

Analysis of Attraction Aspects of Tourism Villages in Bali Based on Tourist Perceptions Using a BERT-ABSA Method

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Abstract

Aspect-Based Sentiment Analysis (ABSA) provides more informative insights than conventional document-level sentiment analysis by identifying sentiment toward specific aspects of a destination. However, existing BERT-based ABSA models often lack domain-specific knowledge, limiting the interpretability of tourism sentiment analysis. This study proposes a Domain-Aware ABSA framework that integrates a tourism-specific domain lexicon with a BERT-based sentiment classification model to analyze tourist reviews of tourism villages in Bali. The proposed framework organizes sentiment into six tourism-related aspects, namely culture, facility, accessibility, service, atmosphere, and price, enabling more structured and interpretable sentiment analysis. Experimental results demonstrate that the proposed framework achieved an overall classification accuracy of 76%, with the highest performance obtained for the positive sentiment class (Precision = 0.94, Recall = 0.77, and F1-score = 0.84). The sentiment distribution indicates that positive reviews account for 66.7% of the dataset, reflecting generally favorable tourist experiences. Aspect-level analysis further reveals that atmosphere, culture, and service receive the highest positive sentiment, whereas facility and price exhibit relatively higher negative sentiment, identifying infrastructure and cost as priority areas for improvement. These findings demonstrate that integrating a Domain-Aware Lexicon with BERT enhances the interpretability of aspect-level sentiment analysis without modifying the underlying transformer architecture. The proposed framework provides actionable insights for tourism managers and policymakers to support evidence-based decision-making and sustainable tourism village development.

Keywords:

Aspect-Based Sentiment Analysis, BERT, Domain-Aware Lexicon, Tourism Village, Sentiment Analysis.

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1. Introduction

Tourism village development has become an important strategy for promoting sustainable tourism by balancing economic, cultural, social, and environmental aspects. In Bali, tourism villages not only preserve local culture and empower local communities but also strengthen regional tourism competitiveness through community-based tourism development [1]. Nevertheless, the rapid growth of tourism destinations and changes in tourist behavior in the digital era have introduced new challenges related to service quality, infrastructure readiness, accessibility, and tourist satisfaction. Therefore, understanding tourists' perceptions has become increasingly important to support evidence-based and sustainable tourism management.

The widespread use of digital platforms has encouraged tourists to actively share opinions, experiences, and evaluations through online reviews. These reviews represent valuable user-generated content that reflects tourists' perceptions and travel experiences

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[2]. Online reviews contain rich information regarding destination attributes, including facility, accessibility, cultural attractions, service quality, atmosphere, and price. Consequently, sentiment analysis has become an effective approach for extracting meaningful insights from tourism-related textual data and supporting evidence-based tourism management [3].

Recent advances in Natural Language Processing (NLP) have significantly improved sentiment analysis through transformer-based language models. Bidirectional Encoder Representations from Transformers (BERT) has demonstrated superior contextual representation compared with conventional machine learning and lexicon-based approaches because it captures bidirectional semantic relationships within text [4]. Furthermore, Aspect-Based Sentiment Analysis (ABSA) enables sentiment classification at the aspect level, allowing comprehensive identification of tourists' opinions toward specific destination attributes [5]. In the era of Generative Artificial Intelligence (Generative AI), large language models have substantially advanced natural language understanding and generation. However, recent studies indicate that transformer models specifically optimized for discriminative tasks, such as BERT, continue to provide robust, stable, and computationally efficient performance for sentiment classification tasks requiring contextual representation and aspect-level prediction [6]. Therefore, BERT-based ABSA remains an appropriate approach for tourism review analysis because it provides contextual representations for aspect-level sentiment classification.

Despite these advances, several limitations remain in existing tourism sentiment analysis studies. Most previous studies focused on generic tourism domains or hospitality services rather than the contextual characteristics of tourism villages [7], [8]. In addition, lexicon-based methods frequently struggle to capture contextual polarity and semantic ambiguity, whereas transformer-based deep learning models generally emphasize prediction performance without explicitly incorporating domain-specific tourism knowledge to improve result interpretability [9]. Consequently, identifying the strengths and challenges of tourism villages at the aspect level remains difficult because tourism-specific contextual information is not adequately represented in existing sentiment analysis frameworks.

To address these limitations, this study proposes a Domain-Aware Aspect-Based Sentiment Analysis framework by integrating a Domain-Aware Lexicon with a BERT-based ABSA model. This research extends the authors' previous work on BERT-based sentiment analysis for tourism village reviews by introducing domain-specific tourism knowledge that enables aspect organization and improves the interpretability of sentiment analysis results without modifying the underlying transformer architecture [10]. The proposed framework incorporates six tourism-related aspects, namely culture, facility, accessibility, service, atmosphere, and price, representing the primary dimensions discussed in tourists' online reviews. The analysis was conducted using English-language reviews collected from Google Reviews across tourism villages in Bali.

The main contributions of this study are summarized as follows. First, this study develops a domain-aware tourism lexicon specifically designed to represent the contextual characteristics of tourism villages in Bali. Second, it integrates tourism-specific domain knowledge with a BERT-based Aspect-Based Sentiment Analysis framework to improve aspect-level sentiment interpretation while preserving BERT's contextual representation capability. Third, it provides interpretable aspect-level sentiment analysis to identify the strengths and challenges of tourism villages based on tourists' online reviews. Finally, the proposed framework offers data-driven insights that can support tourism village managers and policymakers in developing sustainable tourism management strategies.

2. Related Works

ABSA has become an important research topic in NLP because it enables sentiment classification at the aspect level rather than only at the document or sentence level. This capability provides more comprehensive insights into users' opinions toward specific attributes of products, services, or destinations, making ABSA particularly suitable for tourism analytics where a single review may contain different sentiments toward multiple destination aspects [5].

Previous studies have demonstrated the effectiveness of sentiment analysis and ABSA in tourism-related applications. [7] showed that aspect-level opinion mining can improve tourism recommendation systems by capturing tourists' preferences toward specific destination attributes. Similarly, [8] emphasized the importance of online reviews for understanding tourist satisfaction and improving hospitality services. In addition, [11] demonstrated that deep learning approaches effectively classify customer sentiment from hotel reviews, confirming the value of user-generated content for tourism-related decision support. Although these studies achieved promising results, they primarily focused on general tourism or hospitality domains and did not explicitly represent the contextual characteristics of tourism villages.

The rapid development of transformer-based language models has significantly improved sentiment analysis performance. [4] introduced BERT, which substantially improved contextual language representation through bidirectional encoding. More recently, [12] further confirmed that fine-tuned transformer-based models consistently outperform conventional machine learning algorithms in sentiment classification tasks across different application domains. Furthermore, [13] reported that despite the rapid advancement of Generative AI, transformer models specifically optimized for discriminative tasks remain highly competitive for sentiment classification due to their contextual representation capability and prediction consistency.

Despite these advances, several challenges remain in tourism sentiment analysis. Most existing studies focused primarily on improving classification performance while relying on generic tourism aspects that were not specifically designed to represent tourism village characteristics [7]. Conventional lexicon-based approaches frequently fail to capture contextual sentiment polarity and semantic ambiguity, whereas transformer-based models generally provide high predictive performance without explicitly incorporating domain-specific knowledge that improves interpretability [9]. Moreover, [14] demonstrated the effectiveness of deep learning models for sentiment classification. However, the study also highlights that model performance is insufficient to support domain-specific interpretation.

Another challenge frequently reported in tourism sentiment analysis is sentiment imbalance and contextual ambiguity. [3] explained that tourism review datasets are generally dominated by positive sentiment, making neutral and negative sentiment classification considerably more difficult. Likewise, [15] found that contextual ambiguity often leads to misclassification between neutral and positive sentiments in tourism-related reviews. These findings further indicate that contextual sentiment interpretation alone is insufficient unless supported by domain-specific knowledge capable of representing tourism-related aspects more explicitly.

Unlike previous studies, the present research extends the authors' previous BERT-based Aspect-Based Sentiment Analysis framework for tourism village reviews by incorporating a Domain-Aware Lexicon specifically designed to organize tourism-related aspects [10]. While the previous framework focused primarily on contextual sentiment classification, the proposed approach enriches the existing BERT-based model with tourism-specific domain knowledge to improve the organization and interpretability of aspect-level sentiment analysis without modifying the underlying transformer architecture.

3. Proposed Method

This study proposes a Domain-Aware ABSA framework for analyzing tourist reviews of tourism villages in Bali. The proposed framework integrates a tourism-specific domain lexicon with a BERT-based ABSA model to improve aspect-level sentiment classification through the integration of tourism-specific contextual knowledge. The overall workflow consists of seven stages: data collection, textual preprocessing, domain-aware lexicon construction, aspect labeling, ATE, sentiment classification, and sentiment prediction, as illustrated in Fig. 1.

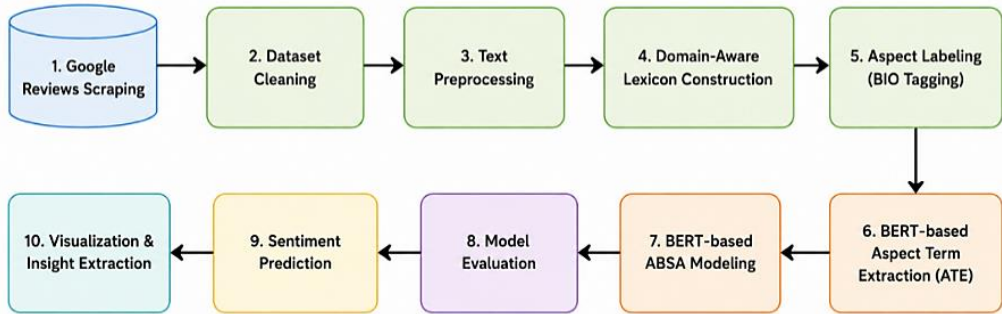


Fig. 1. Proposed Research Workflow

Fig. 1 illustrates the overall workflow of the proposed Domain-Aware ABSA framework used in this study. The workflow was designed to integrate domain-specific knowledge with transformer-based sentiment analysis. The dataset consists of English-language tourist reviews collected from Google Reviews covering 238 active tourism villages in Bali. Prior to model training, all reviews undergo preprocessing, including duplicate removal, URL removal, punctuation cleaning, lowercase conversion, tokenization, stopword removal, and filtering of short reviews. These preprocessing steps reduce textual noise while improving semantic consistency during contextual representation learning [4].

To improve contextual sentiment interpretation, this study constructs a tourism-specific domain lexicon consisting of six tourism village aspects, namely culture, facility, accessibility, service, atmosphere, and price. Aspect annotation is performed using the BIO tagging scheme, where each token is labeled as Beginning-Aspect (B-ASP), Inside-Aspect (I-ASP), or Outside (O) to support the ATE process [5]. Subsequently, the extracted aspects are classified into positive, neutral, and negative sentiment categories using a fine-tuned BERT model. BERT was selected because its bidirectional contextual representation enables effective aspect-level sentiment classification while preserving semantic relationships within tourism reviews [4]. Table 1 summarizes the mathematical notations used throughout the proposed framework.

The Domain-Aware Lexicon was introduced primarily to improve the interpretability of tourism review analysis rather than to modify the underlying BERT architecture. By grouping tourism-related terms into predefined aspect categories, the proposed framework enables tourist opinions to be organized into meaningful tourism dimensions that facilitate data-driven evaluation by tourism managers and policymakers. Consequently, the framework supports not only sentiment classification but also practical interpretation of tourists' perceptions toward tourism village development.

Table 1. Mathematical Notation

Symbol	Description
X	Input review
E	Input embedding representation
H	Contextual hidden representation
W	Weight matrix
b	Bias vector
$P(y X)$	Predicted probability distribution
L	Cross-Entropy Loss
y_i	Ground-truth sentiment label of the i -th sample

The input representation of each review is constructed by combining token embeddings, positional embeddings, and segment embeddings before being processed by the BERT encoder, as expressed in Equation (1).

$$E = E_{\text{token}} + E_{\text{position}} + E_{\text{segment}} \quad (1)$$

where E represents the input embedding vector used as the input representation for BERT.

The contextual encoding process is represented by Equation (2).

$$H = \text{BERT}(E) \quad (2)$$

where H denotes the contextual hidden representation learned through bidirectional encoding.

The contextual representation generated by the BERT encoder is passed through a fully connected layer followed by a Softmax activation function to estimate the probability distribution over the sentiment classes, as defined in Equation (3).

$$P(y | X) = \text{Softmax}(WH + b) \quad (3)$$

where W and b denote the trainable weight matrix and bias vector, respectively.

The model parameters are optimized by minimizing the Cross-Entropy Loss function, as defined in Equation (4).

$$L = - \sum_{i=1}^N y_i \log(P(y_i | X)) \quad (4)$$

where y_i denotes the ground-truth sentiment label of the i -th sample, while $P(y_i | X)$ represents the predicted probability of the corresponding sentiment class generated by the Softmax classifier for the input review X .

During model training, the BERT model was fine-tuned using the labeled dataset. Class weighting was applied to reduce the impact of sentiment imbalance, while stratified sampling preserved the sentiment distribution across the training and validation sets. Model optimization employed the AdamW optimizer with a learning rate of 2×10^{-5} and a batch size of 16. Model performance was evaluated using Accuracy, Precision, Recall, and F1-score to assess the effectiveness of the proposed sentiment classification model. The trained model was subsequently applied to the complete dataset to predict sentiment polarity and identify the strengths and challenges of tourism villages based on tourists' perceptions and experiences. This study evaluates the proposed framework as an integrated sentiment analysis pipeline. Therefore, the Domain-Aware Lexicon is not evaluated as an independent component but functions as contextual knowledge that supports aspect organization and sentiment interpretation throughout the proposed framework.

4. Experimental Setup

This section describes the dataset preparation, domain-aware aspect construction, experimental configuration, and evaluation procedures used to validate the proposed Domain-Aware ABSA framework. The experiments were designed to evaluate the effectiveness of the proposed framework in analyzing tourist reviews of tourism villages in Bali. Google Reviews was selected as the data source because it provides authentic user-generated reviews with broad coverage across tourism villages in Bali, making it suitable for analyzing tourists' perceptions through a large and consistent collection of online reviews.

1) Dataset Collection and Preprocessing

The collected reviews were preprocessed following the workflow described in Section III, including text normalization, duplicate removal, URL and punctuation removal, lowercase conversion, tokenization, stopword filtering while preserving sentiment-bearing words, and the exclusion of reviews containing insufficient textual information. These procedures were performed to improve data quality while preserving contextual information required for BERT-based sentiment classification.

2) Domain-Aware Aspect Construction

To enhance contextual sentiment interpretation, this study developed a Domain-Aware Lexicon representing the characteristics of tourism villages in Bali. The lexicon consists of six predefined aspect categories, namely Accessibility, Price, Facility, Service, Atmosphere, and Culture. These aspect categories were established through a combination of tourism literature review and observations of review patterns collected from tourism village destinations in Bali [7], [8].

Table 2. Tourism Village Aspect Categories

Aspect Category	Example Keywords
ACCESSIBILITY	road, traffic, parking, access, location, transport
PRICE	price, ticket, expensive, cheap, cost, fee
FACILITY	toilet, wifi, facility, clean, dirty, parking, restaurant
SERVICE	staff, service, friendly, helpful, guide
ATMOSPHERE	view, scenery, beautiful, crowded, quiet, peaceful
CULTURE	temple, culture, tradition, ceremony, balinese

Table 2 presents the tourism-specific aspect categories integrated into the proposed Domain-Aware Lexicon. Since a keyword may appear in different semantic contexts, several terms are allowed to belong to multiple aspect categories. Therefore, the lexicon was manually constructed to preserve tourism-specific contextual information and improve the interpretability of aspect-level sentiment analysis. The six aspect categories were selected because they consistently appeared across tourism literature and the collected review dataset, representing the most frequently discussed dimensions of tourism village experiences. Although other tourism-related aspects may exist, these six categories provide sufficient coverage for organizing tourists' opinions within the scope of the present study.

3) Experimental Configuration

The proposed framework employed two BERT-based models to perform Aspect Term Extraction (ATE) and aspect-level sentiment classification, respectively. The dataset was divided into training and validation sets using stratified sampling to preserve the original sentiment distribution throughout the training process. Model optimization employed the AdamW optimizer with a learning rate of 2×10^{-5} , a batch size of 16, and three training epochs. To mitigate the effect of class imbalance, class weighting was incorporated into the Cross-Entropy Loss function during model optimization. This configuration was selected to ensure stable model convergence while preserving contextual representation learned by the pretrained BERT model [4], [5].

Table 3. Model Training Configuration

Parameter	Value
Model	BERT-base-uncased
Optimizer	AdamW
Learning Rate	2e-5
Batch Size	16
Epochs	3
Framework	PyTorch + HuggingFace
Device	CUDA GPU
Dataset Size	5,561

Table 3 summarizes the hyperparameter configuration used for training the proposed Domain-Aware ABSA framework. After the training process, the model performance was evaluated using Accuracy, Precision, Recall, and F1-score. The trained model was subsequently applied to the complete dataset to predict sentiment polarity.

5. Result and Analysis

This section presents the experimental results of the proposed Domain-Aware ABSA framework for analyzing tourist reviews of tourism villages in Bali. The analysis focuses on the performance of the proposed model, the overall sentiment distribution, and the aspect-level sentiment distribution obtained from the Domain-Aware Lexicon. Rather than evaluating sentiment polarity at the document level only, the proposed framework provides interpretable sentiment information for tourism-specific aspects, enabling a more comprehensive understanding of tourists' perceptions toward tourism villages.

Table 4. Performance Evaluation of the Proposed ABSA Model

Sentiment	Precision	Recall	F1-score
Negative	0.60	0.54	0.57
Neutral	0.25	0.59	0.35
Positive	0.94	0.77	0.84

The classification performance of the proposed framework is presented in Table 4. The model achieved the highest performance in the positive sentiment category, obtaining a Precision of 0.94, Recall of 0.77, and an F1-score of 0.84. The negative class achieved a moderate F1-score of 0.57, whereas the neutral class obtained the lowest F1-score (0.35). Overall, the proposed model achieved an accuracy of 76%, indicating that the framework was able to classify tourists' opinions with satisfactory performance despite the contextual complexity commonly found in tourism reviews.

The superior performance of the positive sentiment category is primarily influenced by the sentiment distribution of the dataset, in which positive reviews dominate the collected tourist opinions. Most visitors explicitly describe their travel experiences using favorable expressions related to natural scenery, cultural attractions, hospitality, and environmental comfort. Such explicit contextual information enables BERT to generate robust contextual representation for positive sentiment classification. This observation is consistent with the findings of [3], who reported that tourism-related online reviews are generally dominated by positive opinions, resulting in better classification performance for the positive sentiment class.

In contrast, the neutral sentiment category produced the lowest classification performance. Neutral reviews frequently contain factual descriptions combined with implicit subjective opinions, causing contextual ambiguity between neutral and positive sentiment. Consequently, several reviews predicted as neutral were actually associated with positive contextual expressions, reducing the precision of the neutral class. This finding is consistent with [15], which reported that contextual ambiguity remains one of the primary challenges in tourism sentiment classification.

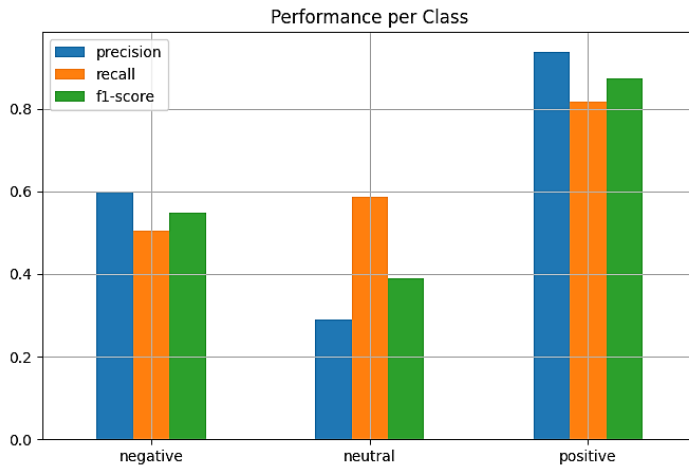


Fig. 2. Performance per Sentiment Class

The performance of each sentiment category is further illustrated in Fig. 2. As shown in the figure, the positive sentiment class consistently achieved the highest Precision, Recall, and F1-score among all sentiment categories. Conversely, the neutral class produced relatively higher Recall but considerably lower Precision, indicating that the model successfully identified many neutral reviews but still misclassified several positive reviews as neutral. This behavior reflects the semantic overlap frequently observed in tourism reviews, where descriptive statements are often accompanied by implicit positive expressions.

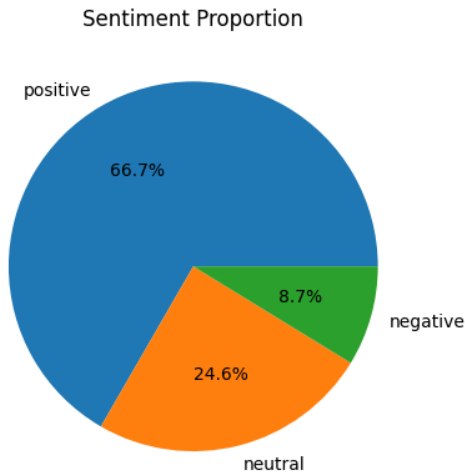


Fig. 3. Overall Sentiment Distribution

The sentiment prediction results for the entire dataset are presented in Fig. 3. Positive sentiment accounts for 66.7% of all reviews, followed by 24.6% neutral sentiment and 8.7% negative sentiment. The predominance of positive sentiment suggests that tourists generally experienced favorable impressions when visiting tourism villages in Bali. This finding indicates that tourism villages have successfully provided satisfying tourism experiences across various destination attributes. Similar sentiment distributions have also been reported by [16], who found that online tourism reviews are typically dominated by positive experiences because visitors are more likely to voluntarily share satisfying travel experiences through digital platforms.

Although positive sentiment dominates the dataset, the presence of neutral and negative reviews remains important for tourism evaluation. Neutral sentiment frequently represents suggestions or objective observations, whereas negative sentiment highlights aspects requiring managerial attention. Therefore, analyzing all sentiment categories provides a more balanced understanding of tourists' perceptions than focusing solely on positive opinions.

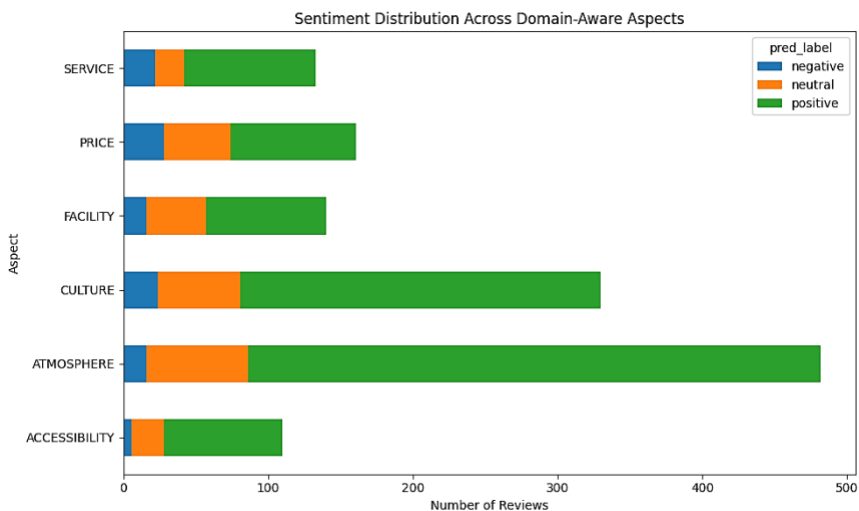


Fig. 4. Sentiment Distribution Across Domain-Aware Aspects

Fig. 4 presents the aspect-level sentiment analysis generated by the proposed Domain-Aware ABSA framework. The results show that atmosphere, culture, and service receive the highest positive sentiment, indicating that tourists highly value the natural environment, cultural experiences, and hospitality offered by tourism villages in Bali. In contrast, facility and price receive relatively higher negative sentiment, suggesting that infrastructure quality and travel costs remain key areas for improvement. By integrating a tourism-specific Domain-Aware Lexicon with BERT, the proposed framework classifies sentiment into predefined tourism aspects instead of providing only overall sentiment polarity. This approach generates more interpretable and actionable insights, enabling tourism managers and policymakers to identify destination strengths and prioritize improvements for sustainable tourism development.

6. Conclusion

This study proposed a Domain-Aware Aspect-Based Sentiment Analysis (ABSA) framework by integrating a tourism-specific domain lexicon with a BERT-based sentiment classification model to analyze tourist reviews of tourism villages in Bali. The experimental results demonstrated that the proposed framework achieved an overall classification accuracy of 76%, with the best performance obtained for the positive sentiment class (Precision = 0.94, Recall = 0.77, and F1-score = 0.84). Furthermore, sentiment analysis revealed that positive opinions dominated the dataset, accounting for 66.7% of all reviews, indicating that visitors generally experienced satisfying tourism experiences. These findings confirm that the proposed framework effectively captures contextual sentiment while providing reliable sentiment classification for tourism-related reviews.

The aspect-level analysis provides more comprehensive insights than conventional document-level sentiment analysis. The proposed framework identified atmosphere, culture, and service as the tourism aspects receiving the highest proportion of positive sentiment, highlighting the natural environment, cultural attractions, and hospitality as the primary strengths of tourism villages in Bali. In contrast, facility and price exhibited relatively higher negative sentiment, suggesting that infrastructure quality and cost-related issues remain important areas for improvement. By integrating a Domain-Aware Lexicon with BERT, the proposed framework organizes sentiment into predefined tourism aspects, enabling more interpretable and actionable information that can support tourism managers and policymakers in prioritizing service improvements and promoting sustainable tourism development.

Although the proposed framework demonstrates promising performance, several limitations remain. The Domain-Aware Lexicon was manually constructed using six predefined tourism aspects, which may not fully capture the diversity of opinions expressed in user-generated reviews. Moreover, this study evaluated the framework as an integrated system without independently assessing the contribution of each component. Future research should investigate adaptive domain lexicons capable of automatically discovering emerging tourism aspects from larger multilingual datasets and compare the proposed framework with alternative ABSA approaches. In addition, incorporating recent transformer architectures and explainable artificial intelligence techniques may further improve sentiment classification performance and enhance the interpretability of aspect-level sentiment analysis for tourism decision support.

Acknowledgment

The authors would like to thank Institut Bisnis dan Teknologi Indonesia for the academic and research support provided during this study. The authors also express their appreciation to all parties who contributed to the completion of this research, including reviewers and colleagues who provided valuable suggestions and feedback. Special acknowledgment is given to the publicly available Google Reviews platform.

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