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Tourists' perceptions of Ubud as a world gastronomy destination: a modified ABSA-BERT analysis

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ABSTRACT

Although Ubud has been designated by the United Nations World Tourism Organization (UNWTO) as a global gastronomy tourism destination, existing research remains limited in assessing its strengths and challenges from a data-driven tourist perspective. Prior studies largely rely on qualitative, supply-side approaches and conventional sentiment analysis that overlook specific experiential aspects. Moreover, the integration of multi-platform data and the application of modified deep learning-based aspect-based sentiment analysis (ABSA) models remain underexplored in gastronomy tourism. This study addresses these gaps by employing a modified ABSA-bidirectional encoder representations from transformers (ABSA-BERT) framework on data from TripAdvisor and social media X to provide a more comprehensive evaluation of tourist perceptions. The model incorporates predefined aspect-based aspect term extraction (ATE), valence aware dictionary and sentiment reasoner (VADER) lexicon labeling, and a novel algorithm for extracting aspect-level opinions. The results demonstrate strong performance, achieving 93.50% accuracy on X data and 91% on TripAdvisor. Findings indicate an overall positive perception of Ubud as a global gastronomic destination, particularly for its authentic local cuisine and appealing natural dining atmosphere, although challenges such as overly spicy dishes and uncomfortable seating arrangements remain.

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1. INTRODUCTION

Ubud, one of Bali's popular destinations, is known not only for its natural beauty and culture but also for its unique cuisine. Its potential in the gastronomic tourism sector is supported by a variety of restaurants, food stalls, and traditional markets that serve dishes based on local ingredients and recipes passed down from generation to generation. The designation of Ubud as a world gastronomic tourism model by the United Nations World Tourism Organization (UNWTO) further strengthens its appeal [1]. Gastronomy research is important because it preserves culinary heritage, strengthens tourism competitiveness, and supports economic growth. It provides data-driven insights for improving dining experiences and helps policymakers develop effective tourism strategies. Additionally, it promotes sustainability by encouraging local sourcing and responsible food practices, making it a key driver of both cultural and destination development. Gastronomic tourism also plays an important role in the local economy, supporting local products, farmers, and culinary businesses. Although Ubud has been designated as a global gastronomic tourism prototype by the UNWTO [1], the destination's strengths and challenges still needs to be evaluated, especially from the perspective of tourists. Tourist perceptions determine competitiveness, attractiveness, and the quality of the culinary experience. Reviews on digital platforms such as TripAdvisor and social media can be an important source of data for understanding tourist expectations. With the increasing number of online reviews, an aspect-based sentiment analysis (ABSA) method is needed to gain deeper insights into Ubud's readiness as a world gastronomic destination. Sentiment analysis is a natural language processing technique for identifying and analyzing opinions in text, with the aim of determining positive, negative, or neutral sentiment. ABSA is an effective approach for this research, as it allows the identification of tourist opinions based on specific aspects such as food taste, price, cleanliness, atmosphere, and staff friendliness, which are commonly examined in tourism and hospitality studies [2]–[6]. Compared to traditional sentiment analysis, which only provides general assessments, ABSA enables more fine-grained sentiment analysis at the aspect level [7].

Various studies have utilized sentiment analysis to evaluate the competitiveness of gastronomic destinations, tourist satisfaction, and factors that influence culinary experiences. In the Algarve, Portugal, Ramos and Pinto [8] using valence aware dictionary and sentiment reasoner (VADER) and gastronomic image online reputation index (GIORI) shows that costa del sol has the highest online reputation, while the Algarve ranks third. A study in Sarawak [9] combined lexicon-based methods (AFINN, VADER, and TextBlob), emotion analysis the NRC emotion lexicon (NRCLex), and approaches such as k-nearest neighbors (KNN), support vector machine (SVM), and long short-term memory (LSTM), with the best results obtained from a combination of N-gram and KNN (accuracy 0.98; F1-score and ROC-AUC 0.99). The machine learning approach was also applied in a study analyzing Google Reviews of tourists in Amman [10], which showed that random forest excelled in cognitive and conative aspects, while neural networks were better for affective aspects. In Phuket [11], Naïve Bayes was used to identify four main attributes of the culinary experience—food quality, service, atmosphere, and price—with findings that tourists were most satisfied with food quality and atmosphere. Barbierato *et al.* [12] analyzed TripAdvisor reviews of wine tours in Tuscany using AFFIN Lexicon, finding that the success of the tour was determined by the integration of wine products with food, landscape, and historic villages. In Granada (Spain) [13], Instagram and Twitter posts were used for tourism analysis with bidirectional encoder representations from transformers (BERT) and Tweeteval, and it was found that entities such as place, event, heritage, gastronomy, and tourist activity were important factors in shaping positive and negative perceptions. Sentiment analysis of TripAdvisor reviews was also conducted by Rita *et al.* [14] for Michelin restaurants in Europe using Semantria, and found that sentiment regarding gastronomic aspects such as food, service, and ambience declined, while sentiment regarding price actually increased after receiving a Michelin Star. Analysis of gastronomic travel vlogs on YouTube, one of which used sentiment analysis [15], found that gastronomic content presents an authentic cultural experience while reducing the Global North–South gap in tourism. In Thailand, Kattiyapornpong *et al.* [16] also analyzed gastronomic tourist reviews using a qualitative approach as well as sentiment analysis and thematic analysis, and found that the most prominent gastronomic experiences included the authenticity of local food, interaction with the community, cultural learning, and the social aspects of food that contribute to the benefits of the local community and the sustainability of the destination.

Several studies have implemented ABSA in sustainable tourism. Li *et al.* [17] used ABSA with conditional survival forest (CSF) to predict restaurant sustainability based on five aspects, showing higher accuracy than general sentiment analysis. Nawawi *et al.* [2] applied zero-shot learning to understand tourist satisfaction without much labeled data, finding that food, accommodation, and culture play an important role. In Indonesia, a study [18] used local context focus-aspect term extraction and aspect polarization classification (LCF-ATEPC) with BERT and multi-task learning for post-pandemic tourism policy recommendations, achieving aspect polarity classification accuracy (APC-ACC) of 83.33%, APC-F1 of 69.5%, and ATE-F1 of 66.83%. APC-F1 refers to the F1-score of APC, which measures the balance between precision and recall in classifying sentiment polarity at the aspect level [19]. Huda *et al.* [20] developed a hybrid model-based tourism recommendation system, combining user-based collaborative filtering (UBCF), demographic filtering (DF), ABSA (DistilBERT), and content-boosted collaborative filtering (CBCF). Carrasco and Dias [5] applied bidirectional and auto-regressive transformers (BART), decoding-enhanced BERT with disentangled attention (DeBerta) and chat generative pre-trained transformer (ChatGPT) to restaurant customer reviews related to food quality, service, atmosphere, price, and location. Kusumaningrum *et al.* [21] used convolutional neural network (CNN) at the document level (F1-score reached 0.95) and LSTM at the aspect level (F1-score reached 0.87) on hotel reviews. ABSA and simple additive weighting (SAW) were implemented by [22] for the case of Central Java, Indonesia, processing tourist reviews based on the 3A aspects (attractions, amenities, and accessibility). Viñán-Ludeña and de Campos [23] used BART and T5 on TripAdvisor reviews of Granada, Spain, to identify factors of tourist dissatisfaction. Jeong and Lee [24] used ChatGPT to analyze hotel reviews on TripAdvisor in an aspect-based manner, with service attribute identification through specific prompts, sentiment analysis assisted by BERT, and topic modeling using BERTopic. Tao *et al.* [25] used the BERT-BiLSTM-Attention model and importance-performance analysis (IPA) on social media data to explore visitors' perceptions of the Xiaohe historical area in Hangzhou. Iswari and Afriliana [26] developed hybrid data augmentation (ChatGPT, Sentence-BERT (SBERT), and masked language modeling (MLM)) to improve ABSA on multilingual tourism reviews in Bali, which was proven to reduce hallucination and increase the F1-score by up to 5.1% for the sanitation aspect.

Although various sentiment analysis studies on gastronomic tourism destinations have been conducted, none have applied ABSA to specifically examine Ubud as a world-class gastronomic destination. Previous studies show that ABSA is effective in the context of sustainable tourism, but it has not been utilized to explore insights from the relationship between aspects and sentiments. Existing research also does not discuss specific methods for preparing ABSA training data. This study aims to enhance the application of ABSA by optimizing BERT hyperparameters and modifying its architecture to accommodate the complexity of aspects in evaluating tourists' perceptions of Ubud's readiness as a global gastronomic destination. The preparation of ABSA training data with an aspect-based lexicon is a novelty in this study. This research also offers a novelty by adding an aspect–sentiment–insight stage to produce a model capable of analyzing tourist reviews in greater depth. Our main innovation lies in the development of the ABSA-BERT model with a predetermined list of aspects, as well as optimization to identify opinion tokens that appear before aspect tokens. This approach differs from the general method, which places insights after aspects in sentences. Not only does this approach map sentiment polarity, it also explores the insights within it through the N-gram method, thereby producing relevant insights that can be used as a basis for decision-making by stakeholders. In this study, this ABSA technique was used to understand tourists' perceptions objectively, identify Ubud's strengths and challenges, with the hope of increasing its competitiveness at the global level. By revealing tourist trends and preferences, sentiment analysis can support more targeted marketing and culinary development strategies. The results of this study are expected to form the basis for strategic recommendations for stakeholders. A positive gastronomic experience not only strengthens Ubud's reputation as a global destination, thereby supporting sustainable tourism, but also contributes to local economic growth.

The novelty of this research also lies in integrating multi-platform data to capture tourists' perceptions more holistically and compare the characteristics of perceptions between platforms. This study uses opinion data from TripAdvisor reviews and the social media platform X. TripAdvisor provides extensive user-generated tourism reviews, whereas X offers large-scale, real-time public opinions shared by tourists. Both platforms are widely recognized as valuable big data sources for tourism analytics and destination perception studies [27], [28]. This choice correlates with different sets of motivations. TripAdvisor is more related to altruism and platform assistance, with the platform stating that only 2.1% of reviews are suspected of being fake reviews, while X is associated with extraversion, social benefits, reduction of dissonance [29], and a wider population segment reach [30].

2. METHOD

This study uses an English-language dataset relevant to the topic of Ubud gastronomy, consisting of restaurant reviews in Ubud collected from TripAdvisor, as well as data from the social media platform X. The data covers 10 years for both reviews and tweets. The list of restaurants was obtained from the Bali Provincial Tourism Office directory, while data collection from the social media platform X used keywords related to Ubud, gastronomy, and food, as shown in Table 1. The keywords were systematically derived to represent the multi-dimensional constructs of gastronomic tourism, including food quality, authenticity, service, environment, accessibility, sustainability, and destination branding, as widely discussed in prior literature. This design aligns with established frameworks emphasizing sensory experience [31], authenticity [32], service quality [33], and the influence of user-generated content [34]. Furthermore, the keywords were tailored to support ABSA by ensuring that each term corresponds to a clearly identifiable aspect in tourist discourse. Compared to generic or ambiguous terms, the selected keywords are domain-specific, operationalizable, and reflective of real-world language used across review platforms and social media, thereby improving both data relevance and analytical precision.

The data collected from data X amounted to 6,239 rows, while the restaurant data amounted to 24,060 rows. This data was then cleaned and preprocessed, such as checking for missing values and duplicates in the tweet and review columns. Preprocessing involved standard text cleaning techniques such as punctuation removal, stopword removal, and lemmatization, as commonly applied in natural language processing tasks [35]. The results of cleaning and preprocessing were 3,247 for data X and 23,646 for TripAdvisor data. The complete research flow is shown in Figure 1. This study constructs an ABSA model based on a predetermined list of aspects, which distinguishes this model from previous studies. A total of

1443 aspect terms related to the topic of Ubud as a world gastronomic destination were used. Aspect tagging was performed to mark aspect terms, non-aspect terms, and aspect explanations in the data as training data for the aspect term extraction (ATE) model. ATE is a fundamental task in ABSA, where the model recognizes aspects that will then be analyzed for sentiment [36]. A novelty in this study is that the results of ATE fine-tuning are then developed to obtain words that explain these aspects. For example, the aspect “food” is related to the words ‘delicious’ and “authentic”, so that insights into these aspects can be obtained later. This stage is explained further in the subchapter on obtaining aspect-opinion. Preparing training data with manual labeling on big data is a time-consuming, inefficient, and error-prone task [37], [38]. Therefore, in this study, the ABSA training data in the form of sentences consisting of aspects and opinions are determined to be sentiment using the VADER Lexicon [39], which distinguishes this study from previous studies. The results from ABSA will then form aspect-sentiment-opinion. From aspect-sentiment-opinion, N-gram calculations are performed and then visualized in the form of a word cloud to gain comprehensive insight into tourist perceptions, as word clouds are commonly used for text visualization based on word frequency [40].

Table 1. Keyword and hashtag for X social media

Keywords				
Ubud food taste	Ubud hygiene standards	Ubud food waste awareness	Ubud walkability	Ubud food tourism
Ubud food variety	Ubud food stalls	Ubud eco-friendly packaging	Ubud online reviews	Ubud authentic food
Ubud authenticity	Ubud cafe culture	Ubud support for local farmers	Ubud food delivery availability	Ubud best food
Ubud freshness	Ubud ambience of eateries	Ubud traditional cooking methods	Ubud transportation to culinary spots	Ubud culinary art
Ubud ingredients	Ubud service quality	Ubud food festival	Ubud international recognition	Ubud culinary destination
Ubud plating presentation	Ubud staff hospitality	Ubud cooking classes	Ubud food bloggers reviews	Ubud food
Ubud traditional recipes	Ubud waiting time	Ubud farm-to-table tours	Ubud media mentions	Ubud food aesthetic
Ubud local flavors	Ubud booking convenience	Ubud culinary workshops	Ubud awards or nominations	Ubud food culture
Ubud restaurant availability	Ubud customer satisfaction	Ubud tasting experiences	Ubud destination branding	Ubud food destination
Ubud fine dining options	Ubud pricing transparency	Ubud food markets	Ubud food hunting	Ubud food experience
Ubud street food	Ubud local sourcing	Ubud signage in english	Food lovers ubud	Ubud food guide
Ubud vegan vegetarian options	Ubud organic food	Ubud location of restaurants	Ubud travel	
Ubud food journey	Ubud food recommendation	Ubud food rating	Ubud food spots	
Ubud food quality	Ubud food review	Ubud food tour	Ubud food tradition	
Ubud instafood	Ubud local cuisine	Ubud gastronomy	Ubud food trends	

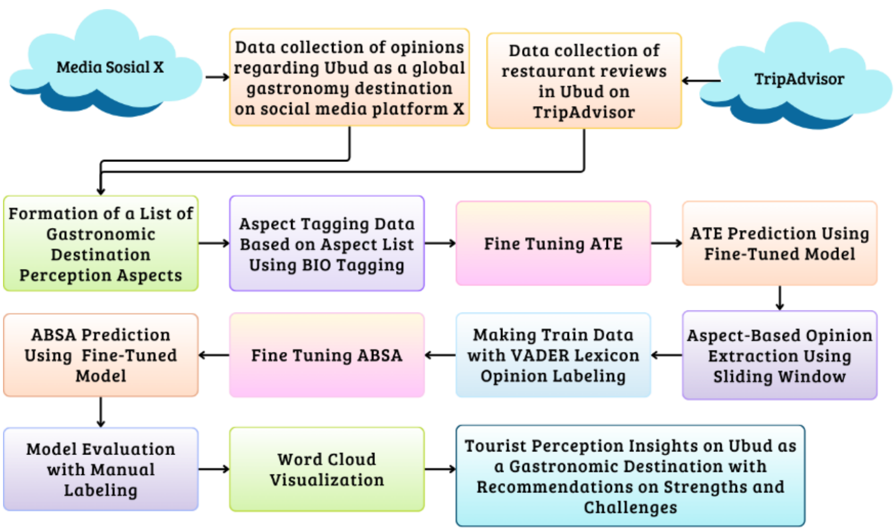


Figure 1. Research process

This study obtained opinions used to gain insight using the sliding window context extraction technique. This sliding window takes tokens to the left and right of the aspect with a size of 3 token sequences or window size=3. From the tokens taken, part-of-speech (POS) tagging is then performed to analyze adjectives and verbs. When the closest adjective or verb to the aspect is found, that token is determined as the boundary of the opinion sentence. The opinion sentence is taken from the opinion boundary found to the aspect, or vice versa. If it is found after the aspect, then the opinion sentence is taken from the aspect to the opinion boundary. A complete description of this stage is shown in Figure 2.

To avoid opinions being used by different adjacent aspects, the opinion taken is confirmed to have not been used by other aspects. In addition, if the same adj or verb is found adjacent to the right or left of an aspect, the opinion taken is the one on the left because the opinion on the right becomes the opinion of the next aspect. In the text "moderate price super delicious food nice live music band strongly recommended go Ubud," the aspects include price, food, and live music. The opinion obtained for the price aspect is "moderate price," for the food aspect is "super delicious food," and "nice live music" for the music aspect.

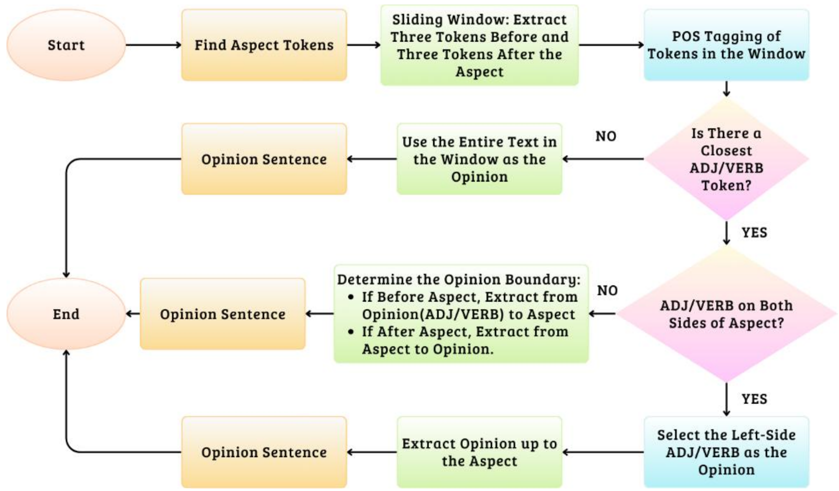


Figure 2. The process of obtaining aspect-opinion

3. RESULTS
3.1. Model testing

The results of the ATE and ABSA fine-tuning evaluation are shown in Table 2. The evaluation results show that ATE and ABSA for data X provide fairly good performance, with ATE accuracy reaching 98.87% and ABSA reaching 97.48%. The high F1-score indicates that the model is capable of recognizing aspects and sentiments with balanced recall and precision. The F1-score is defined as the harmonic mean of precision and recall, calculated as (1):

$$F1 - score = 2 \times (precision \times recall)/(precision + recall) \quad (1)$$

The high F1-score indicates that the model is capable of recognizing aspects and sentiments with balanced recall and precision. For restaurant data, the fine-tuning evaluation of both ABSA and ATE has higher performance compared to data X. This may be due to the larger amount of data, where the more data there is, the more patterns the model can learn. The second reason is that the TripAdvisor data discusses the same domain, namely culinary experiences in restaurants, so it is likely that the vocabulary is not too diverse, allowing the model to recognize it better.

This study also tested the ABSA model by manually labeling 200 data records as ground truth, consisting of random data and data where the polarity of the ABSA model and Lexicon differed. Table 3 shows the evaluation results of the test for the ABSA model and VADER Lexicon.

Table 2. Evaluation of fine tuning ATE and ABSA

Data	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Loss (%)
X	ATE	98.87	95.01	95.12	95.06	4.87
	ABSA	97.49	97.43	97.49	97.45	11.69
Restaurant	ATE	99.85	99.52	99.65	99.58	0.68
	ABSA	99.64	99.64	99.64	99.64	2.32

Table 3. Testing model of ABSA and lexicon

Data	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
X	ABSA	93.50	92.37	94.31	93.12
	Aspect based lexicon	91.00	89.89	92.66	90.63
Restaurant	ABSA	88.56	91.32	86.16	87.52
	Aspect based lexicon	85.07	84.62	85.69	84.84

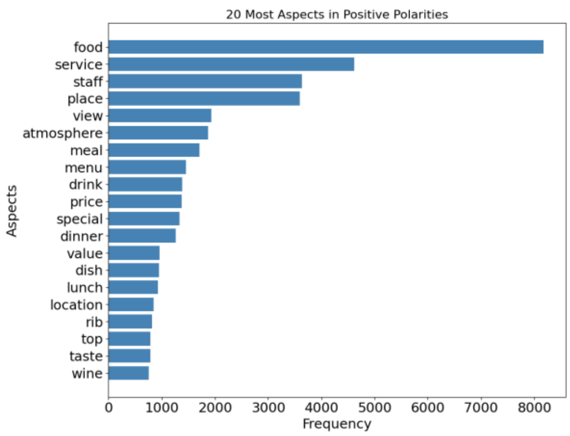
Based on ground truth testing results, ABSA provides good results for data X and restaurant data. For data X, it achieves an accuracy of up to 93.5%, while ABSA for restaurant data achieves 88.56%. The F1-score of 93.12% shows that the model is quite good at recognizing both classes with fairly balanced precision and recall. The ABSA model shows that opinions can be recognized better than the aspect-based Lexicon, as indicated by the lower evaluation results of the aspect-based Lexicon for both X data and restaurant data.

Based on testing against ground truth on data X, several mispredicted opinions can be explained, such as the two opinions “going misses vegan food every day” and “vegan food time misses Indonesian.” The model recognizes the word “miss” as negative, which is possible due to the ambiguity of the word “miss.” Then, for the opinion “low price located soi,” the model still recognizes the word ‘low’ as negative. For negative sentiment that is incorrectly predicted as positive, namely in the opinion “like taste getting worse,” it is possible that the model focuses more on the word “like,” which indicates interest.

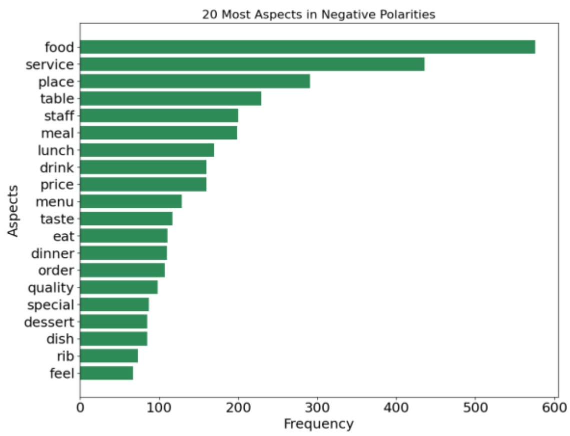
The performance of the proposed model can be contextualized by comparing it with previous studies in tourism-related sentiment analysis. For example, a study in Sarawak [9] reported a very high F1-score of 0.99. In contrast, a study on tourism data from Spain reported lower performance [13], with F1-scores of 0.34 for Spanish data and 0.71 for English data using conventional sentiment classification methods. Compared to these studies, the proposed model achieves competitive performance. Although the Sarawak study reports higher performance, it focuses on general sentiment classification, whereas the proposed model applies ABSA, enabling more detailed insights into tourist perceptions.

3.2. Insight

The results identified the 20 aspects with the highest opinion frequencies, as shown in Figures 3 and 4. Figure 3(a) shows that food received the highest number of positive opinions in the restaurant data, followed by service, staff, and place, indicating high tourist satisfaction with the culinary quality and hospitality of Ubud. Figure 3(b) reveals that although food and service were the most frequently mentioned negative aspects, their frequencies were substantially lower, with place, table, staff, and price appearing less frequently. Likewise, Figure 4(a) indicates that food dominated positive opinions in the tweet data, followed by festivals, suggesting that users associated Ubud with both culinary experiences and gastronomic events. Figure 4(b) shows that food also led to negative opinions, followed by rice, taste, and area, but these mentions remained relatively limited. Overall, both data demonstrate that positive sentiments outweigh negative sentiments across the most frequently discussed aspects. The prominence of food underscores the importance of culinary experiences in shaping tourists' perceptions of Ubud, while positive opinions regarding service and staff emphasize the role of hospitality in enhancing tourist satisfaction [41]. These findings suggest that food quality, hospitality, and the overall dining experience are the principal strengths of Ubud as a gastronomic tourism destination.

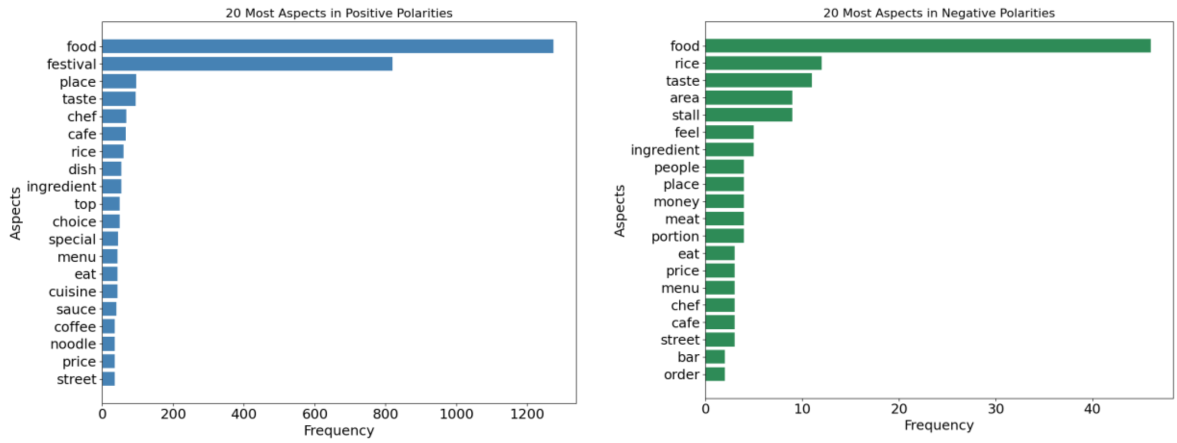


(a)



(b)

Figure 3. Top 20 aspects frequency; (a) positive and (b) negative for restaurant data



(a) (b)

Figure 4. Top 20 aspects frequency; (a) positive and (b) negative for tweet data

Many word clouds can be generated according to the number of aspects, but to obtain significant insights, this study will select several aspects with the highest frequency that reflect Ubud as a world gastronomic destination. Insights from aspects with positive sentiment can be Ubud's strengths that must be maintained and preserved, while insights from aspects with negative sentiment can be challenges and priorities for improvement by stakeholders. The insights generated by this study are summarized in Tables 4-6, with detailed word cloud visualizations available in the supplementary GitHub repository [42]. Due to page limitations, the complete set of word cloud visualizations is provided in an online repository. The following aspects in Table 5 are aspects that are assessed from a positive perspective only because there are minimal negative opinions that can be used as insights for policy making.

Table 4. Insight from aspects with positive and negative opinion polarity

Aspect	Positive insight/the strengths of Ubud	Negative insight/the challenges of Ubud
Food	a. The annual Ubud Festival attracts tourists and can be a powerful tool for promoting Ubud cuisine. b. Ubud is friendly to vegans, offers delicious food, and has plenty of street food. c. Organic food shows a positive perception of ingredients that are organic and free of chemicals. d. Positive response to food from Ubud. e. Positive impressions of both taste and appearance for restaurant food reviews.	a. Tourists have difficulty finding halal food in Ubud. b. Some tourists perceive certain foods as dangerous, possibly because authentic Balinese cuisine tends to be spicy and may not suit tourists' digestive systems. c. Some tourists complain about messy food presentation or unsatisfactory flavors.
Taste	a. The best taste. b. Authentic flavor. c. Rich flavor.	a. Disappointing carbonara flavor. b. Frozen food that tastes stale and bland. c. Lacks richness.
Service	a. Excellent and flawless service. b. Excellent staff service.	a. Long service times. b. Errors in service. c. Poor service.
Staff	a. Friendly and kind staff. b. Very helpful staff.	a. Rude staff. b. Disruptive staff.
Place	a. Best places to eat. b. Favorite places to eat. c. Positive impressions of the festival. d. Ubud is a great place to start your culinary adventure.	a. Incorrect and disappointing dining locations. b. Unsanitary locations. c. Dining locations that have received poor reviews from other tourists and locations that are quiet or quieter than expected cause tourists to doubt the quality and reputation of the restaurant.
Price	a. The prices at food Ubud are still reasonable and worth buying. b. Good prices and cheap.	a. Some tourists have had negative experiences with the prices offered.
Menu	a. The food menu in Ubud is so delicious that there are opinions recommending it and making it the champion menu in Ubud. b. There are also popular and specific menus that have received positive responses, such as Mediterranean-menu-champion, salmon-udon-menu, udon-menu-delicious, and best-menu-meat, popular-menu-item. c. The creativity of the menus is evident in overall-menu-interesting and creative-menu-first.	a. There is dissatisfaction with the menu. b. The menu lacks variety and is not presented appropriately.

Table 5. Insight from aspects with positive opinion polarity only

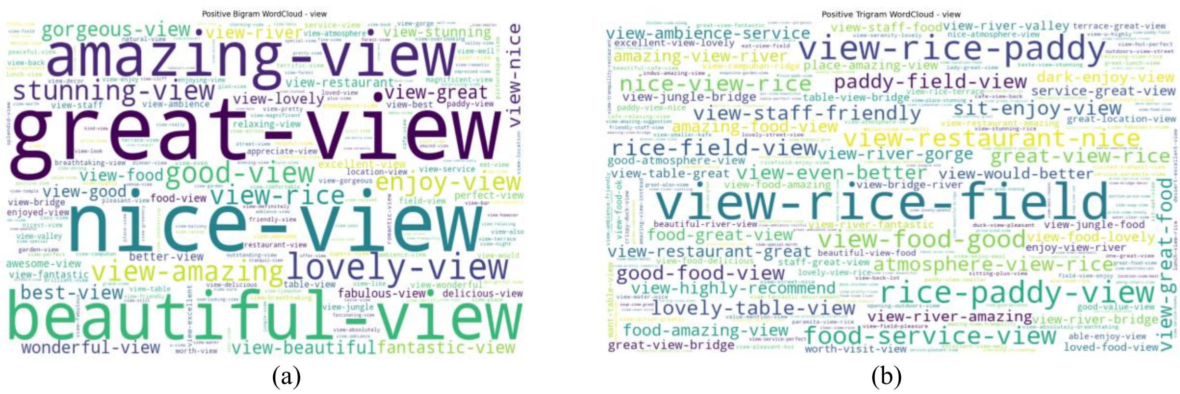
Aspect	Positive insight/the strengths of Ubud
View	a. Satisfaction with the dining experience for tourists with beautiful and breathtaking views.
	b. The strength of dining places in Ubud is that the majority offer views of rice fields.
	c. Tourists also express positive impressions of river views.
Traditional	a. Appreciation for traditional food, in terms of taste, quality, and authenticity of recipes.
	b. Prepared traditional food.
	c. Culinary treat traditional indicates a positive perception of traditional nuances in food preparation in Ubud.
	d. The experience of enjoying traditional dishes is also enhanced by a pleasant traditional atmosphere and ambiance.
	e. Positive perceptions in this aspect are built on a combination of authentic flavors, attractive presentation, a supportive atmosphere, and strong cultural values.
Authentic	a. Customers greatly appreciate flavors that match traditional or regional standards.
	b. The atmosphere, service, and presentation also contribute to creating a good impression of authenticity.
Fusion	a. High appreciation for creativity and innovation in combining various culinary elements.
	b. Asian-fusion identity is most prominent, indicating the popularity of combining Asian flavors with modern or international touches.
	c. The quality of flavor in fusion cuisine is also highlighted through terms such as delicious-fusion, top-notch-fusion, and excellent-fusion-food.
	d. Positive perceptions of menu variety are reflected in terms such as fusion-menu, fusion-cuisine, and lunch-fusion.
Ingredient	a. Natural and fresh are the main values of tourists' perceptions of food ingredients in Ubud.
Value	a. Tourist satisfaction with value in terms of price, food quality, and service.
Festival	a. Tourists show enthusiasm for food festivals.

Several interesting aspects that could be improved are listed in Table 6. These aspects are dominant in the negative class of data X and TripAdvisor data. Insights were generated from negative opinions regarding portion size and tables.

Table 6. Insight from aspects with negative opinion polarity only

Aspect	Negative insight/the challenges of Ubud
Portion	a. The small portions did not meet expectations and some tourists complained that the portions were getting smaller over time.
Table	a. Some tourists expressed discomfort with tables that were too low.
	b. Complaints also arose from sitting on the floor, where the tables were low, with the phrase “low table floor.”
	c. Poor cleanliness and tables that did not match orders.

To support these findings, Figures 5–8 present selected word cloud visualizations that highlight prominent linguistic patterns within the most relevant aspects of the data. Each figure consists of two subfigures, where (a) presents positive bigrams and (b) presents positive trigrams. Figure 5(a) shows that expressions such as great-view, nice-view, and beautiful-view dominate the view aspect in the restaurant data, indicating that tourists frequently associate Ubud's dining experiences with attractive natural scenery. Figure 5(b) further reinforces this perception through positive trigrams such as view-rice-field, view-rice-paddy, and view-restaurant-nice, emphasizing the importance of rice fields and restaurant settings in shaping positive dining experiences.



(a) (b)

Figure 5. Word cloud for view aspect on restaurant data; (a) bigram positive and (b) trigram positive

Figure 6(a) highlights the positive traditional aspect in the X data, where bigrams such as traditional-food, treat-traditional, and beautiful-traditional are most prominent. Figure 6(b) expands these patterns with trigrams including beautiful-traditional-food, culinary-treat-traditional, and enjoy-traditional-food, suggesting that users strongly associate Ubud with traditional culinary experiences and the local food culture. Figure 7(a) shows that the authentic aspect in the restaurant data is characterized by expressions such as authentic-place, fresh-authentic, and great-authentic, while Figure 7(b) reveals more specific descriptions, including authentic-Indonesian-food, food-fresh-authentic, and lime-sweet-authentic, indicating that authenticity is closely linked to fresh ingredients, local flavors, and Indonesian cuisine. Finally, Figure 8(a) illustrates that the ingredient aspect in the X data is dominated by bigrams such as fresh-ingredient, local-ingredient, and best-ingredient, whereas Figure 8(b) highlights trigrams including fresh-local-ingredient, everything-fresh-ingredient, and adventure-learning-ingredient, reflecting tourists' appreciation of fresh, locally sourced ingredients as an essential component of Ubud's gastronomic identity.

(a) (b)

Figure 6. Word cloud for traditional aspect on X data; (a) bigram positive and (b) trigram positive

(a) (b)

Figure 7. Word cloud for authentic aspect on restaurant data; (a) bigram positive and (b) trigram positive

(a) (b)

Figure 8. Word cloud for ingredient aspect on X data; (a) bigram positive and (b) trigram positive

4. DISCUSSION

4.1. Strength and challenges Ubud as gastronomic destination

Table 7 presents a summary of the strengths and challenges of Ubud as a gastronomic destination. Several important factors that contribute to Ubud's strength as a world-class gastronomic destination, based on sentiment analysis of tourist perceptions, are the existence of the Ubud food festival, which has a unique appeal for tourists; Ubud's friendliness towards vegetarian and organic food; delicious food and the existence of street food; rich and authentic flavors; friendly and helpful staff; a good place for culinary adventures; prices that are in line with value for money; creative menus, tourists' appreciation for fusion food, beautiful views of rice fields and rivers in Ubud, authentic traditional flavors, atmosphere, service, and presentation that tourists love, as well as fresh and natural food ingredients.

On the other hand, several challenges still need to be addressed. These challenges include the difficulty tourists have in finding halal food, some foods being considered dangerous, possibly because they are too spicy, improvements needed in food presentation and taste, western and Asian food flavors that need adjustment, improvements needed in service time and quality, improvements needed in staff ethics, improvements needed in dining area cleanliness, a lack of menu variety, and improvements needed in small meal portions and tables that are too low.

Table 7. Summary of strengths and challenges of Ubud as a gastronomic destination

Aspect	Strengths	Challenges
Food	Diverse, high-quality, and organic culinary offerings. With strong appeal, including vegan-friendly and street food options.	Limited availability of halal food and inconsistencies in food presentation and taste. Some food is to spicy.
Taste	Rich, authentic, and flavorful culinary experience.	Inconsistent taste quality, including bland or unsatisfactory flavors.
Service	Generally high-quality and attentive service enhancing dining experience.	Long service times and occasional service errors.
Staff	Friendly, helpful, and hospitable staff.	There is some instances of rude or unprofessional behavior.
Place	Attractive dining locations with strong culinary atmosphere and positive destination image.	Issues with cleanliness, location suitability, and perceived quality of some venues.
Price	Perceived as affordable and offering good value for money.	Negative perceptions of pricing in certain cases.
Menu	Creative and diverse menu offerings with popular and innovative dishes.	Limited variety and dissatisfaction with menu presentation.

5. CONCLUSION

The modified ABSA model has been proven capable of performing sentiment analysis on predetermined aspects. The model provides a good accuracy performance both on X data and TripAdvisor data, which is better than the aspect-based lexicon model. Based on the sentiment analysis results, it can be said that Ubud has a good perception in the eyes of tourists, making it worthy of being called a world gastronomic destination. Tourists tend to have a positive perception of the culinary experience in Ubud, as shown by the number of positive opinions that far outweigh the negative ones. Several important aspects, such as food made with local ingredients with authentic traditional flavors and the support of natural scenery at dining venues, have received good perceptions from tourists. This is a positive aspect or strength for Ubud as a culinary tourism destination. However, several improvements are also needed to enhance Ubud's strength recognized as a gastronomic destination, such as improvements in service and staff, cleanliness, and more ergonomic dining tables.

The study offers clear practical implications for tourism stakeholders. Destination managers can strengthen Ubud's global positioning by promoting its authentic cuisine and culinary events while improving halal availability and hygiene standards. Restaurant operators can enhance visitor satisfaction by refining taste, service quality, cleanliness, menu variety, and dining comfort. Tourism marketers can further develop curated culinary experiences and leverage digital platforms to amplify Ubud's appeal.

However, the study has limitations. It relies on user-generated content that may not represent all tourists, uses predefined aspects that may overlook emerging themes, and may not fully capture linguistic nuances. Additionally, the findings are specific to Ubud and may not be fully generalizable to other destinations. For future work, there is an opportunity to enhance the model by improving its ability to capture contextual nuance, such as sarcasm, cultural language differences, and multilingual expressions. Applying multilingual ABSA models or domain-adaptive fine-tuning could be especially relevant in international tourism contexts like Ubud.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data sharing is not applicable to this article. The data generated during this research is not publicly available due to the sensitive nature of the research, which could impact Bali's tourism image if used inappropriately.

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