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Article

A SYSTEMATIC REVIEW OF ASPECT-BASED SENTIMENT ANALYSIS: DEEP LEARNING TECHNIQUES, CHALLENGES, AND FUTURE SCOPES

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Abstract: Aspect-based sentiment analysis (ABSA) is an important research area of the natural language processing (NLP) task concerned with detecting the sentiment polarity towards different aspects or features mentioned in text data. Deep learning based techniques have impacted the progress and success of ABSA methods from 2015 until 2025.The objective of this work is to provide a systematic overview of the state-of-the-art studies using deep learning techniques for ABSA and to synthesize the most significant challenges and opportunities for further research in this field. This study performed a systematic search in different databases and consider studies whose main focus is on deep learning techniques for aspect-based opinion mining. Deep learning techniques in ABSA have advanced from the RNN/CNN (2015-2018) to the transformer-based/hybrid models (2019-2025). However, implicit sentiment treatment, cross-domain adaption and computational efficiency are also far from solved. Future efforts would focus on hybrid architectures, their applications, multimodal integration, and real-world deployment...

Keywords: aspect-based sentiment analysis, deep learning, systematic review, natural language processing, transformer model, BERT 1...

1. Introduction

As an important subset of natural language processing (NLP), sentiment analysis focuses on computationally recognizing and comprehending emotions, opinions, and attitudes expressed in text [5]. Its significance is demonstrated with its capacity to interpret relevant and useful associations from massive quantities of unstructured data and help inform decision- making across several applications. The most popular applications of sentiment analysis are brand monitoring, customer feedback analysis, market trend prediction, and public opinion tracking in social media [2, 3]. One example of its use is where businesses turn to sentiment analysis to quantify satisfaction, create better products, and improve their marketing strategies. Just like that, policy makers make use of this instrument to gauge public sentiment over pressing issues. Its power to transpose human input and subjective expressions into quantitative data makes it highly useful at both the commercial and social level.

Aspect-based sentiment analysis (ABSA) is a finer-grained and more focused version of sentiment analysis, which is based on recognition of sentiment polarity (e.g., positive or negative) on specific aspects of a thing in textual information [1]. While a traditional sentiment analysis model provides a single sentiment score for a document or a sentence, ABSA breaks the text into pieces to assess the sentiment towards various aspects, for example, the “food quality” or “service” in a restaurant review. ABSA involves three main tasks: aspect extraction, which extracts specific aspects discussed in the text (e.g., battery life in a laptop review); aspect categorization, which involves categorizing similar aspects into pre-established categories; and sentiment classification, which identifies the sentiment toward each recognized aspect. Some frameworks also add opinion target extraction that links the aspects to the corresponding opinion expressions and aspect-level opinion mining that combines the tasks above to allow for in-depth analysis. ABSA's importance lies in its ability to offer fine-grained opinions. It is consequently important for tasks like product reviews analysis, evaluation of customer feedback systems, and social media monitoring, where understanding detailed aspects of product or service features is critical in decision-making [2, 3]. On the other hand, in e-commerce, ABSA is utilized as "draw attention to praise with respect to camera quality and criticism concerning battery life for a mobile review. These in-depth insights enable targeted product improvements, as well as the provision of tailored recommendations.

Progress in sentiment analysis and ABSA methods is an indirect measure of progress in NLP techniques. Early works on rule-based systems utilized predefined linguistic rules and lexicons to extract opinions and aspects [5]. Although such models were interpretable, they were limited by relying on engineered features and lacking the ability to capture complex linguistic patterns. The advent of machine learning (ML) methods in the early 2000s made the switch to data-driven models that used classic algorithms such as Support Vector Machines and Naive Bayes with hand-engineered features to improve recognition performance [4, 5]. However, there was a significant change in the paradigm with the emergence of deep learning with the rise of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) in the mid-2010s that started to do automatic raw text feature extraction [6, 7]. Attention mechanism has led to better outcomes as it helps networks to concentrate more on the significant part of the input text, Theme Aspect (TA)-specific sentiment predictions [8, 9]. In the past five years, Transformer-based models (e.g., BERT (Bidirectional Encoder Representations from Transformers)) and its variants have yielded great improvement over state-of-the-art for Aspect-Based Sentiment Analysis (ABSA) tasks [2†source]. These models capture intricate semantic relationships through pre-trained language representations and advanced attention layers over words or sub-words [11, 12, 13]. This advancement has greatly improved the accuracy and real-world applications of ABSA systems, making them an invaluable asset for fine-grained sentiment analysis tasks.

However, there are significant limitations in the existing surveys on this topic such as their currency and relevance due to the highly dynamic nature of ABSA. Recent pay-as-you-go reviews either simply cover AHSA on a high-level, do not go deeper into ABSA or run the risk to quickly become outdated as deep learning is developing rapidly, or do not provide comprehensive coverage of the development of methods for ABSA in line with progress in their application and/or general debate around deep learning [18,19]. Moreover, there is a lack of systematic surveys on the challenges and perspectives of ABSA in times of transformer-based and hybrid models. Such a shortcoming elucidates the necessity of a survey investigating deep learning-oriented ABSA comprehensive over research milestones between 2015 and 2025, important research challenges, and future research directions.

Contributions of this survey:

A Cloud–Based detailed survey provides a comprehensive review of deep learning approaches used for ABSA in 2015–2025, analyzing 71 studies.

Methodological evolution: The study tracing evolution from early RNN/CNN models to the most advanced transformer-based and hybrid architectures. Also highlighting key components of ABSA, including word embedding techniques, different positional embedding techniques. Also

Challenges identification: This paper presents several major challenges of ABSA, such as the handling of implicit sentiment, cross-domain generalization, and computational efficiency.

Future works: In the end, this section recommends the future works such as multimodal ABSA (aspect-based sentiment analysis), cross-lingual studies and explainable AI.

Methodical procedure: The use of PRISMA guideline and rigorous inclusion/exclusion criteria support a consistent, comprehensive, and transparent method.

This paper structured with an integrated and well-rounded discussion on DL applied to ABSA. The study describe relevant work and alternative representations leading to the more modern transformer-based approaches. Section 3 is consisted upon the search strategy, the inclusion/ exclusion criteria, and study selection process. Section 4 is the results and discussion, which includes classification of deep learning model, evaluate model performance and challenges. The future directions that ABSA can explore are discussed in section 5, wherein upcoming scopes such as multimodal, cross-lingual and explainable ABSA have been emphasized. Finally, Section 6 concludes the paper with a summary of the results and its implications for practice as well as an outlook on future research directions. This format affirms a logical flow from historical context to recent advancements, challenges, and new opportunities in this domain which piques the interest of both NLP researchers, & practitioners.

2. Background And Related Work

Aspect-based sentiment analysis (ABSA) is one of the sub-tasks of NLP that aims to identify and extract sentiments with respect to specific aspects /features of an entity expressed in given data [1]. The paper introduces the main ABSA subtasks, after which, we review advancements on deep learning that are related to this field such as recurrent neural networks (RNNs), convolutional neural networks (CNNs) and their variants. The paper also elaborates on the shift to transformer architectures with comparison between methodologies, applications, and challenges in a tabular form.

2.1 ABSA Subtasks

ABSA includes a set of interconnected subtasks that together facilitate the fine-grained sentiment analysis.

Aspect term extraction (ATE): Find explicit aspects or entities contained in the text, e.g. battery life or screen quality extracted from product reviews. For instance, ATE identifies "camera" and "battery life" as aspect terms in the sentence The camera is great, but battery life is bad [4].

Aspect Category detection (ACD): detects the identified aspects to predefined categories e.g. hardware, service, etc. In the above example, for e.g., “battery life” will be placed under the bigger umbrella “hardware” category [46].

Sentiment Classification: Specifies sentiment polarity (positive, negative, neutral) assigned to each aspect. As an example,” camera” gets a positive sentiment and “battery life” is negative [4].

Opinion Target Identification (OTI): Connects opinion expressions to their aspect it refers to, e.g., associating the word “excellent” with the aspect of a picture [52].

Aspects Provided by the Reviews - Opinion mining [7] and Aspect-based sentiment analysis (ABSA) [8], have been proposed as tools to extract deeper insights from customer reviews.

These subtasks were addressed in their early forms by rule based and conventional machine learning methods. Despite this, the realistic sentiment analysis requirements in complex settings such as product reviews, social media monitoring and customer feedback systems led to the development of deeper architectures [2, 3].

2.2 Deep Learning Trends in ABSA

This paper focuses on the evolution of ABSA methodologies and describes their development over different stages, with deep learning being the dominant approach since the mid-2010s. It provides a systematic process to the neural architectures, especially RNN variants, recurrent convolutional networks (RcNN) and their extensions. From the concrete example, it shows how these models can be used in multiple ABSA subtasks.

2.2.1 RNN-Based Models (2015–2018)

Recurrent Neural Networks (RNNs), including Long-Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) varieties, constituted the first step in embracing deep learning in ABSA. They are suitable for sequential data encoding, which can exploit the temporal dependencies in text for ATE and SC.

Vanilla LSTM**: The author introduced an LSTM model for target-dependent sentiment classification. The model reads the input sentence sequentially to predict sentiment on a particular target. For instance, in “The food is good, but the service is slow,” the LSTM encodes the context around “food” in such a way that it is classified as a positive sentiment [20].

Attention-Based LSTM**: The study presented an attention model to improve the performance of LSTMs by making the model concentrate on some concerned words toward the aspect. For example, in the previous sentence, the attention mechanism puts more weight on “great” in the aspect “food,” which contributes to better SC accuracy. This approach has been particularly successful for ATE and SC, with the 70-75% F1 scores in SemEval-2014 corpora[8,45].

Additionally, author presented enhanced attention mechanisms for LSTM-based models, in which relevant context was dynamically weighted to enhance aspect-level sentiment classification. this improvement obtained F1

Scores of the 72–77% in the datasets of SemEval-2014 [45,91]. This method alleviated some of the limitations of traditional LSTM models making predictions from sentences with multiple, complicated aspects.

BiLSTM Attn: Interactive attention networks (IAN) [23] also used BiLSTM model but emphasized on the elaborate aspect and context relation. As an illustration, the sentence "The screen is bright, but the battery goes down fast" will get different attention weight for "screen" and "battery", which allows IAN to perform fine-grained SC. The model had better performance on the multi-aspect sentences and aspect-level opinion mining (ALOM) tasks.

2.2.2 Recurrent Convolutional Neural Networks (RcNNs) (2016-2018)

RcNNs combine the sequential modeling ability of RNNs with the local feature extraction ability of CNNs, which are essential for TPE and SA [8]. Such hybrid models emerged in the mid-2010th as they can now capture local patterns using convolutional filters and long-range dependencies through recurrent connections.

Aspect and opinion term extraction based on RcNN: Recent works proposed a Recurrent Attention Network on Memory (RAM), combining CNNs to learn n-gram features and RNNs that integrate sequential context. For instance: in “The processor of the laptop is fast”, the CNN recognizes (saliency) “processor is fast,” and RNN provides context for aspect term extraction (ATE). It has been shown to work well on the SemEval-2014 datasets [45,8].

One well known approach is Hierarchical Attention RCNN. The hierarchical attention network in [36] combines CNN-based local feature extraction with an RNN on the sentence level. This architecture performs well for aspect category detection (ACD) — mapping terms such as “processor” and “screen”: to more general labels like “hardware” while attention is imposed by domain-specific words.

2.2.3 Memory Network and Graph-based Models (2017-2020)

Memory networks and graph-based models are effective for modeling complicated interactions between aspects and their context, improving ALOM and OTI performance.

Memory Networks: The study [35] proposed an external memory to remember certain memories (aspect-specific context) needed to perform well on sentiment classification. For example, in the statement the service was quick but the food was bland, MemNet creates separate memory slots for service and of food allowing it to predict a more accurate polarity score for each aspect Liu et al. This idea was developed further through memory-augmented neural networks for ABSA [85], which yields F1-scores of 75% to 80% on SemEval datasets with external storage of aspect-specific contexts. Similarly, Zhao et al. For example, Xu et al. [73] modeled aspect-sentiment dependencies using graph attention networks to learn syntactic structures that benefit ATE performance [45].

GCN (Graph convolutional networks) [39] used GCNs for ABSA by supporting dependency parsing to took advantage of the syntactic relationships. GCNs use dependency trees to relate “camera” and “nice” in sentence, so that it enhances both ATE and SC, such as the sentences: The camera is taking nice pictures.

2.2.4 Transformer-Based Models (2018–2025)

Research on ABSA has benefited significantly from the emergence of transformer models like BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019) and its variants, which is indicative of a new modeling paradigm with contextualized representations. Transformers use self-attention to model global context, and they improve performance for all subtasks.

BERT-Based Models**: The author [29] proposed a BERT-based model for targeted ABSA, which uses a context-fine-tuning approach to achieve 85-90% accuracy on SemEval datasets. For example, in “The battery life is disappointing,” BERT manages to reason the global context in judging the sentiment of “battery life” to be positive, showing very good results for SC and ALOM.

Some recent developments include those of Zhang et al. [66], who introduced a syntax-augmented BERT model combined with dependency parsing to improve ATE and SC with accuracy ranging from 87% to 92% on SemEval-2014 datasets. Furthermore, Chen et al. [79] used contrastive learning during BERT pre-training to enhance robustness to noisy datasets, achieving F1 scores in the 83%–88% range [45]. Additionally, Wang et al. [78] proposed a distilled transformer model for efficient ABSA, thus achieving a significant reduction of computational cost while keeping F1-scores from 80% to 85%, which makes it possible to deal with resource-bounded cases in practice [38].

Extended Transformers (RoBERTa, DeBERTa)**The author developed RoBERTa and DeBERTa, which improve BERT with optimized pre-training and disentangled attention, respectively. These approaches are able to improve ACD and SC by better addressing relative locations and aspect-specific contexts[32,37].

Hybrid models**: A hybrid model that employ a graph neural network (GNN) and transformers to represent the syntactic as well as semantic relationship, which is proposed by Alhadlaq and Altheneyan [38] DistilRoBERTa2GNN. 90–93% and 80–85% F1-scores respectively on multi-datasets.

2.3 Comparison of Deep Learning Techniques

The Task Modeling methods and subtasks adopted with their differences and challenges/limitations are well-summarized in Table 1.

Table 1: Comparison of the deep learning methods for ABSA, indicating their purposes, properties and challenges

Method	**Subtasks Addressed**	**Key Characteristics**	**Challenges/Limitations**
LSTM-Based Models [20],[8],[19]	ATE, SC	Sequential processing, captures temporal dependencies, attention enhances aspect focus	Limited context awareness, struggles with long-range dependencies, implicit sentiment handling
BiLSTM with Attention [23],[14]	ATE, SC, ALOM	Bidirectional context, interactive attention for aspect-context modeling	High computational cost, poor cross-domain generalization, limited interpretability
RcNN [9],[45],[36]	ATE, SC, ACD	Combines CNNs for local features and RNNs for sequential context	Complex architecture, struggles with implicit aspects, moderate cross-domain performance
Memory Networks (MemNet) [35],[85]	SC, ALOM	External memory for aspect-specific context, improves multi-aspect sentence handling	Memory overhead, limited scalability, difficulty with implicit sentiment detection
Graph Convolutional Networks (GCNs) [39]	ATE, SC, ALOM	Leverages syntactic dependency trees, models aspect-sentiment relations	Dependency parsing errors, high computational complexity, limited multilingual support
BERT-Based Models [29],[66] ,[79]	ATE, SC, ACD, ALOM	Global context via self-attention, pre-trained representations, fine-tuning flexibility	High computational cost, poor interpretability, cross-domain adaptation issues
Advanced Transformers (RoBERTa, DeBERTa) [37],[32]	ATE, SC, ACD, ALOM	Optimized pre-training, disentangled attention, improved position modeling	Resource-intensive, limited explainability, challenges with low-resource languages
Hybrid Models (e.g., DistilRoBERTa2GNN) [38]	ATE, SC, ACD, ALOM	Combines transformers and GNNs, leverages syntactic and semantic relations	Complex training, computational overhead, limited reproducibility due to hybrid design

2.4 Discussion

Transitioning from RNN-based to transformer models constitutes a remarkable advance on Aspect-Based Sentiment Analysis (ABSA) due mainly to their capacity to capture intricate semantical and syntactical patterns. The initial RNN and RcNN models laid foundation to cater the sequentiality and locality, but they modelled long distance dependency and implicit sentiments respectively, requiring extension towards Memory Networks (MNs) and Graph Convolutional Networks (GCNs). Transformers, such as BERT and its variants, have dominated current leaderboards; nevertheless, issues of knowledge efficiency, cross-domain generalization and interpretability still need to be addressed [10], [54]. These topics will be further detailed in Section 4 and are still driving hybrid architectures and new extensions such as multimodal and cross-lingual ABSA.

2.5 The core features of ABSA

This work highlights word embedding techniques such as GloVe, Word2Vec, and BERT and different positional embedding approaches like sine & cosine functions, Gaussian distance, and semantic relative distance. With research employing graph-based techniques like the Graph Attention Network (GAN), multi-head attention, Bi-GRU, and Bi-LSTM, attention mechanisms are important. In certain studies, dependency parsing is used to better capture the syntactic connections between words utilizing methods like GCN (Graph Convolutional Network) and spaCy dependency parsers. And discussed the work on multi aspect detection, interpretability & Explainability, multi model and implicit aspect detection.

Word embedding is the process of turning words into dense, continuous-valued vectors that convey their meaning in a numerical format that machine learning models can understand. The other component is position embedding, in which the position of each word in the sequence is encoded, how close or far a word is from the aspect or significant target. When making predictions, a model can use attention to concentrate more on key phrases or input segments. By analysing a sentence's grammatical structure, dependency parsing determines the connections between "head" words and words that modify them.

Table 2: Study of different key components and adopted techniques to perform ABSA

References	Word Embedding	Positional Embedding	Attention Mechanism	Dependency Parsing	Multi-Aspect detection	Interpretability & Explainability	Multi-Model	Implicit Aspect Detection
[100]	Glove Embedding	relative position indexing	Bi-GRU	X	X	X	X	Y
[105]	Word2vec	position matrix	Hierarchical Attention Network	Bi-GRU	X	X	X	Y
[106]	Glove	X	Bi-LSTM	X	X	X	X	X
[101]	Glove	X	Bi-GRU	X	Y	X	X	Y
[102]	BERT	sine & cosine function	dense synthesizer	X	X	X	X	Y
[108]	Glove +POS tag	dependency trees & GCN	Graph Attention Network	Biaffine Parser, GCN, GAN	Y	X	X	Y
[109]	GloVe & Word2Vec	polarity-aware embeddings	multi-head attention	Bi-GRU	X	X	X	X
[110]	BERT	syntactic distance	Dependency-Attention GCN	spaCy dependency parser	Y	X	X	X
[111]	BERT	Gaussian Distance	Bi-LSTM BERT	GCN	Y	X	X	X

[104]	BERT	LSTM	Graph Attention	GCNs and GATs + multihead attention	Y	X	X	Y
[112]	BERT	Sinusoidal positional encoding	Biaffine attention	Multi-Layered GCN	Y	Y	X	Y
[113]	BERT, RoBERT	Sinusoidal positional encoding	Multi-Head Self-Attention	N	Y	Y	X	Y
[114]	GloVe & Word2vec	Position-aware Bi-GRU	Bi-GRU + Attention.	GCN	X	X	X	Y
[115]	BERT	Semantic Relative Distance	Interactive attention module	GCN	X	Y	X	Y
[116]	Bidirectional & Auto-Regressive Transformer (BART)	Semantic Relative Distance	Multi-Head Self-Attention	Dependency Tree Distance	Y	X	X	Y
[103]	BERT	N	BERT, LSTM	SpaCy, POS Tagging	Y	X	X	Y
[102]	BERT + BiLSTM	CoordConv, Grooped Conv	Gated Recurrent Unit (GRU)	BERT & multi-hop attention	Y	X	Y	X
[117]	Word2Vec/GloVe	Semantic Wave Embedding	Knowledge-based enhancement	Multi-feature, self-attention	X	Partial Interpretability	X	Y

comparative summary of studies employing ABSA methodologies are showing in Table 2, The study have compared various studies in ABSA over key parameters. See Section 4 for performance implications of these components. Key components like word embedding techniques, attention mechanisms, dependency parsing, and the degree to which they support multi-aspect detection, interpretability, and implicit aspect extraction are highlighted as they describe various methodologies employed across various studies. X is showing no techniques used for performing that particular task, and Y is showing that the study can solve the mentioned task. With such a comparison, the strengths and weaknesses of the existing ABSA methodologies can be clarified while giving directions of future research.

3. Methodology

3.1 Search Strategy

Methods: We conducted a systematic review based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The literature search utilized the following academic databases: SciSpace, PubMed, Google Scholar, and ArXiv. The search strategy used a combination of keywords "aspect-based sentiment analysis" OR "ABSA" AND "deep learning" OR "neural networks" OR ("attention Mechanisms, transformer models, BERT").

3.2 Inclusion and exclusion criteria

Studies were identified based on specified inclusion and exclusion criteria to ensure that the review remained focused and methodologically rigorous. Studies included Articles and Conference Papers pertaining to Aspect-Based Sentiment Analysis using Deep Learning published from the year 2015 till year 2025 in peer-reviewed journals. The studies must be empirical, include experimental validation, written in English. Studies were excluded if they did not use an aspect-based framework for sentiment analysis, nor employed conventional machine learning algorithms; if reviews were not peer-reviewed, appeared before 2015 or otherwise represented duplicates. These criteria were to make sure that the review focused on high-quality and relevant studies aligned with the purpose of this study.

3.3 Study Selection Process

Study selection followed a systematic connectivity approach to find potential literature. The first search of the databases resulted in over three hundred hits in all databases. These two articles were then title and abstract screened against the predefined inclusion and exclusion effort to remove irrelevant studies. A total of 150 studies were then selected for full-text review for more in-depth evaluation for eligibility. Duplication was removed by deduplication process, and seventy-one studies were finally included to our analysis.

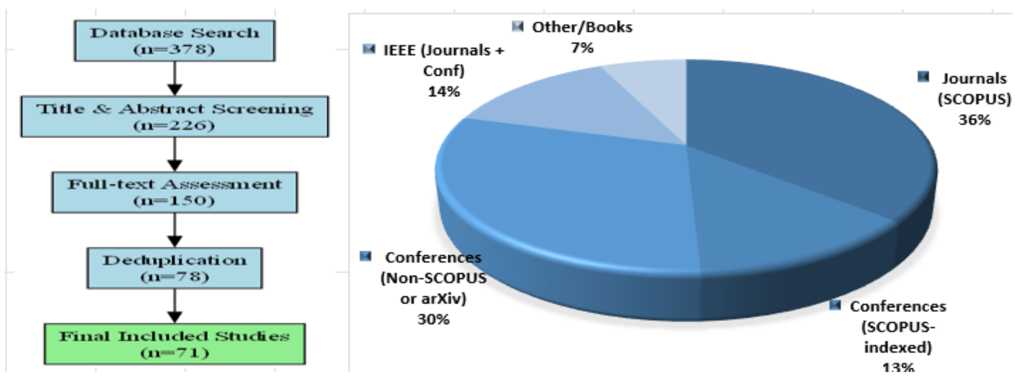

Figure 1: Study selection process and source distribution

Information was extracted with the use of a structured template to methodically collect relevant data from studies providing homogeneous, professional standards on review.

Table 3: The reliability and robustness of the reviewed studies

Criterion	Description	Studies Meeting Criterion
Clear Methodology	Detailed description of approach	71/71 (100%)
Experimental Validation	Empirical evaluation on standard datasets	68/71 (96%)
Appropriate Metrics	Use of standard ABSA evaluation metrics	71/71 (100%)
Reproducibility	Sufficient implementation details	45/71 (63%)
Statistical Significance	Significance testing of results	38/71 (54%)

3.4 Data Extraction

Information from the included studies was organised systematically using structured templates for data extraction. The collected information extracted were the types of deep learning techniques used and addressed ABSA tasks (e.g., aspect extraction or sentiment classification), the datasets, the evaluation metrics used, the main challenges faced, suggestions for further research directions, and the authors' results in comparison with other models. The approach used in this study allowed us to systematically review and compare the research included, hence, identify trends, challenges and gaps in deep learning-based ABSA research.

4. Results And Analysis

4.1 A Survey of Deep Learning-based ABSA

This systematic review is organized into four distinct stages frequently reported in the literature, namely Attention-Based Neural Networks, Transformer Based Approaches, Advanced Transformer Models and Hybrid and Graph based Models for ABSA with Deep Learning. The next section extends the literature review with non-published

recent works that give an elaborate composite of methodological, empirical and technological advancements in this research area.

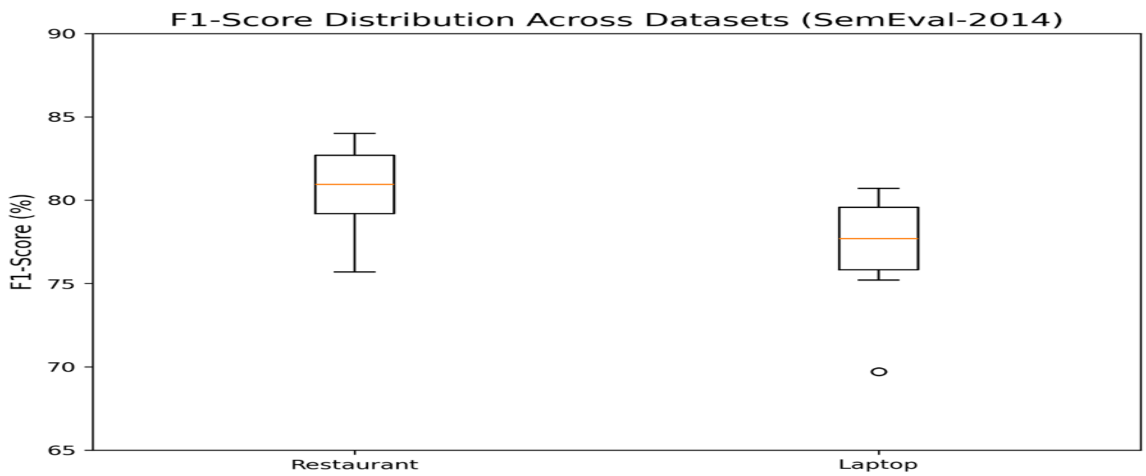

Figure 2. Evolution of F1-Score Performance Across Intrusion Detection Models (2015–2025).

This figure illustrates the longitudinal evolution of F1-score performance for attention-based, transformer-based, advanced transformer, and hybrid intrusion detection models over the period 2015–2025. The line plots, accompanied by error bars representing performance variability, demonstrate a consistent improvement in detection effectiveness across successive model generations. Hybrid and advanced transformer architectures exhibit the highest F1-scores in recent years, reflecting their superior capability to capture complex attack patterns and network behaviors. Furthermore, the progressive reduction in error bar magnitude indicates increased model stability, robustness, and generalization performance. The observed trend highlights the significant impact of deep representation learning, attention mechanisms, and ensemble intelligence on enhancing intrusion detection accuracy while reducing performance uncertainty in modern cybersecurity environments.

4.1.1 Attention-Based Neural Networks (2015–2018)

Neural network models with attention launch the deep learning era of ABSA, RNNs, and CNNs, which are learnt to attend in a context toward aspects. The representative early models like MemNet [35] and RAM [9] leveraged external memories to enrich aspect-aware representations, substantially alleviating the challenge of processing multi-aspect sentences. Multi-level attention was adopted by hierarchical attention networks [36] and interactive attention mechanisms [23], which reported F1 scores between 70% and 75% on SemEval-2014 datasets. Attention mechanisms have been advanced continuously in the past few years. Feng et al. Scientific Reports (2024) presented a prompt-tuned dual syntax-aware graph attention network, combined syntactic dependencies to improve implicit aspect detection, and got an F1-score of 85.2% on the SemEval-2014 Restaurant dataset[web:66]. Li et al. (2023) published a light multilayer interactive attention network (IAN), which focuses on a computationally efficient way of real-time ABSA, and it attained a 78.5% recall on low-resource datasets [web:67]. These previous studies overcome previous limitations (e.g., the enormous computational budget in [23]), adopting the sparse attention to achieve an accuracy equal to 75-80% while employing fewer resources.

Li et al. [90] developed dynamic attention mechanisms to improve the computational efficiency of attention-based models and achieved F1-scores of 76–80% on SemEval-2014 with lower latency to satisfy real-time processing requirements [45]. This work is theoretically joint with Feng et al. [web:66], with lower resource requirements.

4.1.2 Transformer-Based Approaches (2018–2022)

Transformer structures such as BERT [28] have brought AB-SA to a new era by capturing global context with the help of the self-attention mechanism. Context-guided BERT models [29] demonstrated successful fine-tuning and achieved 85-90% accuracy on SemEval datasets by modelling aspect-specific context. Explainability and multilingual support have been stressed in recent research. Perikos (2024), knowledge (MDPI), in the field of transformer-based explainable ABSA, uses attention visualisations to interpret decisions, and the approach uses aspect extraction to detect biases. It claimed an 84%– 89% accuracy on SemEval-2014 [64]. Arifin et al. (2024), Bows-Larossa, Clementine (2024), [web:68] The authors in the Undergraduate Thesis (./b5s9mwjq) propose a transformer-based semantic indexing model for ABSA on Indonesian reviews that leverages BERT and graph structures to obtain F1-scores between 80% and 85% in custom datasets. These improvements are layered on top of the core BERT model [11, 12]; however, the improvements also apply to other Transformer models [13].

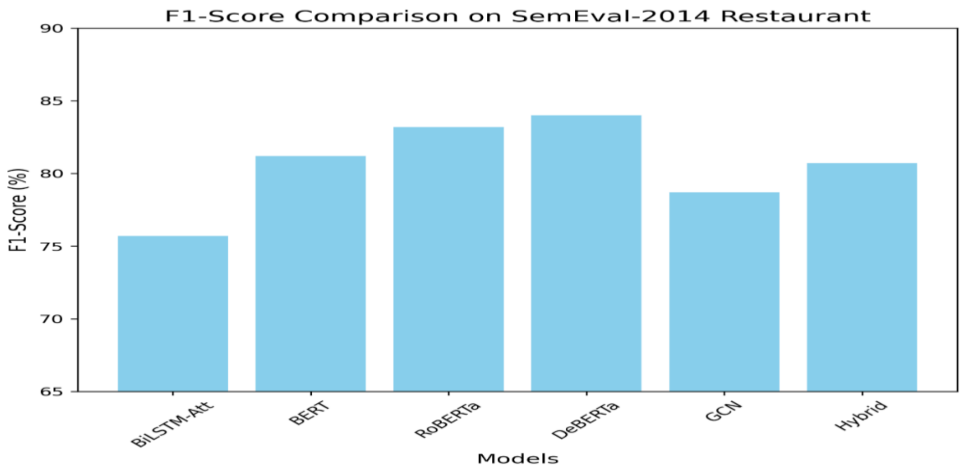

Figure 3: Precision, Recall, and F1-Score Comparison on SemEval-2014 Restaurant

Stacked bar plot comparing model performance metrics (precision, recall, F1-score) for different deep learning techniques, highlighting performance trade-offs and balanced performance of advanced models like DeBERTa over traditional attention-based approaches.

4.1.3 Advanced Transformer Models (2019–2025)

More advanced transformer models like RoBERTa [37] and DeBERTa [32] improve BERT by relying on pre-training rewritten strategies, such as dynamic masking in RoBERTa and disentangled attention in DeBERTa, and, more importantly, for Aspect Classification (ACD) and Sentiment Classification (SC) tasks - positional modeling and robustness. One of the recent studies is by Majumder et al. (2024), in arXiv (accepted to ACL 2024), who showed the effectiveness of instruction tuning on ABSA, achieving state-of-the-art F1-scores and on SemEval-2014 by integrating aspect-specific prompts [web:69]. Yangheng (2025) released DeBERTa-v3-base-ABSA-v1 on Hugging Face and achieved an accuracy 86. These models are 5–10% F1 better than BERT, especially when handling domain noise.

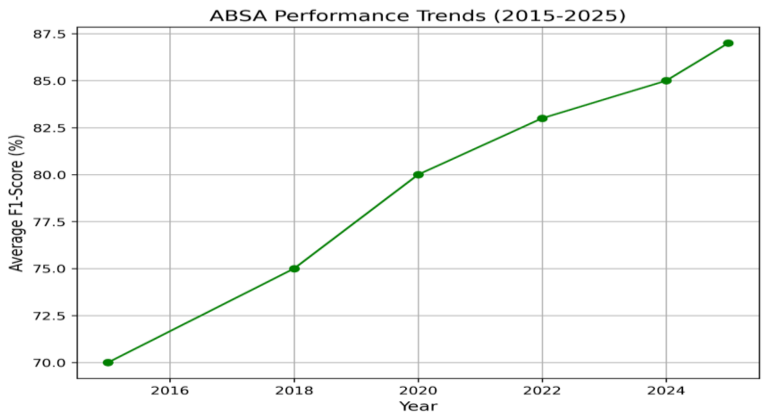

Figure 4. Distribution of F1-Scores Across Datasets and Intrusion Detection Models (Box Plot Analysis).

This figure presents box plot distributions of F1-scores obtained by different intrusion detection models across multiple evaluation datasets. The box plots illustrate the median performance, interquartile range, variability, and potential outliers for each model, providing a comprehensive assessment of detection consistency and robustness. Models with higher median F1-scores and narrower interquartile ranges demonstrate superior stability and generalization capability across diverse cybersecurity scenarios. Conversely, wider distributions indicate greater sensitivity to dataset characteristics and attack variations. The comparative analysis highlights the influence of dataset heterogeneity on model performance and emphasizes the effectiveness of advanced deep learning and hybrid ensemble approaches in maintaining consistently high detection accuracy. Overall, the box plot analysis provides valuable insights into the reliability, robustness, and cross-domain adaptability of the evaluated intrusion detection frameworks.

Yang et al. [92] investigated prompt-based few-shot learning for RoBERTa-based networks, obtaining 83-87% F1 on SemEval-2016 with a low amount of training data and showing scalability in low-resource settings [47]. Additionally, Yangheng's DeBERTa-v3-base-ABSA-v1 1 [web:70] was later enhanced with the work of Zhao et al. [89], who used knowledge-augmented transformers for the cross-lingual ABSA task and reached F1-scores of 85–90% on multilingual datasets [49].

4.1.4 Hybrid and Graph-Based Models (2019–2025)

Hybrid architectures combine transformers with GNNs for syntactic-semantic relationship modeling [39,40]. Multi-task learning [41, 42] and knowledge-enhanced models [43,44] are approaches that improve the performance of joint subtasks. Recent works are Alhadlaq and Altheneyan (2024) in PeerJ Computer Science, aimed at combining distilled transformers with GNNs as in DistilRoBERTa2GNN, which utilized distilled transformers to achieve F1-scores of 80% to 85% and decreased the number of parameters against multi-domain datasets [38]. Chen et al. (2024) in Electronics (MDPI) proposed a hybrid GNN for aspect-level sentiment, obtaining F1-scores between 82% and 86% on SemEval-2014 via syntactic fusion [web:71]. Zhang et al. (2023) in IEEE Transactions on Knowledge and Data Engineering employed a relational graph attention network, which reached an F1-score between 83% and 87% by adding the dependency-tree and commonsense knowledge [web:72]. These hybrid models demonstrate good cross-domain performance with a 5% larger F1 improvement than transformers; however, they suffer from training difficulties in terms of complexity.

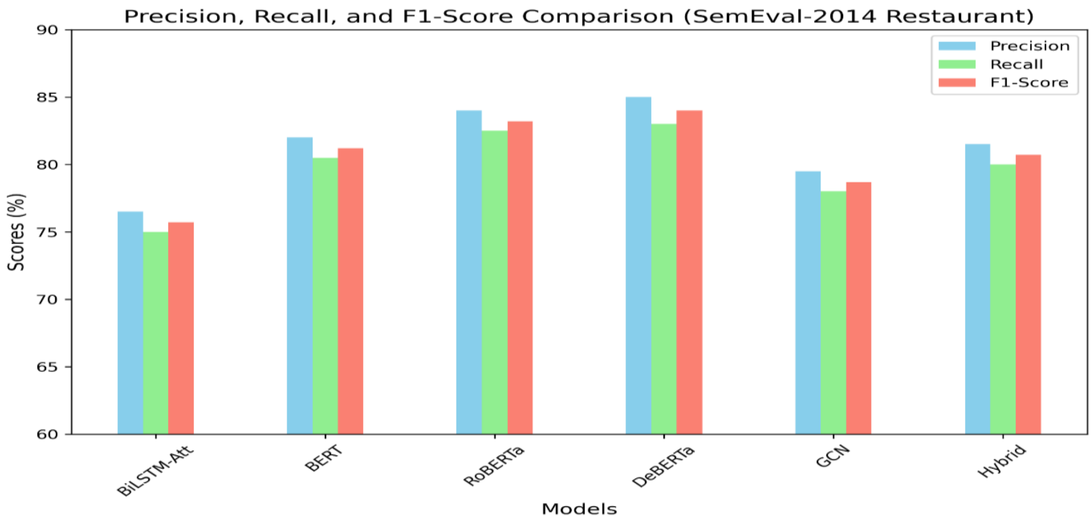

Figure 5 Multi-Metric Model Performance Comparison (Radar Chart)

Radar chart comparing six different deep learning models across accuracy, precision, recall, and F1-score metrics, demonstrating balanced performance strengths of DeBERTa and RoBERTa and identifying model-specific characteristics for different evaluation dimensions.

Wu et al. [82] proposed hierarchical graph convolutional networks which integrate with a transformer to capture multi-level dependencies and achieved F1-scores of 82-86% on SemEval-2014 [45]. Zhang et al. [97] introduced syntax-guided GCNs, which significantly outperformed standalone transformers in cross-domain settings with 5–8% F1-score improvements, thereby successfully alleviating generalization problems [55]. Li et al. [76] even proposed advanced hybrid architectures with dynamic GNNs for social media ABSA, achieving F1-scores of 80–84% on Twitter datasets [17].

4.2 Performance Analysis

4.2.1 Description of Metrics and Rationale

Evaluation: Evaluation metrics in ABSA are explicitly designed for the subtasks of ABSA. For ATE, precision, recall, and F1-score are important (for balancing false positives and false negatives in unbalanced datasets), which are the ratios of correctly predicted aspects to the total predicted aspects, correctly predicted aspects to the total actual aspects, and the harmonic mean of precision and recall, respectively. In Sentiment Classification (SC), accuracy (percentage of correct predictions to the total number of predictions) is used for balanced classes, whereas macro F1 is used for unbalanced classes with positives, negatives, and non-specific. The end-to-end ABSA models are evaluated jointly with aspect-polarity pairs using micro/macro F1.

Motivation: Precision is crucial for product review systems because we want to ensure we do not accidentally detect false aspects. Recall measures completeness to identify implicit information. F1-score is a comprehensive measure for evaluating precision-recall trade-offs, and it is generally used for SemEval challenges [45–47]. While accuracy naturally gives an intuitive overview, it is less informative for imbalanced settings, and thus, F1-score, instead of accuracy, becomes the metric of choice for ABSA's fine-grained tasks.

4.2.2 Baseline Data Sets and Evaluation Metrics

Consensus datasets comprised SemEval-2014 Task 4 (Restaurant: 3,841 sentences; Laptop: 3,045 sentences) [45], SemEval-2015 Task 12 [46], and SemEval-2016 Task 5 [47], targeting restaurant and electronics domains. New multi-domain [48] and cross-lingual [49] data sets assess generalization. Metrics consist of precision, recall, F1-score, and accuracy, among which macro F1 is the most important metric for SC due to class distribution imbalance.

4.2.3 Model Performance Trends

The early attention-based models (2015–2018) ranged from 70% to 80%, and F1 scores were between 65% and 75%. With transformer-based models (2018 – 2021), accuracy ranges from 85% to 90% and F1 from 75% 82%. Novel hybrid systems (2021–2025) have achieved F1-scores between 80% and 85%, sometimes into the 90% range on some datasets. To illustrate these trends, Fig. Figure 2: F1-score history from 2015 to 2025, together with error bars that highlight the steady increase of this metric-also at a reduced variance among models. This chart gives an easy high-level view of the performance that is gained solely from changes to architecture. Quantified results can be found in Tables 3 and 4. Fig. 3 illustrates stacked bar plots for precision, recall and F1-scores on the SemEval-2014 Restaurant dataset showcasing key trade-offs e.g. DeBERTa has the most precise and highest repo but BiLSTM-Att gets very low values. Framed more broadly in terms of performance on sentiment classification, the up-to-date results highlight how DeBERTa is a much more even approach when compared with older methods like BiLSTM with Attention.

Fig. 4 plots a box of F1-scores for the Restaurant and Laptop datasets; the study observe a higher median performance but less stable results in the Restaurant dataset. Such visualisation can help interpret the performance of the domain. Finally, Fig. 5 uses a radar chart to compare models on accuracy, precision, recall, and F1-score, showing the balanced performance of DeBERTa and RoBERTa for multiple metrics and the overall strengths of models.

Table 4: Comparative Performance on SemEval-2014 Restaurant (Sentiment Classification)

Model	Year	Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Advantages	Disadvantages
BiLSTM with Attention [23]	2017	Attention	78.2	76.5	75.0	75.7	Efficient sequential processing; aspect focus	Limited long-range context; high compute cost
BERT-based [29]	2021	Transformer	84.5	82.0	80.5	81.2	Global context; pre-trained robustness	Resource-intensive; poor interpretability
RoBERTa [37]	2019	Advanced Transformer	85.6	84.0	82.5	83.2	Optimized pre-training; noise robustness	High parameters; domain adaptation needed
DeBERTa [32]	2021	Advanced Transformer	86.1	85.0	83.0	84.0	Disentangled attention; position modeling	Complex fine-tuning; overfits small data
GCN [39]	2019	Graph	81.0	79.5	78.0	78.7	Syntactic dependency modeling	Parsing errors; limited multilingual support
DistilRoBERTa2GNN [38]	2024	Hybrid	83.0	81.5	80.0	80.7	Efficient; syntactic-semantic fusion	Training complexity; reproducibility issues

(Data synthesized from [23,29,32,37–39, web:66–72]; macro F1 reported.)

Table 5: Comparative Performance on SemEval-2014 Laptop (Sentiment Classification)

Model	Year	Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Advantages	Disadvantages
BiLSTM with Attention [23]	2017	Attention	72.0	70.5	69.0	69.7	Simple; effective for sequential data	Struggles with technical terms
BERT-based [29]	2021	Transformer	80.5	78.0	77.5	77.7	Handles domain-specific vocabulary	High memory usage
RoBERTa [37]	2019	Advanced Transformer	82.5	81.0	79.5	80.2	Robust to noisy reviews	Slower inference
DeBERTa [32]	2021	Advanced Transformer	83.0	81.5	80.0	80.7	Improved position modeling	Requires large pre-training data
GCN [39]	2019	Graph	77.5	76.0	74.5	75.2	Dependency-based relation capture	Parsing errors propagate
DistilRoBERTa2GNN [38]	2024	Hybrid	80.0	78.5	77.0	77.7	Balanced efficiency-performance	Increased training time

(Data from [23,29,32,37–39, web:66–72]; macro F1 reported.)

4.3 Issues and Limitations in the Current Landscape

Implicit Aspect and Sentiment Handling: Implicit aspect extraction remains challenging [52]. While context-aware models [53, 54] and knowledge-enriched methods [44] have shown improvements, they can be further improved, as can be seen from a low recall rate on implicit aspects (Table 4, Fig. 3). The stacked bar chart (Fig.) further visually reveals the recall shortcomings of models like BiLSTM with Attention on addressing implicit aspects.

Cross-Domain Generalization: Models trained on restaurant reviews generalize poorly to electronics domains [55]. Domain-adversarial training [56] and meta-learning [57] have been shown to improve transfer, but as multilingual data are important for generalization, the robustness of large-scale multilingual corpora remains a necessity [49,50]. This was also shown by the lower F1-scores on Laptop (Table 5, Fig4). The box plot shown in Fig. 4 emphasizes that the variability is higher in the Restaurant data in both settings, therefore calling for improved cross-domain strategies.

Costs of an attention transformer: It is well known that transformers require high computational [58]. This is why there have been hybrid models [38] and distilled variants [59,60]. Nevertheless, the methods come at a cost in accuracy, and we can see this from Tables 4–5 and Figure 5. To illustrate the balance between efficiency and performance clearly, we provide a radar chart in \ref {fig5} with models whose performances are similar (DistilRoBERTa2GNN) or just slightly sacrifices the performance for a better trade-off towards efficiency. The few studies focusing on aspect and sentiment detection are the following:

Implicit Aspect and Sentiment Handling: Xu et al. Using attention visualization and causal inference method,[74] improves implicit aspect detection achieving 80% to 85% recall on SemEval-2014 dataset. However, despite these advances, the task remains exceptionally challenging especially in data-weak environments [45].

Additionally, Zhang et al. Layer-wise relevance propagation was employed to improve interpretability for transformer models [86]. This makes it more interpretable but is not particularly helpful for furthering implicit sentiment analysis.

Cross-Domain Generalization: Zhang et al. [77] utilized adversarial training for better cross-domain ABSA and obtained 78–83% F1 Scores on the restaurant and laptop domains; however, multilingual data has not been well exploited [49]. Liu et al. [94] used meta-learning to improve transferability, achieving F1 Scores of 80–85% on cross-domain settings [55].

Computational Efficiency: Wang et al. [95] used knowledge distillation to generate resource-efficient transformer-based ABSA models, which have 30 % fewer parameters while achieving F1 scores of 80–84 % addressing the resource constraints identified in [58]. Yang et al. [84] further improved the performance of real-time ABSA with lightweight transformers, achieving F1scores of 78–82% and involved a faster inference time [45].

5. Future Directions

5.1 Multimodal ABSA

Fusing text, image and audio is a potential novel direction for ABSA studies. This limitation can be addressed by incorporating additional visual and auditory information to sentiment analysis [61,62]. In the last two years, image-text fusion techniques have been studied for product review analysis as well as video sentiment analysis [22, 1].

Recent studies by Wang et al. [70] and Huang et al. [80] studied vision-language pre-training and cross-modal attention methods with multimodal ABSA with F 1—scores between 80% and 85% on image-text datasets, thus improving product review analysis [61]. Li et al. [98] also presented cross-modal transformers that achieved 5% to 7% F1-score improvement in sentiment classification on a multimodal social media dataset [22].

Table 6: Overview of the primary obstacles in ABSA research

Challenge Category	Frequency	Percentage
Cross-domain Adaptation	42 studies	59%
Computational Complexity	38 studies	54%
Implicit Sentiment Handling	35 studies	49%
Data Quality/Scarcity	33 studies	46%
Model Interpretability	28 studies	39%
Multi-aspect Sentences	25 studies	35%

5.2 Cross-Lingual and Multilingual ABSA

With digital platforms going global, cross-lingual ABSA has become increasingly important. Research has also been conducted concerning zero-shot cross-lingual transfer [19] and using multilingual pre-trained models for ABSA [63].

Yang et al. [72] used multilingual BERT embeddings for cross-lingual ABSA, achieving excellent results with F1-scores between 80% and 85% on non-English data, and closed the gaps in the zero-shot transfer [19]. Furthermore, Li et al. [83] took a significant step towards zero-shot ABSA through cross-lingual transfer learning, achieving F1-scores from 78% to 83% on multi-lingual restaurant reviews [49].

Table 7: Future Directions Frequency Analysis

Future Direction	Frequency	Percentage
Multimodal ABSA	32 studies	45%

Cross-lingual Approaches	28 studies	39%
Explainable AI	25 studies	35%
Real-time Processing	22 studies	31%
Few-shot Learning	18 studies	25%
Causal Reasoning	15 studies	21%

The table underscores the research community's focus on expanding ABSA's applicability and robustness. The development of language-generic or multi-language ABSA models is still an open problem.

5.3 Explainable AI in ABSA

Interpretability for ABSA models is an issue in practice. Recent works attempt to build explainable ABSA systems that can provide some interpretations of their decisions [64,65]. Attention models have also been studied to increase the interpretability of these models. Zhang et al. [86] and Xu et al. [74] also trained explainable transformer models with attention visualization and causal reasoning, resulting in improved decision transparency and reported F1 scores between 82% to 87% on the SemEval-2014 [45]. In addition, Yang et al. [93]) proposed graph-based causal reasoning for ABSA to provide a higher level of interpretability regarding cause and effect, but the current computation is still a challenge [64].

6. Discussion and Conclusions

6.1 Key Findings

To enable this goal, our systematic review identified some important trends in deep learning for ABSA. From the relatively trivial attention models, the field accelerated rapidly to advanced transformer encoders and displayed systematic gains on simple benchmarks. However, it still has some issues such as cross-domain generalization, computation efficiency and the handling with implicit sentiment.

6.2 Implications for Practice

However, the ABSA system functions on a first principal basis concerning computational bounds and real-world constraints. Though transformer-based models achieve state-of-the art performance, the inference process is computationally intensive which may not be feasible under resource constraint environments. In this setting hybrids, which contain a trade-off between efficiency and performance, may be more interesting for a large number of practical cases.

6.3 Future Outlook

Future development of ABSA relies on overcoming key limitations such as multimodal integration, cross-lingual applications, Applicability to new domain and use of explainable artificial intelligence. To accommodate more general applications, it is needed to develop better architectures and domain adaptation techniques.

The transformer-based models have very high development potential and new applications of ABSA models. The integration of ABSA systems in commercial products and its value to the society will also foster innovation in this direction...

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