Sentiment Analysis in Coastal Tourism: A Systematic Literature Review

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ABSTRACT

Coastal tourism is a strategic sector in global economic development, but it faces serious challenges related to sustainability. Understanding tourist perceptions is crucial for maintaining destination competitiveness. Moreover, sentiment analysis based on online reviews offers new opportunities to explore tourist opinions broadly and in real-time. This study aims to conduct a Systematic Literature Review (SLR) of research discussing the application of sentiment analysis in coastal tourism from 2015 to 2025. The literature search was conducted in major databases, namely Scopus, ScienceDirect, IEEE Xplore, and ACM Digital Library, using predetermined search strings. Based on the initial search results obtained from 190 articles, after the duplication removal and Quality Assessment (QA) processes, only 36 articles met the criteria and were further analyzed. The results demonstrate an increasing trend in publications since 2018, peaking in 2024. These studies are spread across various regions of the world, with a predominance of Southeast Asia and Europe. TripAdvisor and Google Maps served as the primary data sources. Analysis methods included lexicon approaches, Machine Learning (ML) algorithms (Naive Bayes, Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Random Forest), Deep Learning (DL) (Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM)), as well as hybrid approaches and Large Language Models (LLM). The labeling schemes used varied, ranging from binary and three-class to emotional categories, satisfaction dimensions, and the Kano model. Overall, tourist reviews of coastal destinations were positive, although complaints about cleanliness, price, service, and sustainability were common. These findings confirm that sentiment analysis is a crucial tool for understanding tourist experiences and can support sustainable coastal tourism management globally.

Keywords-sentiment analysis; systematic literature review; coastal; tourism; online review

I. INTRODUCTION

Coastal tourism is a strategic sector driving economic and regional development in many countries [1]. With vast coastlines, diverse marine ecosystems, and distinctive cultural values, coastal destinations attract significant international tourist flows [2, 3]. According to [4], marine and beach-based tourism represents a major share of global travel and remains among the fastest-growing segments. This sector, thus, serves not only as an economic driver but also as a key instrument for sustainable development, environmental conservation, and community well-being. Understanding tourists' perceptions and sentiments is essential for developing sustainable coastal destinations [5]. Sentiment reflects experiences and satisfaction levels that shape destination reputation and revisit intention [6]. The rise of digital platforms, such as TripAdvisor, Google Maps, and social media, has enabled large-scale analysis of User-Generated Content (UGC), driving the adoption of sentiment analysis as a real-time tool for assessing tourists' opinions. Studies have focused on simple text classification, but advances in data complexity have encouraged the use of ML and DL methods to derive deeper insights from online reviews [7]. Research highlights the growing role of sentiment analysis in sustainable tourism and Natural Language Processing (NLP). Authors in [8-12] demonstrate its contribution to understanding tourist behavior, promoting environmental sustainability, and enhancing destination management. Moreover, the emergence of LLMs, like GPT-4 and LLaMA, offers new possibilities for context-aware and multilingual sentiment interpretation [13, 14], positioning sentiment analysis as both an analytical and decision-support tool in sustainable tourism management. While previous systematic reviews have explored sentiment analysis in general tourism contexts [8, 15], they do not address the distinctive environmental and sustainability challenges of coastal destinations. Despite methodological progress, research applying sentiment analysis specifically to coastal tourism remains limited and fragmented. Existing studies vary in methods, data sources, and analytical depth, highlighting the need for an integrated synthesis. To fill this gap, the present study conducts an SLR to map temporal and geographic research trends, identify major data sources, and classify sentiment analysis methods and algorithms, providing the first domain-specific synthesis that links computational sentiment techniques with sustainable coastal tourism management.

II. BACKGROUND

A. Coastal Tourism

Coastal tourism encompasses a wide range of activities in coastal, marine, and island areas, including beach recreation, water sports, and marine ecotourism [16]. According to [4, 17], it is one of the fastest-growing segments of global tourism and makes a substantial contribution to the world economy. Beyond its economic significance and role in job creation, coastal tourism also supports sustainable development and the preservation of marine ecosystems. Nevertheless, its rapid expansion presents several challenges, such as environmental degradation, biodiversity loss, marine pollution, and the need for adaptive management in response to climate change [18]. An understanding of these dynamics is crucial for formulating effective sustainability strategies.

B. Sentiment Analysis in Tourism

Sentiment analysis, a branch of NLP, aims to extract opinions and emotions from text-based data [19]. In tourism, it is widely applied to assess tourists' perceptions of destinations, services, and experiences [20]. Methodological development has evolved from lexicon-based approaches to ML algorithms, such as SVM, kNN, and Random Forest, and has further progressed to DL models like CNN and LSTM. Hybrid techniques and LLMs have been explored to enhance accuracy and contextual understanding. These methods enable large-scale, real-time analysis of tourist perceptions, supporting data-driven decision-making in destination management [21].

C. Online Reviews' Role in Tourist Decision-Making

Online reviews shape tourist behavior and destination choices. Travelers rely on platforms, such as Google Maps, TripAdvisor, and travel forums, to learn from others' experiences, forming a powerful type of electronic Word-of-Mouth (e-WOM) that conveys information about destinations, services, and environmental conditions [22]. In coastal tourism, where attractions and services vary, these reviews provide valuable insights and serve as indicators of a destination's image and reputation. Understanding this influence helps stakeholders, both businesses and local governments, design better promotional strategies, enhance service quality, and strengthen competitiveness [23].

III. RESEARCH METHOD

The present study follows the SLR guidelines of Kitchenham to ensure a transparent and replicable process, comprising three main stages: planning, conducting, and reporting [24].

A. Planning the Review

The planning stage identified the need for this research, as studies on sentiment analysis in coastal tourism remain fragmented and unmapped. Accordingly, this SLR was designed to address three key questions: What are the temporal and geographic trends in sentiment analysis research on coastal tourism? What platforms or data sources are commonly used? What sentiment analysis methods or algorithms have been applied?

B. Conducting the Review

The implementation phase began with the development of a literature search strategy. Articles were searched in major databases, namely Scopus, ScienceDirect, IEEE Xplore, and the ACM Digital Library. Keywords were grouped into three blocks: sentiment analysis techniques ("sentiment analysis," "opinion mining," "review analysis," "text mining"), tourism domains ("tourism," "travel," "hospitality"), and coastal contexts ("coastal," "marine," "beach," "island," "maritime"). These keyword combinations were arranged using Boolean operators to produce search strings that conform to the format of each database. Article selection was based on established inclusion and exclusion criteria. These criteria ensured that only relevant articles meeting quality standards were included, as shown in Table I.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Category	Inclusion	Exclusion
Type of publication	Journal articles, conference proceedings	Review papers, editorials, book chapters, theses
Language	English	Other than English
Publication period	2015–2025	Before 2015
Relevance	Discusses sentiment analysis in coastal tourism	Studies outside the context of coastal tourism

Each article that passes the initial screening is further evaluated using a QA tool to determine its suitability for inclusion. The QA process involves the following questions:

- Does the article explicitly and relevantly address coastal, marine, beach, island, or maritime tourism?
- Does it clearly identify the data source (e.g., online review platform, social media, or text survey)?
- Does it describe the dataset's characteristics (e.g., data volume, collection period, and language)?
- Does it specify the sentiment analysis method or algorithm used?

- Does it outline the analytical process, including preprocessing, modeling, and evaluation steps?

Each question is scored as Yes = 1, Partial = 0.5, or No = 0. Articles receiving a total score below 3 are excluded from the final synthesis.

C. Reporting the Review

The final stage involves reporting the results using the PRISMA framework, covering identification, screening, eligibility, and inclusion. The selected articles were analyzed to map the publication trends, geographic distribution, data sources, and analytical methods. A synthesis of key findings highlights the sentiment patterns toward coastal destinations and identifies research gaps, offering both theoretical insights and practical implications for sustainable coastal tourism management.

IV. RESULTS

A. General Description of Selected Studies

The literature search, conducted in four major databases (Scopus, ScienceDirect, IEEE Xplore, and ACM Digital Library) using a predefined Boolean search string, initially yielded 190 records. After removing duplicates and redundant articles, the remaining articles were 175. These articles were further selected based on inclusion and exclusion criteria and evaluated using a QA tool. The results of the selection stage indicated that only 36 articles met the requirements for further analysis in this study. The 36 eligible articles used in this study are summarized in Table II.

B. Publication Trends per Year

The articles selected for this study were published between 2015 and 2025. As shown in Figure 1, the publication trend on coastal tourism sentiment analysis demonstrates a steady increase, particularly after 2018. In the early period (2015–2019), only one to two studies were published annually, but the number grew significantly from 2020 onward, with notable peaks in 2021 (seven articles) and 2024 (nine articles). This upward trend reflects the growing academic interest in sentiment analysis within coastal tourism, in line with advances in ML and DL techniques used to process online review data. Although only three articles were identified for 2025, this number is expected to rise as new publications continue to emerge.

C. Geographic Distribution of Research

The studies included in this review encompass diverse geographic contexts, highlighting the global attention given to coastal tourism issues. Rather than being concentrated in a single region, the research spans across Asia, Europe, the Americas, and Oceania. Figure 2 illustrates the geographical distribution of the reviewed studies, with darker shades indicating regions of higher research activity.

TABLE II. GENERAL DESCRIPTION OF THE ELIGIBLE ARTICLES

Article year	Location	Data Source / platform
[25] 2015	Malaysia	Agoda and TripAdvisor
[26] 2017	Indonesia	TripAdvisor
[27] 2018	Australia	Weibo
[28] 2018	Tenerife	Reviews Website
[29] 2019	Indonesia	TripAdvisor
[30] 2019	Pacific Islands	Ctrip
[31] 2020	Indonesia	Twitter
[32] 2020	Italy	Online News
[33] 2021	China	Ctrip.com
[34] 2021	China	Ctrip
[35] 2021	Indonesia	TripAdvisor
[36] 2021	Indonesia	TripAdvisor
[37] 2021	Indonesia	TripAdvisor
[38] 2021	China	Ctrip
[39] 2021	Cape Verde	TripAdvisor
[40] 2022	China	Ctrip
[41] 2022	Indonesia	Google Maps
[42] 2022	Portugal	TripAdvisor
[43] 2022	Italy	Instagram
[44] 2022	Australia	Flickr
[45] 2023	Indonesia	TripAdvisor
[46] 2023	Indonesia	TripAdvisor
[47] 2023	European islands	TripAdvisor
[48] 2023	Indonesia	Google Maps
[49] 2024	Brazil	Booking.com and TripAdvisor
[50] 2024	Global	TripAdvisor
[51] 2024	Baikal region	Reviews Website
[52] 2024	Indonesia	TripAdvisor
[53] 2024	Malaysia	YouTube
[54] 2024	Indonesia	Google Maps
[55] 2024	Indonesia	Google Maps
[56] 2024	Malaysia	TikTok
[57] 2024	Global	Articles
[58] 2025	Indonesia	Google Maps
[59] 2025	South Korea	Naver and Manual Survey
[60] 2025	Turkey	TripAdvisor

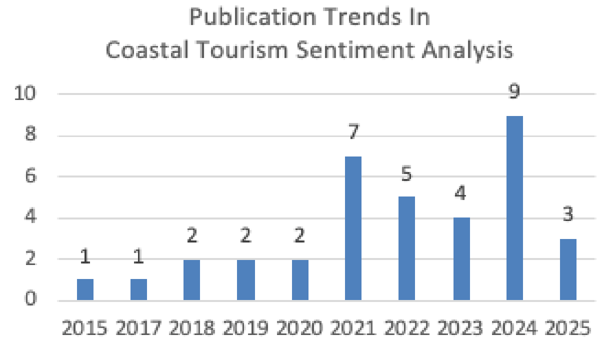

Fig. 1. Publication trends in coastal tourism sentiment analysis.

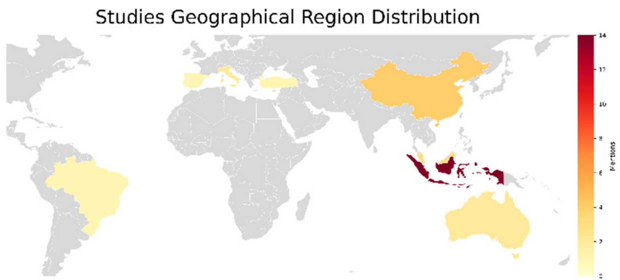

Fig. 2. Geographic distribution of studies on coastal tourism sentiment analysis.

As portrayed in Figure 2, Asia dominates the research landscape, particularly Southeast Asia, with notable contributions from Indonesia (Bali, Madura, Komodo, Karimunjawa, Lombok, Raja Ampat, and Kuta Beach) and Malaysia (Langkawi, Perhentian, Tioman, and other beach resorts). Additional studies are found in China (Qiandao Lake, Ctrip-based reviews) and South Korea (Naver-based analyses). Europe follows with diverse coverage, including Spain (Catalonia, Tenerife), Portugal (Madeira), Italy, Poland, Denmark, and Sweden (the Baltic Islands). Oceania is represented primarily by case studies in Australia and the Pacific Islands, while the Americas (Brazil and the United States) and Africa (Cape Verde) show comparatively limited representation. This distribution indicates that Southeast Asia remains the most extensively studied region, likely due to its high concentration of coastal destinations, economic dependence on tourism, and the availability of online review data in both English and local languages.

D. Platform or Data Source

Most of the research in this study used online reviews as the primary source of data, underscoring the crucial role of e-WOM in understanding tourists' perceptions of coastal destinations. Based on the 36 reviewed studies, the data sources were grouped into six main categories, as presented in Figure 3.

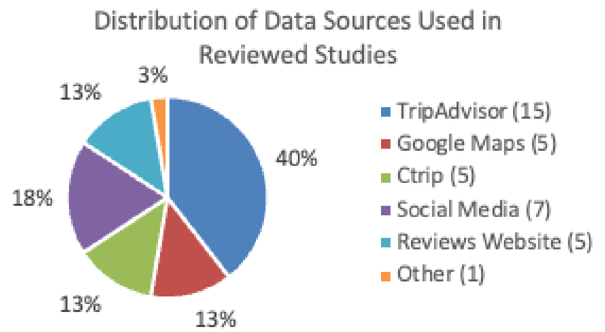

Fig. 3. Distribution of data sources used in the reviewed studies on coastal tourism sentiment analysis.

TripAdvisor is the most frequently used platform, cited in 15 studies, reflecting its global popularity and broad coverage of coastal destinations. Google Maps and Ctrip each appear in five studies, mainly supporting location-based and regional analyses, particularly in China and East Asia. Social media platforms, like Instagram, Naver, TikTok, Twitter, Weibo, YouTube, and Flickr, feature in seven studies, providing richer UGC beyond formal review structures. Review websites, such as Agoda.com, Booking.com, and other travel forums, were used in five studies, while one study relied on non-review sources, such as surveys or mixed datasets. As shown in Figure 3, global review platforms (TripAdvisor and Google Maps) dominate the dataset, followed by regional and social media sources that offer more nuanced insights into traveler experiences.

E. Sentiment Analysis Methods or Algorithms

The sentiment analysis methods employed in the reviewed studies reflect a diverse range of approaches, consistent with ongoing advancements in NLP technology. Table III presents the distribution of articles across different categories of sentiment analysis methods, along with a comparative overview of the techniques used in each category. Table IV provides a further summary of these methods, including their reported accuracy and corresponding dataset characteristics.

TABLE III. DISTRIBUTION OF ARTICLES BASED ON THE SENTIMENT ANALYSIS METHODOLOGY

Category	Articles	Technique / models
DL	[28], [35], [36], [37]	Recurrent Neural Networks (RNN), LSTM, CNN
ML	[26], [34], [48], [54], [55], [56], [58]	SVM, Naïve Bayes, kNN, Decision Tree, Random Forest, k-Means
Lexicon-based	[27], [30], [31], [38], [40], [42], [46], [47], [60]	VADER, TextBlob, ROST CM, SnowNLP, SenticNet, custom lexicon
Hybrid / LLM	[29], [39], [43], [45], [50], [51], [52], [53]	Saiga2 LLM, RoBERTa + LDA + Sentiment Classifier, *LeALSVM*
Other	[25], [32], [33], [41], [44], [49], [57], [59]	Kano Model, Tourist Gaze Theory, Latent Semantic Analysis, etc.

TABLE IV. SUMMARY OF REVIEWED METHODS, EVALUATION METRICS, AND DATASET CHARACTERISTICS

Category	Evaluation	Dataset characteristics
DL	Acc 81-90%; AUC ~0.71-0.87	~10K reviews, binary labels, imbalanced distribution.
ML	Acc 55-98.4%	hundreds to ~2K reviews, three labels (positive, negative, neutral)
Lexicon-based	n/a (studies are descriptive rather than classification-focused)	5K–11K reviews, polarity based on lexicon,
Hybrid / LLM	Acc 73%-92,7%	1K-38K reviews, binary labels, some using use aspect/issue

The identified sentiment analysis methods can be categorized into four main groups. Lexicon-based approaches rely on predefined sentiment dictionaries or rule-based tools, such as VADER, TextBlob, SnowNLP, and ROST Content Mining. These methods are commonly employed in multilingual studies or when computational resources are limited. Classical ML algorithms, including SVM, Naïve Bayes, kNN, Decision Tree, and Random Forest, typically utilize TF-IDF or n-gram features and perform effectively on medium-sized datasets due to their simplicity and interpretability. DL models, such as RNN, LSTM, and CNN, have gained prominence since 2020 for supervised sentiment classification on larger datasets, as they can automatically extract and learn textual features. Finally, hybrid and emerging approaches integrate multiple techniques, for example, combining TF-IDF with LDA and SVM or applying oversampling with kNN, and increasingly incorporating LLMs, like GPT, to enable context-aware and semantically rich sentiment interpretation.

F. Data Labeling Scheme

A review of the 36 studies reveals that most still employ simple labeling schemes, primarily using binary classification (positive versus negative). Others adopt three-class models (positive, negative, neutral) to capture more nuanced opinions. Beyond these approaches, several studies expand the labeling framework through emotion- or satisfaction-based schemes to achieve richer interpretations of tourist sentiment. Emotion-based methods categorize traveler reviews into psychological expressions, such as joy, sadness, anger, fear, disgust, pride, and interest, enabling deeper insights into tourists' emotional experiences. Satisfaction-based approaches, in contrast, classify reviews according to factors, such as service quality, value for money, overall experience, and the natural environment. Some also apply established frameworks, such as the Tourism Experience Model or hotel attribute categories (e.g., accessibility, food and beverage, and room amenities). A smaller subset of studies employs topic-based classifications, focusing on themes, such as destination image (natural resources, culture, infrastructure), tourist segmentation (families, couples, business travelers), or post-disaster recovery.

TABLE V. LABELING SCHEME USED IN THE STUDY

Labeling scheme	Articles
Binary	[28], [30], [34], [35], [36], [37], [46], [48], [50], [52], [53], [54], [55], [56]
Three class	[25], [38], [40], [57], [60]
Emotion categories	[29], [32], [33], [44]
Satisfaction dimension	[26], [42], [45], [51], [58], [59]
Other	[27], [31], [39], [41], [43], [47], [49]

These results indicate that binary labeling remains the most common approach, but research is increasingly shifting toward more detailed, multidimensional schemes to better capture the complexity of tourist experiences.

G. Key Insights from the Study

The synthesis of 36 reviewed studies reveals several consistent patterns in tourist sentiment and research practices.

- Dominance of positive sentiment. Most reviews express positive perceptions, highlighting natural beauty, distinctive seascapes, and relaxing recreational experiences. These findings reaffirm natural attractions as the main strength of coastal tourism.
- Recurring complaints. Negative themes commonly involve cleanliness, pricing, overtourism, safety, and service quality, which remain key drivers of dissatisfaction.
- Geographic variation is evident in tourist priorities: European studies often stress authenticity and sustainability, whereas research in Southeast Asia tends to focus on service quality, facilities, and value for money. Studies of tropical islands, like Bali, Langkawi, and the Maldives, emphasize the appeal of beaches and natural scenery as key factors.
- Methodological shift: Earlier studies relied on lexicon-based approaches, but recent work increasingly applies ML and DL models (SVM, NB, RF, CNN, LSTM), along with emerging hybrid and LLM-based techniques for higher accuracy.
- Richer labeling schemes: Recent studies go beyond simple positive/negative sentiment to incorporate emotion categories (e.g., joy, anger, fear) and dimensions of satisfaction (e.g., service, experience, value for money), providing a greater understanding of tourist experiences.

Overall, the SLR results confirm that sentiment analysis is an effective tool for understanding the tourist perceptions of coastal tourism. Key findings indicate that tourists generally report positive experiences. But critical aspects, like service, cleanliness, price, and sustainability, require attention to ensure the competitiveness and long-term sustainability of coastal destinations.

V. DISCUSSION

This section presents the main findings from the SLR, situating them within the broader research context. It highlights both academic and practical implications and identifies remaining research gaps for future investigation.

A. Synthesis of Main Findings

The SLR results show that coastal tourism is consistently perceived positively by tourists, particularly in terms of natural attractions, beach beauty, and recreational experiences. However, complaints also arise regarding cleanliness, price, service quality, and sustainability, which are recurring issues across various geographic contexts. Methodologically, there is a shift from simple lexicon approaches to the use of ML (SVM, NB, RF, kNN), DL (CNN, LSTM), and even hybrid approaches and LLM. These developments highlight the growing complexity of analyzing online reviews to achieve a more accurate understanding of sentiment.

B. Academic Implications

From an academic perspective, these findings underscore the importance of sentiment analysis as an interdisciplinary approach that combines tourism, computer science, and social sciences. The adoption of advanced methods such as DL and LLM opens opportunities to gain a deeper understanding of tourist perceptions. Furthermore, the diversity of labeling schemes (binary, three-class, emotion categories, and satisfaction dimensions) demonstrates the potential for developing a richer analytical framework in coastal tourism studies. This progression opens opportunities for future research to refine and expand these methodologies.

C. Analytical Comparison and Interpretation

A deeper examination of the reviewed studies reveals clear methodological and contextual patterns. Since 2020, DL models, such as CNN and LSTM, have become dominant due to their ability to capture the semantic and contextual relations in unstructured text, outperforming traditional ML models, like SVM, Naïve Bayes, and kNN, which rely on manual feature extraction. Lexicon-based approaches, meanwhile, remain limited for multilingual or domain-specific data because fixed sentiment dictionaries often fail to recognize idioms, irony, or cultural nuances. More recent studies have explored LLMs, such as GPT-4 and LLaMA, which provide deeper contextual understanding through transformer-based architectures capable of interpreting subtle expressions in long reviews. Despite their promise, LLMs face challenges related to data bias, contextual misinterpretation of slang or idioms, high computational cost, and limited explainability [61-66]. These issues highlight the need for cautious adoption and further methodological refinement. Geographically, research remains concentrated in Southeast Asia and Europe, reflecting both the economic reliance on coastal tourism and the accessibility of online review data in major languages. Underrepresented regions, including Africa and the Pacific, deserve greater focus, especially through cross-lingual and multimodal sentiment analysis that combines text, images, and video to more accurately capture tourist perceptions.

D. Practical Implications

The results suggest that destination managers and policymakers can leverage sentiment analysis as a strategic tool to enhance service quality and strengthen destination competitiveness. Real-time monitoring of online reviews enables rapid identification of service weaknesses, such as cleanliness and security, while simultaneously informing promotional strategies that emphasize core strengths, including natural attractions and local culture. Insights from sentiment patterns can inform the development of coastal tourism sustainability initiatives that explicitly address environmental concerns. Integrating these analytics into routine decision-making is likely to improve customer satisfaction and the overall tourist experience, supporting the long-term viability of coastal destinations.

E. Research Gaps and Further Research

Several research gaps remain in the field of sentiment analysis for coastal tourism. Geographically, existing studies are concentrated in Southeast Asia and Europe, while regions such as the Pacific Islands and Africa remain underrepresented. Expanding coverage to these areas would provide a more balanced understanding of global coastal tourism sentiment patterns. Language and modality also present important limitations. Most studies rely on English-language text reviews, which restricts cultural representativeness. Future research should incorporate multilingual and multimodal data, combining text, images, and videos from platforms, such as Instagram or TikTok, to capture a richer and more diverse range of tourist experiences. Methodologically, the adoption of LLMs is still emerging. Although these models show strong potential for contextual and cross-lingual sentiment interpretation, their effectiveness, bias, and explainability require further evaluation in tourism contexts. Finally, the practical applications of sentiment analysis remain limited. Few studies have assessed how analytical insights are implemented in real-world destination management. Future work should focus on testing sentiment-driven recommendations to improve service quality, marketing strategies, and sustainability outcomes in coastal tourism.

VI. CONCLUSIONS

This study systematically reviewed 36 publications on sentiment analysis in coastal tourism published between 2015 and 2025. The findings reveal a steady increase in related research, particularly over the past five years, reflecting the growing adoption of Machine Learning (ML) and Deep Learning techniques. The studies cover diverse geographic regions, with Southeast Asia and Europe emerging as the most represented areas. Most research draws on online reviews from platforms, such as TripAdvisor, Google Maps, Ctrip, and YouTube, underscoring the importance of electronic Word-of-Mouth (e-WOM) in understanding tourist perceptions. Methodologically, analytical approaches have progressed from lexicon-based and classical ML models to DL and hybrid methods, indicating a maturation of sentiment analysis techniques. Overall, tourist sentiment toward coastal destinations is generally positive, highlighting natural beauty and recreational appeal. However, recurring concerns include cleanliness, pricing, service quality, and sustainability. These findings underscore the value of sentiment analysis as a tool for improving service quality and promoting sustainable development in coastal tourism.

VII. FUTURE WORK

Future research should broaden geographical coverage, integrate multilingual and multimodal data, and further explore the use of LLMs, such as GPT-4 and LLaMA, to enhance contextual and emotional understanding. Evaluating the practical application of sentiment-based insights in destination management is also essential to measure their real-world impact on tourist satisfaction and sustainability. In summary, this review advances the understanding of sentiment analysis in coastal tourism and provides practical guidance for policymakers and destination managers to strengthen sustainable tourism management through data-driven insights.

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