

SENTIMENT-BASED EVALUATION OF TOURIST EXPERIENCES FROM ONLINE REVIEWS

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ABSTRACT

Domestic Online reviews offer tourists additional user-generated data to assess tourist satisfaction and determine what factors impact the tourism experience. A study analysed tourists' experiences by sentiment analysis comprising 20,491 TripAdvisor hotel reviews. Secondary data and a quantitative and cross-sectional design were used. Review texts were cleaned and processed using natural language processing and text-mining techniques. The polarity scores in TextBlob were used to determine the sentiment of the reviews such as positive, neutral, and negative sentiment and relationships between textual sentiment and customer ratings were explored using descriptive statistics, Pearson correlation, chi-square testing, one-way analysis of variance, keyword analysis, and graphical visualisation. The outcome revealed that 86.15% of the reviews were positive, 10.77% were neutral and 3.08% were negative. The combination of four and five stars accounted for 73.66% of the total number of observations. Sentiment polarity was also significantly and positively correlated with customer ratings ($r = 0.647$, $p < 0.001$), and significant differences in polarity were found between the categories of ratings. The main dimensions that influenced tourists' experiences were room conditions, staff behaviour, food and breakfast, location, cleanliness, comfort, service quality, and value for money. The results show that the inclusion of the numerical ratings and the textual sentiment gives a more holistic measure of satisfaction compared to using one measure individually. Through sentiment-based review analytics, hotel management can identify strengths in their services, unearth recurring issues, enhance customer experiences, and aid in evidence-based hospitality decisions.

Key words: sentiment analysis; tourist experience; online reviews; TripAdvisor; customer satisfaction

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1. Introduction

Digital technologies have changed the way tourists find information, plan their trips and assess hospitality services so significantly that it has revolutionised the sector. Digital technologies have revolutionised the sector, specifically in the way tourists search for information, plan their trips and assess hospitality services. Online travel platforms like TripAdvisor, Booking.com, Expedia, and Google Reviews have become a vital source for tourists to share their experiences and experiences, impacting potential visitors' choices. Tourists are increasingly sharing experiences and reviews on online travel platforms like TripAdvisor, Booking.com, Expedia, and Google Reviews, which can influence the decisions of potential visitors. The platforms have created a vast amount of user-generated content (UGC) that is helpful in understanding tourists' perceptions, expectations and satisfaction with the tourism products and services (Hlee, Lee, and Koo 2018; Mariani et al. 2018). The growing volume of these kinds of digital data has transformed the tourism industry into a data-driven sector by observing customers' opinions continuously, which enables the industry to make decisions and enhance the quality and competitiveness of the services offered (Alaei, Becken, and Stantic 2019; Alsharif, Isa, and Alqudah 2024).

One of the most powerful factors influencing tourists' destination selection and booking decisions is electronic word-of-mouth (eWOM). Online reviews are typically believed to be more genuine and credible than conventional marketing communications since they come from other travellers who have personal experience of the trip. While positive reviews build trust in the destination, increase revisit intentions, and reinforce the credibility of tourism businesses, negative reviews can have a detrimental effect on reputation and customer confidence (Abubakar et al. 2017; Filieri et al. 2021). As a result, tourist groups are increasingly turning to online reviews to learn about consumer preferences and adjust their services to the needs of their customers.

Tourist experience is defined as a multidimensional phenomenon that involves affective, cognitive, social and behavioral reactions during the process of traveling. Satisfied customers are linked to memorable tourism experiences, which are related to high-quality accommodation, customer-oriented services, appealing places and meaningful connections, and lead to tourists' loyalty towards the destination in the long term (Bigne, Fuentes-Medina, and Morini-Marrero 2020). It is generally accepted that customer satisfaction is a significant factor influencing positive behavioral intention such as repeat visits, word of mouth, and positive online reviews (Orgaz Agüera and Domínguez-Valerio 2024).

In the hospitality sector, previous studies have shown that various dimensions of the service such as room quality, cleanliness, professionalism of the employees, quality of the food, location, value for money, and technological support affect tourist satisfaction in the hotel environment (Rahman 2023; Teng, Li, and Chen 2025). In the era of technology-driven tourism, the expectations and experiences of tourists are changing, and smart hospitality services are integral to this shift. Smart hospitality services are crucial in shaping the expectations and experiences of tourists, and hospitality managers will need to be vigilant to track tourists' feedback and respond to their evolving service requirements (Alsharif et al. 2024; Casalo, Flavián, and Ibáñez-Sánchez 2020).

The classification of positive, neutral, or negative sentiment in online reviews through NLP and sentiment analysis enables the efficient evaluation of tourists' satisfaction (Alaei et al. 2019; Mehraliyev, Chan, and Kirilenko 2022). The key service attributes that yield a positive impact on the user's experience during the hotel stay are also identified using lexicon-based and machine learning techniques (Mariani et al. 2018; Moro, Rita, and Coelho 2017).

In the tourism sector, these are broadly used for assessing the performance of hotels, destination image, predicting tourist demand, and analysing customers' experiences. They can be integrated into big data to achieve an understanding of tourist behavior and service quality, as well as destination competitiveness (Cheng et al. 2018; Li et al. 2017).

Previous tourism and hospitality research is usually based on a survey that has predetermined questions and limited samples, and does not adequately reflect the spontaneous experiences of tourists expressed online (Hlee et al. 2018).

While previous studies have focused on the credibility of reviews, tourism demand and customer behaviour, few studies have integrated textual sentiment analysis with numerical ratings, using open access datasets (Filieri et al. 2021). This study aims to fill the gap by analyzing TripAdvisor reviews, analyzing user sentiment and ratings, and determining the factors that affect their satisfaction and dissatisfaction.

The aims of this study include analysis of tourists' online reviews through sentiment analysis techniques, assessment of tourist experiences based on the sentiments written in the reviews, investigation of the relationship between the rating level of the reviews and the sentiment of the reviews, and determination of the most important aspects that affect the tourists' satisfaction and dissatisfaction in the hospitality sector.

Materials and Methods

Study Design

The type of quantitative study design employed in this study was an observational type with a cross-sectional secondary data analysis approach to assess the tourist experience expressed in online hotel reviews. The study did not gather primary survey responses but instead analysed user-generated content that is made public to understand the perception of tourists with regard to hospitality services. As all the reviews are independent observations taken at various points in time but analyzed in the same study framework, a cross-sectional design was deemed to be appropriate. The quantitative method allowed the systematic assessment of sentiment, statistical analysis and the application of text mining for identifying factors that affect the tourists' satisfaction and dissatisfaction.

Data Source and Dataset Description

This study's dataset includes 20,491 hotel reviews collected from TripAdvisor website by tourists and has been extensively used for tourism analytics and natural language processing studies (Larxel 2020). The two variables for each observation are Review, which is the written account of the tourist's hotel experience, and Rating, which is the rating on a five-point scale (1–5) that the tourist gives his or her overall experience with the hotel. Ratings of 1 indicate very poor experiences, whereas ratings of 5 represent excellent experiences. The dataset was publicly available and fully anonymised; hence no ethical approval or informed consent was required.

Data Preprocessing

A thorough pre-processing process was carried out to enhance data quality and facilitate accurate sentiment analysis before analysis. This data was checked for duplicate observations and missing data, and no missing data or duplicate observations were found. The text processing was then carried out after converting all texts to lowercase. The punctuation, special characters, numerical symbols and unnecessary white spaces were deleted. The cleaned text was tokenized into individual words, then random words were removed from the text to eliminate words that occur frequently but are semantically insignificant. Lemmatization was used to convert words into their root forms but still maintain the meaning of the word in the context. Lastly, the review corpus was text-normalized to make it uniform before feature extraction and sentiment classification.

Variable Definition

In this study the first independent variable was the textual Review, which consisted of the opinions of tourists writing about the hotel experience. Tourist Experience Sentiment was obtained through sentiment analysis and classified into positive, neutral, and negative classes according to the sentiment polarity score. The sentiment polarity score was used to determine the class of the sentiment. The sentiment polarity score was used to classify the sentiment into positive, neutral, and negative classes, and the dependent variable was the Tourist Experience Sentiment. This original Customer Rating (1-5) is provided as an extra analytical variable to analyse consistency with the textual sentiment; it also enables the use of the information in comparative statistical analysis.

Sentiment Analysis and Text Mining

A lexicon-based Natural Language Processing (NLP) technique was adopted to carry out sentiment analysis. A sentiment analysis tool called VADER (Valence Aware Dictionary and sEntiment Reasoner) was employed for sentiment analysis of the cleaned review texts, which is specifically developed for analyzing opinions from online reviews. VADER-generated compound polarity scores were used for sentiment classification into positive, neutral, and negative sentiment based on threshold values.

Several text mining approaches were used to extract the main themes of tourists' experiences. The importance of words across the review corpus was quantified using the term frequency-inverse document frequency (TF-IDF) vectorization method. The most frequently used words related to tourist satisfaction and dissatisfaction were determined with word frequency analysis and the most common phrases concerning hotel services were detected by the unigram and bigram analyses. The principal aspects of the discussion by tourists were also emphasised in the keyword extraction such as service quality, service personnel's behaviour, cleanliness, location, food, comfort, and value for money.

Exploratory Data Analysis

Initially, Exploratory Data Analysis (EDA) was performed on the dataset to provide a summary of the features of the dataset before carrying out data statistical modelling. The distribution of customer ratings was analyzed to gain insight into the overall satisfaction trends. Textual responses were assessed using review length statistics to determine the range of responses. Positive, neutral and negative sentiment frequency distribution was examined to evaluate the overall tourist perception. Graphical visualisations were also created such as rating distributions, sentiment distributions, and word cloud representations of the text data and common attributes of the hospitality sector.

Statistical Analysis

The characteristics of customer ratings and sentiment categories were summarized using descriptive statistical analysis. Where applicable, frequency statistics, percentages, means and standard deviations were calculated. Pearson's correlation analysis was used to determine the correlation between the review ratings and the sentiment classification. A chi-square test of independence was used to check if there is a significant association between customer ratings and categories of sentiment. When comparing two or more rating groups, one-way Analysis of Variance (ANOVA) was used to assess differences in sentiment polarity scores. All tests were conducted at a 5% significance level ($p < 0.05$).

Machine Learning Classification

To compare the effectiveness of machine learning-based approaches for automated sentiment prediction several supervised machine learning algorithms were implemented based on the generated sentiment labels for sentiment analysis. The classifiers that were evaluated were Logistic Regression, Multinomial Naive Bayes, Support Vector Machine (SVM), and Random Forest. Before training models, the review texts were converted into numerical feature vectors using the TF-IDF representation. The dataset was split into a training set and a test set to test predictive performance and compare classification accuracy of the various algorithms.

Performance Evaluation

Standard machine learning performance metrics were used to assess the predictive performance of the sentiment classification models. Model accuracy was used to measure the overall accuracy of the model; precision and recall were used to measure the reliability and completeness of the model when making predictions for each class. Precision and recall scores were computed and a F1-Score calculated to get a balanced score in the case of class imbalance. In addition, Receiver Operating Characteristic–Area Under the Curve (ROC–AUC) was calculated, if applicable, for the discriminative ability of the classification models.

Results

Descriptive Characteristics of the Dataset

The final dataset included 20,491 TripAdvisor hotel reviews and two original variables: Textual review content and Customer rating. There were no missing values or duplicate observations found. The ratings of the customers were between 1 and 5 stars; the overall mean rating was 3.95 ± 1.23 . On average, reviews included 108.46 ± 105.00 words and the median was 80 words. Table 1 shows that the dataset had sufficient size and completeness to apply the processes of sentiment analysis and text mining.

Table 1. Characteristics of the Online Review Dataset

Characteristic	Result
Total reviews	20,491
Original variables	2
Missing values	0
Duplicate records	0
Mean rating	3.95 ± 1.23
Rating range	1–5
Mean review length	108.46 ± 105.00 words
Median review length	80 words

Distribution of Customer Ratings

The rating distribution was mostly positive. The largest section of the five-star ratings was five-star ratings (9,054 reviews, 44.19%), followed by four-star ratings (6,039 reviews, 29.47%). The four- and five star ratings in total accounted for 73.66% of all observations. As shown in Figure 1, the number of customer evaluations in the 4+ and 5-star category is high, which also suggests that the hotel experiences are generally favourable.

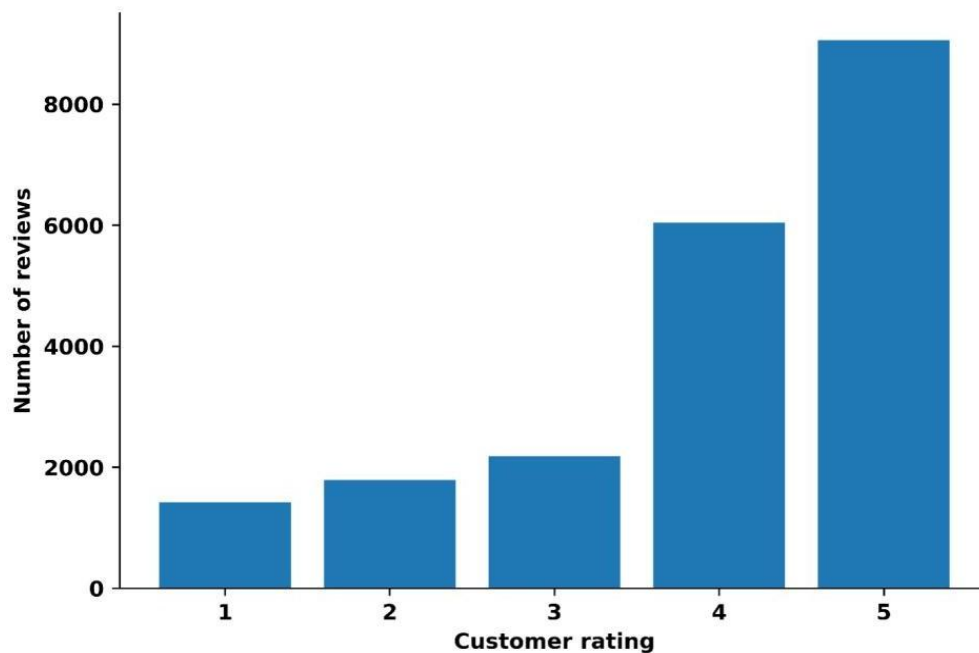


Figure 1. Distribution of Hotel Ratings

Sentiment Classification Results

The polarity scores for the reviews were used to categorize the reviews as negative, neutral, or positive using TextBlob. The polarity score of any review below -0.10 was considered negative, below 0.10 as neutral, and above 0.10 as positive. The majority of the reviews were favourable. As indicated in Table 2, the number of positive

sentiments in the review corpus was the majority, while the number of reviews with explicit negative sentiment was relatively small.

Table 2. Distribution of Review Sentiments

Sentiment	Frequency	Percentage
Positive	17,653	86.15%
Neutral	2,206	10.77%
Negative	632	3.08%
Total	20,491	100.00%

Relationship Between Ratings and Textual Sentiment

There was a continuous rise in positive sentiment in each rating category. In five-star ratings, 8,930 were positive while just 286 were positive in one-star ratings. Negative sentiment, on the other hand, was most common among one-star reviews. Figure 2 shows that while negative and neutral reviews were mostly focused on lower ratings, the percentage of positive reviews grew significantly as the customer rating grew.

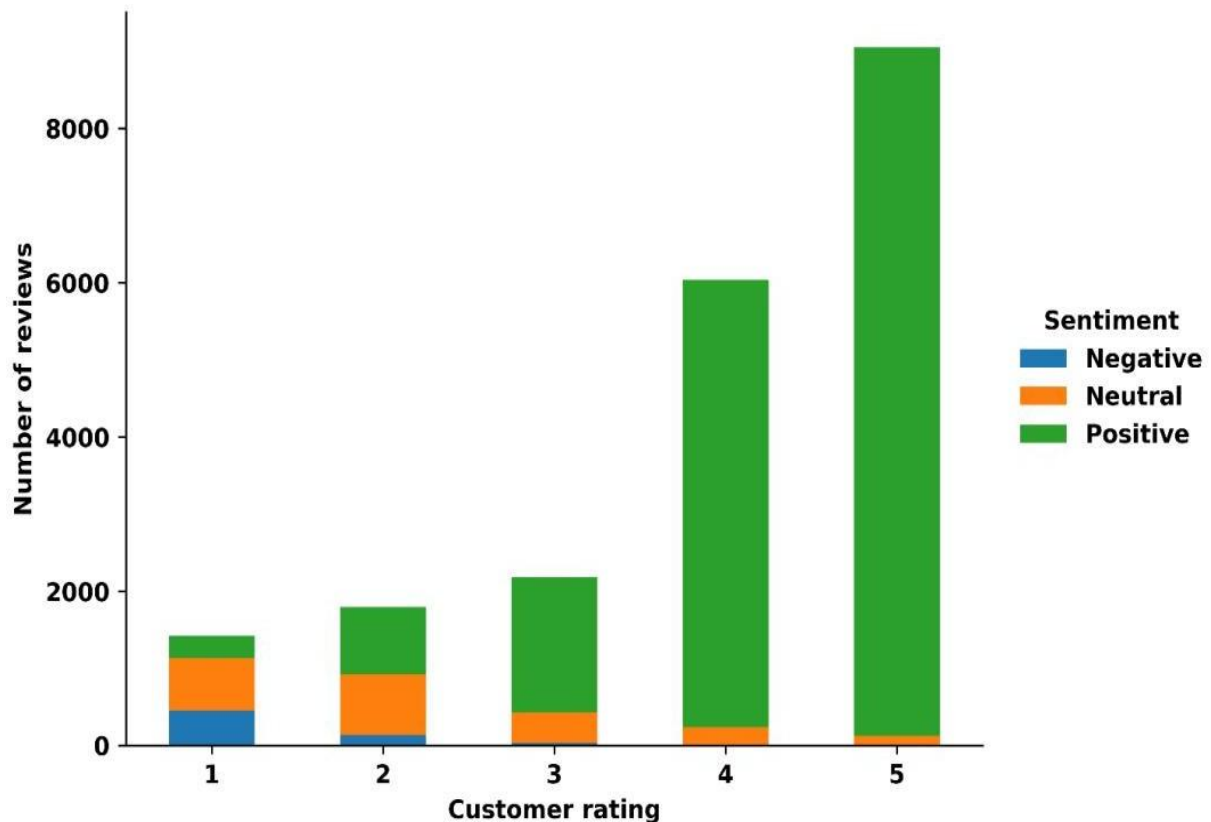


Figure 2. Sentiment Classification Across Customer Ratings

Frequently Discussed Tourist Experience Dimensions

Aspect-based keyword analysis revealed that the most talked about experience dimension was related to room attributes, which were found in 88.05% of the reviews. Other factors also mentioned were staff, food/breakfast, location, price/value, cleanliness, comfort and service. Table 3 indicates that tourists primarily evaluated physical accommodation conditions, staff interactions, dining experiences, location, cleanliness, comfort, service, and value for money.

Table 3. Frequently Mentioned Tourist Experience Dimensions

Experience dimension	Reviews mentioning aspect	Percentage
Room	18,043	88.05%
Staff	13,385	65.32%
Food/Breakfast	12,693	61.94%
Location	12,520	61.10%
Price/Value	8,963	43.74%
Cleanliness	8,750	42.70%
Comfort	8,068	39.37%
Service	7,314	35.69%

Correlation and Statistical Association

Pearson's correlation revealed that there was a statistically significant positive correlation between customer rating and sentiment polarity score, $r = 0.647$, $p < 0.001$. This suggests that reviews with a higher number of stars tended to have a higher number of positive textual expressions. The chi-square test as shown in Table 4 revealed that there is a significant association between star rating and sentiment category. One-way ANOVA also revealed that the means of sentiment polarity were significantly different in the five rating groups.

Table 4. Relationship Between Rating and Sentiment Polarity

Analysis	Statistic	Significance	Interpretation
Pearson correlation	$r = 0.647$	$p < 0.001$	Moderate-to-strong positive relationship
Chi-square test	$\chi^2(8) = 10,412.90$	$p < 0.001$	Significant association
One-way ANOVA	$F = 3,806.63$	$p < 0.001$	Significant polarity differences across ratings

Sentiment Polarity Across Rating Categories

Sentiment polarity was on a steady rise from the negative sentiment polarity for one-star reviews to very positive sentiment polarity for five-star reviews. The trends in the polarity scores also serve as an extra indicator that the text sentiment in reviews was similar to the actual numbers.

Rating	Mean polarity	Standard deviation
1 star	-0.041	0.186
2 stars	0.093	0.138
3 stars	0.197	0.128
4 stars	0.296	0.126
5 stars	0.363	0.138

Overall Tourist Experience Evaluation

The combined rating, sentiment, and text-mining results indicate that tourist experiences were predominantly positive. Reviews with a positive rating constituted 86.15% of the dataset, whereas four- and five-star ratings made up 73.66% of all reviews. Rooms, staff, location, dining facilities, cleanliness, comfort, service and value were mostly related to positive experiences. However, the presence of a neutral or negative textual sentiment in some of the highly rated reviews implies that numerical ratings do not reflect all the elements of the tourist experience. Figure 3 depicts the general percentage of positive, neutral, and negative reviews and validates that there are more positive tourist experiences.

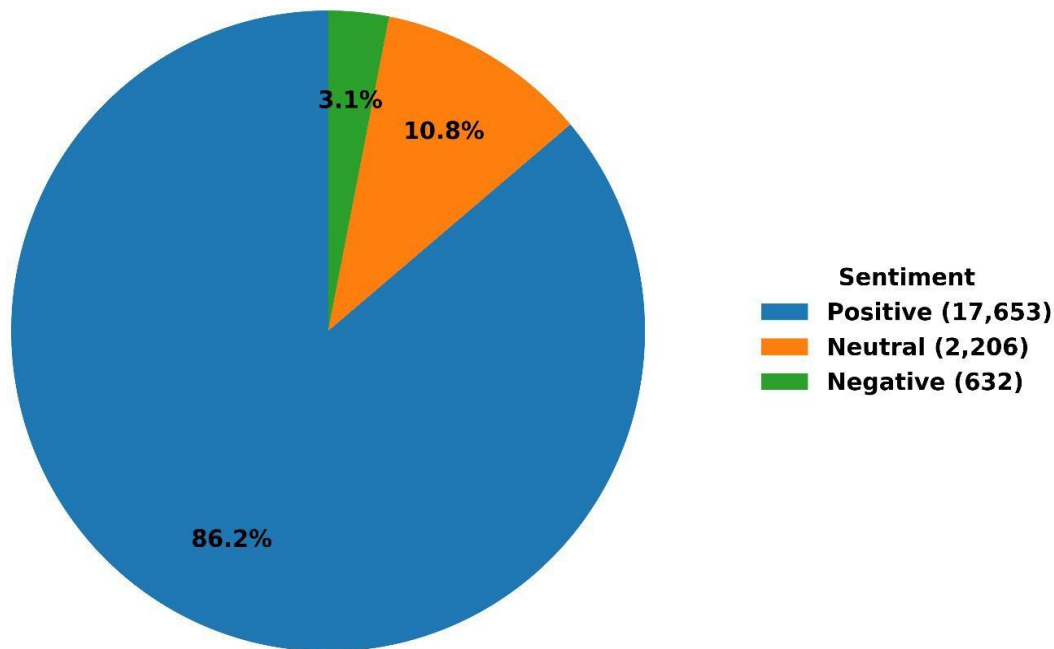


Figure 3. Overall Sentiment Distribution of Tourist Experiences

On the whole, the results indicate that the experience of tourists was quite positive, as the percentage of positive emotions is high, and the four- and five-star ratings prevail. The noticeable correlation between the textual sentiment and the numerical ratings is again another testament to the fact that online reviews can give credible and comprehensive evidence on customer satisfaction and dissatisfaction.

Discussion

The results observed that the majority of the tourist experiences were positive as 86.15% of the reviews were positive and 73.66% of the ratings were rated four or five stars. This shows that the majority of the customers were pleased with their stay experiences and gave positive feedback in both the numeric rating and written feedback. Online reviews thus offer a good source of information generated by the users regarding the perceptions of the tourists and service results. The rising significance of online review studies in tourism and hospitality has also been identified in bibliometric evidence indicating a rise in scholarly interest in online customer feedback (Muritala, Sánchez-Rebull, and Hernández-Lara 2020). The data from such reviews also add to the more general tourism intelligence, as they record spontaneous and experience-based reviews.

The great positive correlation between star rating and textual sentiment indicates that higher ratings tend to be conjoined with more positive language. The sentiment polarity changes gradually between one- and five-star reviews, which means that there is strong consistency in the value of rating and text. Nevertheless, there are still a few positive reviews of higher ratings with neutral or negative comments, indicating a mixed assessment of service factors. Previous studies also indicate that, compared to ratings, textual reviews offer a more in-depth understanding of behaviour, particularly regarding revisit intentions (Park et al. 2020). On the whole, a combination of ratings and text provides a more comprehensive picture of satisfaction.

The most commonly discussed experience dimensions were room conditions, staff behaviour, food and breakfast, location, cleanliness, comfort, service quality and value for money. The high ratio of positive reviews can probably be attributed to positive perceptions towards these factors. These results are consistent with the evidence that the quality of accommodation and customer service are the key factors of hotel satisfaction (Xu et al. 2022). Bespoke digital systems and recommendation technologies can also enhance matching of the services, but the problem of data sparsity is also a drawback (Nilashi et al. 2022). AI and automation can also contribute to a better knowledge of customers preferences and service responsiveness (Tussyadiah 2020).

Even though the proportion of negative reviews was only 3.08% of the sample, they are significant since they point to the occurrence of frequent service failures. The one- and two-star reviews were more dissatisfied and were probably associated with low quality of the rooms, poor service, insufficient cleanliness, uncomfortable facilities, low quality of food, or poor value perceptions. Island tourism experience studies have also indicated that online reviews unearth certain sources of customer dissatisfaction that may not be reflected in traditional surveys (Rita 2018). Negative feedback must then be viewed as actionable operational information as opposed to reputational risk only.

The current results are consistent with the previous studies that indicate that online reviews are effective in gauging satisfaction, behavioural intentions, and hospitality performance. This paper builds on the previous research by combining rating distribution, sentiment analysis, frequency of keywords, and statistical tests within one framework. An increase in the popularity of social media and user-generated content in the process of destination planning further demonstrates the significance of online reviews in destination and accommodation choices (Yuan et al. 2022). On a broader scale, tourism demand and traveller behaviour are also explained using digital information (Song, Qiu, and Park 2023), and even destination image and responsible travel intentions are influenced by user- and government-created content (Zhang and Zhang 2025).

Sentiment analysis can help hotel managers to find out the most and least frequently praised and criticised service attributes, track satisfaction, and prioritize the operation improvement. Analytics of automated reviews can facilitate faster feedback on customer issues and more personalized marketing efforts. It aligns with the broader use of artificial intelligence in marketing and customer-experience management (Verma et al. 2021). Enhanced digital resilience and service adaptation should also be enhanced by tourism stakeholders especially during times of market disruption (Sharma, Thomas, and Paul 2021). The new environment of post-pandemic tourism needs more effective utilization of technology, customer intelligence, and flexible service approaches (Sigala 2020).

One of the strongest aspects of the research is the large dataset of 20491 reviews, which can be used to assess the rating and sentiment patterns. The reliability of the findings is also enhanced by textual analysis coupled with statistical testing. Nevertheless, the data provided does not contain demographic, geographical, hotel-category, or travel-purpose data, and only contains text reviews and ratings. Moreover, lexicon-based sentiment approaches ineffective to represent sarcasm, ambivalent feelings, and situational meanings. The results must thus be viewed as a general analysis of hotel-review sentiment and not a segmental analysis of tourists.

Conclusion

In this work, the experience of tourists was assessed based on 20,491 TripAdvisor hotel reviews through the combination of sentiment analysis, text mining and statistical analysis. The results proved that online reviews can be a good source of information in knowing customer satisfaction and the most important factors that affect hotel experiences. The majority of the reviews were positive, which was in line with the fact that four-and five-star ratings were most common. The finding of a positive and significant relationship between the sentiment of the text and numerical ratings proved that written reviews are effective at summarizing the general perception of customers and also present more detailed information about the particular service attributes. The quality of the room, the staff behaviour, location, food and breakfast, cleanliness, comfort, quality of service and value for money were the key factors of positive tourist experience, and dissatisfaction was largely linked to lower service standards and accommodation problems. These results demonstrate the importance of sentiment analysis as an effective instrument to track customer feedback, enhance service quality, and support evidence-based decision-making in the hospitality sector. The paper also illustrates how a mix of user-generated textual data and quantitative analysis can prove useful in creating a more comprehensive view of tourist experiences than a set of ratings can offer. Future studies need to include more data like traveller demographics, hotel features, the purpose of travel and time series in studying more sophisticated deep learning and aspect-based sentiment analysis methods to better evaluate the experience of tourists and customer satisfaction.

References

1. Abubakar, A. Mohammed, Mustafa Ilkan, Raad Meshall Al-Tal, and Kayode Kolawole Eluwole. 2017. "eWOM, Revisit Intention, Destination Trust and Gender." *Journal of Hospitality and Tourism Management* 31:220–27.
2. Alaei, Ali Reza, Susanne Becken, and Bela Stantic. 2019. "Sentiment Analysis in Tourism: Capitalizing on Big Data." *Journal of Travel Research* 58(2):175–91. doi:10.1177/0047287517747753.
3. Alsharif, Ahmed, Salmi Mohd Isa, and Mohammad N. Alqudah. 2024. "Smart Tourism, Hospitality, and Destination: A Systematic Review and Future Directions." *Journal of Tourism and Services* 15(29):72–110.
4. Bigne, Enrique, María Lilibeth Fuentes-Medina, and Sandra Morini-Marrero. 2020. "Memorable Tourist Experiences versus Ordinary Tourist Experiences Analysed through User-Generated Content." *Journal of Hospitality and Tourism Management* 45:309–18.
5. Casaló, Luis V., Carlos Flavián, and Sergio Ibáñez-Sánchez. 2020. "Influencers on Instagram: Antecedents and Consequences of Opinion Leadership." *Journal of Business Research* 117:510–19.
6. Cheng, Mingming, Deborah Edwards, Simon Darcy, and Kylie Redfern. 2018. "A Tri-Method Approach to a Review of Adventure Tourism Literature: Bibliometric Analysis, Content Analysis, and a Quantitative Systematic Literature Review." *Journal of Hospitality & Tourism Research* 42(6):997–1020. doi:10.1177/1096348016640588.
7. Filieri, Raffaele, Fulya Acikgoz, Valentina Ndou, and Yogesh Dwivedi. 2021. "Is TripAdvisor Still Relevant? The Influence of Review Credibility, Review Usefulness, and Ease of Use on Consumers' Continuance Intention." *International Journal of Contemporary Hospitality Management* 33(1):199–223.
8. Hlee, Sunyoung, Hanna Lee, and Chulmo Koo. 2018. "Hospitality and Tourism Online Review Research: A Systematic Analysis and Heuristic-Systematic Model." *Sustainability* 10(4):1141.
9. Larxel. 2020. "Trip Advisor Hotel Reviews." <https://www.kaggle.com/datasets/andrewmvd/trip-advisor-hotel-reviews>.
10. Li, Xin, Bing Pan, Rob Law, and Xiankai Huang. 2017. "Forecasting Tourism Demand with Composite Search Index." *Tourism Management* 59:57–66.
11. Mariani, Marcello, Rodolfo Baggio, Matthias Fuchs, and Wolfram Höepken. 2018. "Business Intelligence and Big Data in Hospitality and Tourism: A Systematic Literature Review." *International Journal of Contemporary Hospitality Management* 30(12):3514–54.
12. Mehraliyev, Fuad, Irene Cheng Chu Chan, and Andrei Petrovich Kirilenko. 2022. "Sentiment Analysis in Hospitality and Tourism: A Thematic and Methodological Review." *International Journal of Contemporary Hospitality Management* 34(1):46–77.
13. Moro, Sérgio, Paulo Rita, and Joana Coelho. 2017. "Stripping Customers' Feedback on Hotels through Data Mining: The Case of Las Vegas Strip." *Tourism Management Perspectives* 23:41–52.
14. Muritala, Babajide Abubakr, Maria-Victoria Sánchez-Rebull, and Ana-Beatriz Hernández-Lara. 2020. "A Bibliometric Analysis of Online Reviews Research in Tourism and Hospitality." *Sustainability* 12(23):9977.
15. Nilashi, Mehrbakhsh, Rabab Ali Abumalloh, Mesfer Alrizq, Ahmed Almulihi, O. Alghamdi, Murtaza Farooque, Sarminah Samad, Saidatulakmal Mohd, and Hossein Ahmadi. 2022. "Research Article A Hybrid Method to Solve Data Sparsity in Travel Recommendation Agents Using Fuzzy Logic Approach." https://pure.plymouth.ac.uk/ws/portalfiles/portal/49379617/Mathematical_Problems_in_Engineering_-_2022_-_Nilashi_-_A_Hybrid_Method_to_Solve_Data_Sparsity_in_Travel_Recommendation.pdf.
16. _2022_-_Nilashi_-_A_Hybrid_Method_to_Solve_Data_Sparsity_in_Travel_Recommendation.pdf.
17. Orgaz Agüera, Francisco, and Cándida María Domínguez-Valerio. 2024. "'Cocoa-Based Tourism': Exploring Tourists' Image, Satisfaction and Loyalty Regarding a Cultural Heritage Destination." *Journal of Quality Assurance in Hospitality & Tourism* 1–24. doi:10.1080/1528008X.2024.2400659.

18. Park, Eunil, Jiwon Kang, Daejin Choi, and Jinyoung Han. 2020. "Understanding Customers' Hotel Revisiting Behaviour: A Sentiment Analysis of Online Feedback Reviews." *Current Issues in Tourism* 23(5):605–11. doi:10.1080/13683500.2018.1549025.
19. Rahman, Md Taufiqur. 2023. "Guest Attitudes to the Use of Smart Technology in Hospitality-A Study on Bangladesh." PhD Thesis, National University.
20. Rita, Maria Cristina de Souza Oliveira. 2018. "Evaluating Island Tourism Form the Customer's Perspective: An Analysis of Online Reviews." PhD Thesis, ISCTE-Instituto Universitario de Lisboa (Portugal).
21. Sharma, Gagan Deep, Asha Thomas, and Justin Paul. 2021. "Reviving Tourism Industry Post-COVID-19: A Resilience-Based Framework." *Tourism Management Perspectives* 37:100786.
22. Sigala, Marianna. 2020. "Tourism and COVID-19: Impacts and Implications for Advancing and Resetting Industry and Research." *Journal of Business Research* 117:312–21.
23. Song, Haiyan, Richard TR Qiu, and Jinah Park. 2023. "Progress in Tourism Demand Research: Theory and Empirics." *Tourism Management* 94. <https://ira.lib.polyu.edu.hk/handle/10397/99390>.
24. Teng, Hsiu-Yu, Ming-Way Li, and Chien-Yu Chen. 2025. "Does Smart Technology, Artificial Intelligence, Robotics, and Algorithm (STARA) Awareness Have a Double-Edged-Sword Influence on Proactive Customer Service Performance? Effects of Work Engagement and Employee Resilience." *Journal of Hospitality Marketing & Management* 34(3):443–66. doi:10.1080/19368623.2025.2449853.
25. Tussyadiah, Iis. 2020. "A Review of Research into Automation in Tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism." *Annals of Tourism Research* 81:102883.
26. Verma, Sanjeev, Rohit Sharma, Subhamay Deb, and Debojit Maitra. 2021. "Artificial Intelligence in Marketing: Systematic Review and Future Research Direction." *International Journal of Information Management Data Insights* 1(1):100002.
27. Xu, Jian, Xuequn Wang, Jing Zhang, Songshan Sam Huang, and Xingchen Lu. 2022. "Explaining Customer Satisfaction via Hotel Reviews: A Comparison between Pre-and Post-COVID-19 Reviews." *Journal of Hospitality and Tourism Management* 53:208–13.
28. Yuan, Yuke, Chung-Shing Chan, Sarah Eichelberger, Hang Ma, and Birgit Pikkemaat. 2022. "The Effect of Social Media on Travel Planning Process by Chinese Tourists: The Way Forward to Tourism Futures." *Journal of Tourism Futures*. <https://www.emerald.com/jtf/article/doi/10.1108/JTF-04-2021-0094/1254441>.
29. Zhang, Na, and Su Zhang. 2025. "Bridging Personality and Responsibility: How UGC & GGC Influenced Heritage Destination Personality Shape Tourists' Responsible Intentions." *Asia Pacific Journal of Tourism Research* 1–25. doi:10.1080/10941665.2025.2608950.

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