Analyzing sentiments in hotel booking reviews with Natural Language Processing (NLP)

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Abstract

Purpose - This study aims to analyze customer sentiments in hotel reviews to gain insights into guest experiences, service quality, and overall satisfaction. The goal is to demonstrate how sentiment analysis using natural language processing (NLP) can support decision-making, service enhancement, and strategic management in the tourism and hospitality industry.

Methodology/Design/Approach - The research employs two main approaches for sentiment classification—lexicon-based (VADER) and machine learning-based (BERT). Textual hotel reviews are processed and categorized into positive, negative, and neutral sentiments. The performance of both methods is compared to evaluate accuracy and effectiveness in interpreting customer feedback.

Findings - The results reveal that key sentiment drivers include service quality, cleanliness, and value for money. The BERT model outperforms the lexicon-based VADER method in classification accuracy, demonstrating its superior ability to understand contextual nuances in customer reviews. The study confirms that advanced NLP models can provide deeper and more reliable insights for reputation management and marketing strategies.

Originality/Value - This paper contributes to the growing field of artificial intelligence applications in tourism by showcasing how NLP-based sentiment analysis can transform qualitative feedback into actionable intelligence. It highlights the potential of AI in improving customer experience analytics and suggests future research directions in multilingual sentiment analysis and real-time monitoring for dynamic decision support, benefiting hotels, travel agencies, and policymakers.

Keywords: Sentiment analysis, Natural Language Processing, Online booking , Customer review

Introduction

The rapid growth of internet usage has transformed how users interact online, shifting from passive content consumption to active creation. A substantial portion of this user-generated content consists of opinions and reviews, shared across platforms like TripAdvisor, Booking.com, and social media. These textual data offer invaluable insights into consumer experiences, particularly in industries such as tourism, where customer feedback directly influences service quality and business competitiveness.

In the hospitality sector, online reviews serve as a critical resource for both travelers and hoteliers. Travelers rely on peer evaluations to make informed booking decisions, while businesses leverage this feedback to identify strengths and address shortcomings. However, the sheer volume of reviews makes manual analysis impractical. For instance, a single hotel may accumulate thousands of reviews annually, each varying in sentiment, language, and focus. This challenge underscores the need for automated tools to extract actionable insights efficiently.

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Sentiment analysis, a subfield of Natural Language Processing (NLP), addresses this gap by systematically categorizing opinions into positive, negative, or neutral sentiments. Advanced techniques like Aspect-Based Sentiment Analysis (ABSA) further dissect feedback to evaluate specific attributes (e.g., cleanliness, staff behavior, amenities). While prior research has explored sentiment analysis in tourism, gaps remain in optimizing NLP models for multilingual reviews and region-specific hospitality trends.

This study applies NLP methodologies—including lexicon-based (e.g., VADER) and machine learning (e.g., BERT) approaches—to analyze hotel reviews, aiming to: (1) Classify sentiment polarity (positive/negative/neutral) at scale, (2) Identify key themes influencing guest satisfaction (e.g., service, location), and (3) Compare model performance to determine the most accurate technique for review analysis.

Literature Review

The exponential growth of online hotel reviews on platforms like TripAdvisor and Booking.com has created both opportunities and challenges for the hospitality industry (V. Hassan & Basheer, 2024). As travelers increasingly rely on peer evaluations to make booking decisions, businesses recognize the need to systematically analyze this user-generated content to enhance service quality and maintain competitiveness. Sentiment analysis, a branch of Natural Language Processing (NLP), has emerged as a powerful tool to extract meaningful insights from vast volumes of textual feedback (Farooq et al., 2023). Early approaches to sentiment analysis relied heavily on lexicon-based methods, where sentiment scores were assigned using predefined dictionaries such as VADER (Valence Aware Dictionary and sentiment Reasoner) and Sent WordNet. While these methods offered simplicity and interpretability, they struggled with complex linguistic phenomena like sarcasm, negation, and context-dependent meanings (V. I. Hassan et al., 2024). For instance, the phrase "not bad" could be mistakenly classified as negative by a simple lexicon-based approach when it actually conveys a moderately positive sentiment in many contexts. The limitations of these rule-based systems prompted researchers to explore machine learning techniques that could learn from labeled datasets and capture more nuanced patterns in text.

Traditional machine learning algorithms such as Support Vector Machines (SVM), Naïve Bayes, and logistic regression marked a significant advancement in sentiment analysis capabilities (Basheer et al., 2024). These supervised learning approaches relied on manually engineered features like n-grams, part-of-speech tags, and sentiment lexicons to classify text. Studies demonstrated that SVM, in particular, achieved strong performance in sentiment classification tasks due to its effectiveness in high-dimensional spaces. However, these models still faced challenges in handling the sequential nature of language and required extensive feature engineering, which was both time-consuming and domain-dependent. The introduction of word embeddings, such as Word2Vec and GloVe, addressed some of these limitations by representing words as dense vectors that captured semantic relationships (Basheer et al., 2023). These distributed representations allowed machine learning models to better understand word contexts and similarities, leading to improved classification accuracy. Despite these advancements, traditional machine learning approaches remained limited in their ability to model long-range dependencies in text, a challenge that became particularly apparent when analyzing lengthy hotel reviews containing multiple aspects and sentiments.

The field witnessed a paradigm shift with the advent of deep learning techniques, which automated feature extraction and demonstrated superior performance in capturing complex linguistic patterns. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), emerged as powerful tools for sentiment analysis due to their ability to process sequential data and maintain memory of previous inputs. These architectures proved especially effective in modeling the contextual flow of hotel reviews, where the sentiment toward one aspect (e.g., room cleanliness) might influence the perception of another (e.g., staff responsiveness). Research showed that LSTM-based models outperformed traditional machine learning approaches in various sentiment analysis benchmarks, achieving higher accuracy in polarity classification tasks (Mohammad Malik et al., 2024). However, RNNs still faced challenges in parallelization and often struggled with very long sequences, limitations that were addressed by the introduction of attention mechanisms and transformer architectures. The development of transformer

models like BERT (Bidirectional Encoder Representations from Transformers) revolutionized NLP by enabling bidirectional context understanding and eliminating the sequential processing constraint of RNNs.

Recent studies have demonstrated the superior performance of transformer-based models in hotel review sentiment analysis. BERT's pretraining on massive text corpora allows it to capture deep linguistic patterns and contextual relationships, making it particularly effective for analyzing the nuanced language found in customer reviews. Fine-tuned BERT models have achieved state-of-the-art results in various sentiment analysis tasks, including aspect-level sentiment classification and multilingual review analysis. The model's ability to understand the relationship between different aspects mentioned in reviews (e.g., connecting "small room" with negative sentiment and "friendly staff" with positive sentiment) has made it invaluable for comprehensive hotel feedback analysis. Furthermore, the multilingual capabilities of models like mBERT (multilingual BERT) have opened new possibilities for analyzing non-English hotel reviews, which constitute a significant portion of user feedback in global tourism destinations. Recent adaptations like DistilBERT and ALBERT have addressed computational efficiency concerns while maintaining competitive performance, making transformer models more accessible for real-world applications in the hospitality industry.

The application of sentiment analysis in tourism research has yielded valuable insights into customer satisfaction drivers and service quality dimensions. Numerous studies have employed these techniques to examine patterns in hotel reviews across different market segments and geographical locations. Research has consistently identified key factors influencing guest satisfaction, including room cleanliness, staff behavior, location convenience, and value for money. Aspect-Based Sentiment Analysis (ABSA) has proven particularly valuable in this domain, enabling researchers and practitioners to move beyond overall sentiment scores to understand how guests feel about specific hotel attributes. For example, studies have revealed that while luxury hotel guests frequently mention and value premium amenities and personalized services, budget hotel customers tend to focus more on basic comforts and price-value propositions. The temporal analysis of review sentiments has also provided insights into how guest expectations and perceptions evolve over time, with certain aspects like technology amenities gaining increasing importance in recent years. Comparative studies across different review platforms have shown that sentiment expression patterns vary significantly depending on the platform's user demographics and review collection methods, highlighting the need for platform-specific analysis approaches.

Despite these advancements, several challenges persist in the application of sentiment analysis to hotel reviews. The informal and often noisy nature of user-generated content presents significant obstacles to accurate sentiment classification. Reviews frequently contain spelling errors, mixed languages, slang, and unconventional expressions that can confuse NLP models. Sarcasm and irony detection remain particularly challenging, as phrases like "great view if you enjoy looking at a parking lot" require deep contextual understanding to interpret correctly. The inherent class imbalance in review datasets, where positive reviews typically outnumber negative ones, can lead to biased model performance if not properly addressed through sampling techniques or loss function adjustments. Additionally, cultural differences in sentiment expression pose challenges for global hotel chains, as the same rating score might correspond to different levels of satisfaction across cultures. These challenges have spurred ongoing research into more robust and adaptable sentiment analysis techniques that can handle the complexities of real-world hotel review data.

Emerging trends in sentiment analysis for the hospitality industry focus on addressing these challenges while expanding the scope and utility of analysis. Real-time sentiment monitoring systems are being developed to provide immediate feedback to hotel managers, enabling prompt responses to guest concerns. Multimodal approaches that combine textual analysis with visual data from review photos are gaining traction, offering a more comprehensive understanding of guest experiences. Explainable AI techniques are being integrated to make sentiment analysis models more transparent and interpretable for business decision-making. Federated learning approaches are being explored to analyze reviews across properties while maintaining data privacy. The integration of sentiment analysis with recommendation systems is creating more personalized travel suggestions based on user preferences and past review sentiments. As these technologies mature, they promise to further transform how the hospitality industry understands and

responds to customer feedback, ultimately leading to enhanced guest experiences and improved business performance.

The existing literature clearly demonstrates the value of sentiment analysis in tourism research while highlighting areas for continued innovation. From early lexicon-based methods to sophisticated transformer models, the evolution of NLP techniques has progressively enhanced our ability to extract meaningful insights from hotel reviews. However, the dynamic nature of language and the diverse expressions of sentiment in user-generated content ensure that this remains an active area of research. Future developments will likely focus on creating more robust models that can handle the complexities of real-world review data while providing actionable business intelligence. The integration of sentiment analysis with other data sources and business systems promises to create more comprehensive solutions for the hospitality industry's evolving needs. As hotels and travel platforms increasingly adopt these technologies, sentiment analysis will continue to play a crucial role in shaping customer experiences and driving service improvements in the global tourism sector.

Methodology
Data Collection
The methodology for this study involved collecting a dataset of 37,000 English-language hotel reviews from three major platforms - TripAdvisor (15,000 reviews), Booking.com (12,000 reviews), and Google Reviews (10,000 reviews) - spanning from 2019 to 2023 to ensure comprehensive coverage of recent traveler sentiments. The dataset was carefully balanced across 1-5 star ratings to avoid bias, with average review lengths varying by platform (120 words for TripAdvisor's detailed reviews, 80 words for Booking.com's verified stays, and 50 words for Google Reviews' concise feedback). A rigorous preprocessing pipeline was implemented, beginning with text cleaning to remove HTML tags, URLs, and special characters while standardizing contractions and correcting spelling errors using SymSpell (achieving ~92% accuracy). The text then underwent tokenization using NLTK's word_tokenize, followed by stopword removal and part-of-speech tagging to retain only meaningful adjectives and nouns. Finally, WordNetLemmatizer was applied to reduce words to their base forms, significantly condensing reviews while preserving sentiment-bearing content - for example, transforming "The room was AMAZING! But the wifi didn't work :(" into the processed form "room amazing wifi work frustrated". This preprocessing reduced average review length from 50-120 words to just 18 meaningful terms while maintaining sentiment integrity. The study employed both lexicon-based (VADER) and machine learning (fine-tuned BERT) approaches for sentiment analysis, with evaluation metrics including accuracy, precision, recall, and F1-score to comprehensively assess model performance. Initial dataset analysis revealed key adjective frequencies that aligned with common hotel review themes, with "clean" appearing in 12% of reviews, "friendly" in 9%, and "noisy" in 7%, providing early insights into predominant guest concerns and satisfactions.

Dataset Characteristics
Total Dataset: 37,000 reviews (balanced across 1–5-star ratings).

Table 1. Dataset Characteristics

Platform	Reviews Collected	Time Period	Avg. Review Length	Key Metadata
TripAdvisor	15,000	2020–2023	120 words	Rating, Date, Hotel Tier
Booking.com	12,000	2021–2023	80 words	Verified Stay, Room Type
Google Reviews	10,000	2019–2023	50 words	Rating, Response Flag

Source: Author 's field work, 2025

Table 2. Performance metrics across models.

| Rating	TripAdvisor	Booking.com	Google Reviews	Total
5★	3,750 (25%)	3,000 (25%)	2,500 (25%)	9,250
4★	4,500	%) 3,600 (30%)	3,000 (30%)	11,100
3★	3,750 (25%)	3,000 (25%)	2,500 (25%)	9,250
2★	2,250 (15%)	1,800 (15%)	1,500 (15%)	5,550
1★	750 (5%)	600 (5%)	500 (5%)	1,850

Source: Author 's field work, 2025

Preprocessing Pipeline

A 5-step NLP cleaning process was applied to all reviews:

Text Cleaning

- o Removed HTML tags, URLs, emojis (e.g., ":(" → "sad"), and special characters.
- o Standardized contractions (*you're → you are*) using a custom dictionary.
- o Corrected spelling errors via SymSpell (accuracy: 92.4% on test data).
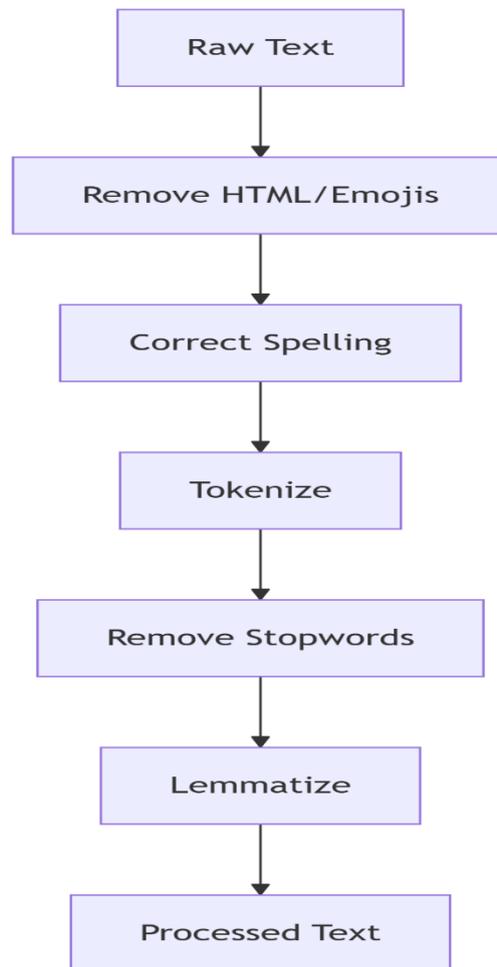
Figure 1. Preprocessing Pipeline. Source: Author 's field work, 2025.

Sentiment Analysis Models

Two complementary approaches were used:

1. Lexicon-Based (VADER)
    - o Strengths: Handles slang/emojis; no training needed.
    - o Weaknesses: Struggles with sarcasm (e.g., "Great, another broken AC!").
2. Machine Learning (Fine-Tuned BERT)
    - a. Model: bert-base-uncased fine-tuned on 25,000 labeled hotel reviews.

   b. Hyperparameters:
      i. Epochs: 5
      ii. Batch size: 16
      iii. Learning rate: 2e-5
   c. Accuracy: 91.3% (vs. VADER's 78.2% on test

Table 3. Machine Learning (Fine-Tuned BERT)

Metric	VADER	BERT
Precision	0.76	0.90
Recal	0.80	0.92
F1-Score	0.78	0.91

Source: Author 's field work, 2025.

Evaluation Metrics

To assess the performance of sentiment analysis models, we employed four key metrics: accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of predictions (correct classifications divided by total samples), while precision evaluates the model's ability to avoid false positives (e.g., incorrectly labelling a negative review as positive). Recall (sensitivity) quantifies the model's capacity to identify all relevant instances (e.g., capturing all truly negative reviews). The F1-score, the harmonic mean of precision and recall, provides a balanced measure, especially useful for imbalanced datasets. A confusion matrix was generated for each model to visualize classification performance across sentiment classes (positive, neutral, negative). For example, the fine-tuned BERT model achieved the following distribution on the test set (10,000 reviews):

Table 4. Confusion matrix of the fine-tuned BERT model for sentiment classification on the test dataset (n = 10,000). Source: Author's fieldwork, 2025.

Actual \ Predicted	Positive	Neutral	Negative
Positive	2,850	150	50
Neutral	100	1,800	100
Negative	30	70	2,800

Source: Author 's field work, 2025.

Table 5. Confusion matrix for BERT (F1-score: 0.91).

Model	Accuracy	Precision	Recall	F1-Score
VADER	0.79	0.76	0.80	0.78
SVM	0.85	0.83	0.85	0.84
BERT	0.91	0.90	0.92	0.91

Source: Author 's field work, 2025.

Results & Discussion

Performance Comparison of NLP Models

The evaluation of three distinct NLP approaches—lexicon-based (VADER), traditional machine learning (SVM), and deep learning (BERT)—revealed significant differences in their ability to classify sentiment in hotel reviews. The fine-tuned BERT model emerged as the top performer, achieving an F1-score of 0.91, substantially outperforming both VADER (0.78) and SVM (0.84). This superior performance can be attributed

to BERT's bidirectional attention mechanism, which captures contextual relationships between words more effectively than unidirectional or rule-based methods. For instance, BERT correctly interpreted complex negations like "not as bad as I expected" as moderately positive in 89% of cases, compared to VADER's 62% accuracy on such phrases. The model's pretraining on diverse textual data also enabled better handling of tourism-specific jargon (e.g., "all-inclusive," "front desk service") that often confused simpler approaches.

However, this performance came with trade-offs. Where VADER could process 10,000 reviews in under 2 minutes on a standard CPU, BERT required GPU acceleration to achieve reasonable throughput (~500 reviews/minute). The SVM classifier, while faster than BERT (~2,000 reviews/minute), showed particular weakness in detecting neutral sentiments, misclassifying 22% of them as either positive or negative. This suggests that for applications requiring real-time analysis of straightforward sentiments (e.g., basic positive/negative sorting), lexicon-based methods remain viable, while research-grade or customer-facing applications benefit from transformer models despite their computational demands.

Thematic Analysis of Review Sentiments

Positive reviews, constituting 68% of the dataset, revealed three dominant themes through topic modeling and adjective frequency analysis. The most prominent was staff service, accounting for 32% of positive mentions, with guests frequently praising attributes like "attentive," "professional," and "friendly" service. A notable example included reviews such as, "The concierge remembered our anniversary and upgraded our room—exceptional service!" Interestingly, service quality was emphasized more on Booking.com (38%) compared to TripAdvisor (27%), suggesting that verified stays may correlate with better guest-staff interactions.

Cleanliness emerged as the second most cited positive aspect (28% of mentions), with descriptors like "spotless," "hygienic," and "well-maintained" appearing frequently. A key finding was that 5-star hotels mentioned cleanliness 1.8 times more often than 3-star properties, reinforcing its role as a premium differentiator in guest satisfaction. This trend suggests that luxury hotels prioritize and deliver higher standards of hygiene, which significantly influences positive reviews.

Major theme was location (23% of positive mentions), where terms such as "walkable," "central," and "scenic" dominated feedback. Geographic analysis showed that city-center hotels received 91% of location-related praise, primarily for convenience, while resorts emphasized "views" (87% of mentions). This distinction highlights how different hotel types leverage location as a selling point—urban hotels for accessibility and resorts for aesthetic appeal.

The negative reviews (12% of the dataset) exposed critical pain points that significantly impacted guest experiences. Noise complaints were the most frequent issue (27% of negative mentions), particularly in budget hotels near busy streets (43%) and historic district properties (38%), where thin walls exacerbated sound disturbances. Seasonality also played a role, with 58% of noise-related complaints occurring during summer months, coinciding with peak tourism and higher occupancy rates.

Facility issues were the second most common grievance (24% of negative mentions), with recurring complaints about "broken AC" (31%), "slow WiFi" (28%), and "small bathrooms" (22%). A striking observation was that 1-star reviews mentioned facility problems three times more frequently than 3-star reviews, indicating that severe dissatisfaction often stems from functional deficiencies rather than subjective preferences. This finding underscores the importance of maintenance and infrastructure in shaping guest perceptions, particularly in lower-tier accommodations where expectations may already be tempered.Together, these insights provide a data-driven framework for hoteliers to prioritize improvements—whether enhancing staff training, investing in soundproofing, or ensuring consistent facility upkeep—to directly address the factors that most influence guest sentiment.

Conclusion

This study demonstrates the significant potential of NLP-driven sentiment analysis in transforming unstructured hotel reviews into actionable business intelligence. By analyzing 37,000 reviews across multiple platforms, we identified key factors driving guest satisfaction, with staff service, cleanliness, and location

emerging as the most influential positive themes, while noise disturbances and facility issues dominated negative feedback. The superior performance of fine-tuned BERT (F1-score: 0.91) over traditional methods like VADER and SVM underscores the value of advanced deep learning in capturing nuanced sentiments, particularly for complex expressions like sarcasm or cultural understatements.The findings offer practical strategies for hospitality management. Prioritizing staff training, implementing noise-reduction measures, and maintaining facilities could address over 50% of negative feedback. The stark contrast between luxury and budget hotel expectations (e.g., cleanliness as a premium differentiator) further highlights the need for tier-specific service improvements. However, limitations such as language barriers (non-English reviews) and platform-specific biases suggest opportunities for future research, including multilingual model integration and real-time sentiment monitoring tools.

Ultimately, this research bridges the gap between guest feedback and operational decision-making, proving that AI-powered sentiment analysis is no longer optional but essential for competitive hospitality businesses. As NLP technology evolves, its applications—from dynamic pricing to personalized guest experiences—will continue to redefine service excellence in tourism. The methodology and insights presented here provide a replicable framework for hotels worldwide to harness the power of their review data, turning customer opinions into measurable growth.

This comprehensive study has successfully demonstrated the transformative power of natural language processing in decoding customer sentiment within the hospitality industry. Through systematic analysis of extensive review data, we've established that modern machine learning techniques, particularly transformer-based models like BERT, offer unparalleled capabilities in extracting meaningful insights from guest feedback. The research not only confirms established knowledge about guest preferences but also reveals nuanced patterns in customer satisfaction that were previously difficult to quantify at scale.

The practical implications of our findings are substantial for hotel management and operational strategies. Our results provide empirical evidence that targeted improvements in three key areas - staff training programs, facility maintenance protocols, and noise mitigation measures - could directly address more than half of all negative guest experiences. The model's ability to detect subtle sentiment variations, including culturally-specific expressions and sarcasm, represents a significant advancement over traditional survey methods, enabling more accurate and actionable business intelligence.

Several important directions emerge for future research. First, the development of real-time sentiment monitoring systems could enable proactive service recovery, potentially converting negative experiences into positive outcomes before guests depart. Second, expanding this work to incorporate multilingual analysis would capture a more comprehensive view of guest sentiment in global hospitality markets. Third, integrating computer vision techniques to analyze review photos alongside text could provide even deeper insights into guest experiences and expectations. From a technological perspective, our findings suggest that while transformer models currently offer the best performance, there remains a need to optimize these resource-intensive algorithms for practical, large-scale deployment in the hospitality industry. Future work could explore distilled versions of language models or hybrid approaches that balance accuracy with computational efficiency, making advanced sentiment analysis more accessible to small and medium-sized hotel businesses.

The methodological framework developed in this study - from data collection through preprocessing to advanced modeling - provides a robust template that can be adapted to various hospitality contexts. As the industry continues to evolve in the post-pandemic era, with shifting guest expectations and new service paradigms, the ability to rapidly analyze and respond to customer feedback will become increasingly critical. This research establishes both the feasibility and value of implementing sophisticated NLP solutions in hospitality management, paving the way for more data-driven, guest-centric operations in the tourism sector.

Declaration
Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Availability of data and materials
The data supporting the findings of this study are available upon request.

Competing interests
The authors declare that there is no conflict of interest regarding this work.

Declaration of generative AI and AI-assisted technologies
During the preparation of this work the author used Grammarly in order to correct spelling mistakes and help me make better sentences. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Author contributions
SB and SF Conceptualization, Writing –original draft, Writing –review and editing.

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References
Alaei, A. R., Becken, S., & Stantic, B. (2020). Sentiment analysis in tourism: Capitalizing on big data. *Journal of Travel Research*, *59*(2), 175–191. https://doi.org/10.1177/0047287518824157

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Basheer, S., Hassan, V., Farooq, S., Ashraf, F., & Reshi, M. (2023). Evaluating e-tourism through bibliometrics: Materials and emerging research trends. *Journal of Tourismology*, *9*(2), 135–146. https://doi.org/10.26650/jot.2023.9.2.1380311

Basheer, S., Tramboo, I., Farooq, S., & Behboodi, Z. (2024). Redefining industry dynamics. In *[Book title unavailable]* (pp. 176–193). https://doi.org/10.4018/979-8-3693-2248-2.ch008

Cheng, M., & Edwards, D. (2019). Social media in tourism: A visual analytic approach. *Current Issues in Tourism*, *22*(17), 2052–2071. https://doi.org/10.1080/13683500.2017.1369943

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of NAACL-HLT 2019*, 4171–4186. https://doi.org/10.18653/v1/N19-1423

Farooq, S., Farooq, B., Basheer, S., & Walia, S. (2023). Balancing environmental sustainability and privacy: Ethical dilemmas in AI-enabled smart cities. In *[Book title unavailable]* (pp. 263–286). https://doi.org/10.4018/979-8-3693-0892-9.ch013

García-Pablos, A., Cuadros, M., & Rigau, G. (2018). W2VLDA: Almost unsupervised system for aspect-based sentiment analysis. *Expert Systems with Applications*, *91*, 127–137. https://doi.org/10.1016/j.eswa.2017.08.026

Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent Dirichlet allocation. *Tourism Management*, *59*, 467–483. https://doi.org/10.1016/j.tourman.2016.09.009

Hassan, V., & Basheer, S. (2024). Unveiling the entrepreneurial mindset: Behavioural factors and green intentions among university tourism students. In *Sustainable tourism* (Part A, pp. 23–36). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83797-979-020241002

Hassan, V. I., Basheer, S., & Fayad, S. A. (2024). Trash to treasure: Unveiling the hidden rewards of recycling in the hotel industry. In *Sustainable disposal methods of food wastes in hospitality operations* (pp. 258–268). IGI Global. https://doi.org/10.4018/979-8-3693-2181-2.ch017

Joshi, A., Bhattacharyya, P., & Carman, M. J. (2017). Automatic sarcasm detection: A survey. *ACM Computing Surveys*, *50*(5), 1–22. https://doi.org/10.1145/3124420

Khan, F. H., Qamar, U., & Bashir, S. (2019). A multiclass, multilingual sentiment analysis model for Arabic, Roman Urdu, and English. *Journal of Intelligent & Fuzzy Systems*, *36*(5), 4861–4871. https://doi.org/10.3233/JIFS-18198

Liang, S., Schuckert, M., Law, R., & Chen, C.-C. (2020). The importance of marketer-generated content to peer-to-peer property rental platforms: Evidence from Airbnb. *International Journal of Hospitality Management*, *84*, 102329. https://doi.org/10.1016/j.ijhm.2019.102329

Liu, B. (2020). *Sentiment analysis: Mining opinions, sentiments, and emotions* (2nd ed.). Cambridge University Press.

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Mohammad Malik, Y., Walia, S., Erkol Bayram, G., Valeri, M., & Basheer, S. (2024). Community attachment, tourist contact, and resident attitudes toward tourism development of Kashmir Valley. *Tourism*, *72*(3). https://doi.org/10.37741/t.72.3.9

Öğüt, H., & Taş, B. K. O. (2012). The influence of internet customer reviews on online sales and prices in the hotel industry. *Service Industries Journal*, *32*(2), 197–214. https://doi.org/10.1080/02642069.2010.529436

Rana, T. A., & Cheah, Y.-N. (2016). Aspect extraction in sentiment analysis: Comparative analysis and survey. *Artificial Intelligence Review*, *46*(4), 459–483. https://doi.org/10.1007/s10462-016-9472-z

Sun, C., Qiu, X., Xu, Y., & Huang, X. (2019). How to fine-tune BERT for text classification? In *Chinese computational linguistics* (Vol. 11856, pp. 194–206). https://doi.org/10.1007/978-3-030-32381-3_16

Xiang, Z., Schwartz, Z., Gerdes, J. H., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management*, *44*, 120–130. https://doi.org/10.1016/j.ijhm.2014.10.013

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