



Cleanliness, Crowds, and Conservation: A Multi-Method Approach using Sentiment Analysis and Spatial Mapping for Sustainable Tourism Management in Thailand

Tobthong Chancharoen¹, Asamaporn Sitthi², Parinya Nakpathom³, Suwitchaya Rattarom⁴, and Narong Pleerux^{1*}

¹ Faculty of Humanities and Social Sciences, Burapha University, Chonburi, 20131, Thailand

² Faculty of Social Sciences, Srinakharinwirot University, Bangkok, 10110, Thailand

³ International College, Burapha University, Chonburi, 20131, Thailand

⁴ Faculty of Computer Science and Information Technology, Rambhai Barni Rajabhat University, Chanthaburi, 22000, Thailand

* Correspondence: narong_p@go.buu.ac.th

Citation:

Chancharoen, T.; Sitthi, A.; Nakpathom, P.; Rattarom, S.; Pleerux, N. Cleanliness, crowds, and conservation: a multi-method approach using sentiment analysis and spatial mapping for sustainable tourism management in Thailand. *ASEAN J. Sci. Tech. Report.* 2026, 29(6), e262164. <https://doi.org/10.55164/ajstr.v29i6.262164>

Article history:

Received: October 31, 2025

Revised: March 26, 2026

Accepted: April 12, 2026

Available online: May 10, 2026

Publisher's Note:

This article is published and distributed under the terms of the Thaksin University.

Abstract: Natural attractions are among Thailand's most important tourism resources, drawing a large number of international tourists and contributing substantially to national revenue. However, persistent issues such as overcrowding, pollution, and declining environmental quality remain critical challenges for sustainable management. In the digital era, online reviews on travel platforms strongly influence destination choice, providing a rich source of behavioral insights. This study applies sentiment analysis to 124,066 TripAdvisor reviews of natural attractions across all 77 provinces of Thailand, collected between 2014 and 2023. The reviews were processed using text mining techniques—data cleansing, tokenization, lemmatization, and stop-word removal—and analyzed with the Pysentimiento model, a BERT-based deep learning framework, achieving an overall accuracy of 76% and a precision of 87% on the validation dataset in distinguishing positive, negative, and neutral sentiments. Beyond thematic analysis, this research employs Kernel Density Estimation (KDE) to visualize the geographical concentration of dissatisfaction. Results indicate that beaches and islands received the most negative reviews, with recurring issues related to cleanliness, pollution, overcrowding, and unregulated commercial activities. The KDE analysis further reveals that negative sentiment intensity is highly concentrated in specific coastal hotspots (e.g., Phuket, Krabi, and Pattaya). This study contributes methodologically by demonstrating the integrated effectiveness of large-scale sentiment analysis and spatial mapping in tourism research, effectively addressing the implementation gap, providing actionable, precision-based insights for the National Tourism Development Plan (2023–2027). The findings support policymakers and stakeholders in formulating strategies that align with the BCG (Bio-Circular-Green) economic model and balance economic growth with sustainable environmental management by enabling location-specific resource allocation.

Keywords: Natural Language Processing (NLP); sentiment analysis; spatial analysis; sustainable tourism; Thailand natural attraction

1. Introduction

The tourism industry is a vital pillar of the Thai economy, contributing approximately 17.79% of the country's GDP [1] and generating substantial employment. Thailand's appeal to international tourists stems from its rich resources, encompassing both diverse natural attractions—such as renowned beaches, mountains, and waterfalls—and captivating historical and cultural sites [2]. Natural attractions, in particular, remain key points of interest, drawing large numbers of international tourists and offering a wide range of activities such as trekking and snorkeling [2-4]. The digital landscape has fundamentally changed how tourists research and share experiences. Today, online media is the primary channel for travel information, with 60.54% of international visitors using platforms such as Instagram, Facebook, and TikTok [5-7]. Among these, TripAdvisor stands out as the world's largest and most utilized source for sharing and accessing travel reviews [8]. Among these, TripAdvisor remains a critical source of electronic word of mouth (e-WOM), providing valuable, real-time data that reflects tourist behavior and satisfaction [8]. While platforms like Google Reviews and Booking.com have gained prominence, TripAdvisor's structured review system for specific natural landmarks remains a gold standard for longitudinal tourism research [9, 10]. The proliferation of this user-generated content presents a significant opportunity for tourism research [11, 12].

Analyzing this massive volume of textual data requires sophisticated techniques, such as Sentiment Analysis (or opinion mining), a key component of Natural Language Processing (NLP) [13-15]. Sentiment analysis, particularly when conducted with advanced deep learning models such as BERT-based architectures, including the Pysentimiento framework used in this study [16, 17], is highly effective for big data. Unlike traditional Lexicon-based approaches or earlier Recurrent Neural Networks (RNNs), BERT-based models utilize bidirectional transformers to capture the context of words in tourism reviews, effectively handling linguistic nuances such as sarcasm or multi-word descriptors of environmental quality [18]. This methodology allows stakeholders—including entrepreneurs and policymakers—to gain deep insights into tourist satisfaction, identify complex behaviors, and understand which specific aspects influence decision-making [19, 20]. Positive reviews can guide enhancement strategies, while negative feedback directly informs necessary improvements in quality, services, and infrastructure [21].

However, despite Thailand's success in attracting large numbers of tourists, persistent challenges remain, including the deterioration of natural resources, infrastructure limitations, and concerns about sustainability [1]. These challenges are currently being addressed through the National Tourism Development Plan (2023–2027) [4], which increasingly incorporates the Bio-Circular-Green (BCG) economy model as a supplementary strategic framework to enhance resource efficiency and environmental resilience [22]. Prior research has widely applied sentiment analysis to tourism reviews globally, including studies on hotels and general attractions using TripAdvisor data [23-25]. Within Southeast Asia, studies have begun leveraging e-WOM to evaluate destination sustainability in countries such as Indonesia [26, 27]; however, much of the existing literature in Thailand remains focused on general sentiment or specific local contexts, without a national-level spatial perspective [28, 29]. A critical gap remains: most existing Thai studies lack an in-depth, aspect-based sentiment analysis that identifies localized issues—such as cleanliness, crowds, or conservation—that concern international tourists at natural attractions [7, 30].

This research aims to address the identified gap by conducting an in-depth, aspect-based sentiment analysis of international tourist reviews regarding natural attractions in Thailand collected over ten years (2014–2023). Utilizing high-accuracy deep learning techniques, the study is structured around three primary objectives: (1) assess the sentiment towards these attractions: to quantitatively evaluate the distribution of positive, neutral, and negative perceptions across various natural attraction types, (2) identify specific issues and emotional keywords: to qualitatively extract thematic concerns related to cleanliness, crowds, and conservation through N-Gram analysis, and (3) map the geographical concentration of dissatisfaction: to visualize spatial sentiment hotspots using Kernel Density Estimation (KDE) to pinpoint localized management crises. The findings will provide actionable, detailed insights for relevant government agencies and tourism stakeholders, enabling them to make targeted improvements to resource management, service quality, and future development plans more effectively and efficiently.

The remainder of this paper is structured as follows: Section 2 outlines the Materials and Methods; Section 3 presents the Results and Discussion; and Section 4 provides the Conclusion.

2. Materials and Methods

2.1 Study Area and Data Collection

This study focuses on natural attractions across all 77 provinces of Thailand (Figure 1). Data was systematically collected from TripAdvisor over a decade (2014-2023). Attractions were categorized into 17 distinct types based on the Natural Tourist Attraction Quality Assessment Manual [31]. These types include: Beach, Botanical Garden, Cave, Forest Park, Fossil, Island, Lookout & Scenic Walking Area, Mangrove Forest, Mountain & Hill, Nature & Wildlife Area, Rapid, Special Geography & Topography, Special Plant & Wildlife, Thermal Spring, Water Resource, and Waterfall.

Web scraping was performed using a Python-based pipeline [32] to extract 124,066 international tourist reviews. Selenium [33] was specifically utilized to navigate dynamic JavaScript-rendered content and manage automated pagination, while BeautifulSoup [34] was employed to parse and extract specific HTML elements from the loaded pages. The extracted data was then structured and cleaned using the Pandas library [35] before being stored in CSV format. To ensure research integrity, the scraping process adhered to ethical data acquisition standards. This included strictly collecting only publicly available review content, regulating request frequencies to comply with TripAdvisor's robot.txt directives, and ensuring alignment with the platform's Terms of Service regarding non-commercial, academic data usage.

The collected data encompassed the attraction's name, type, date, title, content, and location. Regarding categorization, attractions were manually assigned to the 17 types by the researchers, cross-referencing TripAdvisor's location data with the official definitions in the Quality Assessment Manual [31] to ensure thematic accuracy.

2.2 Sentiment Analysis Framework and Data Preprocessing

The research follows a three-stage text mining framework: (1) Data Collection and Preprocessing, (2) Sentiment Analysis, and (3) Issue Identification (Figure 2). Reviews were rigorously preprocessed [36]. Since the study aims to capture the perspectives of international tourists using the Pysentimiento English-language model, only English-language reviews were included in the final dataset. Reviews in other languages were excluded during the initial filtering phase to avoid translation inaccuracies; however, this targeted language focus is further addressed and discussed in the subsequent recommendations section of this paper.

The cleaning involved converting text to lowercase, removing irrelevant components (URLs, punctuation, symbols, and special characters) [37], and selectively removing stop words [38]. Following standard NLP practices, the text was first tokenized into individual word IDs [39]. These tokens were then lemmatized to reduce words to their base forms (e.g., "beaches" to "beach") [36], ensuring that morphological variation did not skew the frequency analysis.

2.3 Deep Learning Model Selection and Analysis

The study used deep learning models for sentiment analysis due to their superior performance on large, redundant social media datasets [16, 17].

2.3.1 Model Selection

Before final implementation, multiple robust deep learning models were comparatively analyzed to ensure optimal accuracy, including RoBERTa-base [40], XLM-roBERTa-base [41], DistilBERT-base [42], and BERT [43], as well as a lexicon-based model (VADER) [44]. The Pysentimiento model, a Python toolkit based on BERT architecture [45], was ultimately selected for its superior capability and proven high performance in sentiment analysis tasks on social media data. While RoBERTa-base showed a slightly higher overall accuracy, Pysentimiento demonstrated the highest Precision (0.87), as shown in Table 1. This high precision is particularly critical for this study, as it ensures that the negative sentiments—the primary focus for identifying tourist dissatisfaction and management hotspots—are identified with the greatest reliability, minimizing false positives. The model classifies reviews into three categories: positive (e.g., "best bay"), negative (e.g., "dirty

water"), or neutral (e.g., "ordinary tourist place"). Optimal performance was achieved through hyperparameter fine-tuning, including the Number of Epochs (3, 4, 5), Batch Size (32), and Learning Rate ($2e-5$ to $1e-4$) [43, 45].

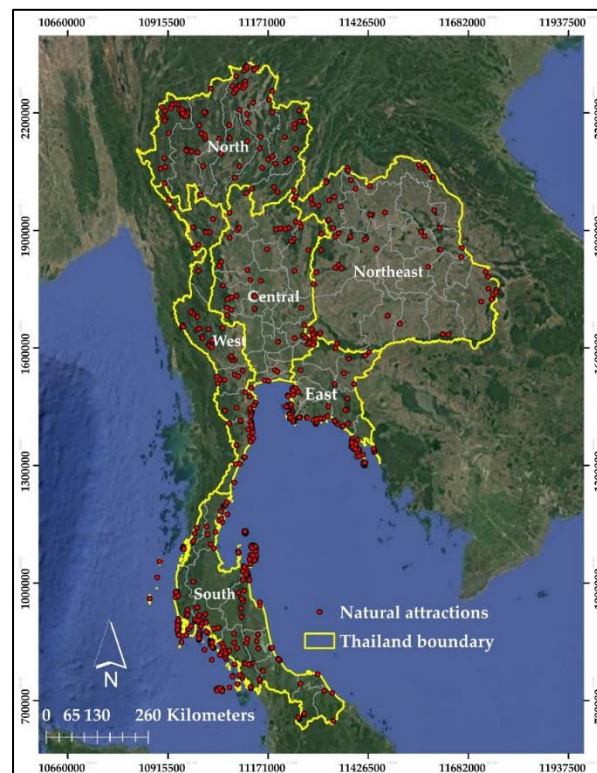


Figure 1. Study Area Map: Natural Attractions in All 77 Provinces of Thailand

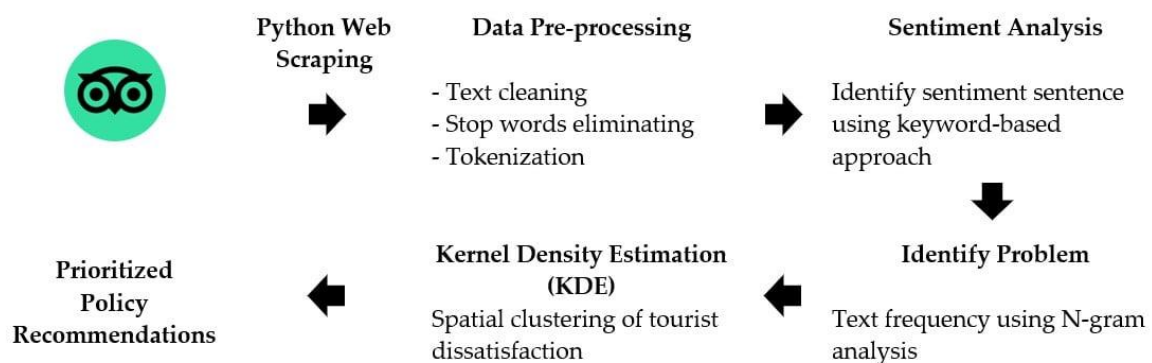


Figure 2. Sentiment Analysis Framework

Table 1. Comparative Performance of Sentiment Analysis Models

Model	Precision	Recall	F1-Score	Accuracy
RoBERTa-base	0.83	0.69	0.76	0.78
XLM-roBERTa-base	0.60	0.87	0.71	0.70
DistilBERT base	0.68	0.82	0.75	0.73
BERT	0.78	0.60	0.68	0.70
Pysentimiento	0.87	0.65	0.74	0.76
VADER	0.77	0.83	0.51	0.68

2.3.2 Model Evaluation

The Pysentimiento model was evaluated using a specific TripAdvisor dataset of 4,509 expert-labeled reviews, comprising 2,642 positive, 575 neutral, and 1,292 negative samples (80% for training, 10% for testing, and 10% for evaluation). To ensure the quality of the ground truth data, these reviews were independently manually annotated by three researchers with expertise in tourism management and linguistics. Each review was categorized as positive, negative, or neutral based on explicit sentiment indicators. To validate the consistency of this manual labeling, Cohen's Kappa (K) was calculated to evaluate inter-rater agreement while accounting for chance. The calculation follows the formula:

$$K = \frac{p_o - p_e}{1 - p_e} \quad (1)$$

where p_o represents the relative observed agreement, and p_e is the hypothetical probability of chance agreement. In this evaluation, the researchers achieved an observed agreement (p_o) of 0.91 (representing consensus on 4,103 reviews). Given the distribution of the categories, the probability of chance agreement (p_e) was calculated at 0.50, resulting in a final Kappa coefficient of 0.82. According to Landis and Koch [46], this "almost perfect agreement" confirms the high reliability of the ground truth dataset.

The model's performance was rigorously assessed against three key criteria: pre-trained English-language classification, hyperparameter fine-tuning, and fairness assessment [45, 47]. Model performance was then assessed using a Confusion Matrix (Table 2), a statistical tool that analyzes the correlation between predicted and actual outcomes [27].

Table 2. The Confusion Matrix used to Verify Pysentimiento Analysis

Actual / Prediction	Positive	Neutral	Negative
Positive	a	b	c
Neutral	d	e	f
Negative	g	h	i

The overall model efficacy was calculated using standard metrics derived from the Confusion Matrix: Precision (P), Recall (R), F1-Score (F1), and Accuracy (A). The equations for these metrics are as follows:

$$P(neg) = \frac{i}{(c+f+i)} \quad (2)$$

$$R(neg) = \frac{i}{(g+h+i)} \quad (3)$$

$$F1(neg) = \frac{2P(neg) \times R(neg)}{P(neg) + R(neg)} \quad (4)$$

$$A = \frac{a+e+i}{a+b+c+d+e+f+g+h+i} \quad (5)$$

2.4 Identifying Issues

Issues were identified through qualitative content analysis on the sentiment results using the Natural Language Toolkit (NLTK) [48]. While the primary focus of this study is to identify management crises through negative sentiment, a comparative N-Gram analysis was also applied to positive reviews to provide a balanced overview of destination strengths, aligning with the principles of Aspect-Based Sentiment Analysis (ABSA). These insights are specifically integrated into the policy recommendations to ensure that future management strategies not only resolve existing problems but also leverage and sustain Thailand's competitive advantages in its natural attractions.

Word Frequency Analysis: Counting word frequency to identify the top 30 most recurring tokens over the decade.

N-Gram Analysis: Determining the co-occurrence of contiguous words (Uni-Gram through Quart-Gram) to identify specific problems associated with each of the 17 attraction types (Figure 3). The researchers acknowledge that for certain categories with lower review volumes (e.g., Botanical Gardens or Mangrove Forests), the extracted N-Grams may yield more generic descriptors. These instances are explicitly noted in the results to distinguish them from the data-rich insights in high-volume categories such as Beaches and Islands. **Thematic Categorization:** Extracted keywords were grouped into broader themes (e.g., Environmental, Service, and Accessibility). To ensure the reliability of this inductive coding process, the thematic mapping was cross-validated by three independent researchers, following the same inter-rater reliability protocol used in the sentiment validation phase to minimize subjective bias. This methodology enables stakeholders to classify negative reviews by specific, recurrent issues, thereby supporting prioritized problem resolution in tourism and environmental policy [49].

['beach', 'not', 'clean', 'expected', 'services', 'good']

Mono-Gram	beach	not	clean	expected	services	good
Bi-Gram	beach not	not clean	clean expected	expected services	services good	
Tri-Gram	beach not clean	not clean expected	clean expected services	expected services good		
Quart-Gram	beach not clean expected	not clean expected services expected	clean expected services good			

Figure 3. N-Gram Analysis

2.5 Spatial Analysis: Kernel Density Estimation (KDE)

To provide actionable spatial insights for tourism management, the geographic distribution of negative sentiments was analyzed using Kernel Density Estimation (KDE). KDE is a non-parametric spatial analysis method used to estimate the probability density function of point data, effectively transforming discrete points (the locations of attractions with negative reviews) into a continuous surface that illustrates the spatial concentration (hotspots) of events [50, 51]. The estimated density at any location x is calculated as:

$$\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \quad (6)$$

Where: $\hat{f}(x)$ is the estimated density, n is the number of negative review observations, h is the bandwidth (smoothing parameter), K is the kernel function, and x_i represents the location of each negative review.

The input data comprised the complete set of negative reviews, with the review count for each attraction serving as the Population Field (weight). This ensures that high-volume attractions contribute proportionally to the density surface. While this weighting reflects actual intensity, the researchers acknowledge that the inherent density of data in high-traffic areas (e.g., popular beaches) naturally dominates the KDE surface compared to niche sites (e.g., fossil sites). This inherent data characteristic is addressed in the limitations and interpreted within the context of destination popularity. The KDE was executed using Python's SciPy [52] and Scikit-learn [53] libraries. A critical parameter in KDE is the bandwidth (h). In this study, a 0.5-kilometer bandwidth was strategically selected to identify "hyper-local" hotspots. This fine-scale resolution is essential for distinguishing between specific management crises within adjacent but distinct tourist zones, such as different beach segments or neighboring national park entrances. However, to address the broader national-level policy perspective and ensure spatial robustness, a sensitivity analysis was conducted by comparing the 0.5 km setting against wider bandwidths (5 km, 25 km, and 50 km) as recommended in spatial tourism research. The 0.5 km setting provided the highest precision for localized intervention, while the larger bandwidths offered a generalized view of regional trends.

Furthermore, to ensure comparative clarity across regions, the final density maps (Figure 5) use a standardized continuous scale with absolute numerical density values rather than a simple relative gradient. This allows for the direct comparison of negative sentiment intensity across different provinces.

3. Results and Discussion

3.1 Understanding Sentiment and Annual Trends

Reviews from international tourists regarding natural attractions across all 77 provinces of Thailand were collected from the TripAdvisor platform, yielding a substantial total of 124,066 reviews. This volume of data serves as a valuable proxy for understanding real-world tourism trends [15, 54].

3.1.1 Annual Trend and Contextual Shifts

The analysis of the dataset's temporal distribution reveals significant shifts in tourist behavior towards sharing experiences online [9]. Figure 4 illustrates the annual trend, showing that the number of reviews peaked in 2016 before declining markedly toward the end of 2019. This decline is directly correlated with the global impact of the COVID-19 pandemic [55], which led to a significant decrease in arrivals. While the volume decreased during 2020–2023, the core concerns regarding environmental quality remained consistent with pre-pandemic patterns, though health-related sentiments saw a temporary increase.

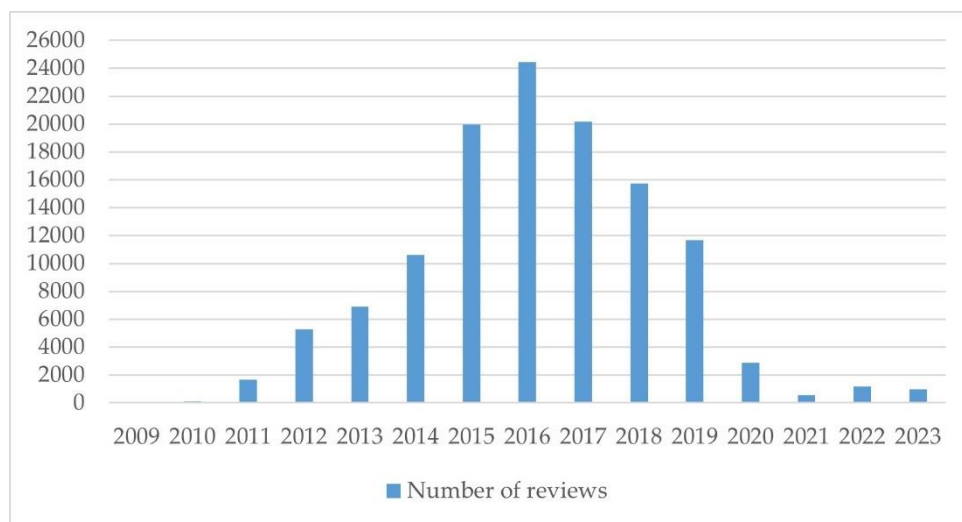


Figure 4. Number of Reviews from International Tourists of Natural Attractions in Thailand from TripAdvisor

3.1.2 Sentiment Analysis Performance and Overall Distribution

The sentiment analysis of the 124,066 reviews was performed using the Pysentimiento deep learning model [43, 45]. The model was prioritized for its high Precision (0.87), ensuring that negative sentiments—the primary focus for crisis identification—were identified with 87% reliability [17, 56, 57]. The overall sentiment distribution is strongly positive, with 91,145 positive reviews (73.47%), 17,883 neutral reviews (14.41%), and 15,038 negative reviews (12.12%). This predominant positivity is consistent with a general positive bias in online reviews. Table 3 presents an in-depth aspect-based sentiment analysis categorized by the 17 attraction types. The results show that while overall satisfaction is high, certain attraction types (such as Beach and Island) receive the vast majority of reviews, highlighting where positive perceptions are most concentrated, reflecting Thailand's world-renowned natural splendor.

Table 3. The Results of Sentiment Analysis of Natural Attractions Types in Thailand

Types	Positive		Neutral		Negative		Total reviews	%
	Number	%	Number	%	Number	%		
Beach	53,414	72.63	9,737	13.24	10,394	14.13	73,545	59.28
Botanical Garden	75	78.13	17	17.71	4	4.17	96	0.08
Cave	1,900	68.03	648	23.20	245	8.77	2,793	2.25
Forest Park	112	78.32	21	14.69	10	6.99	143	0.12
Fossil	10	71.43	4	28.57	-	-	14	0.01
Island	15,162	73.77	2,944	14.32	2,446	11.90	20,552	16.56
Lookout & Scenic Walking Area	23	85.19	4	14.81	-	-	27	0.02
Mangrove Forest	99	78.57	21	16.67	6	4.76	126	0.10
Mountain & Hill	9,204	80.97	1,608	14.15	555	4.88	11,367	9.16
Nature & Wildlife Area	-	0.00	1	100.00	-	-	1	0.01
Rapid	138	75.41	32	17.49	13	7.10	183	0.15
Special Geography & Topography	2,518	70.39	704	19.68	355	9.92	3,577	2.88
Special Plant & Wildlife	93	76.86	27	22.31	1	0.83	121	0.10
Thermal Spring	1,073	66.07	308	18.97	243	14.96	1,624	1.31
Water Resource	2,525	71.11	771	21.71	255	7.18	3,551	2.86
Waterfall	4,799	75.62	1,036	16.33	511	8.05	6,346	5.12
Total	91,145		17,883		15,038		124,066	
%		73.47		14.41		12.12		100.00

3.2 Identifying Core Issues through Content

While overall sentiment is positive, a deeper analysis of negative reviews is crucial for identifying areas requiring improvement [58, 59]. In alignment with the study's objective to analyze international tourist perspectives, English-language reviews were specifically selected as the primary data source. As the most widely used language for global communication on TripAdvisor, these reviews provide a consistent and representative dataset for evaluating how a diverse international audience perceives Thailand's natural attractions. This focus ensures that the resulting management insights and policy recommendations directly address the expectations and experiences of the global travel market.

3.2.1 N-Gram Analysis and Specific Issues

Issue identification focused on negative reviews using Word Frequency and N-Gram Analysis (Uni-Gram through Quart-Gram) via NLTK [48]. Table 4 highlights the most frequently mentioned keywords. For high-volume categories like Beaches and Islands, the N-Grams yield specific actionable insights (e.g., "dirty," "rip prices"). For niche categories with fewer reviews (e.g., Botanical Garden), the results show more generic terms (e.g., "walk," "place"), which are noted as preliminary indicators due to the smaller sample size.

3.2.2 Thematic Categorization of Dissatisfaction

The N-Gram analysis provided critical insights by systematically categorizing tourist dissatisfaction into three main groups: Environmental & Maintenance, Service & Facility, and Accessibility & Infrastructure (Table 5). To ensure the reliability of this inductive coding, the mapping was cross-validated by three independent researchers to minimize subjective bias.

Table 4. The Results of N-Gram Analysis of Natural Attractions Types in Thailand

Types	The highest number of mentions in the N-Gram analysis
Beach	dirty, rubbish, not clean, many people, would not recommend, people trying to sell stuff
Botanical Garden	go, place, walk
Cave	people, crowded, climb, entrance, dark, tourist trap, waste time, not worth it, do not speak English
Forest Park	plastic, roads, fee, place, walk, car, 10 min fill
Island	crowded, snorkeling, not worth it, long tail boats, 400 baht per person, rip prices captive market
Mangrove Forest	place, walkway, walk, road, disappointed, entrance, drive, restaurant, information
Mountain & Hill	pay, people, walk, tourist, climb, drive, not worth, entrance fee, tourist trap
Rapid	price, drive, trail, walk, steep, entrance, restaurant, fee 30 baht
Special Geography & Topography	nothing, tourist, people, parking, walk, shop, stall, tricky, tourist trap, not worth
Special Plant & Wildlife	tree, spoilt, lame, stall
Thermal Spring	people, pay, entrance fee, tourist, dirty overall, 300 baht entry, would not recommend
Water Resource	tourist, dirty, tricky, tourist trap, long tail boats, not much to see, total waste of time and money
Waterfall	walk, people, pay, small, swim, climb, no water, dry season, fee 300 baht

Environmental & Maintenance Issues: Keywords such as "dirty," "rubbish," and "plastic" highlight critical problems related to cleanliness and pollution (common at Beach and Water Resource destinations). Problems of Overcrowding & Overuse ("crowded," "many people") indicate recurring management issues, consistent with challenges identified in Thailand's National Tourism Development Plan [4]. Furthermore, Natural Condition issues, such as "no water" during the dry season (common at Waterfalls), underscore the need for better management of tourist expectations regarding seasonal factors. Service & Facility Issues: Negative sentiments concerning Worthiness ("not worth," "waste time," "rip prices") and High costs/fees (e.g., "300 baht entry") are primary indicators of a mismatch between tourist expectations and the actual quality received. These issues are most commonly reported in paid attractions (e.g., Cave, Mountain & Hill, Thermal Spring). Challenges related to the overall Travel Experience ("tourist trap," "not speak English") highlight the need to enhance service-provider quality. Accessibility & Infrastructure Issues: Keywords related to Access & Transport ("road," "long tail boats," "climb") found across various natural attractions indicate that overly challenging routes and inadequate transportation systems diminish the travel experience. Similarly, issues with Amenities ("walkway," "dark," "restaurant") are pressing micro-level problems requiring urgent improvement.

Table 5. The Results of All Levels in N-Gram Analysis of Natural Attractions Types in Thailand

Main Issues	Sub-Issues	Keywords	Types
Environmental & Maintenance	Cleanliness & Pollution	dirty, rubbish, plastic, water not clean, dirty overall, not worth it	Beach, Forest Park, Thermal Spring, and Water Resource
	Crowding & Overuse	people, crowded, tourist trap, many people	Beach, Cave, Island, Mountain & Hill, Special Geography & Topography, and Water Resource
	Natural Condition	no water, dry season, nothing to see, not much to see, nothing special	Cave, Special Geography & Topography, Special Plant & Wildlife, and Waterfall
Service & Facility	Worthiness	not worth, waste time, not worth time, money, rip prices, not worth the trip	Cave, Island, Special Geography & Topography, Thermal Spring, Water Resource, and Waterfall
	High costs/fees	price, fee, entrance fee, pay, 300 baht per person	Forest Park, Mountain & Hill, Rapid, Thermal Spring, and Waterfall
	Travel Experience	tourist trap, would not recommend, people trying to sell stuff, do not speak English	Beach, Cave, Island, Mountain & Hill, Special Geography & Topography, and Water Resource
Accessibility & Infrastructure	Access & Transport	road, way, walk, drive, climb, long tail boats, speed boat	Botanical Garden, Cave, Island, Forest Park, Mangrove Forest, Mountain & Hill, Water Resource, and Waterfall
	Amenities	place, walkway, dark, restaurant, shop, stall	Botanical Garden, Cave, Mangrove Forest, Rapid, Special Plant & Wildlife, Special Geography & Topography, and Thermal Spring

3.3 Spatial Visualization and Priority Recommendations

Following issue identification, Kernel Density Estimation (KDE) was performed on 15,038 negative reviews to visualize spatial clustering.

3.3.1 Spatial Analysis of Negative Sentiment Hotspots

A bandwidth (h) of 0.5 km was utilized to capture "hyper-local" clustering patterns. This precision is essential for site-specific management, despite larger bandwidths (5–50 km) being common for regional overviews. The resulting density map, presented in Figure 5, incorporates a numerical density scale (Reviews/km²) to allow direct quantitative comparison between hotspots. Figure 5 reveals that the highest density is concentrated in Phuket (Patong, Kata, Karon), Krabi (Phi Phi, Ao Nang), Chonburi (Pattaya, Ko Larn), and Surat Thani (Koh Samui, Koh Phangan). This concentration provides location-specific validation of high-priority issues such as cleanliness and overcrowding.

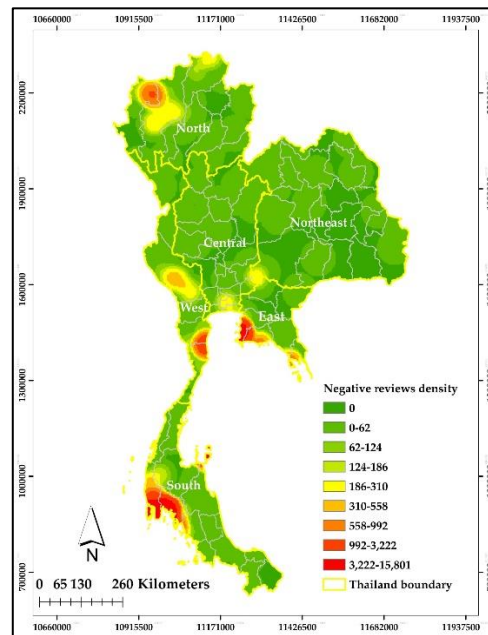


Figure 5. Kernel Density Map of Negative Reviews in Thailand

3.3.2 Prioritized Policy Recommendations

Based on empirical evidence from sentiment and N-Gram analyses, and supported by spatial validation from the KDE analysis, this study categorizes the identified problems into three priority levels. These recommendations directly support the Department of Tourism's Action Plan (2023–2027), specifically by integrating the BCG model to transition Thailand toward high-value, sustainable tourism. However, our empirical findings reveal a critical implementation gap: while the national plan aims for 'High Value' tourism, the recurring N-Grams of 'tourist traps' and 'dirty' environments in high-density KDE hotspots indicate that local management still struggles to align with these national strategic goals. This study provides the necessary spatial precision to bridge this gap by identifying exactly where national policies fail to translate into positive tourist experiences.

(1) High Priority Issues: Immediate Crisis Management

These issues have a direct, immediate impact on tourist perceptions and require urgent intervention to prevent long-term reputational damage:

Cleanliness and Environmental Quality: Geographically validated by KDE hotspots in Phuket, Krabi, and Chonburi. This requires strict enforcement of waste management regulations consistent with Circular Economy principles to mitigate the impact of 'rubbish' and 'plastic' on natural capital (e.g., MNRE, DNP). Resources should be specifically diverted to high-density negative sentiment zones identified in Figure 5.

Value for Money: Beyond simple pricing standards, this study suggests a need for optimized pricing strategies based on tourists' "Willingness to Pay" (WTP) for premium natural capital. High entry fees (e.g., 300-400 Baht) must be justified by visible improvements in facility quality and service transparency (e.g., TAT, DNP). A mismatch here, as shown in the "not worth it" N-Grams, indicates that current pricing exceeds perceived value, necessitating a more dynamic or value-added pricing model.

(2) Medium Priority Issues: Strategic Adjustments

These issues act as barriers to sustainable development and require coordinated cross-agency planning. **Overcrowding and Carrying Capacity:** Since overcrowding is a primary driver of KDE hotspots, we propose a "Spatial Dispersion Strategy." Using the KDE results, authorities should redirect tourist traffic from "Saturated Hotspots" (e.g., Phi Phi, Patong) toward identified "Potential Alternative Destinations"—areas with high-quality natural resources but low negative sentiment density (e.g., secondary coastal zones in Trang or Satun). This aligns with the TAT's mission to promote secondary cities. **Information and Communication:** To

manage expectations regarding seasonal factors (e.g., "no water" at waterfalls), a multi-language digital platform (MOTS, TAT) should provide real-time updates on site conditions, reducing dissatisfaction caused by misinformation.

(3) Long-term Priority Issues: Structural and Infrastructure Development

These structural issues require long-term investment to ensure the resiliency of Thailand's tourism sector. Infrastructure and Accessibility: Plans must prioritize improving transportation routes (DOH, DRR) and supporting local entrepreneurs. Strategic infrastructure investment should focus on enhancing access to non-hotspot areas to naturally facilitate tourism dispersion and reduce the environmental load on currently saturated zones. Attraction Quality and Resource Restoration: Long-term environmental restoration plans (MNRE) must be synchronized with seasonal attraction closures. This ensures that natural capital is sustained in accordance with the BCG (Bio-Circular-Green) economic model promoted in the National Tourism Development Plan.

4. Conclusions

This study successfully integrated Transformer-based Deep Learning with spatial analytics to provide a high-precision diagnostic of Thailand's natural tourism sector. The findings offer a robust framework for transitioning from generalized national policies to evidence-based, localized interventions.

4.1 Methodological Contributions

Validated Sentiment Precision: The application of the Pysentimiento (BERT-based) model demonstrated superior performance in capturing the linguistic nuances of 124,066 international reviews. The model's reliability was supported by an inter-rater agreement (Cohen's Kappa) of 0.82, indicating "almost perfect agreement" in the ground-truth data used for validation. Spatial Specificity: By utilizing Kernel Density Estimation (KDE) with a 0.5 km bandwidth, this research moved beyond traditional statistical summaries to identify "hyper-local" hotspots of dissatisfaction. This spatial precision allows stakeholders to pinpoint specific management crises within adjacent but distinct tourist zones.

4.2 Core Empirical Findings

Thematic Clusters of Dissatisfaction: Through N-Gram analysis, the study categorized the drivers of negative sentiment into three primary pillars: Environmental & Maintenance (e.g., "dirty," "rubbish"), Service & Facility (e.g., "tourist trap," "not worth"), and Accessibility & Infrastructure (e.g., "road," "long-tail boat fees"). Geographic Vulnerability: The highest concentration of negative sentiment is critically localized in major coastal hubs—Phuket, Krabi, Chonburi, and Surat Thani. The intensity of issues in these zones (quantified in Reviews/km²) highlights a significant "Implementation Gap" where local management struggles to keep pace with the high volume of international arrivals.

4.3 Strategic Policy Recommendations

The study proposes a three-tier priority framework aligned with the Department of Tourism's Action Plan (2023-2027). High Priority (Immediate): Urgent waste management and Value-for-Money optimization (aligning pricing with "Willingness to Pay") are required in the identified KDE hotspots to protect Thailand's international reputation. Medium Priority (Strategic): Implementing Spatial Dispersion Strategies to redirect traffic from saturated hotspots to potential alternative destinations (e.g., secondary coastal cities) with low negative sentiment density. Long-term (Structural): Synchronizing resource restoration with the BCG (Bio-Circular-Green) economic model to ensure the long-term resiliency and sustainability of Thailand's natural tourism assets.

4.4 Limitations and Future Directions

Language and Platform Scope: This study strategically focused on English-language reviews on TripAdvisor as a proxy for the global international market. While representative of a significant segment, future research should incorporate multi-lingual data (e.g., Chinese or East Asian platforms) to capture a more holistic view of diverse cultural expectations. Temporal Dynamics: While the analysis accounts for the COVID-19 disruption, ongoing monitoring is essential to evaluate if post-pandemic expectations regarding environmental standards and value-for-money have undergone a permanent shift. Analytical Rigor: Future studies could

benefit from multi-scale KDE analysis to compare local micro-hotspots with broader regional trends, further refining the granularity of national tourism planning.

5. Acknowledgments

The authors would like to thank TripAdvisor for providing the valuable information used in this research. Special thanks to the reviewers for their constructive comments and suggestions, which helped to improve the quality of this manuscript.

Author Contributions: Methodology, validation, investigation, resources, visualization, writing—original draft preparation, TB; writing—review and editing, NP; conceptualization—AI, AS; conceptualization—tourism, PN; software, formal analysis, and data curation, SR. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

- [1] Ministry of Tourism and Sports. *Tourism Economic Review, Year 2, Issue 1/2021*; 2021. <https://www.mots.go.th/news/category/708> (accessed December 2, 2025).
- [2] Ministry of Tourism and Sports. *National Tourism Development Plan No. 2 (2017–2021)*; 2016. https://secretary.mots.go.th/strategy/more_news.php?cid=9 (accessed December 2, 2025).
- [3] Ministry of Tourism and Sports. *Tourism Economic Review, Year 1, Issue 3/2020*; 2020. https://www.mots.go.th/more_news_new.php?cid=605 (accessed December 2, 2025).
- [4] Ministry of Tourism and Sports. *National Tourism Development Plan No. 3 (2023–2027)*; 2023. <https://anyflip.com/zzfck/kiel> (accessed December 2, 2025).
- [5] Cui, Y.; He, Q. *Travel Behavior Analysis with Social Media Data and Smartphone GPS Data*; Transportation Informatics Tier I University Transportation Center, University at Buffalo: Buffalo, NY, 2019.
- [6] Lassen, N. B.; Madsen, R.; Vatrappu, R. Predicting iPhone Sales from iPhone Tweets. In *Proc. IEEE 18th Int. Enterp. Distrib. Object Comput. Conf.*; Ulm, Germany, September 1–5, 2014. <https://doi.org/10.1109/EDOC.2014.20>
- [7] Ministry of Tourism and Sports. *Survey Project for Analysis of International Tourist Behavior 2024: Final Report*; 2024. <https://intelligencecenter.tat.or.th/articles/35286> (accessed September 30, 2025).
- [8] Valdivia, A.; Luzón, M. V.; Herrera, F. Sentiment Analysis on TripAdvisor: Are There Inconsistencies in User Reviews? In *Hybrid Artificial Intelligence Systems (HAIS 2017)*; Lecture Notes in Computer Science; Springer: Cham, 2017; Vol. 10334, pp 15–25. https://doi.org/10.1007/978-3-319-59650-1_2
- [9] Donthu, N.; Kumar, S.; Pandey, N.; Mishra, A. Mapping Electronic Word-of-Mouth (eWOM) Research. *J. Bus. Res.* **2021**, *135*, 758–773. <https://doi.org/10.1016/j.jbusres.2021.07.015>
- [10] Cenni, I. Sharing Travel Experiences on TripAdvisor. *J. Pragmat.* **2024**, *221*, 76–88. <https://doi.org/10.1016/j.pragma.2023.12.015>
- [11] Li, H.; Hu, M.; Li, G. Forecasting Tourism Demand with Multisource Big Data. *Ann. Tour. Res.* **2020**, *83*, 102912. <https://doi.org/10.1016/j.annals.2020.102912>
- [12] Song, H.; Qiu, R. T. R.; Park, J. Tourism Demand Forecasting: A Review. *Ann. Tour. Res.* **2019**, *75*, 338–362. <https://doi.org/10.1016/j.annals.2018.12.001>
- [13] Sarker, I. H. Deep Learning: A Comprehensive Overview. *SN Comput. Sci.* **2021**, *2*, 420. <https://doi.org/10.1007/s42979-021-00815-1>
- [14] Liu, B. *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*; Cambridge University Press: New York, 2015. <https://doi.org/10.1017/CBO9781139084789>
- [15] Lu, Y.; Kong, X.; Quan, X.; Liu, W.; Xu, Y. Exploring the Sentiment Strength of User Reviews. In *Web-Age Information Management (WAIM 2010)*; Lecture Notes in Computer Science; Springer: Berlin, Heidelberg, 2010; Vol. 6184, pp 471–482. https://doi.org/10.1007/978-3-642-14246-8_46

- [16] Alaei, A.; Becken, S.; Stantic, B. Sentiment Analysis in Tourism. *J. Travel Res.* **2019**, *58*, 175–191. <https://doi.org/10.1177/0047287517747753>
- [17] Yuan, X. Evaluation of Rural Tourism Development Level Using BERT-Enhanced Deep Learning Model. *Sci. Rep.* **2024**, *14*, 25748. <https://doi.org/10.1038/s41598-024-77444-0>
- [18] Devlin, J.; Chang, M. W.; Lee, K.; Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv* **2019**. <https://doi.org/10.48550/arXiv.1810.04805>
- [19] Agüero-Torales, M. M.; Cobo, M. J.; Herrera-Viedma, E.; López-Herrera, A. G. Sentiment Analysis in TripAdvisor Reviews. *Procedia Comput. Sci.* **2019**, *162*, 392–399. <https://doi.org/10.1016/j.procs.2019.12.002>
- [20] Paolanti, M.; Mancini, A.; Frontoni, E.; Felicetti, A.; Marinelli, L.; Marcheggiani, E.; Pierdicca, R. Tourism Destination Management Using Sentiment Analysis. *Inf. Technol. Tour.* **2021**, *23*, 241–264. <https://doi.org/10.1007/s40558-021-00196-4>
- [21] Hashim, R.; Omar, B.; Al-Samarraie, H. The Application of Sentiment Analysis in Tourism Research. *Int. J. Bus. Tour. Sci.* **2020**, *8*, 51–60.
- [22] National Science and Technology Development Agency. *Bio-Circular-Green Economy Action Plan 2021–2027*; 2021. https://www.bcg.in.th/eng/wp-content/uploads/2022/07/BCG_Action_Plan_-Eng_Small.pdf (accessed December 2, 2025).
- [23] Jabbar, M. A.; Widjanarti, A.; Zulen, A. A.; Okfantia, A. D. Sentiment Analysis of Tourist Reviews. In *Data Science in Central Banking: Applications and Tools*; 2023. https://www.bis.org/ifc/publ/ifcb59_18.pdf
- [24] Giftson Jeba Selva Raja, J.; Juliet, S. Deep Learning-Based Sentiment Analysis of TripAdvisor Reviews. In *Proc. 2nd Int. Conf. Appl. Artif. Intell. Comput.*; Salem, India, May 4–6, 2023. <https://doi.org/10.1109/ICAAC56838.2023.10140848>
- [25] Santibáñez-Cortés, E.; Carrillo-Cabrera, A.; Castillo-Castillo, Y. A.; Moctezuma-Ochoa, D. A.; Muñoz-Sánchez, V. BERT and Data Augmentation for Sentiment Analysis. In *IberLEF@SEPLN*; 2022. <https://ceur-ws.org/Vol-3202/restmex-paper6.pdf>
- [26] Musyafah, A. A.; Prasetyo, M. H.; Prananda, R. R.; Jati, O. E. Sustainable Marine Tourism Policy. *Int. J. Multidiscip. Res. Anal.* **2025**, *8*. <https://doi.org/10.47191/ijmra/v8-i01-20>
- [27] Irena, L. Sentiment Analysis of Super Priority Tourism Destination Labuan Bajo. In *ICEBSH*; **2025**; pp 177–187. https://doi.org/10.2991/978-2-38476-495-2_17
- [28] Pleerux, N.; Boonpook, W.; Chaiyo, A.; Nardkulpat, A. TripAdvisor Restaurant Reviews Analysis in Bangkok. In *Proc. Int. Conf. Cyber Manag. Eng.*; 2023; pp 536–539. <https://doi.org/10.1109/CyMaEn57228.2023.10050971>
- [29] Taecharungroj, V.; Mathayomchan, B. Analysing TripAdvisor Reviews of Tourist Attractions in Phuket. *Tour. Manag.* **2019**, *75*, 550–568. <https://doi.org/10.1016/j.tourman.2019.06.020>
- [30] Shadrina, N. K.; Sutoyo, E.; Widartha, V. P. Sentiment Analysis in Reviews about Beaches in Bali Using RNN. In *Proc. IEEE Inf. Technol. Int. Semin.*; Surabaya, Indonesia, October 6–8, 2021. <https://doi.org/10.1109/ITIS53497.2021.9791501>
- [31] Ministry of Tourism and Sports. *Natural Tourist Attraction Quality Standard Assessment Manual*; 2018. <https://www.dot.go.th/ebooks/ebooks-view/417> (accessed December 2, 2025).
- [32] van Rossum, G. *Python Tutorial*; CWI: Amsterdam, 1995. <https://ir.cwi.nl/pub/5007/05007D.pdf>
- [33] Muthukadan, B. *Selenium Python Bindings*; 2024. <https://selenium-python.readthedocs.io/> (accessed September 30, 2025).
- [34] Richardson, L. *Beautiful Soup*; 2025. <https://www.crummy.com/software/BeautifulSoup/> (accessed September 30, 2025).
- [35] McKinney, W. Data Structures for Statistical Computing in Python. In *Proc. 9th Python Sci. Conf. (SciPy 2010)*; 2010; pp 56–61. <https://doi.org/10.25080/Majora-92bf1922-00a>
- [36] Ramadhani, A.; Sutoyo, E.; Widartha, V. P. LSTM-Based Deep Learning Architecture of Tourist Reviews in TripAdvisor. In *Proc. Int. Conf. Inform. Comput.*; Jakarta, Indonesia, November 3–4, 2021. <https://doi.org/10.1109/ICIC54025.2021.9632967>

- [37] Prabha, M. I.; Srikanth, G. U. Survey of Sentiment Analysis Using Deep Learning Techniques. In *Proc. Int. Conf. Innov. Inf. Commun. Technol.*; Chennai, India, April 25–26, 2019; pp 1–9. <https://doi.org/10.1109/ICIICT1.2019.8741438>
- [38] Lima, T. O.; Colaço, M., Jr.; Prado, K. H. J.; Jesus, I. D., Jr.; Oliveira, F. R. Big Data Experiment on Opinion Mining. In *Proc. IEEE Int. Conf. Big Data*; Orlando, FL, 2021.
- [39] Chakriswaran, P.; Vincent, D. R.; Srinivasan, K.; Sharma, V.; Chang, C. Y.; Reina, D. G. Emotion AI-Driven Sentiment Analysis: A Survey. *Appl. Sci.* **2019**, *9*, 5462. <https://doi.org/10.3390/app9245462>
- [40] Loureiro, D.; Barbieri, F.; Neves, L.; Anke, L. S.; Camacho-Collados, J. TimeLMs: Diachronic Language Models from Twitter. *arXiv* **2022**. <https://doi.org/10.48550/arXiv.2202.03829>
- [41] Barbieri, F.; Anke, L. E.; Camacho-Collados, J. XLM-T: Multilingual Language Models in Twitter. *arXiv* **2021**. <https://doi.org/10.48550/arXiv.2104.12250>
- [42] Sanh, V.; Debut, L.; Chaumond, J.; Wolf, T. DistilBERT: A Distilled Version of BERT. *arXiv* **2019**. <https://doi.org/10.48550/arXiv.1910.01108>
- [43] Devlin, J.; Chang, M. W.; Lee, K.; Toutanova, K. BERT: Pre-Training of Deep Bidirectional Transformers. *arXiv* **2018**. <https://doi.org/10.48550/arXiv.1810.04805>
- [44] Hutto, C.; Gilbert, E. VADER: A Rule-Based Model for Sentiment Analysis. In *Proc. Int. AAAI Conf. Web Soc. Media*; 2014; Vol. 8, pp 216–225. <https://doi.org/10.1609/icwsm.v8i1.14550>
- [45] Pérez, J. M.; Rajngewerc, M.; Giudici, J. C.; Furman, D. A.; Luque, F.; Alemany, L. A.; Martinez, M. V. pysentimiento: A Python Toolkit. *arXiv* **2024**. <https://doi.org/10.48550/arXiv.2106.09462>
- [46] Landis, J. R.; Koch, G. G. The Measurement of Observer Agreement for Categorical Data. *Biometrics* **1977**, *33*, 159–174. <https://doi.org/10.2307/2529310>
- [47] Pérez, J. M. *Bertweet-Sentiment-Analysis*; Hugging Face, 2024. <https://huggingface.co/finiteautomata/bertweet-base-sentiment-analysis> (accessed September 30, 2025).
- [48] Bird, S.; Klein, E.; Loper, E. *Natural Language Processing with Python*; O'Reilly Media: Sebastopol, CA, **2019**.
- [49] Singgalen, Y. A.; Wahyuningtyas, S. Y.; Widodo, Y. E.; Dasra, M. N. A.; Setiawan, R. W. Sentiment Analysis for Tourism Destination Reviews. *J. Theor. Appl. Inf. Technol.* **2024**, *102*.
- [50] Rogel-Salazar, J. Density-Based Clustering. 2022. <https://domino.ai/data-science-dictionary/density-based-clustering> (accessed December 2, 2025).
- [51] Mission, R. S. Spatial Analysis Using GIS and Kernel Density Estimation. *J. Inf. Technol. Commun.* **2024**, *6*, 95–104. <https://doi.org/10.69478/JITC2024v6n2a10>
- [52] The SciPy Community. *SciPy*; 2008. <https://scipy.org/> (accessed December 2, 2025).
- [53] Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B. Scikit-Learn: Machine Learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.
- [54] Serrano-Guerrero, J.; Olivas, J. A.; Romero, F. P.; Herrera-Viedma, E. Sentiment Analysis: A Review. *Inf. Sci.* **2015**, *311*, 18–38. <https://doi.org/10.1016/j.ins.2015.03.040>
- [55] Ministry of Tourism and Sports. *Tourism Economic Review*; 2020. <https://elibrary.tceb.or.th/Publication/Others/6121> (accessed December 2, 2025).
- [56] González-Carvajal, S.; Garrido-Merchán, E. C. Comparing BERT against Traditional Machine Learning. *arXiv* **2020**. <https://doi.org/10.48550/arXiv.2005.13012>
- [57] Wang, G.; Jaber, M. A Deep Learning Approach to Sentiment Analysis of Hotel Reviews. *Int. J. Adv. Artif. Intell. Mach. Learn.* **2025**, *2*, 67–75. <https://doi.org/10.58723/ijaauml.v2i2.403>
- [58] Borrajo-Millán, F.; Alonso-Almeida, M. M.; Escat-Cortes, M.; Yi, L. Sentiment Analysis to Measure Quality in Tourism. *Sustainability* **2021**, *13*, 6015. <https://doi.org/10.3390/su13116015>
- [59] Bucur, C.; Tudorica, B.; Andrei, J. V.; Dusmanescu, D.; Paraschiv, D.; Teodor, C. Sentiment Analysis of Global News on Environmental Issues. *Front. Environ. Sci.* **2024**, *12*. <https://doi.org/10.3389/fenvs.2024.1360304>