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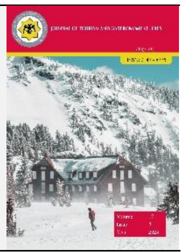

Application of Rule-based Sentiment Analysis and Machine Learning For Sentiment Analysis of Restaurant Reviews in Cappadocia, Türkiye

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Abstract

It is crucial to understand customers' sentiments and opinions about restaurants for both restaurant owners and academics in order to increase customer satisfaction and profitability. The aim of this study was to investigate customer sentiments of restaurants in Cappadocia, Türkiye. 38380 customer reviews of 386 restaurants in Cappadocia were obtained from Tripadvisor. Two different methods were used: rule-based sentiment analysis (RBSA) and machine learning (ML). The topics extracted from the reviews by RBSA were food, place, service, price, view, and staff and the percentages of these topics in the reviews were 41.45%, 23.94%, 11.36%, 9.23%, 8.18%, and 5.84%, respectively. For each topic, sentiment analysis was performed with ML to determine the proportion of positive, negative, and neutral sentiments. The highest positive sentiment content was found in food (40.15%), followed by staff (35.07%) and view (33.78%). Price (4.11%) and service (3.90%) were found to have the highest negative sentiment rates. The percentage of positive sentiment in reviews in Western languages was usually higher than in Far Eastern languages. Combining RBSA and ML techniques can enable both grammatical rules and artificial intelligence techniques while producing appropriate results. By understanding these sentiment patterns, restaurant owners can identify areas for improvement, while researchers can gain valuable insights into consumer behavior and sentiment analysis techniques.

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INTRODUCTION

Cappadocia is located in the Central Anatolia Region of Türkiye and it is mainly associated with the province of Nevşehir. The borders of Cappadocia region are Ürgüp, Göreme, Avanos, Uçhisar, Derinkuyu, Kaymaklı, Gülşehir and its surroundings (Özen, 2018). Fairy chimneys and underground cities are the first items that come to mind when it comes to Cappadocia. The areas where fairy chimneys and underground cities are located were formed by erosion as a result of natural phenomena such as wind, rain and temperature and were used by many civilizations for purposes such as protection, shelter and hiding (Berkmen, 2015). Bixio et al. (2016), in their study on Cappadocia, mentioned that there are approximately 179 underground cities, including 71 in Nevşehir and surrounding provinces. In addition to these, there are important buildings in terms of religious tourism such as mosques, churches and tombs made of rock carvings in Cappadocia. Cappadocia is the fifth most visited tourism destination in Türkiye after Antalya, Istanbul, Izmir and Muğla (TUIK, 2014). In 2019, 2.5 million tourists visited the Cappadocia region (before the Covid-19 pandemic) (Şener, 2022). Therefore, 10% of the approximately 50 million tourists coming to Türkiye visit the Cappadocia region (Culture and Tourism Ministry of Türkiye, 2023). Avanos pottery, Derinkuyu dried beans, creamy dried cream, creamy doughnuts, Nevşehir pumpkin seeds, Nevşehir bagels and Nevşehir pottery kebab are geographically registered products. The region is renowned for its diverse agricultural products, including strawberries, raisins, garlic, and meatballs, as well as unique handicrafts like Kitre dolls. Additionally, the area boasts a rich history and natural beauty, with famous winemaking and grape-growing traditions, distinctive geological formations, popular hot air balloon rides, and ancient underground cities. These attributes, along with the region's unique product applications, as evidenced by the Turkish Patent Institute (2022), contribute to its distinctive identity.

Eating and drinking behavior constitutes the most basic need of tourists during their accommodation and travels. With this feature, eating and drinking serve not only as essential physiological needs during tourism activities but also as integral components of the overall tourism experience. As gastronomic tourism gains prominence, food and beverage consumption evolves into a central focus, offering tourists opportunities for social, emotional, technical, and cultural engagement beyond mere sustenance (De Albeniz, 2018). Therefore, gastronomic experience is closely related to many elements such as spatial features, stories, lifestyle and local products (Akyürek & Kutukız, 2020). In addition, gastronomic experience has a significant impact on emotional satisfaction. In this regard, Cappadocia is a significant tourist destination.

To fully appreciate the impact of tourism on Cappadocia, it is crucial to understand the experiences and perceptions of visitors. In recent years, social media platforms have emerged as powerful tools for sharing experiences and opinions. By analyzing user-generated content, researchers can gain valuable insights into consumer behavior, preferences, and satisfaction levels. Social media platforms, including Yelp, Google Maps, Booking, and TripAdvisor, have become forums for travelers to share their experiences with restaurants and destinations. This surge in user-generated content offers valuable insights for businesses and researchers alike. By leveraging advanced social media technologies, it is possible to efficiently gather, analyze, and utilize this information to enhance management practices and decision-making processes (Zhang et al., 2022). User-generated content also plays an increasingly important role in a potential customer's decision-making process. Artificial intelligence techniques have recently been utilized to process such a large amount of feedback from customers (Alamoudi & Alghamdi, 2021). Özen (2021), evaluated foreign tourist reviews of restaurants serving local specialties in Gaziantep province on

TripAdvisor using view-based sentiment analysis, one of the text mining methods. While the restaurants in the region were found to be positive in terms of taste, cleanliness and ambient features, the expensive and crowded nature of the restaurants were identified as negative aspects. These findings highlight the importance of utilizing AI techniques in analyzing customer feedback to understand their preferences and improve overall satisfaction. By leveraging sentiment analysis, it is possible to can gain valuable insights to make informed decisions and enhance the customer experience. While user-generated content can provide valuable insights, it is important to consider the potential biases and inaccuracies that may exist in these reviews. Additionally, not all customers may be active on social networks or trust online reviews, limiting the reach and impact of this information.

The specific focus of this study was to investigate customer sentiments towards restaurants in Cappadocia. By employing advanced sentiment analysis techniques, we aim to identify key themes, patterns, and trends in customer reviews. This research will provide valuable insights for restaurant owners, policymakers, and tourism stakeholders to improve the overall dining experience and enhance the region's tourism appeal. The objective of this study was to apply the most recent methodologies to reveal the customer sentiments and customer satisfaction of restaurants serving in Cappadocia. It was also aimed to determine the languages mentioned in the reviews and to identify customer sentiment by country.

Materials and Methods

Materials

Customer reviews and ratings from TripAdvisor were utilized as the dataset for this study (TripAdvisor Inc., 2023). A total of 386 restaurants were available and 38380 customer reviews were collected. All restaurants and reviews were from the Cappadocia region. In the data preprocessing step, Turkish reviews were discarded, the data was spell checked, and non-English reviews were translated into English (Figure 1). All words were then lowercased and the punctuations were removed. The sentences were tokenized and lemmatization was performed. A string of words is broken up into smaller pieces, commonly referred to as tokens, through the tokenization process. For instance, “Food was amazing and plentiful” to be “Food”, “was”, “amazing”, “and”, “plentiful”. On the other hand, lemmatization refers the reduction of a word to its most fundamental form. For instance, “smiles”, “feet”, “children” and after the lemmatization, it transforms into “smile”, “foot”, “child” (Zahoor et al., 2020). Two alternative methods were employed in this study to evaluate customer sentiment. Rule-based sentiment analysis (RBSA) is the first, while machine learning (ML) is the second.

Rule-based Sentiment Analysis (RBSA)

Grammatical tagging, also known as part-of-speech tagging, is the process of assigning tags to words in sentences depending on their function and definition (Schmid, 1994). Here is an example of a review; "Very strong coffee, friendly staff and most important, it is the earliest that is open. Perfect for after a hot air balloon ride.". Grammatical tagging result: ('Very', 'RB'), ('strong', 'JJ'), ('coffee', 'NN'), ('friendly', 'JJ'), ('staff', 'NN'), ('and', 'CC'), ('most', 'RBS'), ('important', 'JJ'), ('it', 'PRP'), ("is", 'VBZ'), ('the', 'DT'), ('earliest', 'JJS'), ('that', 'DT'), ("is", 'VBZ'), ('open', 'JJ'), ('Perfect', 'NNP'), ('for', 'IN'), ('after', 'IN'), ('a', 'DT'), ('hot', 'JJ'), ('air', 'NN'), ('balloon', 'NN'), ('ride', 'NN').

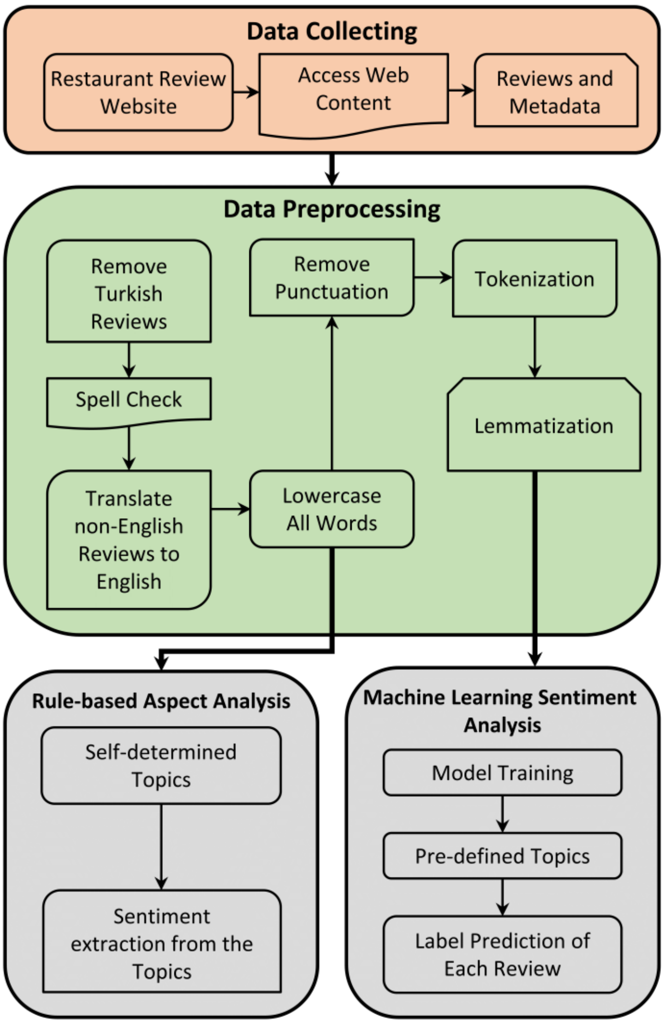


Figure 1. Architecture diagram of the research framework

In this study, since other words do not provide any logical information for sentiment, we focused on adjectives (tagged as "JJ", "JJR", "JJS", "RB", "RBR", "RBS") and nouns (tagged as "NN", "NNS", "NNP", "NNPS") to extract features. Python programming language (version 3.9) and NLTK module (Wagner, 2010) were utilized in this implementation.

Artificial neural network (ANN) Regression Machine Learning (ML)

In natural language processing (NLP), ML is frequently used because RBSA cannot capture all the information from the phrases. An ANN model was built using Python 3.9 for this purpose. The model training performed with Word2Vec class from the Gensim module (Rehurek & Sojka, 2010). Number of vector size was set as 200, learning rate as 0.03, number of epochs as 150, minimum count as 10, and window as 5. The computer used in this study has an Intel Core i7-8750-H CPU with 2.20 GHz and 16 GB physical memory.

T-Distributed Stochastic Neighbor Embedding (T-SNE)

In order to investigate the relationships between the topics, t-SNE was used to examine variations among the topics that were captured by RBSA. The topics and all words were converted to vectors (size = 200) by the previously built ML model and decomposed into 2 dimensions with t-SNE. Thus, vectors converted into human-readable form and demonstrated with a scatter plot. The t-SNE model was built with a learning rate of 50, distance metric of "Euclidean", number of nearest neighbors (perplexity) of 3, and a maximum number of iterations for the optimization of 1000 (Van der Maaten & Hinton, 2008).

Results and Discussion

Rule-based Sentiment Analysis (RBSA)

After data cleaning and preparation for analysis, identifying the most prevalent terms offers foundational insights into the dataset. Utilizing a word cloud facilitates a straightforward visual depiction of this representation, wherein terms appearing frequently in the dataset are visually emphasized through boldness and enlarged size. Figure 2 displays the top 100 words from the dataset. Positive words like "great", "delicious", "excellent", and "best" are the first words that strike the eye at first glance. There are also plenty of neutral words, such as "people", "service", "table", "lunch", and "family".

RBSA can provide comprehensive details regarding the corpus. A technique called part-of-speech tagging (POS tagging) analyzes the sentence and tags each word with its part of speech, such as an noun, verb, adjective, etc. (Bagheri et al., 2013). After conducting POS tagging, the resultant tags can be leveraged to extract sentiment information from the sentences. Employing the RBSA method enables the identification of topics within reviews, allowing for the extraction of individual words associated with each topic. Figure 3A shows 38380 reviews categorized as positive, negative and neutral. The percentages of positive and negative reviews were 93.92% and 5.21%, respectively, while neutrals were only 0.87%. Pantelidis (2010) obtained customer reviews of 791 restaurants operating in London between 2005 and 2007 from a website and reported the percentage of positive and negative reviews as 77.62% and 22.38%, respectively. Alamoudi and Al Azwari (2021) stated that the percentages of positive, negative and neutral sentiments in a restaurant dataset obtained from Yelp (https://www.yelp.com) were 64.6%, 21.8%, and 13.6%, respectively, while Dosoula et al. (2016) reported the positive sentiment percentage as 58.7% in web-based restaurant data. This indicates a higher proportion of positive reviews compared to negative and neutral reviews in the dataset.

Figure 2. Word cloud for restaurant reviews

Sentiment analysis frequently incorporates the identification of subjective content and the determination of sentiment polarity. The polarity value ranges between -1 and 1, and the more negative or positive the review is, the closer it is to these values. Hence, polarity refers to the strength of sentiment. On the other hand, the degree to which a person is personally invested in an object is referred to as subjectivity. Hence, subjectivity refers to the strength of personal experiments. The distribution of polarity and subjectivity values of the reviews were demonstrated in Figure 3A. The fact that both the polarity value of a restaurant review is close to -1 and the subjectivity value is close to 1 indicates that there is an intense sentiment in this review and that personal experience is extremely negative about that restaurant (upper left corner of Figure 3). It is desirable to have as few comments of this nature as possible, which can be said to be quite few for Cappadocia restaurants. The fact that the subjectivity value is close to 0 is extremely important and trustable that reviews of this kind describe the real situation rather than personal opinions. This suggests that the reviews for Cappadocia restaurants are generally objective and reliable in providing an accurate depiction of the dining experience. It is crucial for potential customers to consider these types of reviews when making decisions about where to dine in the area.

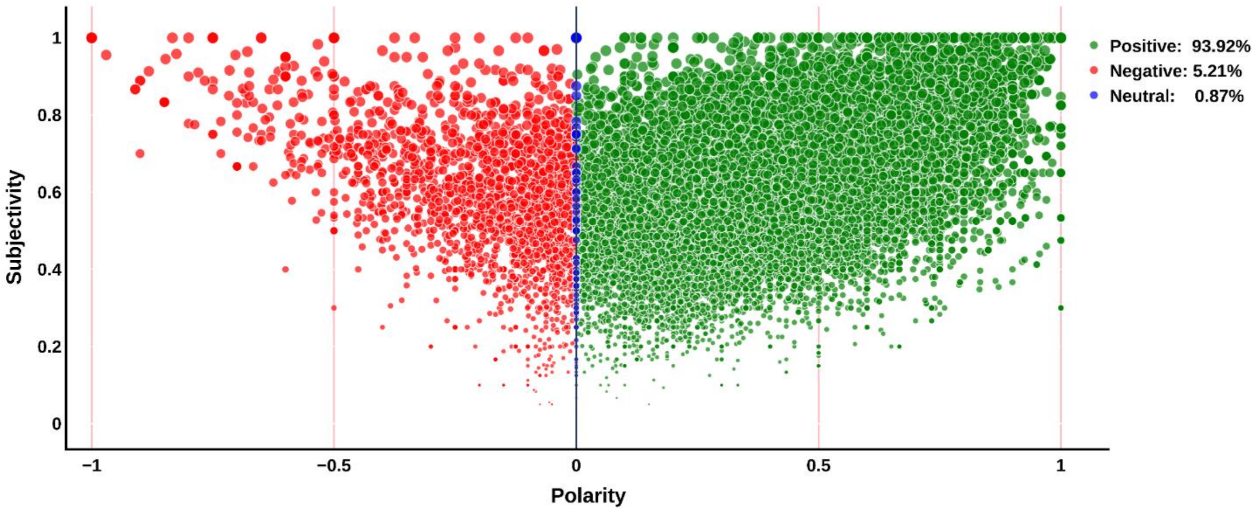
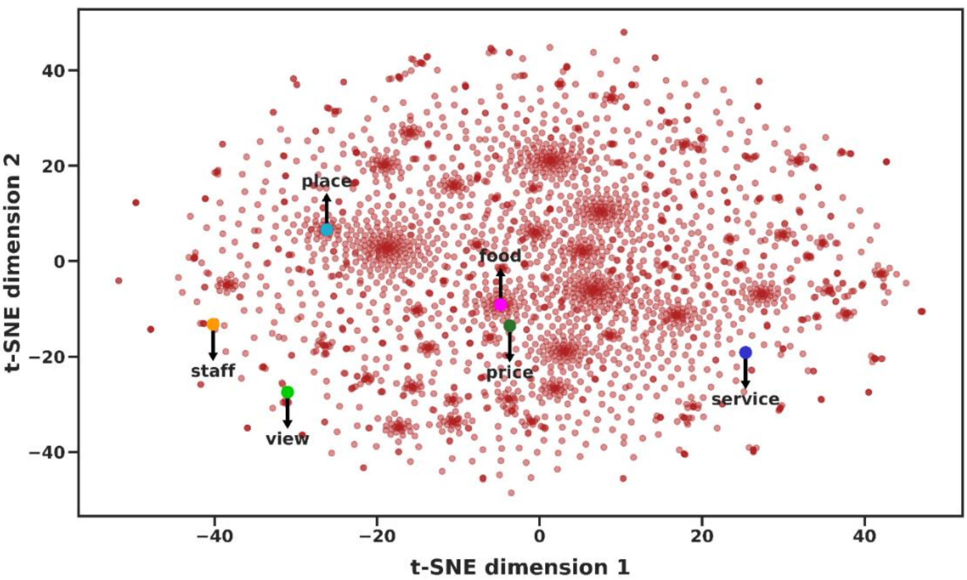
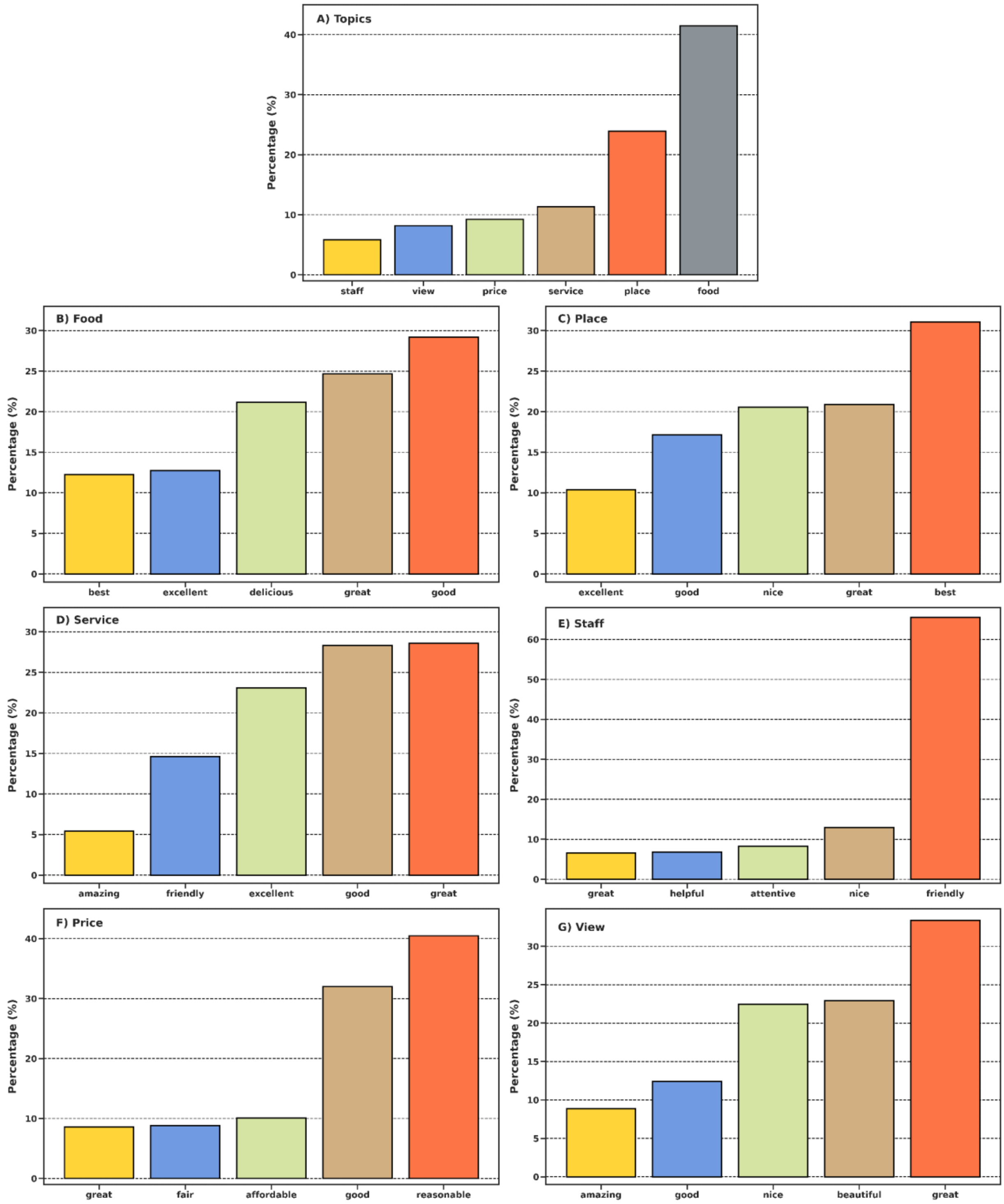


Figure 3. Percentages of positive, negative, and neutral reviews and polarity-subjectivity distribution of reviews (A), Vector visualization of words in reviews with t-SNE (B)



Food, place, service, staff, price, and view were the 6 topics that were extracted from the corpus (Figure 4). Since nouns were included as topics in the current study, the frequencies of these topics were found to be higher than that of other nouns. Pantelidis (2010) identified these topics as food, service, atmosphere, price, menu, and design/decor in his study, while Mathayomchan and Taecharungroj (2020) obtained service, value, price, and atmosphere in the data of some restaurants in the UK obtained from Google maps (https://www.google.com/maps).

Alamoudi and Alghamdi (2021) declared the topics as ambience, service, price, and food in restaurant reviews obtained from Yelp website, whereas Dosoula et al. (2016) detected as price, service, food, and anecdotes/miscellaneous in web-based restaurant data. This suggests that very similar topics have been identified in different studies and that the topics in this study are similar to those in other studies. It was found that customers mostly commented about food with 41.45%, followed by place with 23.94% (Figure 4A). This outcome is consistent with the observation that customer reviews typically concentrate on the culinary experience and the overall environment of the establishment. The number of reviews on other topics is quite close to each other and varies between 5.8% and 11.4%. Dosoula et al. (2016) observed the percentages of topics price, ambiance, service, and food as 8.14%, 16.22%, 22.54%, and 53.10%, respectively. Tian et al. (2021) used web-based restaurant data belonging to Las Vegas, Nevada in USA and reported the topics as expenditure, social, service, food, and miscellany with the percentages of 2%, 3%, 13%, 37%, and 45%, respectively. These findings suggest that customers tend to focus more on food and service when leaving reviews for restaurants. It is interesting to note the variations in topic percentages across different studies, indicating potential cultural or regional differences in customer preferences.



A) Topics, B) Food, C) Place, D) Service, E) Staff, F) Price, G) View

Figure 4. Sentiment analysis results obtained by rule-based aspect analysis

The aim was to reveal customer sentiments about the topics by constructing sub-groups for each topic. These subgroups were formed from adjectives that exhibited higher frequencies compared to other adjectives in the corpus. The most frequently used words by customers for each topic were shown in Figure 4. In general, customer reviews were found to be quite positive. The fact that Cappadocia receives about 10% of all international visitors to Türkiye is regarded to be a result of the locals' extensive knowledge and expertise in the tourism industry, which has contributed to the customers' overall pleasure (Culture and Tourism Ministry of Türkiye, 2023). This highlights the importance of the locals' role in enhancing the overall tourism experience in Cappadocia. Additionally, it underscores the significance of their expertise and knowledge in attracting international visitors to the region.

Machine Learning (ML) Sentiment Analysis

Word2Vec implementation from Gensim module transformed every word in the restaurant reviews into vectors. The artificial neural network (ANN) employed in this implementation is specifically designed for text processing. Each word was transformed into a vector composed of 200 float numbers using a process known as word vectorization, also known as model training. Since it is not possible to display 200-size dimensional data in a way that is human-readable, the vectors were transformed into 2D space using the t-SNE technique. t-SNE is a nonlinear dimensionality reduction algorithm that produces a low-dimensional distribution of high-dimensional data for data representation (Belkina et al., 2019). Figure 3B shows the word vectors displayed in 2D space in the ML model. The plot shows many clusters. This is due to the fact that the words in these clusters have close meanings with each other. Another reason is that the words in these clusters are used in close proximity to each other in the same sentence. In this study, the window was set to 5 for model training. Thus, when a word is converted into a vector, the vectors of the words 2 to its right and 2 to its left will converge to the vector of the word in question. The reason why the words food and price are very close to each other in Figure 3B is because they were used close to each other many times in the sentences. Tsai et al. (2016) stated that if the review refers to price, food is usually mentioned first. It can be seen that the food topic is located in the center of the plot. This makes sense considering that reviews of restaurants frequently include comments about the food.

Figure 5A shows the sentiment analysis results obtained by the ML of each topic. Positive, negative and neutral percentages for each topic were given on the plot. The highest positive evaluation was found for food with 40.15%, followed by staff with 35.07%. Food topic has the lowest percentage of negative sentiment with 1.84% and the highest percentage of positive sentiment with 40.15%. It can be concluded that the restaurants serve highly satisfying food. Price topic received the most unfavorable rating (4.11%), followed by service (3.90%). Considering that service also has the lowest positive sentiment rate (23.45%), it can be inferred that there were often some issues with service in these restaurants. This could be due to some factors such as slow or cold service or the wrong food being delivered. According to Vu et al. (2019), international tourists give the most attention to service. In our study, the fact that service is the second least rated topic (3.90%) may be due to the importance given to this topic by tourists. Zhang Tian et al. (2021) also indicated that compared to food, consumers use more sentiment words (both positive and negative) when discussing restaurant service. It is reasonable that price has the lowest sentiment percentage because customers generally complain about price. Alamoudi and Alghamdi (2021), Tian et al. (2021), and also reported the lowest sentiment percentage in price. Nevertheless, price was stated to be less important than food quality, speed, service, interior design, cleanliness, comfort, scent, and lighting (Hu et al., 2009).

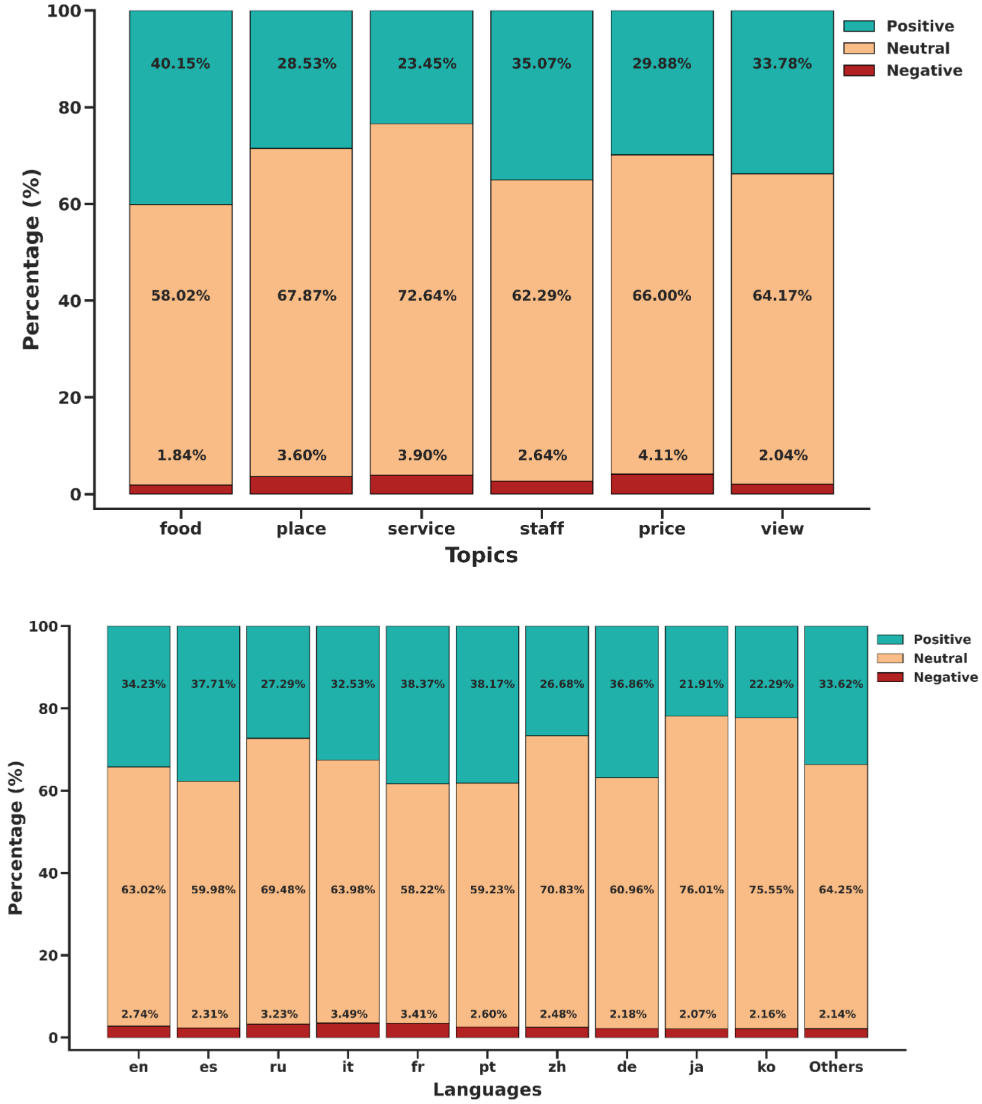


Figure 5. The results of the sentiment analysis obtained by the ML for each topic (A), The results of the sentiment analysis obtained by the ML for each language (B)

* en = English, es = Spanish, ru = Russian, it = Italian, fr = French, pt = Portuguese, zh = Chinese, de = German, ja = Japanese, ko = Korean

Mathayomchan and Taecharungroj (2020) obtained 5010 restaurant reviews from Google maps in different cities of England and determined the lowest sentiment rate in price, followed by atmosphere, service, and food. Overall, price seems to be a common factor contributing to low sentiment percentages in customer reviews across various studies. It is important for restaurants to consider not only price, but also other aspects such as food quality and service in order to improve overall customer satisfaction.

It was observed that there were 32 different languages used in the restaurant reviews. The 10 most frequently used languages and their usage proportions were given in Table 1.

Table 1. Review counts and percentages of languages used in restaurant reviews

	en	es	ru	it	fr	pt	zh	de	ja	ko	Others	Total
Review count	24614	2430	2362	2301	1750	1337	1090	741	604	578	573	38380
Percentage (%)	64.13	6.33	6.15	6.00	4.56	3.48	2.84	1.93	1.57	1.51	1.50	100

* en = English, es = Spanish, ru = Russian, it = Italian, fr = French, pt = Portuguese, zh = Chinese, de = German, ja = Japanese, ko = Korean

The majority of reviews were in English (64.13%), followed by Spanish (6.33%), Russian (6.15%) and Italian (6.00%). In 2014, Japanese tourists (10%) visited Cappadocia the most, followed by German (8%), French (5%) and US (4%) citizens (TUIK, 2014). This indicates that many customers would rather comment in English than their native tongue. Sentiment results for each language were demonstrated in Figure 5B. The percentages of negative sentiments did not significantly vary among the languages and ranged from 2.07% (Japanese) to 3.49% (Italian). Reviews containing positive sentiments were most frequently commented in French (38.37%), Portuguese (38.17%), Spanish (37.71%), and German (36.86%), and least frequently in Japanese (21.91%), Korean (22.29%), Chinese (26.68%), and Russian (27.29%). It was found interesting that the tourists from Far Eastern countries had fewer reviews with positive sentiments. There may be many reasons for this situation. This is probably due to the fact that people from these countries like Turkish cuisine less. Oral and Çelik (2013) stated that the cuisine and culture of the Far East is quite different from Turkish cuisine and this has a significant impact on the level of appreciation. Nakayama and Wan (2019) Nakayama and Wan (2019) found that Japanese reviewers placed more emphasis on food quality and were more negative about the ambience than Western reviewers. Therefore, it is possible that tourists from Far Eastern countries may have different expectations and preferences when it comes to dining experiences in Türkiye. Understanding these cultural differences can help businesses cater to the needs and preferences of tourists from different regions.

Conclusion

In this study, sentiment analysis of 386 restaurants serving in the Cappadocia region was performed with 2 different methods: rule-based sentiment analysis (RBSA) and machine learning (ML). RBSA identified key topics, including food, place, service, staff, price, and view, and quantified sentiment polarity. ML analysis, using t-SNE, visualized the semantic relationship between words, revealing a strong connection between price and food.

Our findings indicate a high level of overall customer satisfaction, with positive sentiment dominating. Food quality was the most frequently discussed and positively rated aspect, followed by staff and place. Conversely, price and service received the highest negative sentiment. The multilingual nature of the reviews, with English, Spanish, Russian, Italian, and French being the most prevalent languages, highlights the global reach of the Cappadocia tourism industry.

Future research could delve deeper into the specific factors influencing customer satisfaction and dissatisfaction. By examining the sentiment associated with individual dishes, service experiences, or ambiance, businesses can identify areas for improvement. Additionally, exploring the impact of cultural differences on review patterns and sentiment expression could provide valuable insights for tourism stakeholders. Ultimately, the insights gained from such research can contribute to enhancing the overall customer experience and promoting sustainable tourism in the region.

Declaration

All authors of the article contributed equally to the article process. The authors have no conflicts of interest to declare.

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