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Mapping Digital Sentiment Landscapes of Hotel Reviews: A Machine Learning-Based Cross-Platform Analysis

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Abstract
The expansion of online travel agencies (OTAs) has produced large volumes of user-generated hotel reviews, offering important resources for sentiment analysis of consumer perceptions. However, prior studies largely rely on single-platform datasets and focus on classification performance, with limited attention to cross-platform sentiment consistency and the impact of data imbalance. This study aims to analyse and compare sentiment patterns across Traveloka, Tiket.com, and Accor, while evaluating a machine learning framework under imbalanced data conditions. This study adopts a quantitative experimental design using 3,000 Indonesian-language reviews collected via web scraping. The independent variable is reviewing text, and the dependent variable is sentiment classification (positive/negative). Data were preprocessed and transformed using TF-IDF, and classified using Multinomial Naïve Bayes, with performance evaluated by accuracy, precision, recall, and F1-score. The results show that positive sentiment consistently dominates across all platforms, with Accor achieving the highest performance, followed by Tiket.com and Traveloka. However, very high recall values for the positive class indicate substantial class imbalance, which biases predictions and reduces sensitivity to negative sentiment. This study provides empirical evidence of cross-platform sentiment consistency and highlights the importance of addressing data imbalance in sentiment modelling.

Keywords: class imbalance; cross-platform analysis; multinomial naïve bayes; sentiment analysis; tf-idf

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INTRODUCTION

The increasing adoption of digital platforms in the tourism and hospitality industry has transformed how consumers access information and evaluate services. Online travel agencies (OTAs) serve as dominant intermediaries that facilitate hotel search, comparison, and booking, while also hosting user-generated reviews that function as a key source of electronic word-of-mouth (e-WOM). These reviews significantly influence consumer perceptions, trust formation, and purchase decisions, as they reflect direct experiential evaluations of service quality and overall satisfaction (Kirilenko et al., 2024; Wąsowicz-Zaborek, 2025; Zhang et al., 2026). In this context, online reviews have become an essential component of digital consumer behaviour and a strategic asset for hospitality service providers (Ameur et al., 2023; Mehraliyev et al., 2022; Sharma et al., 2023).

This study is grounded in e-WOM theory, which posits that consumer-generated content shared through digital platforms plays a critical role in shaping attitudes and behavioural intentions. To operationalise e-WOM at scale, sentiment analysis has been widely applied as a computational method for extracting evaluative information from textual data. Prior research demonstrates that machine learning techniques, including Multinomial Naïve Bayes, Support Vector Machines, and deep learning models, can effectively classify sentiment in hotel reviews and support decision-making processes in tourism analytics (Burkov & Gorgadze, 2023; Lyu et al., 2022; Mariani & Baggio, 2022; Ren et al., 2023; Sánchez et al., 2022; Wasaya et al., 2024; Zhang et al., 2022). However, most existing studies primarily emphasise classification performance and predictive accuracy, often overlooking broader analytical dimensions such as cross-platform variability and data distribution characteristics (Anubha et al., 2025; Chen et al., 2022; Shariffuddin et al., 2023).

Existing research on sentiment analysis in the hospitality domain shows several limitations. First, most studies utilise single-platform datasets, which restricts the ability to examine whether sentiment patterns are consistent across different OTA platforms (Darraz et al., 2025; Madzik et al., 2023; Núñez et al., 2024). Second, prior studies tend to emphasise evaluation metrics such as accuracy and recall, while giving limited attention to the influence of data distribution, particularly class imbalance, on model performance (Cui et al., 2023; Obiedat et al., 2022). Third, many studies rely on static datasets, which limit the capacity to capture dynamic and real-time consumer perceptions in continuously evolving digital environments (Bi et al., 2024; Quach et al., 2026; Wu et al., 2025).

These limitations indicate the need for a more comprehensive analytical framework that integrates cross-platform comparison, real-time data acquisition, and explicit consideration of data imbalance. In highly skewed datasets, where positive reviews dominate, classification models may produce inflated performance metrics that do not accurately reflect model robustness or sensitivity to minority classes (Abdullah & Ahmet, 2022; Kadhuim & Al-Janabi, 2023; Suhaimin et al., 2023; Trisna & Jie, 2022). As a result, it becomes difficult to determine whether observed sentiment patterns represent actual consumer consensus or are influenced by platform-specific characteristics and dataset bias (Altalhan et al., 2025; Ghosh et al., 2024; Ren et al., 2023). This issue is essential to enhance methodological rigor and to strengthen the theoretical understanding of e-WOM dynamics within digital platform ecosystems.

Therefore, this study aims to analyse and compare sentiment patterns of hotel reviews across Traveloka, Tiket.com, and Accor using a TF-IDF and Multinomial Naïve Bayes framework. This research introduces a cross-platform analytical approach based on real-time web-scraped data and explicitly evaluates the impact of class imbalance on classification performance. The novelty of this study lies in the integration of cross-platform sentiment comparison with data distribution analysis, which has been largely overlooked in prior research. The contributions of this study are twofold: (1) providing empirical evidence on the consistency of sentiment patterns across OTA platforms, and (2) highlighting the methodological implications of imbalanced datasets in probabilistic text classification, thereby contributing to both sentiment analysis research and e-WOM theory development.

METHOD

This study employs a quantitative experimental design to analyse and compare sentiment patterns in hotel reviews across three OTA platforms: Traveloka, Tiket.com, and Accor. The unit of analysis is individual textual reviews collected from the Google Play Store. A total of 3,000 Indonesian-language reviews were obtained using automated web scraping to ensure scalability and consistency in data collection. Web scraping is widely used for extracting large-scale user-generated content from digital platforms in a systematic and reproducible manner (Mydyti & Ware, 2025).

Following preprocessing, the normalized review texts were transformed into numerical feature vectors using the Term Frequency-Inverse Document Frequency (TF-IDF) weighting method. TF-IDF assigns weights to words based on their frequency within a review relative to their distribution across the full corpus, allowing sentiment-relevant terms to receive higher importance while reducing the influence of very common words. A unigram-based TF-IDF representation was applied to maintain interpretability and computational efficiency for large scale text classification. Sentiment classification was performed using the Multinomial Naive Bayes algorithm. This probabilistic classifier estimates the likelihood of each sentiment class given the

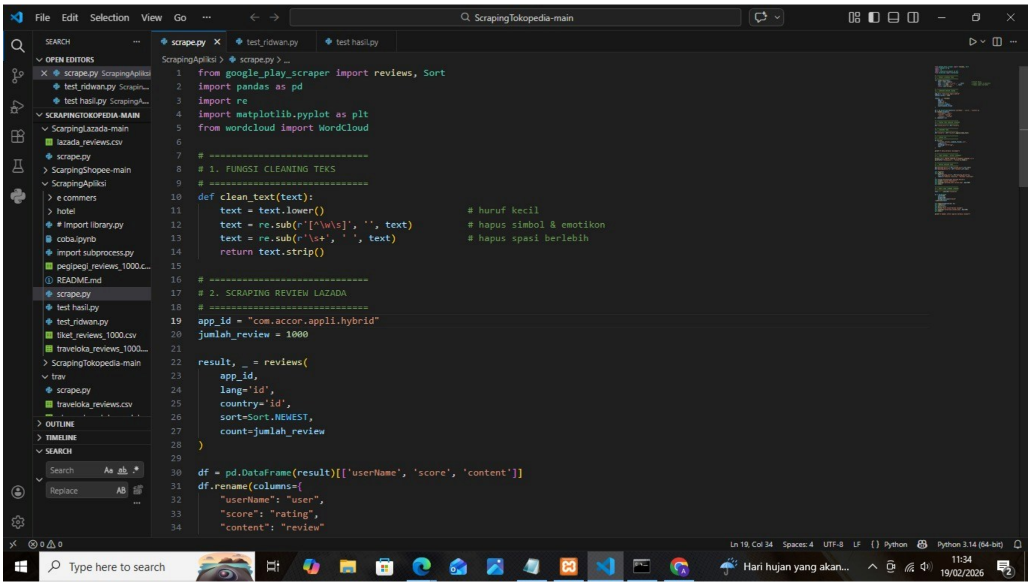

Figure 1. Process scraaping with python

The automated data acquisition process is illustrated in Figure 1, which outlines the structured scraping workflow implemented in Python. The process begins with library initialization and application ID specification to define the scraping target. The reviews() function retrieves review data according to predefined parameters, after which the output is transformed into a structured DataFrame. A custom preprocessing function is integrated within this pipeline to normalize textual content by applying case folding, removing non-alphanumeric characters using regular expressions, and eliminating excessive whitespace. Figure 1 therefore represents the initial stage of the analytical framework, highlighting methodological transparency and scalability in handling large-scale review datasets. Following data collection, textual preprocessing was performed to ensure consistency and reduce noise. The independent variable in this study is the cleaned review text, while the dependent variable is the predicted sentiment category (positive or negative). Feature extraction was conducted using the Term Frequency Inverse Document Frequency (TF-IDF) method, which assigns weights to terms based on their importance within the corpus and is widely applied in text classification tasks (Méndez et al., 2025).

Sentiment classification was performed using the Multinomial Naïve Bayes algorithm due to its effectiveness in probabilistic text modelling and computational efficiency. To ensure robust evaluation, the dataset was divided into training and testing subsets. Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive assessment of classification performance under imbalanced data conditions.

RESULTS AND DISCUSSION

Results

The web scraping process yielded a total of 3,000 hotel reviews collected from three OTA platforms Tiket.com, Traveloka, and Accor with approximately 1,000 reviews per platform. Each record consists of textual reviews and rating attributes, which were subsequently processed for sentiment classification. A representative sample of the dataset, along with sentiment labels, is presented in Table 1. The sample illustrates a clear predominance of positive expressions, particularly those related to ease of use, affordability, and booking convenience. This initial observation suggests an imbalanced sentiment distribution prior to model training.

Table 1. Scarping results data

No	Application	Data	Sentiment
1	Tiket.com	can help to book hotels and other things	Positive
2	Accor	Easy and practical, cheaper prices, always book hotels using this application	Positive
3	Traveloka	With Traveloka, find plane tickets anywhere and find hotels anywhere easily.	Positive

Table 1 presents a sample of the scraped data along with the corresponding sentiment labels. The examples demonstrate a predominance of positive expressions, particularly highlighting ease of booking and affordable pricing. This structured dataset serves as the empirical foundation for subsequent preprocessing, TF-IDF feature extraction, and sentiment classification using the Multinomial Naïve Bayes model.

Table 2. TF-IDF comparison between applications

Application	Negative	Positive	Difference
Accor	-8.116628	-8.205286	-0.088658
Tiket.com	-8.629926	-8.656305	-0.026379
Traveloka	-8.355658	-8.425972	-0.070314

The comparison of TF-IDF feature weights across platforms is presented in Table 2. The results show relatively small differences between positive and negative class representations. Accor exhibits slightly higher magnitude values, suggesting stronger feature weighting, while Tiket.com shows the smallest difference between sentiment classes. However, these differences are not sufficiently distinct to enable robust separation between positive and negative sentiment. This finding implies that the vocabulary used in the dataset does not provide strong discriminative signals, which further contributes to the model's bias toward the majority class. In other words, the overlap in feature representation between sentiment classes reduces the effectiveness of probabilistic classification.

The confusion matrices for each platform are presented in Figures 1–3, providing detailed insight into classification behaviour. For Tiket.com (Figure 1), the model correctly classified 266 out of 291 test instances, achieving a relatively balanced distribution between classes. Specifically, 79 negative reviews were correctly identified (true negatives), and 187 positive reviews were correctly classified (true positives). However, 21 negative reviews were misclassified as positive (false positives), and 4 positive reviews were misclassified as negative (false negatives). This indicates that while the model performs well overall, there is still a tendency to over-predict the positive class.

The model correctly classified 245 out of 293 instances. However, the confusion matrix reveals a substantial imbalance in classification outcomes. Only 3 negative reviews were correctly identified, while 47 negative reviews were misclassified as positive (Figure 2). In contrast, 242 positive reviews were correctly classified, with only 1 misclassified. This pattern indicates that the model strongly favors the positive class, resulting in poor sensitivity toward negative sentiment.

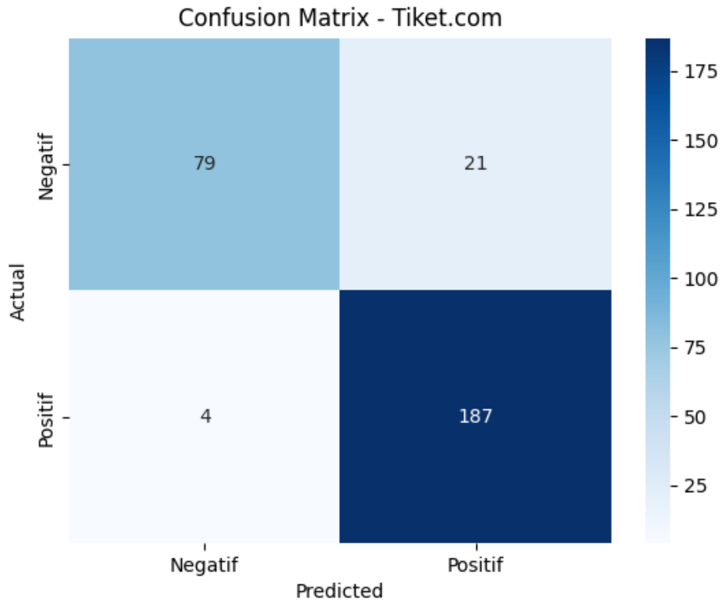

Figure 1. Confusion matrix - tiket.com

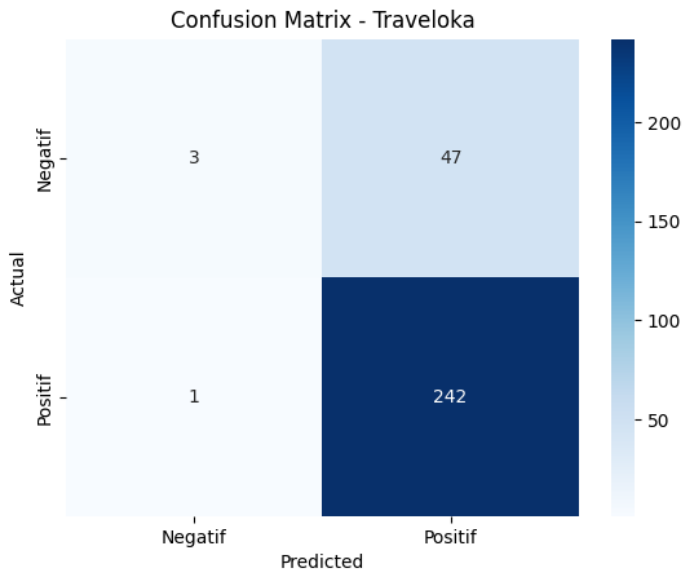

Figure 2. Confusion matrix - traveloka

A more extreme case is observed in the Accor dataset (Figure 3). Out of 295 test instances, 273 reviews were correctly classified as positive, while 22 negative reviews were misclassified as positive. Notably, no reviews were classified as negative, indicating that the model completely failed to identify the minority class. This outcome highlights a severe imbalance effect, where the classifier effectively collapses into a single-class prediction.

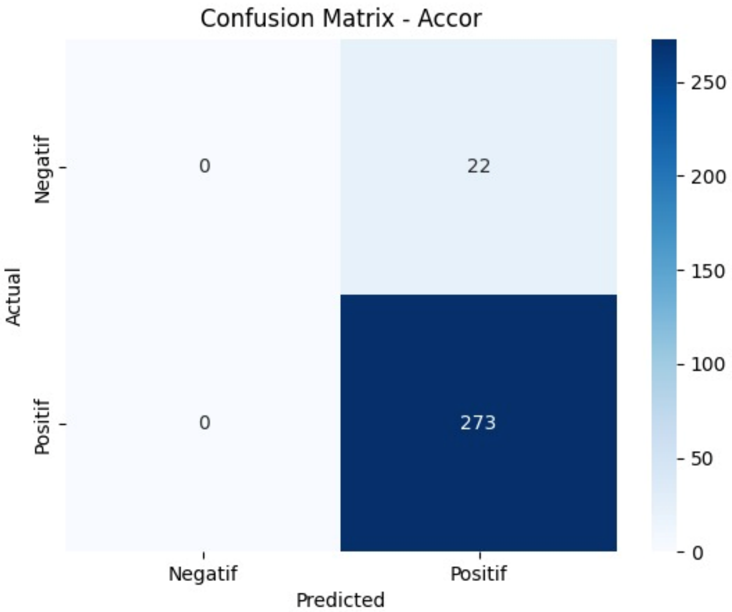

Figure 3. Confusion matrix – accor

The overall classification performance across platforms is summarised in **Table 3**. Accor achieved the highest accuracy (92.54%) and F1-score (96.13%), followed by Tiket.com (91.41% accuracy; 93.73% F1-score) and Traveloka (83.62% accuracy; 90.98% F1-score). Precision values range from 83.74% to 92.54%, while recall values are consistently high, reaching 100% for Accor and 99.59% for Traveloka.

Tabel 3. Performance comparison between applications

Platform	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Tiket.com	91,41	89,90	97,91	93,73
Traveloka	83,62	83,74	99.59	90,98
Accor	92,54	92,54	100,00	96,13

Although these metrics suggest strong classification performance, further examination reveals that the high recall values are largely driven by the dominance of positive predictions. In particular, the perfect recall in the Accor dataset reflects the model's tendency to classify all instances as positive rather than its ability to distinguish between classes. This indicates that performance metrics alone may not fully capture the model's discriminative capability under imbalanced conditions.

When comparing across platforms, several patterns emerge. Tiket.com demonstrates the most balanced classification performance, with relatively better identification of both positive and negative sentiments. Traveloka shows moderate performance but is strongly biased toward positive predictions. Accor, while achieving the highest numerical performance metrics, exhibits the weakest classification capability in terms of class discrimination. These findings suggest that differences in platform data characteristics, particularly sentiment distribution, play a crucial role in influencing model performance. The observed variation also indicates that high accuracy does not necessarily imply better classification quality, especially in imbalanced datasets.

Discussion

The findings demonstrate that positive sentiment consistently dominates across all examined OTA platforms, indicating a stable pattern of consumer perception in digital hotel review environments. This pattern aligns with electronic word-of-mouth (e-WOM) theory, which explains that consumers tend to share favourable experiential evaluations in online environments, particularly when satisfaction levels are high (Mehraliyev et al., 2022; Sánchez et al., 2022). The predominance of positive sentiment reinforces the role of user-generated content as a mechanism that shapes platform reputation and influences consumer decision-making behaviour (Ameur et al., 2023).

A cross-platform comparison indicates that sentiment distribution patterns remain relatively consistent across Tiket.com, Traveloka, and Accor, regardless of differences in platform characteristics. This finding extends prior studies that primarily focus on single-platform datasets by providing empirical evidence that sentiment consistency may occur across different OTA ecosystems (Kirilenko et al., 2024; Núñez et al., 2024). However, such consistency should not be interpreted solely as a reflection of homogeneous consumer experiences. Platform-specific factors, including review system design, rating mechanisms, and moderation policies, may influence how opinions are expressed and distributed (Chen et al., 2022; Shariffuddin et al., 2023).

A central finding of this study concerns the substantial influence of class imbalance on classification performance. Although high accuracy, precision, and recall values were observed, further examination reveals that these metrics are strongly affected by the dominance of positive sentiment within the dataset. In particular, the perfect recall observed in the Accor dataset reflects a classification bias rather than an actual improvement in model discrimination. Previous studies on imbalanced learning emphasise that conventional evaluation metrics may produce misleading interpretations under skewed data distributions, particularly when minority classes are underrepresented (Ghosh et al., 2024; Obiedat et al., 2022; Cui et al., 2023).

The analysis of TF-IDF feature representation further supports this interpretation. The relatively small differences between positive and negative class weights indicate limited discriminative power in the textual features. This condition reduces the effectiveness of probabilistic classifiers such as Multinomial Naïve Bayes, as overlapping feature distributions weaken class separation. Similar observations have been reported in sentiment analysis studies, where feature overlap and data imbalance jointly reduce classification robustness (Zhang et al., 2022; Trisna & Jie, 2022).

When compared with previous research reporting high classification performance in sentiment analysis tasks, the present study provides a more critical perspective by demonstrating that high performance metrics do not necessarily indicate strong generalisation capability. Instead, the findings highlight the importance of integrating data distribution analysis into model evaluation frameworks characteristics (Altalhan et al., 2025; Ren et al., 2023). This perspective contributes methodologically by extending evaluation beyond conventional metrics and incorporating a more comprehensive assessment of classification bias and dataset

Theoretically, these findings contribute to the development of e-WOM research by suggesting that observed sentiment consistency across platforms may be partially shaped by data distribution effects rather than purely reflecting consumer consensus. This interpretation offers a more nuanced understanding of how digital opinions are formed and represented across platforms. In practical terms, the results indicate that platform managers and hospitality providers should interpret aggregated sentiment metrics cautiously and consider minority negative feedback as a critical input for service improvement and decision-making processes (Bi et al., 2024; Wasaya et al., 2024).

Several limitations should be acknowledged. The use of a single classification algorithm restricts the generalisability of the findings across different modelling approaches. In addition, the absence of data balancing techniques limits the ability to evaluate how classification performance may improve under more balanced conditions (Abdullah & Ahmet, 2022;

Suhaimin et al., 2023). Future research is recommended to incorporate multiple machine learning models, apply imbalance handling techniques such as resampling or cost-sensitive learning, and conduct statistical validation to enhance methodological robustness and reliability

CONCLUSION

This study examined sentiment patterns in hotel reviews across Tiket.com, Traveloka, and Accor using TF-IDF feature representation and the Multinomial Naïve Bayes classification approach. The findings indicate a consistent predominance of positive sentiment across all platforms, suggesting a relatively stable structure of consumer perceptions within digital review environments. Nevertheless, the classification outcomes are substantially influenced by class imbalance, leading to prediction bias and limited sensitivity toward minority negative sentiment. These results demonstrate that conventional evaluation metrics, such as accuracy and recall, may overestimate model performance under skewed data conditions. This study contributes empirical evidence on cross-platform sentiment consistency and highlights the importance of incorporating data distribution considerations into sentiment modelling frameworks, while also emphasising the need for cautious interpretation of aggregated sentiment indicators in practical contexts. Future research is recommended to explore the application of multiple classification models, implement data balancing techniques, and conduct comparative statistical validation to improve model robustness and generalisability in sentiment analysis studies.

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