficial especially for unlabeled dataset where there is no prior classification regarding the subject of the text reviews by visitors. LDA has Bayesian approach inside, and it assumes that fundamentally corpuses are made of documents, documents are consisted by words. Furthermore, each determined topic is depicted by a distribution of words, and each document in dataset is depicted by a distribution of determined topics. This approach allows us to identify which topics are most highlighted in guest' reviews. In addition to facilitating the thematic clustering, this model also aids profound interpretability in text mining and NLP studies. By revealing the latent features in dataset, it helps to figure out not only what users are written about in the text, but also how frequently these topics appear in whole dataset. This approach is significantly beneficial for sectors like tourism, where visitor preferences, standarts and satisfaction drivers are embedded with unstructured textual feedback. The LDAvis tool in the Python Gensim library was used to visualize the topics and the numerical distribution of words found in each topic using the datamining program. After applying sentiment analysis and topic modeling to each review individually, each review was assigned a sentiment score and categorized as positive, neutral, or negative. Additionally, a total of eight topics were identified, and each review was labeled with the topic that had the highest distribution in that review. Thus, both the sentiment and topic category of the reviews were integrated.

Following this integration, logistic regression analysis was conducted. Since the target class variable needed to be categorical, sentiment categories positive, neutral, and negative were used as the dependent variable. The independent variables consisted of the distribution of each topic within the text dataset. By estimating the coefficients of topics affecting the three sentiment classes in the target variable, the study evaluated the degree to which each topic influenced reviewers' sentiment. In addition to identifying the overall influence of each topic on sentiment, the multinomial logistic regression model allowed for a more granular understanding of transitional sentiment shifts particularly from negative to neutral and from neutral to positive. This feature is especially valuable in-service quality research, as it reveals which service aspects are effective at mitigating dissatisfaction (e.g., shifting from negative to neutral) and which aspects actively contribute to delighting customers (e.g., shifting from neutral to positive). Such insights provide a hierarchical view of service recovery versus service enhancement, guiding managers not only in solving problems but also in identifying emotional leverage points for improved customer experience.

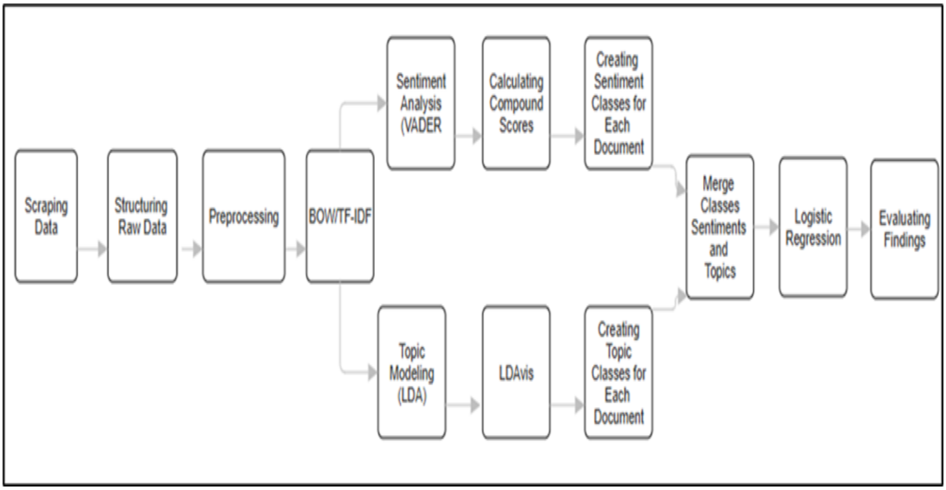

Figure 1. Workflow Diagram of the Methodology (Authors' Own Research Design)

3. Findings

Content analysis of 40,691 English-language hotel reviews from Alanya, sourced from TripAdvisor, indicates that high satisfaction ratings are predominant. Specifically, 54.7% of the reviews (n = 22248) assigned the maximum score of 5 out of 5, suggesting a substantial level of customer satisfaction. Ratings of 4 constituted an additional 19.1% of the total, reinforcing the overall positive assessment trend. In contrast, low ratings defined as scores of 1 or 2 comprised only 15.5% of the dataset, indicating that negative user experiences were relatively infrequent. These findings collectively suggest that the hotel sector in Alanya is largely successful in meeting or exceeding guest expectations, as reflected in the overwhelmingly favorable user-generated content.

Table 1. The Distribution of the Scores in the Dataset

Evaluation Point	Number of Reviews	Percentage of Reviews (%)
1	3788	9.3
2	2510	6.2
3	4369	10.7
4	7776	19.1
5	22248	54.7
Total	40691	100

In the topic modeling phase of the study, both perplexity and coherence scores were considered when determining the optimal number of topics. At this stage, efforts were made to identify topic numbers that not only yielded favorable perplexity and coherence values but also preserved the semantic coherence of the terms constituting each topic. While low perplexity and high coherence scores are essential indicators in topic modeling, ensuring that the resulting topics are semantically meaningful and interpretable remain equally critical. Based on these two criteria, the modeling process was iterated 200 times to reach an optimal number of topics. When the number of topics is too low, words from distinct semantic categories tend to co-occur within a single topic, thereby reducing topic distinctiveness and interpretability. Conversely, when the number of topics is excessively high, the model may generate redundant, overlapping, or insufficiently distinct topics, which in turn undermines the interpretability and explanatory power of the model.

Figure 2. and Figure 3. present the perplexity and coherence scores, respectively. The results indicate that when the number of topics exceeds 50, perplexity values increase, suggesting heightened model complexity. Conversely, coherence scores begin to decline after 10 topics, indicating a reduction in semantic consistency. Considering the need for semantic clarity in interpreting the word groups that constitute each topic, the optimal number of topics was determined to be eight.

An important consideration in the application of topic modeling was the observation that users sharing their experiences with accommodation services on social platforms tend to mention various attributes of both the facility and the destination within a single review. Words such as “great” or “bad” may co-occur with terms referring to room conditions, entertainment activities, staff behavior, available amenities, or food and beverage services. As a result, similar sentiment-laden words frequently appear across multiple topics. The critical analytical point lies in identifying the co-occurrence patterns namely, which groups of words these sentiment terms are most frequently associated with. The topics derived from the model are illustrated in Figures 4. through 11. Topic labels were assigned based on the semantic coherence of the associated terms, resulting in the following categories: amenities, animation, destination, food and beverage, front office, reservation, room, and staff. In these figures, gray indicates the overall frequency of a given term within the corpus, while red denotes its frequency of co-occurrence with the respective topic. For instance, in Figure 4., the term resort appears approximately 10500 times in the dataset, with around 9000 instances occurring in the context of the amenities topic. Although the term also appears in other contexts, its strongest association is observed within this topic.

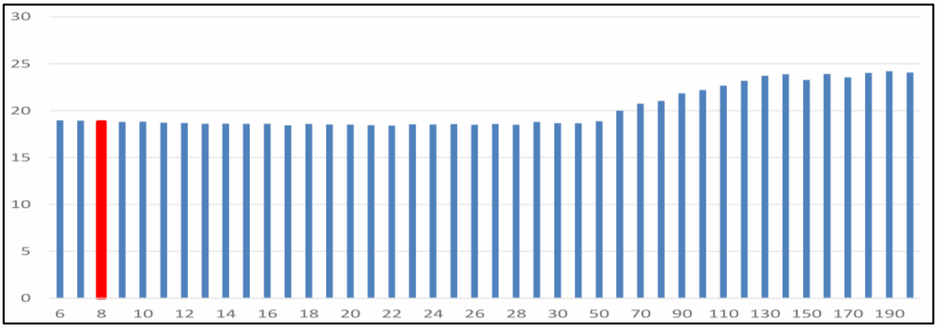

Figure 2. Perplexity Scores of the Topics to be Generated

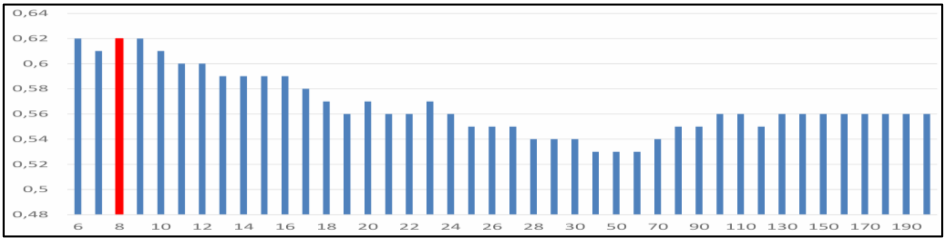

Figure 3. Coherence Scores of the Topics to be Generated

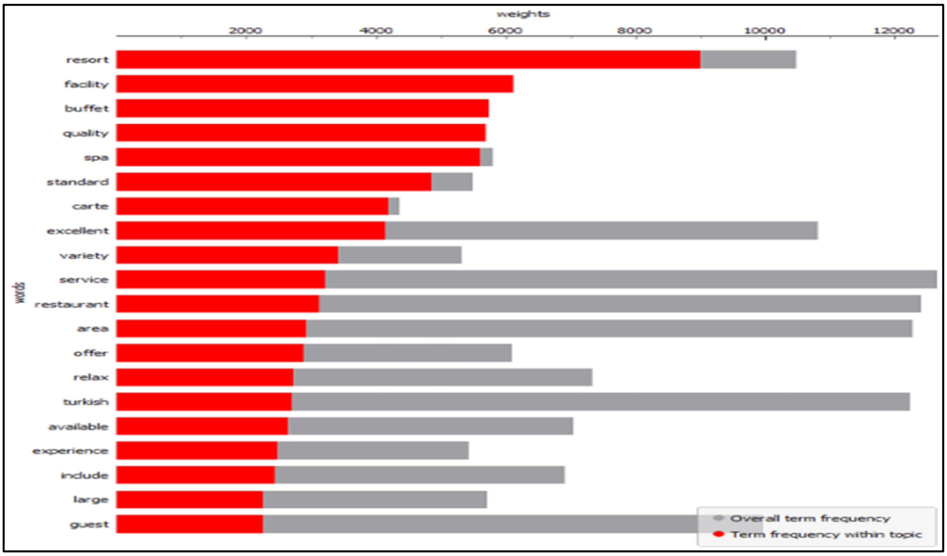

Figure 4. Words Related to "Amenities" Topic

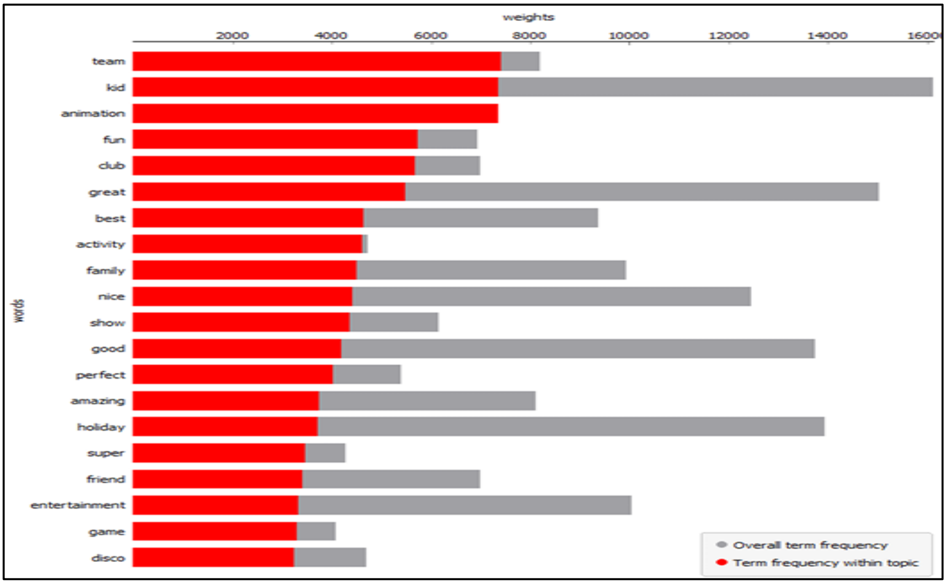

Figure 5. Words Related to "Animation" Topic

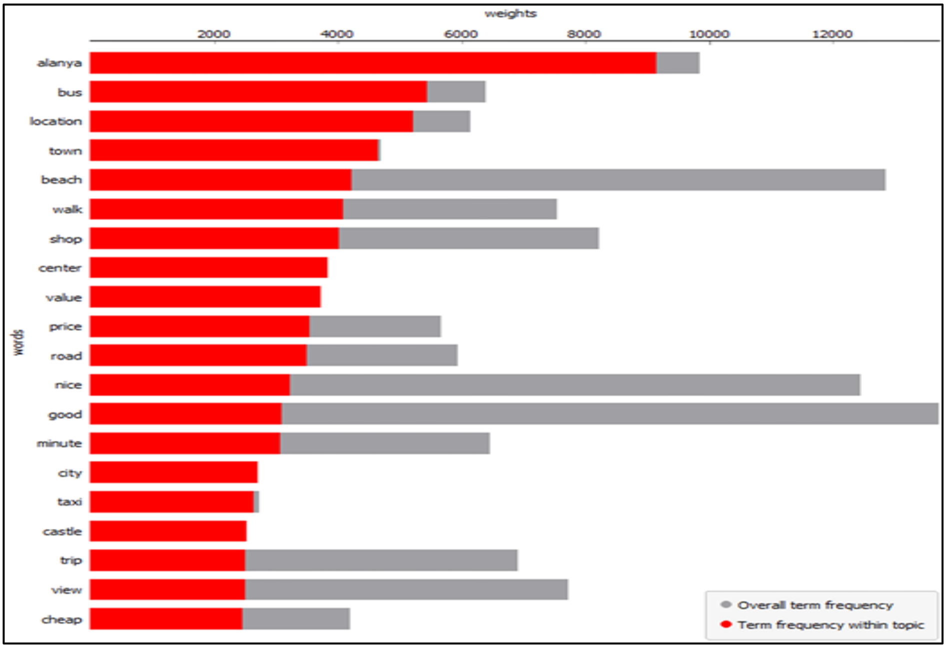

Figure 6. Words Related to "Destination" Topic

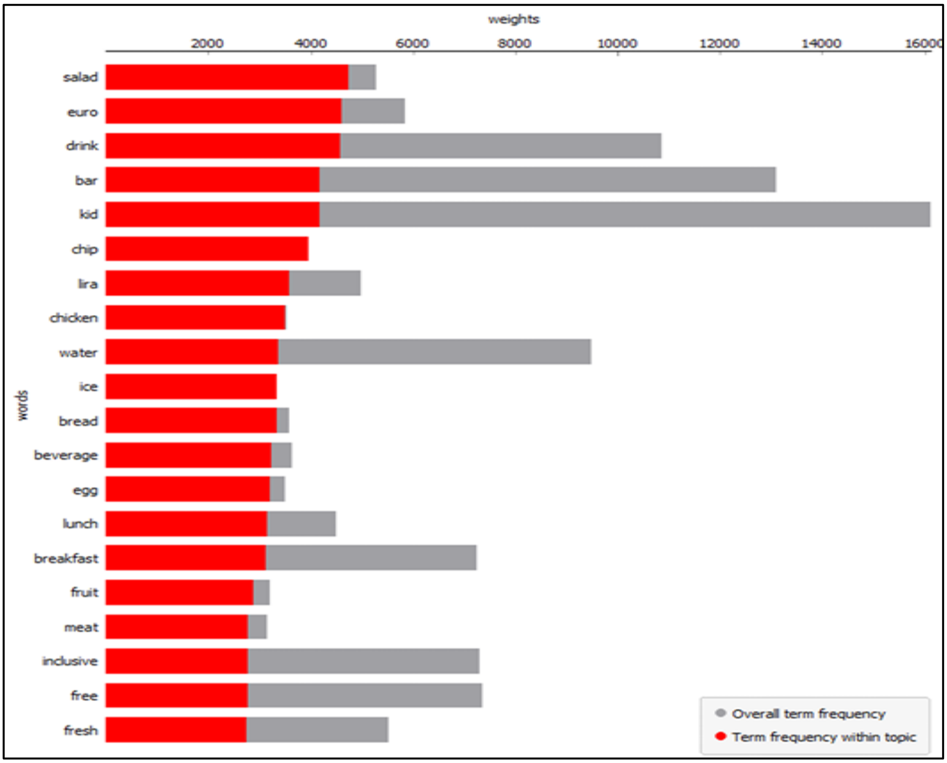

Figure 7. Words Related to "Food and Beverage" Topic

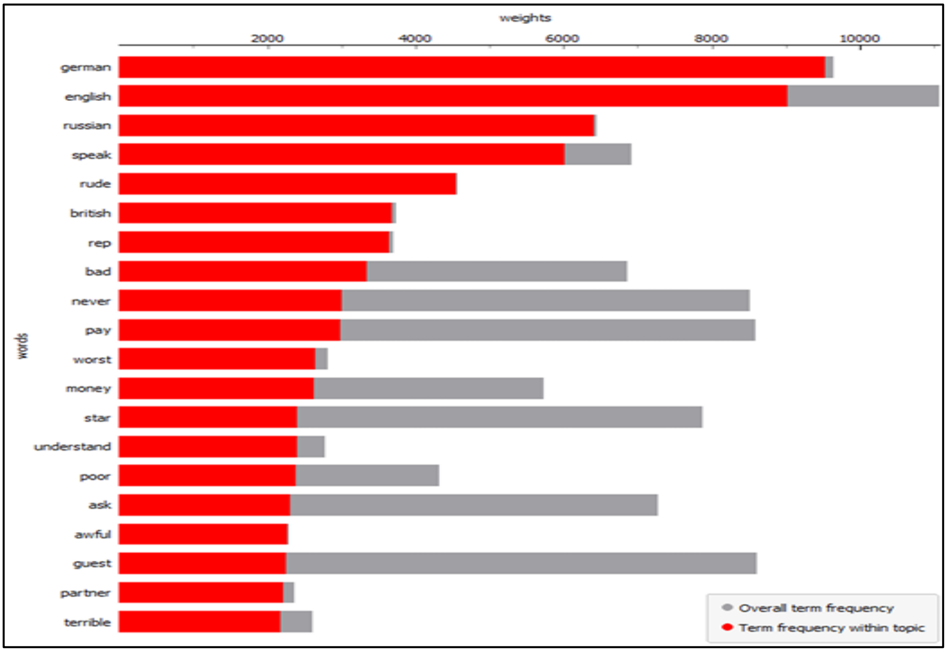

Figure 8. Words Related to "Front Office" Topic

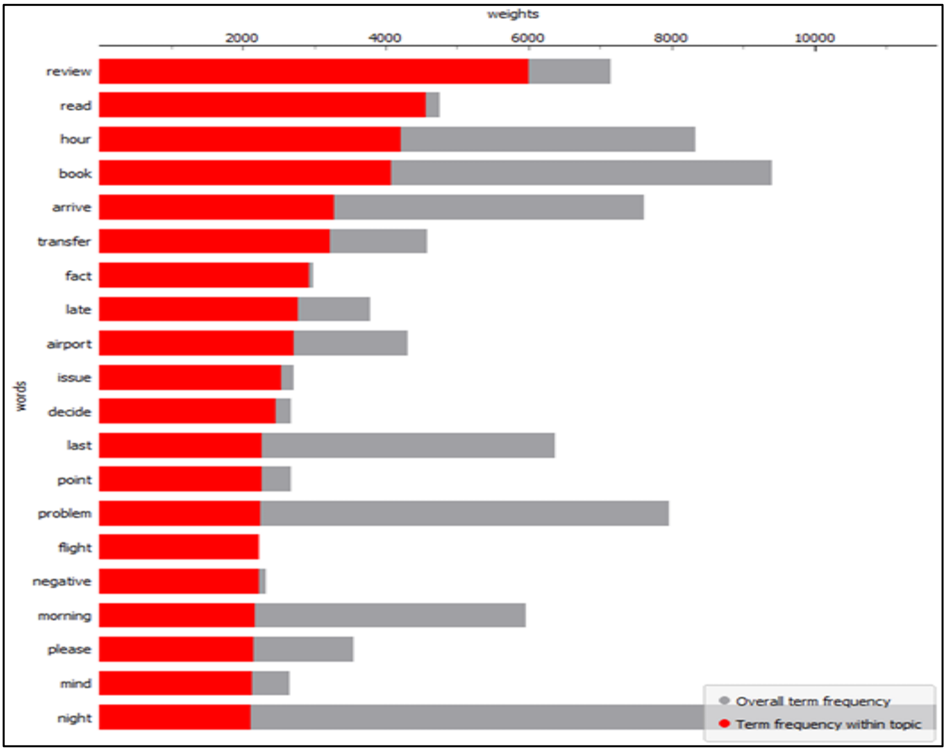

Figure 9. Words Related to "Reservation" Topic

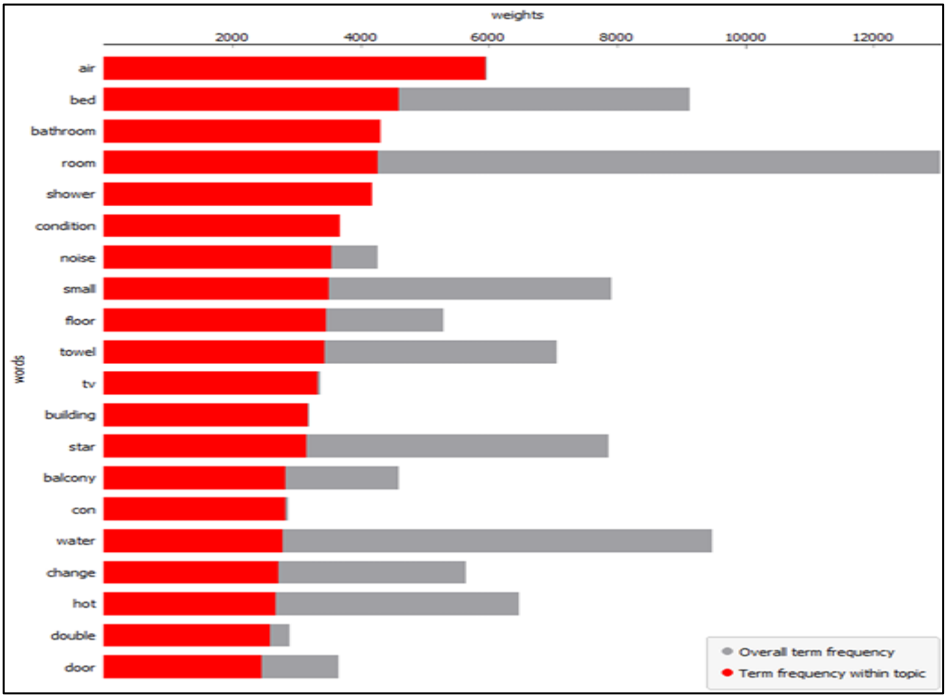

Figure 10. Words Related to "Room" Topic

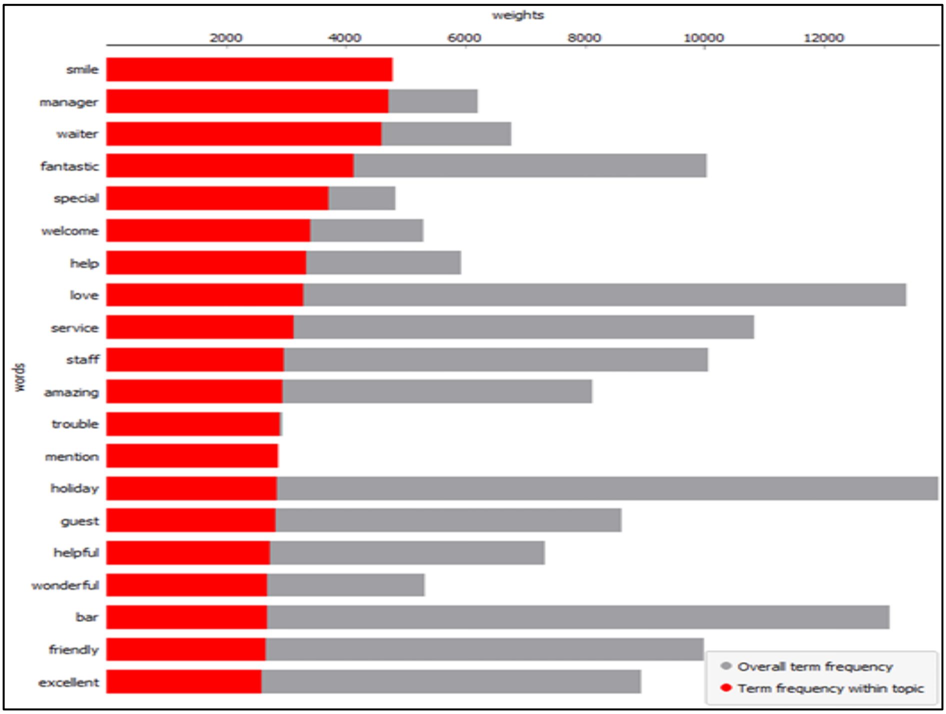

Figure 11. Words Related to "Staff" Topic

On the other hand, sentiment analysis was implemented to collected dataset. The results show table 2 and figure 12. Findings indicate that the positive sentiments in customer reviews related to hotels in Alanya are concentrated around specific thematic categories. The *Animation* topic exhibits the highest proportion of positive sentiment, with 71%, across all categories. Similarly, high levels of positive sentiment are observed in the *Staff* (59.07%) and *Amenities* (58.59%) topics. These findings suggest that guests are generally satisfied with aspects of their holiday experience related to human interaction, recreational activities, and the physical facilities of the hotel. This supports the argument that service experiences are shaped not only by functional attributes but also by emotional and social dimensions like entertaining people and interactions as an important part of service industry.

Furthermore, the *Destination* topic also shows a relatively high level of positive sentiment (45.05%) compared to many other categories, indicating that guests are largely satisfied with their choice of destination. This underscores the importance of evaluating hotel services in conjunction with environmental and cultural factors, rather than in isolation. In contrast to the positive sentiment observed in socially and emotionally engaging service aspects such as animation and staff interaction, certain operational and functional service areas exhibit a significantly higher proportion of negative sentiment. Notably, the Front Office and Room topics show predominantly negative perceptions, with 53.06% and 43.14% respectively, while Reservation and Food and Beverage also exhibit high levels of dissatisfaction. This pattern suggests that foundational service elements, such as check-in/check-out efficiency, room conditions, and reservation accuracy, remain key pain points for guests. These findings highlight a critical service gap: while hotels are succeeding in creating emotionally satisfying experiences, basic service failures may be undermining overall guest satisfaction. Therefore, improving operational consistency is not only necessary to reduce negative sentiment but also essential to support and amplify the positive emotional experiences already being delivered in other service dimensions.

Table 2. Sentiment Distribution of Each Topics in Dataset

Topics	**Positive (%)**	**Neutral (%)**	**Negative (%)**
Amenities	58.59	26.5	14.91
Animation	71	17.52	11.48
Destination	45.05	35.9	19.05
Food and Beverage	28	36.92	35.08
Front Office	10.2	36.73	53.06
Reservation	24.92	37.38	37.69
Room	16.06	40.79	43.14
Staff	59,07	22,91	18.02

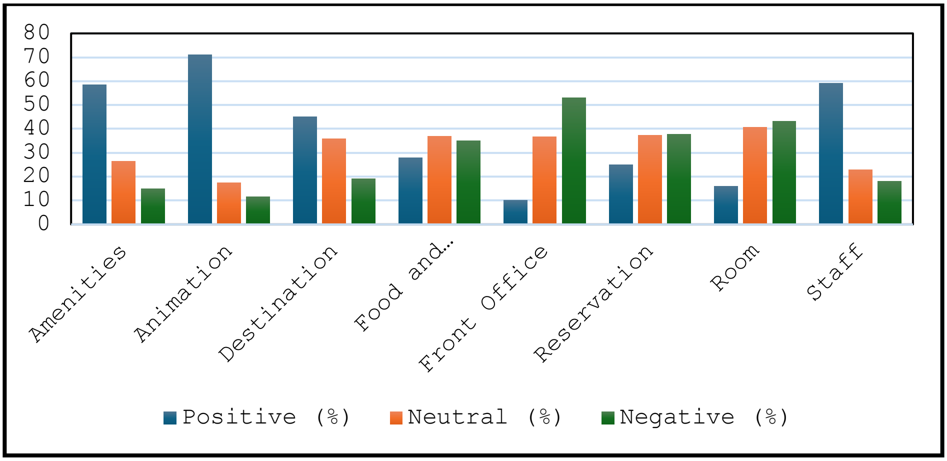

Figure 12. Sentiment Distribution of Each Topics in Dataset

In the final phase of the study, a logistic regression analysis was conducted to examine the relationship between the sentiment polarity (positive, neutral, or negative) and the thematic content of each review. The objective was to statistically assess how different topics influence the likelihood of specific emotional responses. The results of the logistic regression are presented in Table 3.

The findings indicate that emotional transitions in hotel reviews are significantly associated with specific thematic categories. In the transition from negative to neutral sentiment, the topics *Room* (β = 0.2418) and *Front Office* (β = 0.1499) exhibit positive coefficients. This suggests that dissatisfaction related to rooms and front desk services may not always convert into positive experiences but can evolve into a more neutral evaluation. Similarly, the *Reservation* topic (β = 0.1492) also increases the likelihood of neutral sentiment, indicating that these service touchpoints may serve as critical intervention areas for hotel managers seeking to reduce negative feedback.

In the shift from neutral to positive sentiment, the most prominent contributing factors were the *Staff* (β = 0.4194), *Animation* (β = 0.2373), and *Amenities* (β = 0.1383) topics. These themes appear to emotionally enrich the guest experience and have the potential to transform neutral evaluations into expressions of satisfaction. In this regard, interpersonal interactions and recreational services emerge as high-yield investment areas for hotel operators aiming to enhance customer satisfaction.

Conversely, the topics *Room* (β = –0.4532) and *Front Office* (β = –0.4554) demonstrate negative associations with positive sentiment, indicating that experiences in these domains continue to pose significant barriers to achieving higher satisfaction levels. These findings imply that, beyond functional improvements, the design of emotionally engaging service encounters is essential for the generation of positive sentiment.

Furthermore, some topics, such as *Reservation* and *Food and Beverage*, exhibit relatively low explanatory power across all sentiment classes and tend to align more closely with emotionally neutral responses. These results highlight that emotional reactions vary across topics and that each service dimension leaves a distinct emotional imprint on customer perception

Table 3. Logistic Regression Results of each Topics Considering Sentiment Type

Topics/Coefficients	Negative	Neutral	Positive
Intercepts	-0.5627	-1.2137	1.7764
Amenities	-0.0446	-0.0937	0.1383
Staff	-0.2072	-0.2122	0.4194
Front Office	0.3055	0.1499	-0.4554
Destination	0.2348	-0.0868	-0.148
Reservation	-0.0224	0.1492	-0.1268
Animation	-0.1808	-0.0564	0.2373
Food and Beverage	0.1362	0.002	-0.1382
Room	0.2113	0.2418	-0.4532

Conclusion

The present study aims to investigate the key themes related to customer satisfaction and service quality by analyzing online reviews of hotel establishments in Alanya using multiple natural language processing techniques. Through the application of sentiment analysis and topic modeling, the study provides a comprehensive and systematic understanding of consumer evaluations and perceptions of hotels. These methods elucidate the thematic dimensions shaping customer experiences and reveal the distribution of emotional tendencies across these themes. The findings offer valuable insights for hotel operators regarding the enhancement of service quality through more effective utilization of customer feedback.

In the study, a systematic procedure was followed to uncover the findings from scraped dataset. First of all, sentiment classification for each review was conducted using the VADER method. After this, topic modeling was employed to identify the main subjects mentioned by consumers within the review corpus. Finally, a logistic regression analysis was performed using the derived topics and sentiment classes to examine how specific topics influence the likelihood of positive, neutral, or negative sentiment.

The study yielded important insights that may be utilized by hotel managers to enhance operational and service quality. According to findings, room and front office topics play an important role in reducing negative sentiment and moving it toward a neutral viewpoint. On the other hand, these topics seem to be lacking for producing positive emotional reaction during visit of hotels in Alanya. Nonetheless, Staff, Animation, and Amenities have possible potential for converting neutral evaluations to positive emotions. This situation emphasizes and highlights the importance of investing not only in diminishing complaints and problems but also in encouraging emotionally vibrant and powerful service experiences.

In addition to the key findings in this study, the regression coefficients of sentiments in terms of revealed topics proposed that Food and Beverage and Destination topics deploy relatively limited influence across each sentiment class transitions. Although these features are one of the essential elements of the overall hotel experience, these two topics’ weaker emotional impact suggest that they may act more as basic requirements than as unique contributors to guest satisfaction in hotels.

Considering the findings of the study, it also shows that strategic priorities and decisions should be given to settle core service issues before attempting to enhance negative emotional appeal. Therefore, hotel and department managers should focus on creating and developing interaction-oriented service confronts that exceed upgrading and optimizing their technical quality and support implementing emotional connections and communications with their past and potential guests. These approaches help to gain strategic advantages in the future of their business life cycle in terms of sustainable customer satisfaction and brand loyalty for the long-term period. Moreover, Alanya hosts many large-scale hotels and they operate under the all-inclusive system. Guest profiles of these hotels particularly contain families with children. Within this outline, improving service offerings that request to guests' positive emotions and entertainment needs like animation programs and strengthening staff attitudes has the potential to considerably enhance overall guest satisfaction level.

In strategic approach, this situation demonstrates that while preserving a pleasing standard in these areas is mandatory to prevent dissatisfaction, extensive and meaningful improvements and enhancements in overall emotion are more likely to be achieved through investments in high-impact areas such as staff interaction and communication between hotel guests, entertainment facilities and programs, and service personalization. Therefore, implementing a comprehensive strategy that maintains operational efficiency and speed while simultaneously enhancing emotionally salient service elements appears to be an effective way for hotels to maximize their guest satisfaction and long-term loyalty to hotel brands.

Findings of the study also provide related theoretical contributions to the eWOM literature by demonstrating how emotional valence in online hotel reviews is shaped by specific service encounters. Consumers share online reviews primarily to express emotions, seek social interaction, and provide guidance to others. The strong positive sentiment identified in animation, staff and amenities-related topics aligns with the positive self enhancement and altruistic motives driving eWOM creation (Hennig-Thurau ,2004), Conversely, negative sentiment patterns observed in room, front office, and reservation processes support the argument that online platforms serve as outlets for complaint behavior and dissatisfaction (Cheung & Lee, 2012). The findings also indicate that the destination and amenities categories generate high positive emotions, indicating tourists' choice confirmation behavior. The high positivity of animation and staff reviews reinforces the role of experience sharing. On the other hand, the intense negativity in the front office and guest rooms supports the stimulating and informative role of eWOM. Thus, the findings confirm the functions of the information, persuasion and experience transfer (Litvin et al, 2008). Moreover, the study's high positive sentiment in categories like animation, staff, and amenities confirms the eWOM effect, which enhances brand appeal. However, the predominance of negative sentiment in room and front desk topics are fully consistent with negative eWOM that product risk perception mechanism. Thus, hotel operational shortcomings can be identified as critical negative eWOM risk areas that may negatively impact purchase decisions (Vermeulen & Seegers, 2009).

The results of this study have similarities and differences in terms of lodging sector quality literature. The strong negative sentiment in reservation, room and front office topics corresponds to shortcomings in reliability and responsiveness dimensions, affirming that operational failures are key drivers of dissatisfaction. Conversely, the high positive feelings about staff and animation demonstrate that empathy and enthusiasm dimensions are strong. In other words, hotels provide relational quality, but a SERVQUAL mismatch emerges in the technical quality components. (Parasuraman et al, 1988; Gronroos, 1984). These findings also extend the destination service quality framework by showing that environmental and contextual attributes of the destination content contribute meaningfully to perceived service quality (Chen & Tsai, 2007). Furthermore, the negative sentiment generated by the hotel reviews confirms a problem with the LODGSERV cleanliness dimension. Negative results from the front office also indicate critical service deficiencies, consistent with the problem-solving and communication dimensions of the scale. Positivity in staff and animation indicates a strong employee behavior dimensio which is one of the core components for hotel businesses (Knutson et al, 1990). Furthermore, the concentration of positive emotion in the staff and the animation support HOLSERV's high performance in the employee and service quality dimension. However, the negativity in the room and front office indicates a serious flaw in the operational quality and physical environment dimensions. According to HOLSERV, these results prove that hotels provide experiential quality but underperform on operational quality (Mei et al, 1999). Moreover, the high positive sentiment regarding staff confirms the strength of HOTELQUAL's staff dimension. However, the negativity regarding rooms, reservations, and front office indicates a quality gap in the physical features and additional services dimensions (Falces Delgado et al, 1999). The positive sentiment generated by animation in large, especially for all-inclusive hotels in Alanya demonstrates that HOTELQUAL's additional services dimension creates significant value.

This study was conducted using Tripadvisor data on English reviews of hotels in Alanya. Future studies could expand the scope of the study by focusing on different destinations in Turkey. Because Alanya is primarily known for its resort tourism, comparative analyses could be conducted by including reviews from both Turkey and other destinations around the world where resort tourism is important. Furthermore, reviews in different languages, particularly Turkish, Russian, German, Arabic, and Persian, could be analyzed to compare the positive and negative aspects of hotels across nationalities.

Additionally, the scope of the research could be expanded by tailoring the natural language processing models used in future studies to specific time periods, hotel types, guest demographics, and travel types. Furthermore, the structure and scope of the findings could be improved by approaching the research with different methods, using different models and algorithms in both topic modeling, sentiment analysis and other machine learning based text mining and natural language processing techniques. Especially by categorizing customer reviews by year, month, or season, it may help to reveal how satisfaction and complaint trends change over time. This may help hotels optimize their service improvement strategies based on seasonal demand and customer expectations. Furthremore, conducting aspect-based sentiment analysis methods for each aspect of hotel services, such as staff, cleanliness, food, room conditions, and location can provide a detailed overview of which service elements most significantly impact customer satisfaction. Moreover, complex and nuanced sentiment analysis or topic classification may be performed using transformer-based models such as BERT, RoBERTa, XLM-R. These methods may allow to get more accurate than logistic regression or simple NLP methods, especially for short, neutral or contradictory reviews.

Article Information

Değerlendirme Evaluation	İki Dış Hakem / Çift Taraflı Körleme Two Outside Referees, / Double-Sided Blinding
Etik Beyan	Bu çalışma Etik Kurul beyanı gerektiren çalışmalar kapsamına girmemektedir. Bu çalışmanın hazırlanma sürecinde bilimsel ve etik ilkelere uyulduğu ve yararlanılan tüm çalışmaların kaynakçada belirtildiği beyan olunur.
Ethical Consideration	This study does not fall within the scope of studies requiring an Ethics Committee declaration. It is hereby declared that scientific and ethical principles were followed during the preparation of this study and that all studies utilized were indicated in the bibliography.
Benzerlik Taraması Similarity Scan	Yapıldı-intihal.net Done-intihal.net
Etik Bildirim Ethical Statement	artuklutourismstuidies@artuklu.edu.tr
Yazar Katkıları Author Contributions	Çalışma tek yazarlıdır. The study has a single author.
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