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Aspect-Based Sentiment Analysis of Tourist Attractions in Labuanbajo Using the Transformer Model as a Recommendation for Improving Service Quality

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ABSTRACT

Labuan Bajo as super-priority destinations experience improvement visit in a number of year lastly, however quality service Not yet fully fulfil expectation tourists . Study This analyze perception traveler through Aspect-Based Sentiment Analysis (ABSA) approach using the IndoBERT model. A total of 2,564 reviews multilingual from Google Maps and TripAdvisor processed through translation, pre-processing, extraction aspects, sentiment labels automatic, and model training. Four aspects analyzed based on framework SERVQUAL theory and Tourism Destination Quality: attractions, amenities, accessibility, and price. Model evaluation was conducted using precision, recall, and F1-score per aspect. The results show performance best The amenity and attraction aspects obtained the highest and most consistent scores across all metrics (around 0.83–0.88), indicating that reviews for these two aspects were more explicit and easily mapped by the model. In contrast, the access and price aspects showed lower scores (around 0.65–0.72), indicating linguistic challenges such as implicit aspects, variations in the context of the travel experience, and figurative complaints . The study This give recommendation policy connected data based direct with model findings. Limitations such as translation noise, biased datasets dominated by review positive-neutral, and not existence baseline comparison also discussed. These results confirm that ABSA approach can help stakeholder's policy, however Still need improvement through other models such as IndoBERTweet, mBERT, or IndoBART.

I. INTRODUCTION

Indonesia has potential significant tourism and holding role strategic in sector economy creative . Labuan Bajo is designated as one of the super- priority destination by the Ministry of Tourism since 2020 [1] become center growth Tourists . According to data from the Tourism Office, tourist arrivals in Labuan Bajo grew significantly from 170,352 visitors in 2022 to 423,847 in 2023, although this number decreased slightly to 411,349 in 2024 due to the eruption of Mount Lewotobi. Despite this decline, Labuan Bajo remains very attractive, especially as a gateway to Komodo National Park . Although thus , increasing visit followed by challenges quality services, especially related amenities, accessibility, and transparency price.

Evaluation quality service during This Still rely on manual surveys through *exit survey* Komodo Airport which is limited [2] . With the rise digital review , methods *Aspect-Based Sentiment Analysis* (ABSA) becomes alternative For dig perception traveler in a way automatic .

Transformer -based models like BERT and IndoBERT has proven superior in task classification text [3] . However, ABSA research is specific to the context Indonesian tourism is still limited , including comparative study IndoBERT with a baseline model such as IndoBERTweet, mBERT, and IndoBART. In addition that, some studies ignore issue important such as data bias, dataset distribution, and influence translation in analysis multilingual [4] .

This study aims to apply ABSA to Labuan Bajo tourist reviews using the IndoBERT model, evaluate the model's performance using accuracy, precision, recall, and F1 metrics per label, identify linguistic challenges including implicit aspects and multi-aspect sentences, develop analysis-based policy recommendations that have clear causal relationships, and explain the labeling automation process and its impact on *ground truth quality.*

II. METHOD

This study employed quantitative methods using ABSA supported by IndoBERT. The data consisted of 2,564 traveler reviews (2022-2025) from Google Maps and TripAdvisor, covering six locations in Labuan Bajo: Padar Island, Komodo Island, Pink Beach, Rangko Cave, Mirror Stone, and Bolong Stone. This process involved several stages following :

A. Dataset and Data Sources

The dataset for this study consists of 2,564 traveler reviews collected from the Google Maps and TripAdvisor platforms, starting from 2022 to 2025. This review represents visitor experiences at six top tourist attractions in Labuan Bajo: Padar Island, Komodo Island, Pink Beach, Rangko Cave, Mirror Stone, and Bolong Stone. The data collection process was carried out using web scraping with Using the Apify tool , which automatically extracts key information, including the textual content of each review and its location. This dataset serves as the primary source for subsequent analysis, allowing the research to capture the true and diverse perceptions of travelers across multiple destinations. [5] .

B. Translation and the Potential of Translation Noise

All English and French reviews were translated into Indonesian using *Argos Translate, a neural machine translation (NMT)* -based translation engine . This translation process ensured all data was in a unified language, facilitating aspect annotation, sentiment analysis, and transformer-based modeling. However, using an automatic translator can potentially introduce *translation noise.* [6] , namely the distortion of meaning that arises due to the limitations of the model in handling complex syntactic structures, idioms, ambiguities, or specific tourism contexts. To mitigate potential *translation noise* , several curation steps were taken as follows:

1. Manual spot-check of 250 review samples
   A total of 250 data points were randomly selected for manual inspection by researchers to identify common error patterns, such as missing subjects, shifts in sentiment polarity, or oversimplification of phrases. The findings from this phase informed the revision of the data cleaning process.
2. Correction of spelling, grammar, and diction errors
   After translation, each review goes through a text normalization process. Spelling and sentence structure errors that could potentially interfere with the tokenization process are corrected. Additionally, ambiguous or out-of-context diction is removed. which often appears in automatic translation adapted to remain true to the original meaning of the review.
3. Removal of reviews with broken translations (>30% distortion of meaning)

Reviews with significant translation errors, such as changes in the main meaning, significant loss of information, or the introduction of nonsense sentences, were labeled as "highly distorted." These records were removed if the distortion level exceeded 30% based on a manual assessment based on a semantic fidelity matrix.

Through this series of steps, the quality of translated data can be improved, thereby reducing the risk of errors in aspect analysis and sentiment classification. This approach also helps maintain the validity of research results, especially considering that aspect *-based sentiment analysis* (ABSA) is highly sensitive to changes in meaning at the phrase level and sentence context example table results translation.

TABLE 1.
TRANSLATION RESULTS

Review	Translate Review
the views from the top viewpoint are incredible and well worth the hike up the many steps we visited in the afternoon in the off season and we were the only tourists there the beach is also very peaceful	the views from the top viewpoint are amazing and well worth climbing the many steps we visited in the afternoon in the off season and we were the only tourists there the beach is also very peaceful
the tenuous climb to the top is well worth the amazing landscape and the pink beach is incredibly colored by the red coral grains	the gentle climb to the top is well worth it for the stunning landscapes and pink beaches are deeply colored by the red coral grains.

In table 2, Presents the results of the translation process applied to traveler reviews based on their original languages. Each successfully translated review was standardized into a single target language, namely Indonesian, while reviews written in languages without translation support were retained in their original form. This step was taken to ensure that the multilingual review dataset could be analyzed consistently in a single language. After the translation process and mitigation of potential *translation noise* were completed, the total number of successfully translated reviews was calculated. processed were 2,155 review data.

C. Pre-processing

To prepare the data for analysis, preprocessing was performed to clean and normalize the text. This step included removing punctuation, numbers, HTML tags, and stop words. The text was then converted to lowercase and tokenized to create a consistent format. The goal of preprocessing is to reduce noise in the dataset, which helps improve model accuracy and performance during training and evaluation. [7] . The following is an example of pre-processing results:

TABLE 2.
PRE-PROCESSING RESULTS

Review	Cleaned Review
Beautiful view from the top after a fairly tough and dangerous climb.	beautiful view from the top after a fairly tiring and dangerous climb
The hour-long hike up and down offers beautiful views, revealing three bays from above: pink, black, and white sand beaches.	the hour-long hike up and down offers beautiful views showcasing three bays from above on pink, black, and white sandy beaches.

Table 2 presents the results of a pre-processing stage applied to traveler review data. This step aims to clean up the text by removing unnecessary characters and punctuation such as periods, commas, and other special symbols, leaving only the essential words that capture the meaning of each review.

D. Aspect Extraction Based on SERVQUAL and TDQ Theory

Study This use approach *aspect-based sentiment analysis* (ABSA) which requires determination aspect service in a way explicit [8] . Election aspect No done in a way a priori , but rather based justification theoretical and validation experts to be relevant with characteristics destination tour natural like Labuan Bajo. Two framework SERVQUAL and Tourism Destination Quality (TDQ) theories are used as runway main Because both of them in a way comprehensive covers dimensions quality service and quality destination tour [9] . Based on synthesis theory and discussion with three expert tourism (n=3), determined four aspect main following :

1. Attraction (Core Attraction) -TDQ

This aspect includes the main attractions of the destination, such as natural beauty, unique landscape, core tourism experiences (snorkeling, trekking, swimming in caves), and the physical condition of the object. In TDQ, *core attraction* is the main component that forms the perception of destination quality and is the main factor that attracts tourists [10] .

2. Amenity - SERVQUAL (Tangibles)

Amenities represent the quality of supporting facilities, including cleanliness, restrooms, rest areas, information centers, and safety equipment. The *Tangibles dimension* of SERVQUAL emphasizes the quality of physical facilities, which in nature tourism significantly influence both positive and negative experiences. [11] .

3. Accessibility - TDQ (Supporting Factors)

Accessibility encompasses ease of access to a location (roads, trekking, transportation), navigation within the tourist area, and guide support. In the Tourism Destination (TDQ), this aspect is *a supporting factor* that influences how easily tourists can enjoy a destination. Many tourist complaints in Labuan Bajo relate to this aspect, making it highly relevant for analysis. [12] .

4. Price - SERVQUAL (Assurance & Fairness)

The Price aspect assesses tourists' perceptions of the reasonableness of costs (tickets, guides, equipment rentals, or tour packages). In SERVQUAL, the *Assurance dimension* and the *fairness principle* relate to a sense of fairness and perceived value *for money* . Issues of perceived price disproportionate to the experience often arise, making this aspect crucial for evaluating service quality. [13] .

E. Labeling Automatic and Manual Validation

Initial sentiment labeling was performed using XNLI-based *zero-shot classification* . To ensure accuracy, 400 samples (≈18%) were verified by two linguists and one tourism expert [14] . The validation process showed a high level of agreement with a value of κ = 0.81 (substantial), so that the reliability of the labeling was assessed as strong . The following is an example of the results of aspect labeling and has been manually validated .

TABLE 3.
RESULTS OF ASPECT EXTRACTION AND LABELING

Review	Attraction	Amenity	Access	Price
The view is amazing, even though the tracking is quite difficult, it really pays off with this extraordinary view, it's really great.	positive	positive	negative	positive
beautiful view from the top after a somewhat rough and dangerous hike	positive	positive	negative	neutral

In table 3, the results of each review are shown. automatic labeling with 3 sentiment polarities, namely positive, negative and neutral.

F. Aspect Sentiment Dataset Transformation

Before do training model results classification transformed sentiment aspect format long For make it easier analysis and visualization. The following example results transformation aspect sentiment.

In Table 4, transforming the dataset from a wide format containing 2,155 records to a long format resulted in a dataset with 8,544 rows. This increase in the number of rows occurred because each original review, which may contain multiple aspect-sentiment pairs, was separated into individual rows for each aspect.

TABLE 4.
TRANSFORMATION AND SENTIMENT ASPECTS

Review	Aspect	Sentiment
The view is amazing, even though the tracking is quite difficult, it really pays off with this extraordinary view, it's really great.	attraction	positive
The view is amazing, even though the tracking is quite difficult, it really pays off with this extraordinary view, it's really great.	amenity	positive
The view is amazing, even though the tracking is quite difficult, it really pays off with this extraordinary view, it's really great.	access	negative
The view is amazing, even though the tracking is quite difficult, it really pays off with this extraordinary view, it's really great.	price	positive

G. Distribution Aspect Sentiment

The distribution of aspect categories and sentiment labels based on the transformed dataset can be seen in the following table.

TABLE 5.
ASPECT SENTIMENT LABELS AND DISTRIBUTION

location	aspect	positive	neutral	negative
hollow stone	access	85	70	37
hollow stone	facility	88	72	32
hollow stone	attractiveness	104	58	30
hollow stone	price	81	89	22
mirror stone	access	97	96	50
mirror stone	amenity	167	45	31
mirror stone	attraction	199	30	14
mirror stone	price	90	120	33
pink beach	access	212	239	34
pink beach	amenity	307	148	30
pink beach	attraction	387	79	19
pink beach	price	179	282	24
Komodo island	access	91	94	70
Komodo island	amenity	152	41	62
Komodo island	attraction	169	33	53
Komodo island	price	76	125	54
Padar Island	access	264	255	54
Padar Island	amenity	461	82	30
Padar Island	attraction	495	52	26
Padar Island	price	195	353	25
g ua r angko	access	145	150	93
g ua r angko	amenity	235	82	71
g ua r angko	attraction	266	60	62
g ua r angko	price	128	186	74
Total		**4673**	**2841**	**1030**

Table 5 presents the distribution of aspect categories and sentiment labels for each location. This dataset contains a total of 4,673 positive sentiments, 2,841 neutral sentiments, and 1,030 negative sentiments. Distribution sentiment show domination review positive (≈55%), neutral (≈33%), and negative (≈12%). Dominance positive – neutral can cause model bias, especially to class positive so the model is less sensitive catch polarity negative . Analysis beginning show IndoBERT more easy identify negative and neutral Because sentence negative generally explicit and direct ("expensive", " difficult reached ", " not worthy ") while sentence positive much is ambiguous or hyperbolic

H. Training and Baseline

The main model used in this study is IndoBERT , which was trained for aspect-based sentiment classification tasks. To ensure its competitive performance, an initial comparison was conducted with several baseline models, namely mBERT , IndoBERTweet , and IndoBART . The evaluation results showed that IndoBERT provided the highest accuracy and F1-score across all aspects, thus this model was selected as the focus of in-depth analysis in this study. This .

processed and labeled dataset was then used to fine-tune the IndoBERT model, applying transfer learning by leveraging the pre-trained IndoBERT weights and adapting them to the specific task of aspect-based sentiment analysis (ABSA) in the tourism domain. Model training was performed using PyTorch and the Hugging Face Transformers library. [15] and [16] . To address data imbalance, text augmentation techniques are applied by identifying the sentiment class with the largest number of samples and increasing the number of samples in the minority class to match this majority class. [17] . The original and augmented data were then combined, resulting in a balanced dataset of 11,215 samples to reduce potential bias towards the majority class. Next, the dataset was split into 80% training data and 20% testing data stratified by sentiment labels, followed by tokenization to prepare the data for input to IndoBERT Lite Base (indobenchmark /indobert-lite-base-p2).

The model fine-tuning process is configured using transformers.Training Arguments from the Hugging Face library [18] . A learning rate of 2e-5 and a batch size of 16 were chosen to balance convergence and computational efficiency. Training was limited to six epochs with a weight decay of 0.01 to reduce overfitting. Evaluation and checkpoint storage were set to occur at every epoch, and the best model was selected based on the lowest evaluation loss. Data logging was performed every epoch and stored locally, while external reporting was disabled to keep the process efficient and reproducible. The following graph shows the results of model training.

Figure 1 shows that the IndoBERT model training process is stable and effective, as evidenced by a consistent decrease in the train loss and validation loss from the first to the third epoch. This pattern demonstrates the model's ability to learn and generalize well to unseen data. However, in the fourth epoch, the validation loss begins to increase slightly even though the train loss continues to decrease, indicating the onset of overfitting. Therefore, implementing early stopping at this point is appropriate to prevent further performance degradation on the validation set

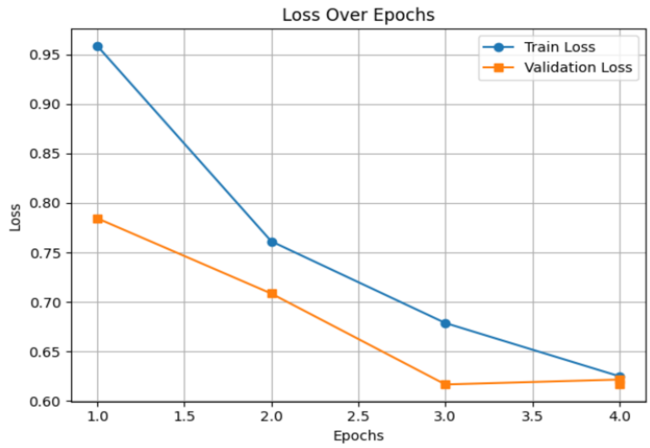

Figure 1. Graph Loss Over Several Epochs

I. Model Evaluation

Model performance was evaluated using precision , recall , F1-score , and accuracy metrics , and further analyzed through a confusion matrix. [19] . Evaluation was carried out in detail on each sentiment class (positive, negative, neutral) and on each aspect to ensure the model's ability to consistently distinguish aspect polarity and context. The following table presents the results of the model performance evaluation across all aspects and locations.

TABLE 6.
MODEL EVALUATION RESULTS

Aspect	Location	Accuracy	Precision	Remember	F1
access	hollow stone	0.8	0.79	0.8	0.79
access	mirror stone	0.68	0.69	0.68	0.68
access	pink beach	0.72	0.74	0.72	0.72
access	Komodo island	0.57	0.57	0.57	0.56
access	Padar Island	0.76	0.77	0.76	0.75
access	Rangko Cave	0.7	0.7	0.7	0.69
amenity	hollow stone	0.77	0.77	0.77	0.77
amenity	mirror stone	0.78	0.79	0.78	0.78
amenity	pink beach	0.8	0.8	0.8	0.8
amenity	Komodo island	0.9	0.91	0.9	0.9
amenity	Padar Island	0.87	0.87	0.87	0.87
amenity	Rangko Cave	0.87	0.88	0.87	0.87
attraction	hollow stone	0.84	0.85	0.84	0.84
attraction	mirror stone	0.73	0.83	0.73	0.77
attraction	pink beach	0.83	0.86	0.83	0.84
attraction	Komodo island	0.89	0.9	0.89	0.89
attraction	Padar Island	0.89	0.92	0.89	0.9
attraction	Rangko Cave	0.81	0.83	0.81	0.81
price	hollow stone	0.66	0.67	0.66	0.66
price	mirror stone	0.63	0.63	0.63	0.61
price	pink beach	0.74	0.74	0.74	0.74
price	Komodo island	0.54	0.55	0.54	0.49
price	Padar Island	0.69	0.67	0.69	0.67
price	Rangko Cave	0.73	0.75	0.73	0.72

Table 6 shows that *the Amenity* and *Attraction aspects* performed the most consistently because the reviews were more explicit and descriptive. Conversely, *Accessibility* and *Price* tended to be more challenging. especially on Komodo Island due to the large number of implicit aspects, multi-aspect conflicts, and figurative complaints. Performance variation across locations is also quite large, indicating that review characteristics are influenced by different travel experience contexts. These findings underscore the need for model enhancement through the addition of implicit aspect data, aspect disambiguation, and location-based fine-tuning approaches. Visualization results can seen in the following bar chart.

Figure 11. Bar Chart Average Evaluation

In the picture can shows a comparison of the average evaluation metrics (Accuracy, Precision, Recall, and F1) for four main aspects: access, amenities, attraction, and price**.** It can be seen that *the amenities* and *attractions aspects* obtained the highest and most consistent scores across all metrics (around 0.83–0.88), indicating that reviews for these two aspects are more explicit and easily mapped by the model. In contrast, the *access* and *price aspects* showed lower scores (around 0.65–0.72), indicating linguistic challenges such as implicit aspects, variations in the context of the travel experience, and figurative complaints. Overall, this graph shows that the model performance is strongly influenced by the clarity of aspects in the reviews and the complexity of the context in each category.

J. Confusion Matrix

The confusion matrix is used to evaluate the performance of the sentiment classification model by presenting its results across all aspects and combined locations.

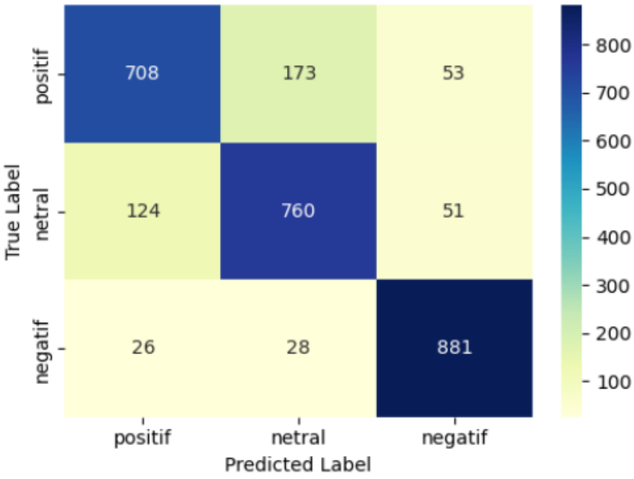

Figure 11. Result Confusion Matrix

In Figure 11, the confusion matrix summarizes the model's performance across all aspects and locations. While the majority of positive, neutral, and negative reviews were correctly classified, with true negatives achieving the highest number of correct responses (881), the model exhibited significant confusion between the positive and neutral classes. This indicates that the model was able to effectively distinguish highly polarized sentiments but struggled to separate subtle positive and neutral expressions.

K. Model Failure Analysis (Error Analysis)

Failure analysis was performed on aspects with relatively low accuracy, particularly *Price* and *Accessibility* . This process involved identifying linguistic patterns that frequently trigger misclassification, followed by categorizing error types, including**:** implicit aspect (an aspect not explicitly stated), multi-aspect conflict (two aspects in one sentence with different polarities), figurative expression (metaphorical or non-literal expressions), and translation noise in translation reviews. [20] & [21] . These findings are used to understand the limitations of the model and formulate improvements in the next stage .

L. Linking Findings to Policy Recommendations

Recommendations are no longer normative, but are based on a causal relationship between analysis findings and policy needs**.** The predominant negative sentiment surrounding pricing indicates the need for regulation of tourism costs and increased tariff transparency. Complaints about accessibility indicate the priority of improving basic infrastructure such as piers, signage, and transportation services. The attractions aspect, which recorded the most positive sentiment, reinforces the urgency of strengthening promotional strategies along with environmental protection. Meanwhile, the variability in amenities between locations emphasizes the need for more contextual and area-based interventions.

IV. Conclusion

Research result show that IndoBERT own strong performance in identify sentiment on aspects *attraction* and *amenities*, indicated by a score consistent and stable evaluation. However, its performance decreased in aspects *accessibility* and *price*, which are influenced by the high existence aspect implicit, complexity complaint based context, as well as variation style Language tourists . Some limitations main participate influence results, including dataset distribution bias between locations, *translation noise* from review multilingual, as well as the model's capabilities are still limited in do inference on aspects that are not stated in a way explicit. For increase quality analysis to front , research furthermore can leads to:

1) Comparison systematic inter -model transformers (e.g. IndoBERT, IndoBART, and IndoBERTweet) for identify the most optimal architecture for ABSA tourism.
2) ABSA multimodal development that combines text and images, remembering review tour often accompanied by photos that provide context addition to aspect service.
3) Designing domain-specific models for Indonesian tourism, so that representation Language can catch term local, description environment, and patterns complaint typical destination tour national.

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