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Aspect-Based Sentiment Analysis for Hospitality Industry Applications: A Systematic Literature Review

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***Abstract* – One of the most important methods in Natural Language Processing (NLP), especially in the hospitality sector, is Aspect-Based Sentiment Analysis (ABSA). The fine-grained analysis of user-generated information that the method allows enables organizations to comprehend attitudes related to particular characteristics, such as amenities, cleanliness, and service quality. This study presents a holistic literature analysis of ABSA methodology, datasets, and applications in the hospitality industry with 57 research papers published within the last seven years. Some significant developments are the use of pre-trained transformer models, multimodal analysis that combines textual and visual data, and creative aspect extraction methods. However, the problems still exist, such as multilingual data deficiency, implicit aspect detection, and huge language model computation cost. The paper gives an extensive review of ABSA in enhancing customer happiness through actionable insights derived from sentiment analysis, underlining existing trends and gaps.**

***Keywords* – Aspect-based sentiment analysis, deep learning, large language models, natural language processing.**

I. Introduction

The hospitality industry has increasingly been using Natural Language Processing (NLP) to enhance customer experiences. In a 2021 poll, 24 % of hoteliers globally responded that the main reason for technology implementation was to improve the visitor experience [1].

NLP enables machines to comprehend and interpret human language; hence, it helps facilitate effective and more personalized communication with clients. This covers programs that enhance customer service and interaction, like chatbots, virtual assistants, and sentiment analysis tools.

The NLP market is rapidly growing all over the world. By the end of the period, the market size is projected to reach in excess of $156.80 billion, from a projected valuation of about $36.42 billion in 2024, advancing at a Compound Annual Growth Rate (CAGR) of 27.55 % from 2024 to 2030.

While the NLP market in the US is expected to reach $9.71 billion in 2024 and $41.79 billion by 2030, recording a CAGR of 27.54 % during the same period, these projections signal increased significance of NLP technologies in improving customer experience, especially as companies increasingly use AI-driven solutions to meet customer expectations and improve service quality [2].

With user-generated content growing fast, especially on review sites like TripAdvisor, Google, and Booking, companies are paying more attention to fine-grained customer feedback analysis. In this context, Aspect-Based Sentiment Analysis (ABSA) has emerged as an important tool that makes extracting opinions regarding a particular feature of a good or service possible. By linking opinions to specific attributes, such as the cleanliness of hotel rooms or the level of service, ABSA provides a deeper understanding of client feedback beyond simple sentiment classification [3]. Other than typical sentiment analysis, which would consider the overall polarity of the text, ABSA enables insights tailored to allow organizations to improve particular aspects of the customer experience [4].

Recent works have focused on the benefits of ABSA in the hospitality domain, where reviews about guests are often filled with conflicting opinions on various aspects of amenities, location, and customer service. ABSA will enable a hotel to understand and manage its guest preferences and concerns much better by identifying and classifying the attitudes related to these elements. This improves customer happiness and loyalty [5]. Since hotel reviews are intricate and can portray several aspects in one review, the ABSA is an essential approach when it comes to sentiment analysis of this industry [6].

From the simplest machine learning model to very complex deep learning architecture, there has been a significant variation in the methodologies for ABSA. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and attention mechanisms are advanced methods of extracting contextual linkages in text when many aspects have to be processed. Special attention has been given to transformer-based models such as BERT since these models contribute significantly representation that advances performance in an ABSA task [7]. In addition, for the increased accuracy of sentiment analysis, methods like Latent Dirichlet Allocation

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(LDA) and semantic similarity metrics have been used in the improvement of aspect identification and classification of sentiment in hotel reviews [8].

Recently, ABSA has evolved to include both textual and visual information are combined for a proper capture of attitudes. This happens especially in the hospitality industry where customers review along with photos of the hotel amenities or food served at the restaurant. Therefore, sentiment analysis across diverse information sources implies that multimodal ABSA-meditated consideration of both texts and images can gain more profound insight into the thinking of the clients. This is a promising research avenue to increase the accuracy of sentiment analysis in visually impacted environments, such as hospitality and travel [9].

Since ABSA allows for recommendations considering complex consumer preferences, ABSA has also helped in the development of personalized recommendation systems in the hospitality and tourism industries. This may increase user happiness by recommending with greater individualization by studying attitudes along several dimensions. For example, recent studies in restaurant recommendations have shown that, when targeting specific aspects such as ambiance, food quality, and service efficiency, ABSA-based models may provide significantly enhanced relevance for suggestion improvement [10].

However, ABSA has yet to be appropriately implemented. The main challenge remains the extensive use of annotated datasets, which is a limitation for some languages and contexts. This limitation has been the motivating factor for the hybrid approaches that combine machine learning with lexicon-based techniques to surmount such data limitations and improve model generalizability. Besides, negative, implicit attitudes and complicated linguistic structures add extra challenges to handle, which require sophisticated pre-processing and feature extraction methods [11]. Recently, some research has also been proposed for graph-based models to solve the challenge of sentence dependency. One of them is the Attention-based Graph Convolutional Network, which refines sentiment predictions by separating aspect-specific words apart and eliminating noise from superfluous dependencies [5]. Specialised data set creation is an important part of ABSA research in the hospitality industry. For instance, the HRAST dataset comprises labelled data on various aspects such as staff behaviour, cleanliness, and value for money, created to enable aspect-based analysis in hotel reviews. These datasets make focused sentiment analysis easier to carry out, helping models perform well in applications particular to a given area [9].

In all aspects, ABSA has made reasonable progress toward effective sentiment analysis in hotel reviews; however, further refinement is still necessary to overcome limitations at this point. With the focus being on technique, findings, and pending issues as part of comprehensive understanding that showcases the contribution of ABSA in enhancing the experience of customers, the following systematic review examines the status of ABSA in the hospitality industry. The main findings and contributions of this study are as follows:

- it uses a systematic literature review methodology to offer a structured review of previous works addressing ABSA in the hospitality industry;
- it targets at revealing current trends, methods, data sets, and challenges in the domain, as well as highlighting the added value of the use of ABSA in improving customer experience;
- it filters, reviews, and analyses the 57 selected works to answer the research questions of interest;
- the characteristics of the selected works are analysed in terms of the used data sets, methods, and performance measures;
- it organises the findings around eight research questions to offer a holistic view of the considered ABSA applications and related developments in the hospitality industry.

The rest of the study is organised as follows: The research methodology of the systematic review is explained in Section II. Section III contains the literature study. The answers and graphs of the questions we created using the research methodology are given in Section IV. Section V expresses the results of the systematic review.

II. Research Methodology

This section outlines the research methodology. The study adopted a methodology similar to the approach suggested by [12], [13]. The systematic review process, illustrated in Figure 1, was organized to minimize bias risks. Initially, research questions were formulated, and relevant papers were retrieved from scientific databases. After data extraction and synthesis, a final subgroup of studies, comprising 57 papers, was chosen to address the research questions. All 57 papers were thoroughly reviewed, and the research questions were answered. Table I presents the research questions for this study.

These papers were retrieved from the following databases: IEEE Xplore, ScienceDirect, ACM Digital Library, Wiley Online Library, SpringerLink, and Google Scholar. To find recent studies, the search was restricted to the last seven years. The exclusion criteria of this review are given in Table II. The query used to perform the search was ((“machine learning” OR “artificial intelligence”) AND “aspect-based sentiment analysis” AND (“hotel review” OR “survey”)). Figure 2 shows the number of articles identified from different academic databases – namely Google Scholar, Springer Link, IEEE Xplore, Science Direct, Wiley Online Library, and ACM Digital Library – used in the various steps of the review process, including the initial query, application of exclusion criteria [13], [14].

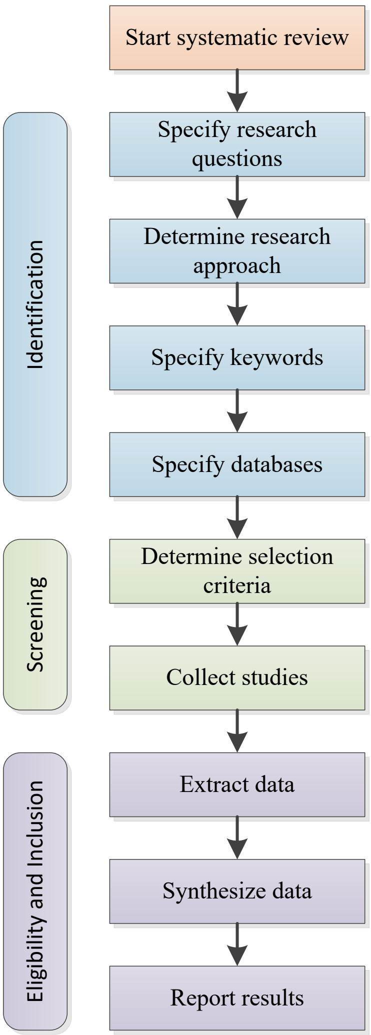

Fig. 1. Systematic literature review process.

TABLE I

RESEARCH QUESTIONS (RQS) IN THIS RESEARCH

Question Number	Question Description
RQ1	Which data sets are used in aspect-based sentiment analysis studies?
RQ2	In which industries has aspect-based sentiment analysis been applied?
RQ3	What machine learning algorithms are used in aspect-based sentiment analysis studies?
RQ4	What methods are used to reveal different aspects in aspect-based sentiment analysis studies?
RQ5	Which major language models are used in aspect-based sentiment analysis studies?
RQ6	Which evaluation metrics are used in aspect-based sentiment analysis?
RQ7	Which languages have been the focus of aspect-based sentiment analysis studies?
RQ8	What are the challenges and research gaps in aspect-based sentiment analysis?

TABLE II

EXCLUSION CRITERIA

ID	Exclusion Criteria
1	Only an abstract is included in the paper (we included both open-access and subscription-based publications, so this criterion is not about the paper's accessibility).
2	English is not used in the writing of the paper.
3	It is not a primary research paper.
4	There are no experimental results in the paper.
5	The application of machine learning is not thoroughly explained in the paper.

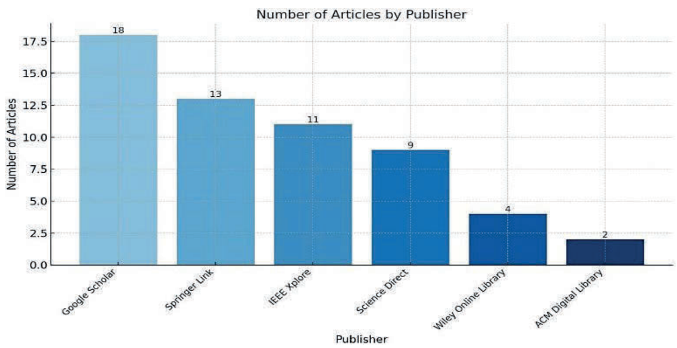

Fig. 2. Distribution of the selected papers.

Figure 3 displays the yearly distribution of selected publications, revealing an upward trend in the past five years, which suggests that the field remains highly engaged.

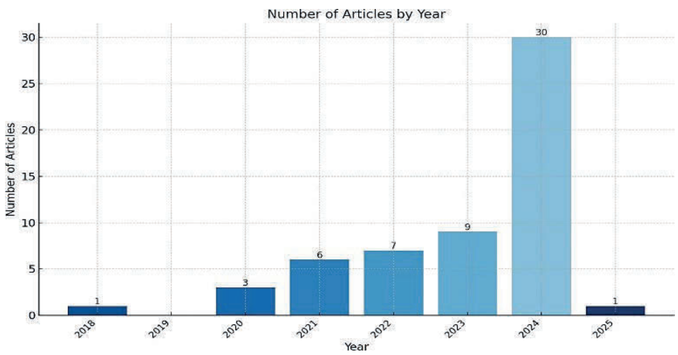

Fig. 3. Selected publications per year.

As seen in Fig. 4, the distribution of articles by type provides valuable insights into the research focus and dissemination methods in the field of Aspect-Based Sentiment Analysis (ABSA):

Journal Articles (39): The dominance of journal articles, as seen in Fig. 4, suggests that the ABSA domain has reached a level of maturity where researchers prioritize comprehensive and peer-reviewed studies. These publications often feature rigorous evaluations and detailed methodologies, reflecting the theoretical advancements in the field.

Conference Papers (13): The substantial number of conference papers indicates that ABSA remains a dynamic and evolving research area. Conferences, as highlighted in Fig. 4, serve as crucial venues for presenting cutting-edge techniques, novel models, and practical applications, fostering innovation and collaboration.

Preprints and Theses (5): The presence of preprints shows the importance of rapid dissemination in ABSA research, enabling early feedback from the community. Theses represent foundational academic contributions that often pave the way for further exploration.

Figure 4 effectively demonstrates the balance between detailed journal publications and the timely presentation of new ideas through conferences and preprints, underscoring the vibrant research ecosystem within ABSA.

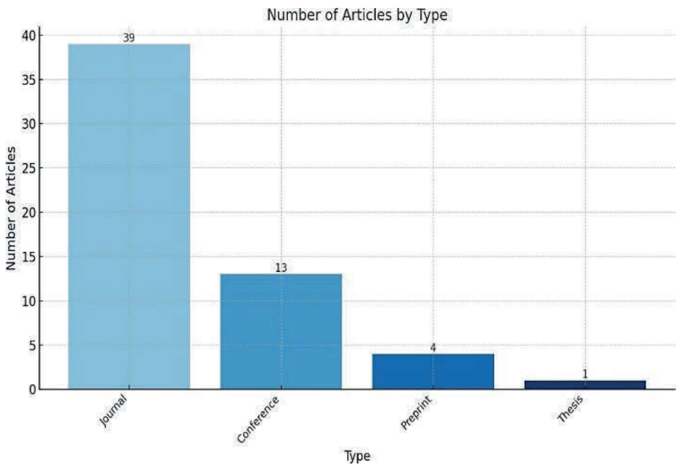

Fig. 4. Distribution of type of publications.

III. Literature Review

The evolution of ABSA, present difficulties, and data sets utilised with roughly 57 publications, together with their methodologies and outcomes, are discussed in this title.

A. Evolution of ABSA Techniques

Through the use of supervised algorithms and annotated datasets, machine learning models brought a more dynamic approach to ABSA. Naive Bayes, Random Forests, and Support Vector Machines (SVMs) were popular methods. Although these models improved sentiment categorization, they were not scalable or adaptable to large, heterogeneous datasets due to the need for considerable human feature engineering [15].

ABSA was transformed by the introduction of deep learning technology. Sequential data patterns were collected by RNNs and their variations, such as Long Short-Term Memory (LSTM) networks, which enhanced comprehension of intricate textual linkages. CNNs also performed exceptionally well in extracting local features, particularly in analysis at the sentence level. The merits of both approaches were integrated in hybrid architectures such as CNN-GRU models to improve performance on a variety of ABSA tasks [16].

B. Transformer-Based Approaches

First transformer models, such as BERT and GPT, were developed with general pre-training and task-specific fine-tuning. These methods involve substantial resources by creating large labelled datasets. They cannot often be adapted to specific-domain tasks. Subsequent ideas introduced multitask learning combined with task descriptions, represented by T5, laying the bedrock for an expanded adaptation of tasks in general [17].

InstructABSA brings all these developments together by incorporating a procedure called instruction tuning: a process of priming large language models with definitions of tasks in general and relevant examples (positive, negative, and neutral) to assist the model in generalizing across diverse ABSA subtasks. It thus brought a transition of transformers from static fine- tuning to dynamic and instruction-driven learning that enabled models like Tk-Instruct to perform state-of-the-art tasks like ATE and ATSC. It significantly outperforms all benchmark datasets and performs much better than traditional fine-tuning methods; it even outperforms larger models, such as GPT-2, considering efficiency and accuracy [17].

Including instruction tuning, InstructABSA is a further advance on the previous transformer-based approaches, which have a growing interest in adaptability, efficiency, and generalization. This new paradigm underlines the development of transformers from basic task adaptation to active context-sensitive learning frameworks, setting up a new standard for fine-grained sentiment analysis and offering a solid template for further advancement in natural language understanding [17].

It has thrown light on how models like BERT, DeBERTa, and RoBERTa have wrought a revolution in ABSA by exploiting self-attention mechanisms and pre-trained contextual embeddings that capture subtle linguistic patterns. Among these, DeBERTa, with disentangled attention and enhanced position embeddings, is at the forefront of performance in domain-specific ABSA tasks [18].

The proposed hybrid model, Instruct-DeBERTa, combines the powers of two state-of-the-art transformer-based models: InstructABSA for aspect term extraction and DeBERTa-V3-base-absa-V1 for sentiment polarity classification. This pipelined approach lets it handle aspect extraction and sentiment classification uniformly with improved performance on benchmark datasets like SemEval Res-14 and Lap-14 [18].

A major novelty of this research is using instruction-tuning, the new fine-tuning paradigm that adapts transformer models to specific tasks by including natural language prompts and examples; this allows for better adaptability, generalization, and efficiency of the model, especially under multi-task scenarios, with the benchmark for future research on ABSA. This hybrid framework overcomes challenges in the combination of aspect extraction and sentiment classification effectively. It proves the power of task-oriented tuning and modular design for transformer-based models [18].

Eventually, it really means that this is what Instruct-DeBERTa stands for: a move of transformer-based approaches from generalized natural language understanding to a more specialised and fine-grained application such as ABSA. The novelty in architecture and strong performance underpin the potential of embedding the state-of-the-art models in developing scalable and efficient solutions with very high accuracy, opening up new perspectives and ways for further sentiment analysis and NLP improvement [18].

C. Integration of Large Language Models

Owing much to LLMs like GPT-4 and LLaMA, state-of-the-art ABSA research has developed capabilities across multiple lingual few-shot or even zero-shot settings with specific improvements observed in few-resourced settings. Enriched datasets through data augmentation by the ChatGPT-like data augmentation method have provided gains in increased precision and generalization performance [19].

A big invention shown in this paper is In-Context Learning (ICL). It means LLMs can do MABSA tasks without needing fully new training. Instead, specific examples for tasks guide the predictions showing how flexible LLMs are when adapting to complicated situations. But some limits are revealed in what is found: LLMs have trouble with the detailed demands of MABSA. They find it hard to identify more than one aspect-sentiment pair within one single instance. Also, the computational cost is higher when compared to regular supervised learning methods. Despite these challenges still existing, the potential is shown in LLMs for doing multimodal sentiment analysis. They help join textual and visual data together. The paper talks about how it would be good to have task-specific instruction tuning, better ways to sample data and make the computation more efficient for fully using LLMs in ABSA. Altogether, this work puts LLMs in an important place in ABSA method development, offering some new chances for handling the complexities of multimodal sentiment. However, they mention main areas for future study [20].

Although this survey has surveyed applications and challenges of sentiment analysis in different domains, such as healthcare, finance, customer support, education, and e-commerce, the hospitality domain (including hotels, restaurants, and tourism) has received indirect attention at best. However, the hospitality domain is expected to pose unique challenges for LLMs, such as different linguistic challenges (e.g., informal and multilingual) and unique contextual challenges (rich feedback emotions and service-specific expressions such as cleanliness, behaviour of staff, or amenities), which may affect the behaviour of general-purpose LLMs. As a result, the sentiment analysis in hospitality may result in different behaviour than in other more structured domains, such as finance or healthcare. Future surveys should thus close this gap by considering hospitality-specific applications and analysing the behaviour of domain-adapted LLMs for the unique expressions used in the hospitality domain [21].

D. Multimodal ABSA

MACSA represents a significant development in the domain of Multimodal Aspect-Based Sentiment Analysis. It extends beyond the standard ABSA approach, which was solely concerned with text and involves both textual and visual modalities to deal with the implicit category challenge of a number of multimodal datasets. The study contributes by leveraging a novel model, MGAM, which efficiently captures fine-grained text-image interactions through heterogeneous graph structures and convolutional graph neural networks. A specially designed dataset, Hotel-MACSA for the task, enriches the field by providing, for the first time, multimodal aligned annotations for aspect-category sentiment analysis. Experimental results demonstrate that the MGAM model is a robust model, achieving the best accuracy and outperforming baseline models in every regard, hence proving that it has the potential for dealing with challenges in implicit aspect detection and sentiment analysis tasks over multimodal data [22].

The proposed ASFEN performs a manifold improvement in the area of multimodal ABSA by effectively addressing some fatal flaws in the existing methods. While many approaches fail in capturing the fine-grained visual sentiment information and suffer from misalignment issues between modalities due to inconsistent granularity, the ASFEN effectively integrates the aspect-aware semantic and sentiment cues of both text and images. The model develops a deep fusion of syntactic and semantic information with the help of graph convolution, dependency syntax trees, and multi-layer syntax masks while translating images into fine-grained textual emotional cues. Many experiments were performed on two multimodal Twitter datasets, which established the superiority of ASFEN over state-of-the-art methods, thereby making it a strong solution for sentiment polarity prediction in text-image pairs while establishing a good benchmark for further research in Multimodal ABSA [23].

E. Applications in Specific Domains

The ACOS_LLM model for ABSA in tourism can make the significant improvement in understanding tourists' evaluation to a specific attraction for driving innovation and development within such industries. Most of the pipeline models used to this day suffer from error propagation and incomplete extraction of sentiment elements, hence are not that effective in performance. In view of these problems, ACOS_LLM proposes an auxiliary knowledge generation and quadruple extraction-based two-stage approach for solving ACOSQE. The model heavily relies on Adalora in fine-tuning large language models that provide high-quality auxiliary knowledge, using SparseGPT in order to compress the fine-tuned model by 50 % with efficiency. Thus, this allows for an accurate auxiliary knowledge-based extraction, e.g., using positional information along with sequence modelling of text. Experiments show that the F1 score increases by 7.49 % on the self-built tourism dataset, and further improvements are reported on the datasets Rest15 and Rest16, hence confirming the model's superiority. ACOS_LLM reaches a new state of the art in tourism ABSA, thus providing an effective and robust approach to sentiment analysis that overcomes limitations of traditional models and has immediate applicability to inform strategies for the tourism industry [24]. The comparison and summary of existing ABSA studies is shown in Table III.

TABLE III

COMPARISON AND SUMMARY OF EXISTING ABSA STUDIES

Study	Year	Dataset	Methods	Performance
Agarwal et al. [25]	2018	Kaggle hotel reviews dataset	Word2Vec for clustering, Stanford Dependency Parser, sentiment classification using WordNet similarity	Improved accuracy over predefined aspect-based methods
Abro et al. [15]	2020	SemEval-2016 Task 5 dataset with restaurant reviews	N-gram with TF-IDF, Word2Vec, classifiers: SVM, Naïve Bayes, Logistic Regression, and Random Forest	Task A (71 %), Task B (69 %), Task C (81 %) using SVM with Word2Vec
Tran and Bui [26]	2020	Vietnamese hotel reviews	BERT-based hierarchical model for joint aspect extraction and sentiment analysis	Aspect-based F1-score: 81.26 %, Polarity-based F1-score: 82.45 %
Lanin and Smirnova [27]	2020	Booking.com reviews from UK	Corpus-based semantic analysis using UCREL Semantic Analysis System (USAS)	Identified significant gender-based semantic differences
Liu et al. [28]	2021	Nine real-world datasets from Amazon and Goodreads, containing multilingual reviews, Trip-MAML (TripAdvisor hotel reviews) and restaurant reviews (English and French)	MrRec model integrates multilingual aspect-based sentiment analysis and dual interactive attention for recommendations.	Outperformed state-of-the-art baselines in recommendation tasks across multiple datasets
Samy et al. [29]	2021	Angry Birds game reviews (Google Play Store)	LDA for aspect extraction, Apriori algorithm for classification	Improved accuracy by 5.68 % over Naive Bayes, 7.58 % over SVM
Lakmisagar and Sumathi [30]	2021	Indian hotel reviews dataset	Web crawling for data, feature extraction via TF-IDF, and SVM for classification	The highest accuracy was achieved using SVM compared to other models like Naive Bayes
Zhao et al. [16]	2021	Chinese online reviews (hotels and cars)	Combined CNN-GRU model for aspect extraction and sentiment classification, utilizing local features with CNN and long-term dependencies with GRU	The AUC scores for these tasks are 83.06 % and 83.17 % for the hotel dataset, 86.93 % and 77.42 % for the car dataset.
Azhar and Khodra [31]	2021	Indonesian hotel reviews	Multilingual BERT (m-BERT) fine-tuned for ABSA tasks, using sentence-pair classification. Improved F1-score through sequential transfer learning techniques.	Achieved 8 % improvement in F1-score over previous CNN-XGBoost models
Ray et al. [32]	2021	TripAdvisor hotel reviews	BERT-based sentiment classification, Random Forest for categorization, and fuzzy logic for aspect grouping. Achieved 84% Macro F1-score.	Achieved 84 % macro F1-score. Test accuracy: 92.36 %. Promising results with compact clusters for aspect grouping.
Andono et al. [8]	2022	Hotel review dataset with terms categorized using LDA and TF-ICF	LDA for aspect extraction, TF-ICF for term weighting, BERT embedding, cosine similarity	Aspect categorization: precision: 0.86, recall: 0.92, f1-measure: 0.89; ABSA: precision: 0.96, recall: 0.98, f1-measure: 0.97
Pratama et al. [33]	2022	TripAdvisor hotel reviews	LDA for topic modeling, semantic similarity, cosine similarity, SVM	SVM achieved an average performance of 0.94 across five aspects with enhanced LDA-based similarity.
Jayanto et al. [34]	2022	Traveloka hotel reviews, Indonesian language dataset	LSTM with Word2Vec, improved hidden layers, and neurons	F1-measure: 75.28%, improved model achieved 10.16% higher accuracy than baseline LSTM.
Priporas et al. [35]	2022	Airbnb reviews in Athens, Greece, focusing on negative aspects	Dependency parsing with rule-based approach, noun phrase extraction, lexicon-based sentiment classification	The article does not provide direct numerical performance metrics; rather, it shares the findings of textual analysis by providing a methodological framework.
Ozcan et al. [36]	2022	TripAdvisor hotel reviews	Aspect-based sentiment analysis combined with deep multi-criteria collaborative filtering, local/global attention mechanisms to enhance recommendation accuracy	Achieved an F1-score of 0.8328 and a MAE of 0.0984, outperforming traditional methods like SVD and KNN. It successfully integrates ABSA and multi-criteria ratings with attention mechanisms to enhance recommendation accuracy.
Ghosal and Jain [37]	2022	TripAdvisor, Booking.com, Datafiniti tourism datasets	Weighted aspect-based sentiment analysis using Majority Additive OWA (MAOWA), Selective MAOWA (SMAOWA), and Word2Vec embeddings	RMSE improvements: 14.68 %, 59.03 %, 12.97 %; Pearson correlation improvements: 30.63 %, 23.34 %, 32.61 %, respectively.
Kuppusamy and Selvaraj [38]	2022	Benchmark product reviews and hotel reviews datasets	Hybrid model combining CNN and Bi-LSTM to extract and classify sentiment aspects.	Accuracy: 93.6 % (product reviews), 92.7 % (hotel reviews). Outperformed state-of-the-art techniques.

Study	Year	Dataset	Methods	Performance
Harjo et al. [7]	2023	Hotel review dataset focusing on implicit aspects	Attention-based sentence extraction, rule-based algorithm, BERT embedding, semantic similarity	Aspect categorization accuracy: 91.31 %, ABSA accuracy: 98.10 %
Namee et al. [6]	2023	TripAdvisor hotel review dataset	Aspect clustering with BM25, sentiment classification with SVM and CNN	Sentiment classification AUC: 0.87, precision: 0.87, recall: 0.85, F1-measure: 0.86
Hidayati [39]	2023	Indonesian-language hotel reviews from IndoNLU dataset with 10,283 records	LDA with Word2Vec, Doc2Vec, and machine learning classifiers (LGBM, SVM, RF)	LDA with Word2Vec and LGBM: Average F1-Score 86.6 % across 10 aspects
Andreou et al. [40]	2023	HRAST dataset: 23,114 sentences from Booking.com reviews	Manual classification of sentences into 21 topics (hotel aspects) and sentiment polarities. Benchmarked aspect-based sentiment analysis and topic modelling methods.	Dataset established for benchmarking; no performance metrics provided as the dataset is intended for experimental use in ABSA and topic modelling.
Chhutlani et al. [41]	2023	OYO hotel reviews from Maharashtra, India	Aspect extraction using keyword-based categorization, sentiment classification with polarity scores (−1 to 1) for key aspects like room, food, staff.	Demonstrated effective sentiment categorization for hotel amenities, with user interface visualizations such as word clouds and score charts.
Priya and Deepalakshmi [42]	2023	Social network data and hotel reviews	Fine-tuned BERT for sentiment analysis, LSTM-RNN for comparative study.	The BERT model demonstrated superior performance compared to the LSTM-based RNN, highlighting its effectiveness in sentiment analysis tasks for unstructured hotel reviews. LSTM-based RNN: Test accuracy of 90.60 %. Tuned BERT model: Achieved a weighted F1-score of 94.45% and identified 97.22 % positive sentiments accurately.
Horsa and Tune [43]	2023	2800 movie Reviews from YouTube	Machine learning models (SVM, Random Forest, Logistic Regression) with BoW and TF-IDF feature extraction.	Accuracy: 88 % (SVM and RF with BoW and TF-IDF). Achieved optimal hyperparameter settings.
Simmering and Huoviala [44]	2023	SemEval-2014 (Restaurant, laptop datasets)	GPT-3.5, GPT-4 (fine-tuned and zero/few-shot settings). Compares cost-performance trade-offs, prompt engineering, and JSON schema standardization.	F1-score: GPT-3.5 fine-tuned (83.8), 5.7 % improvement over InstructABSA (SemEval-2014 Task 4).
Scaria et al. [17]	2023	SemEval-2014, SemEval-2015, SemEval-2016	Instruction-tuned Tk-Instruct model for six ABSA subtasks. Combines task-specific prompts with fine-tuning techniques for comprehensive ABSA.	F1-scores: Rest14 ATE (92.76), Rest15 ATSC (84.50), Lapt14 AOPE (79.34), achieving state-of-the-art results.
Solomenko and Charalabides [45]	2024	TripAdvisor reviews of Vietnamese hotels	Multinomial logistic regression, SGD classifier, Naive Bayes, vocabulary-based aspect identification	68 % accuracy, precision, recall, and F1-score.
Iswari et al. [46]	2024	Google Maps reviews of tourist attractions	Semantic similarity using SBERT and Cosine Similarity, Naïve Bayes, Decision Tree, Maximum Entropy	Without Semantic Similarity: The Naive Bayes model achieved the highest F1-Score of 0.96 for the “Scenery” aspect. With Semantic Similarity: The Decision Tree model demonstrated improved accuracy and F1-Score for “Scenery” (F1-Score: 0.94) and “Dusk” (F1-Score: 0.94) aspects. The methodology highlights the potential for enhancing sentiment classification through advanced semantic techniques.
Nawawi et al. [47]	2024	TripAdvisor reviews	Zero-shot learning with RoBERTa, KeyBERT, Sentence-BERT, VADER sentiment analysis	Not explicitly mentioned; the utility of Zero-Shot Learning and RoBERTa in extracting and analysing sentiment-related aspects effectively.
Jayakody et al. [18]	2024	SemEval datasets (Res-14, Lap-14, Res-15, Res-16)	Hybrid pipeline of InstructABSA for aspect extraction and DeBERTa-V3-base-absa-v1 for sentiment classification. Evaluated using various datasets for joint aspect extraction and sentiment polarity detection.	F1-Scores: Res-14: 88.63 %, Lap-14: 89.65 %, Res-15: 81.26 %, Res-16: 79.35%. Outperformed existing models for ABSA.
Jiang et al. [48]	2024	Dataset in English and Chinese	Scope detection model for filtering irrelevant information, biaffine-based span detection, aspect-based simplification model for sentiment classification clarity	Aspect term extraction: Achieved the highest macro F1-score across datasets, significantly outperforming baseline models like SPAN and BiSELF-CRF. Aspect-Based Sentiment Classification: Records the best accuracy on all datasets, demonstrating the effectiveness of scope detection and simplified clause integration.
Mughal et al. [49]	2024	SemEval-2016, MAMS, DOTSA, YASO, and	Evaluated ATAE- LSTM, DeBERTa-v3-base, FLAN-T5-large, PaLM, GPT-3.5-Turbo for	DeBERTa achieved 93.1% accuracy for DOTSA/hotel, while PaLM scored 93.5 % for

Study	Year	Dataset	Methods	Performance
		SentiHood datasets covering multiple domains like restaurants, hotels, laptops, books, and clothing	ATSA (Aspect Term Sentiment Analysis) and ACSA (Aspect Category Sentiment Analysis) tasks.	SemEval-2016. GPT-3.5 excelled in challenging datasets like MAMS, surpassing baseline models.
Yang et al. [50]	2024	Twitter-2015, Twitter-2017, MASAD	Multimodal network integrating textual and image data with attention-based GCN and image gating mechanisms for noise reduction.	Twitter-2015 Dataset: Accuracy: 78.69 %, F1-score: 75.50 %; Twitter-2017 Dataset: Accuracy: 72.29 %, F1-score: 70.21 %; MASAD Dataset: Accuracy (varied by aspect): Up to 98.94 %, F1-score (varied by aspect): Up to 98.89 %
Ahmad et al. [5]	2024	SemEval-2014 (Laptop, Restaurant), Twitter, MAMS	Combines parsimonious segmentationwith attention-based GCN to enhance syntactic and semantic feature extraction.	Restaurant Dataset: Accuracy: 83.47 %, F1-score: 76.18 %; Laptop Dataset: Accuracy: 78.96 %, F1-score: 76.09 %; Twitter Dataset: Accuracy: 76.66 %, F1-score: 75.23 %; MAMS Dataset: Accuracy: 83.23 %, F1-score: 82.36 %
Fu et al. [51]	2024	Restaurant, Laptop, and CLIPEval datasets	Combines supervised contrastive learning (SCL) with knowledge-enhanced fine-tuning (KEFT) on BERT for implicit sentiment and aspect detection.	Restaurant Dataset: Accuracy: 89.78 % F1-score: 84.04 %; Laptop Dataset: Accuracy: 83.70 %, F1-score: 80.41 %; CLIPEval Dataset: Accuracy: 87.12 %, F1-score: 86.54 %
Dey and Jenamani [52]	2024	Custom dataset from e-commerce reviews	Introduces UAN-OACIS framework for unsupervised extraction of Opinion-Aspect-Category-Irrealis-Sentiment quintuples using attention-based DNNs.	Comparable performance to supervised baselines; improved precision with irrealis marker inclusion.
Subbaiah and Bolla [53]	2024	Amazon product reviews	Employs weakly supervised learning (WSL) with hybrid BiLSTM-CNN models for aspect and sentiment identification using Snorkel framework.	F1 scores: 0.78 (aspect identification) and 0.79 (sentiment classification).
Yang et al. [10]	2024	Yelp restaurant reviews	Combines ABSA with matrix factorization (MF) for personalized restaurant recommendations using deep learning techniques.	Outperformed traditional models by 7–10 % in recommendation accuracy.
Yang et al. [54]	2024	Three Twitter datasets for MABSA tasks	Multi-task learning framework (CMMT) combining intra-modal tasks for text (TASE) and images (VAOP), and Text-Guided Cross-Modal Interaction Module (TGCMI).	Outperformed baseline JML by 3.1 %, 3.3 %, and 4.1 %. Absolute points across datasets.
Doan et al. [55]	2024	Hospitality reviews dataset from Booking.com and TripAdvisor	HOSSemEval-EB23 dataset, TAS-BERTMedium, T5 generative models for aspect-based sentiment classification and aspect extraction.	F1-score: 79.74% on TAS-BERTMedium; improved multi-aspect sentiment detection compared to existing datasets.
Cheng et al. [56]	2024	Google Maps reviews of BNBs	Multi-task framework using BERT, LDA, and Kano model to categorize aspects and sentiments.	Aspect Term Extraction (ATE): Precision: 0.7251, Recall: 0.4977, F1-Score: 0.5903 Aspect Category Detection (ACD): Macro F1-Score: 0.7438, Accuracy: 0.7491 Sentiment Classification (SC): Macro F1-Score: 0.7737, Accuracy: 0.8515
Yang et al. [22]	2024	Hotel-MACSA dataset: 42K image-text pairs	Multimodal Graph- based Aligned Network (MGAM), integrating text and image features via convolutional graph neural networks.	Accuracy: 86.06 % (normal test set), 75.25 % (hard test set). Improved multimodal sentiment alignment and analysis.
Wang et al. [57]	2024	SemEval 2014 datasets (Restaurant, Laptop)	Semiotic Signal Integration Network (SSIN): Combines syntax-aware isomorphic GCN and semantic-guided attention modules for sentiment classification.	Accuracy: Restaurant 85.07 %, Laptop 79.68%; Macro-F1: Restaurant 78.11 %, Laptop 77.04%. Outperformed SSEGCN by 1–2 %.

Study	Year	Dataset	Methods	Performance
Chen and Pan [58]	2024	SemEval-2016 (English) and Chinese datasets from Dianping and JD E-commerce platforms	Multi-XLNet-RCNN for cross-language sentiment analysis, with multi-channel XLNet encoding and multi-head attention.	Accuracy: 85.1 % (Dianping), 79.2 % (JD E-commerce). Significant improvement over previous models.
Kalaivaani et al. [59]	2024	Product reviews	Combines Hierarchical Attention Network (HAN) and CNN for aspect term extraction and sentiment classification.	Accuracy: 91.7 %, Recall: 90.6 %, F1-score: 91.2 %. Improved performance over individual HAN and CNN meth
Zhu and Ding [60]	2024	Laptop14, Restaurant14, Twitter, Restaurant15, Restaurant16 datasets	Dual Graph Convolutional Network (GCN) integrating syntax and semantic graphs with a residual network to enhance sentiment representation.	Accuracy: Laptop14 82.56 %, Restaurant14 87.75 %, Twitter 77.35 %, Restaurant15 86.01 %, Restaurant16 91.60 %.
Zeng et al. [61]	2024	Twitter-2015, Twitter-2017	Multimodal sentiment analysis combining graph convolution for syntactic-semantic augmentation and aspect-aware visual alignment.	Twitter-2015 Dataset: Accuracy: 81.50 %, F1-score: 78.99 %; Twitter-2017 Dataset: Accuracy: 75.69 %, F1-score: 75.38 %.
Jiang et al. [62]	2024	Restaurant14, Laptop14, Twitter	Combines Deep Bidirectional LSTM (DBiLSTM) with Dense Graph Convolutional Networks (DGCN) for nuanced contextual understanding and sentiment polarity detection.	Improved accuracy by 1.07 % and F1-score by 1.68% compared to baselines.
Aziz et al. [63]	2024	SemEval datasets (Restaurant, Laptop)	Uses BERT for contextual encoding and multi-layered graph convolution for integrating linguistic features, including syntax and semantics.	F1-score: Restaurant 85.7 %, Laptop 82.1 %.
Wadawadagi et al. [64]	2024	SemEval 2014 Task 4, Restaurant and Laptop Dataset	Combines Bi-LSTM-CRF for aspect term extraction and Bi-GRU-based polarity-aware attention network for sentiment classification.	Restaurant Dataset: Accuracy: 81.76 %, F1-score: 80.23 %; Laptop Dataset: Accuracy: 75.64 %, F1-score: 74.79 %.
Dubey et al. [65]	2024	SemEval datasets (Rest14, Lap14, Res15, Res16) for restaurant and laptop reviews	EKIG-GBERT model combining BERT with Dynamic Sentiment-Specific Knowledge Graph (DSSKG) and Gated Domain Graph Convolutional Network (GD-GCN). Uses KG-BERT and affective adjacency matrices for nuanced sentiment representation.	Rest14: 97.5 %, Lap14: 98.5 %, Res15: 94 %, Res16: 92 % accuracy. Superior aspect-level Sentiment detection confirmed through confusion matrix analysis.
Du et al. [66]	2024	Twitter-15 and Twitter-17 multimodal datasets	Few-shot learning framework transforming image modalities into textual captions using ResNet-based Caption Transformer. Finetunes Sentence-BERT with Supervised Contrastive Learning and Sentence-Level Multi-feature Fusion (SCL-SMF).	Twitter-15: Accuracy: 70.54 %, F1-score 68.38 % (256 samples); Twitter-17: Accuracy: 67.76 %, F1-score: 66.85 % (256 samples). Significant performance improvements in few-shot scenarios.
Xu et al. [24]	2024	Rest15, Rest16, Self-created tourism datasets	ACOS_LLM framework with Adalora fine-tuned LLMs, SparseGPT compression, positional modelling using BiLSTM and BiGRU.	F1-score: +7.49 % (tourism dataset), +1.06 % (Rest16), +0.0 5% (Rest15).
Huang et al. [67]	2024	Twitter-2015, Twitter-2017	MABSA-RL framework: Text decomposition via LLMs, multimodal aspect sentiment analysis using RoBERTa and Vision Transformer, optimized with reinforcement learning (REINFORCE).	F1 improvement: Twitter-2015 (+1.9 %), Twitter-2017 (+1.1 %); Precision gains: Twitter-2015 (+3.0 %), Twitter-2017 (+3.8 %). Reduced recall in imbalanced data.
Xu et al. [19]	2024	SemEval 2014 Laptop and Restaurant datasets	Proposed ChatGPT-based data augmentation strategies: Context-focused (CDA), Aspect-focused (ADA), and Context-Aspect-focused (CADA). Incorporated contrastive learning with BERT.	Laptop dataset: Accuracy: +1.41 %, Macro F1: +3.06 % (CADA); Restaurant dataset: Accuracy: +1.16 %, Macro F1: +1.42 %.
Song [68]	2024	Twitter-2015, Twitter-2017	Evaluated LLMs (Llama2, ChatGPT, LLaVA) on multimodal ABSA using text and visual inputs. Benchmarked against traditional supervised methods like RoBERTa and AoM.	F1-scores: Llama2 (Twitter-2015: 54.29, Twitter-2017: 58.19), ChatGPT (Twitter-2015: 51.40, Twitter-2017: 55.80).

Study	Year	Dataset	Methods	Performance
Alturayeif and Ahmad [69]	2025	SemEval Restaurants and Laptops datasets, AWARE dataset for app reviews	Active learning with Uncertainty Sampling, incorporating sample diversity and data augmentation. Reduces manual labelling effort by selecting informative and diverse samples.	SemEval Restaurants Dataset: Accuracy: 90.18% with the full dataset, reduced to 89.99% with EASE (240 labelled samples). F1-Score: 0.93 (full dataset) and 0.93 (EASE). SemEval Laptops Dataset: Accuracy: 86.94% with the full dataset, reduced to 86.83% with EASE (328 labelled samples). F1-Score: 0.90 (full dataset) and 0.90 (EASE).

IV. Results

In this section, we explain our responses to each research question.

A. RQ-1: Datasets

The analysis of datasets used in Aspect-Based Sentiment Analysis (ABSA) reveals significant trends and preferences among researchers. Figure 5 depicts the Hotel Dataset as the most frequently utilized dataset, accounting for nearly 30 % of the total usage. This dominance can be attributed to the nature of the studies, as many ABSA applications focus on analysing hotel reviews, a critical domain for customer sentiment understanding and service improvement.

The second most frequently used dataset is the SemEval Dataset (23 %), widely recognized as a benchmark dataset for sentiment analysis tasks. Its frequent usage reflects the research community's reliance on standardized datasets to compare and validate models effectively. Other notable datasets include Twitter Dataset (13 %), emphasizing the analysis of short, informal customer opinions, and the Restaurant Dataset (11 %), focusing on reviews in the hospitality sector.

Interestingly, datasets like Amazon Dataset, TripAdvisor Dataset, and Booking Dataset each contribute a smaller percentage, highlighting their specialised usage for specific types of sentiment analysis tasks. The presence of datasets such as the Traveloka and Taobao Datasets, though less frequent, indicates a growing interest in multilingual and domain-specific ABSA applications.

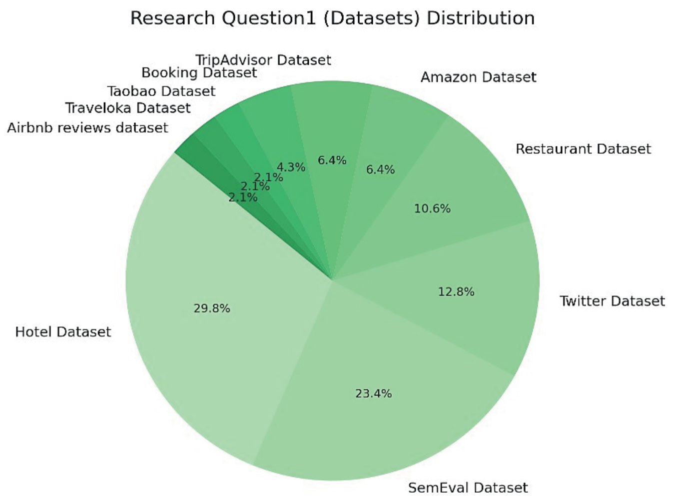

Fig. 5. Distribution of datasets used in ABSA studies.

B. RQ-2: Industries

The donut chart in Figure 6 illustrates the industries addressed in Aspect-Based Sentiment Analysis (ABSA) research. A significant portion of studies (48.3 %) concentrated on the hospitality industry. This dominance reflects the industry's reliance on customer feedback to enhance service quality and customer satisfaction.

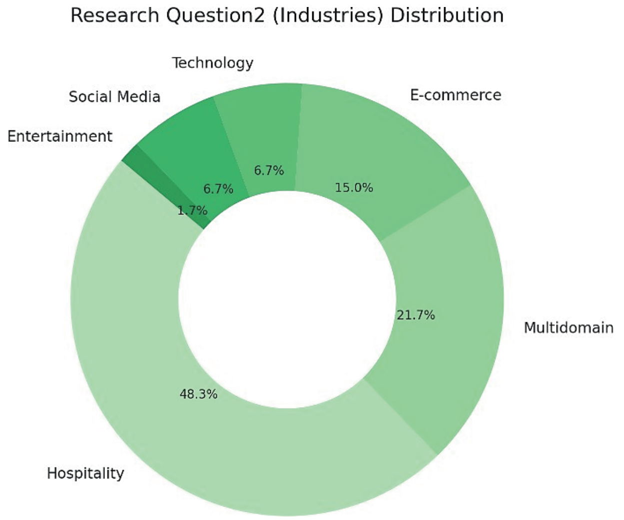

Fig. 6. Industries addressed in ABSA studies.

ABSA aligns with the hospitality industry's focus on aspect-level input like amenities, staff conduct, and room quality, by being able to extract sentiment from structured reviews. Just for this alignment, its importance as a major domain for ABSA applications can be justified.

After the Hospitality Industry, which is the largest category, multi-domain is the second largest at 21.7 %, showing ABSA's flexibility in dealing with datasets from many different industries. Along this line, academics frequently include data from websites like TripAdvisor or Amazon, whose reviews span many areas of interest rather than just one area.

E-commerce Sector: ABSA is highly instrumental in this 15 % when it comes to analysing consumer sentiment through website reviews, such as Amazon and Taobao. These studies make up a large part of understanding product quality, delivery experiences, and customer satisfaction, showing how dependent the industry is on review analysis for competitiveness.

Other industries, in order of less prominence but still emergent fields in ABSA applications, include technology at 6.7 %, social media at 6.7 %, and entertainment at 1.7 %. In the case of social media, it focuses on dynamic and informal text to understand sentiment from tweets or postings while the technology industry uses ABSA for comments to improve their products and services. Entertainment, which copes more with the sentiment about the reviews in music, games, and films, is rather understudied as yet.

C. RQ-3: Algorithms

The methods frequently employed in Aspect-Based Sentiment Analysis (ABSA) are displayed in the horizontal bar chart in Fig. 7. With 20 studies using them, Pre-trained Language Models (PLMs) are the most widely used category, demonstrating their critical contribution to the advancement of ABSA research. Pre-trained representations provided by PLMs, including BERT and GPT, greatly enhance performance on aspect-specific sentiment tasks. Their dominance highlights the significance of transfer learning in contemporary sentiment analysis.

The second most popular category is Deep Learning approaches, which include CNNs, LSTMs, and Attention Mechanisms (15 studies). These techniques are quite successful at extracting aspect-level sentiments because they are excellent at identifying intricate patterns in text. With ten recorded occurrences, conventional machine learning algorithms like SVMs and Random Forests are still useful, especially in situations with smaller datasets or when interpretability is important.

Other noteworthy techniques include Graph-based Models (6 studies), which employ links between words and aspects to improve prediction accuracy, and Statistical Analysis (8 studies), which are used for interpretable insights. Rule-based Approaches, Hybrid Models, and Specialised Methods are less common categories that address particular ABSA difficulties. These reflect novel or specialised approaches.

This distribution reflects the dynamic growth of ABSA research methodologies by highlighting a shift towards more complex approaches like PLMs and neural networks while maintaining the applicability of established and cutting-edge techniques.

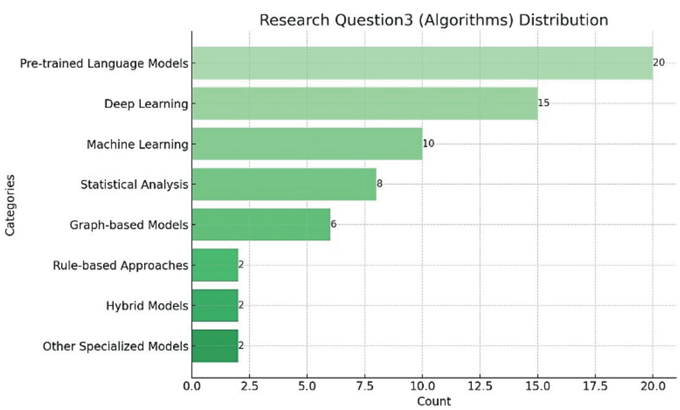

Fig. 7. Distribution of algorithms used in ABSA studies.

D. RQ-4: Aspect Extraction Methods

The techniques employed for Aspect Extraction in ABSA study demonstrate a definite preference for particular strategies, as seen in Fig. 8. The techniques for Aspect Extraction in ABSA research are depicted in the line chart. Given its crucial significance in recognising both explicit and implicit aspects, the combined category – Aspect Extraction Methods – is the most commonly used approach (12 instances). Another well-liked technique is topic modelling (six instances), which is especially useful for revealing hidden meanings in unstructured material.

Emerging methodologies such as Hybrid Methods (three instances) and Multimodal Methods (4 instances) demonstrate a move toward integrating the advantages of several approaches and utilizing various data sources. Less common techniques, including Semantic Similarity Methods and Model Fine-tuning (2 occurrences each), indicate creativity in tackling particular issues like linguistic complexity and domain adaptation.

While highlighting the increasing use of multimodal and hybrid approaches to improve aspect extraction in ABSA, the distribution shows a preference for reliable, straightforward solutions.

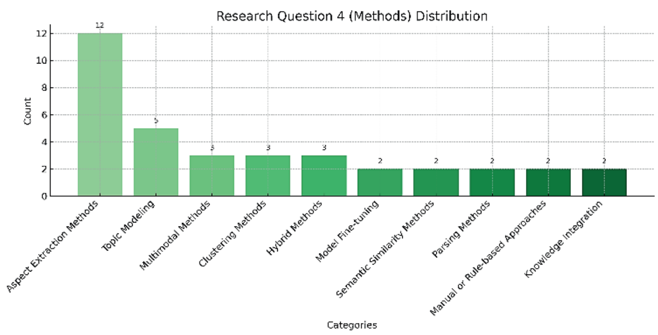

Fig. 8. Distribution of aspect extraction methods used in ABSA studies.

E. RQ-5: Language Models

The distribution of language models utilized in ABSA research, as shown in Fig. 9, demonstrates the dominance of BERT-based Models (23 instances), demonstrating their substantial influence on the field. These models, built on transformer architectures, are widely adopted for their robustness and pre-trained capabilities, which enable fine-tuning for aspect-specific tasks.

GPT-based Models (six instances) are the second most utilized, reflecting the growing importance of generative pre-trained models in ABSA. Other notable categories include Other Pre-trained Models (four instances) and Multimodal Models (three instances), which leverage diverse data sources for improved performance.

Less frequently used methods, such as T5-based Models (3 instances), Custom Models (2 instances), and Knowledge Integration Models (1 instance), represent specialised or domain-specific applications, pointing to innovation in tackling unique challenges in ABSA.

The chart underscores the strong preference for BERT-based Models, while the presence of emerging and less common approaches highlights opportunities for further exploration in diversifying the use of language models in ABSA research.

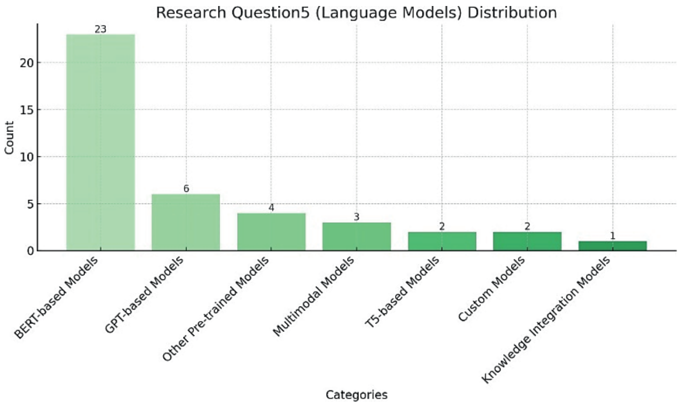

Fig. 9. Distribution of language models used in ABSA studies.

F. RQ-6: Metrics

As seen in Fig. 10, the distribution of evaluation metrics used in ABSA research highlights Accuracy (41 instances) as the most frequently employed metric. This dominance reflects the central importance of model correctness in measuring the effectiveness of aspect-based sentiment analysis methods.

Precision (19 instances) and Recall (18 instances) are the second and third most common metrics, respectively. These metrics emphasize the balance between true positives and false positives/negatives, critical for understanding model performance in terms of identifying sentiment accurately at the aspect level.

Other metrics, such as Root Mean Square Error (RMSE, three instances), are less commonly used and are likely applied in regression-based tasks or scenarios requiring numerical predictions. Rarely used metrics, including AUC, F1-Measure, Cross-Entropy Loss, and Statistical Significance Tests (one instance each), reflect specialised or experimental applications tailored to specific research challenges.

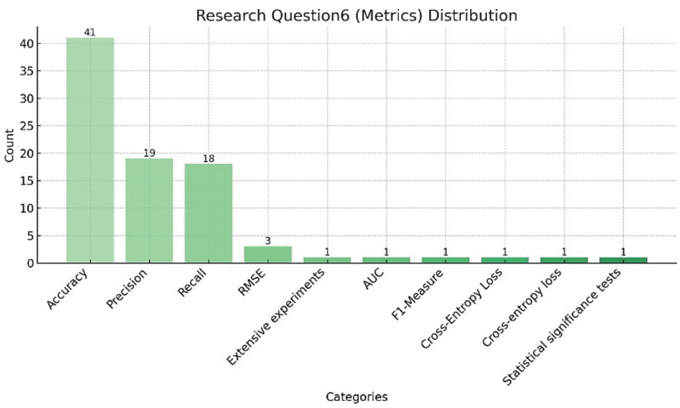

Fig. 10. Distribution of metrics used in ABSA studies.

G. RQ-7: Languages

As seen in Fig. 11, the distribution of languages used in ABSA research highlights a clear dominance of English (40 instances). This overwhelming preference reflects the availability of abundant resources, datasets, and pre-trained models for English, making it the default language for most ABSA studies.

Multilingual (12 instances) research, which includes datasets or models capable of handling multiple languages simultaneously, ranks second. This reflects the growing interest in expanding ABSA applications to address diverse linguistic contexts, emphasizing the importance of inclusivity in global sentiment analysis.

Other languages, such as Chinese (four instances) and Indonesian (three instances), indicate increasing efforts to apply ABSA in specific regional or domain-specific contexts. Rarely researched languages, like Vietnamese and Afaan Oromo (one example), indicate attempts to address marginalized languages and represent emerging fields of study.

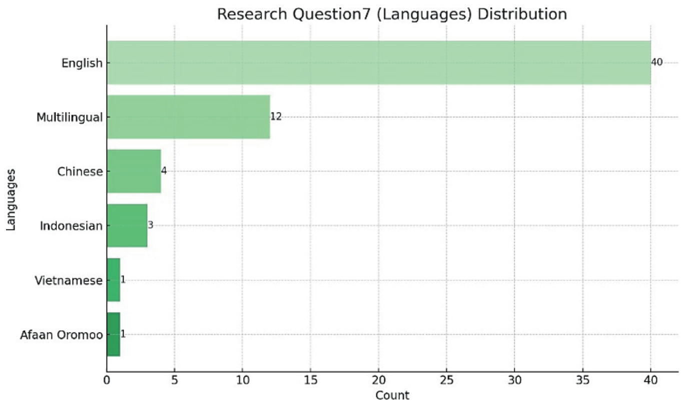

Fig. 11. Distribution of languages used in ABSA studies.

H. RQ-8: Challenges and Gaps

Some of the challenges and gaps regarding algorithms, techniques, and models have been discussed in this subsection. These and their details are listed item by item below:

- Multilingual and low-resource language problems
  - Another important limitation is the presence of multilingual reviews, in particular for low-resource languages such as Indonesian and Vietnamese.
  - Since their performance is worse when dealing with out-of-vocabulary words, their performance is generally worse in SA and aspect-based analysis.
  - This is due to the lack of annotated pre-training datasets concerning such languages.
- Overlapping and noisy aspect terms
  - Unique challenges in handling overlapping and noisy aspect terms by aspect-based techniques increase the computational overhead in fine-grained sentiment extraction.
- Implicit elements and semantic similarity
  - There are still problems to be resolved regarding managing implicit elements.
  - Striking a balance between semantic similarity in reviews remains a challenge.
- Feature selection and aspect polarity categorization
  - Better feature selection methods are needed.
  - More reliable aspect polarity categorization techniques are obviously needed.

- Modelling subtle sentiments
  - Often, subtleties such as irony, phony evaluations, and conflicting emotions are beyond the reach of models.
  - Capturing subtle feelings from datasets with sparse or unbalanced annotations is a challenge.
- Textual-visual sentiment alignment
  - There are issues in aligning textual and visual sentiment cues.
  - Sentiment inconsistencies in multi-aspect phrases are difficult to resolve.
- Lack of cross-domain generalizability
  - Many solutions suffer from overfitting to specific industries, e.g., large language models and deep learning.
  - This reduces their applicability across different domains.
- Scalability issues
  - High computation costs make it difficult to scale fine-tuned large language models or optimized methods like LDA.
  - Sophisticated techniques (e.g., Word2Vec, BERT) may no longer improve contextual comprehension significantly.
- Sparse and noisy data
  - The analysis becomes more difficult due to the presence of noisy or irrelevant evaluations.
  - New methods of filtering and optimization should be explored for sparse data.
  - Problems arise regarding integrating textual and visual data more effectively for multimodal content.
- Multimodal data fusion challenges
  - There are challenges in effectively combining textual and visual elements in multimodal data.
- Impact of framework-specific defects on model robustness
  - Model robustness can be affected by framework-specific defects.
  - Few-shot learning, for example, depends on weak signals for labelling.
- Long-term and local dependencies
  - Problems persist in handling long-term and local dependencies for personalized suggestions.
- Cultural, contextual, and language variability
  - Sentiment modelling is complicated by cultural, contextual, and language-specific variations.

The following detailed overview of challenges indicates that creative solutions along with improved model optimization is in dire need for promoting the approaches of sentiment and aspect-based analysis in different datasets and domains.

V. Conclusion

This systematic review discusses the power that is transformative of ABSA in hotel service. Hints for enhancement in the quality of service and personal-type adaptations through ABSA will be given by the depth extraction of sentiments on specific feedback aspects from customers. Some key developments noticed included the use of transformer-style models, approaches that combined modalities, and top-notch extraction techniques, making sentiment analysis more effective and correct, especially in complex datasets like hotel reviews.

Nevertheless, the study sheds light on some critical issues: complicated identification due to implicit aspects is hard; scarcity in multilingual datasets that are annotated is a problem; and state-of-the-art models demand significant computing resources. For reliable and scalable ABSA systems, these challenges need a solution. Besides, while ABSA is expanding, ethical concerns like fairness and transparency in sentiments are gaining more momentum.

In this respect, future research might need to look at making big models that combine very smart machine-learning things with specialised knowledge relating to graphs and data treatments that work well. While the ABSA has a potential revolution in how the hospitality business makes its customers happy, such a future requires interdisciplinary collaboration and continuous innovation.

That will serve as a basis for later studies on what people are interested in about this topic, stating what an important job ABSA does now is how the computer programs understand customer feelings for improving their experiences.

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