Context-Aware Transformer-Based Model for Aspect-Based Sentiment Analysis: A Systematic Literature Review

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Abstract. *Aspect-Based Sentiment Analysis (ABSA) is a critical natural language processing task aimed at identifying specific aspects within text and determining the sentiment polarity toward each aspect. Transformer-based models, particularly BERT and its variants, have demonstrated significant advances in ABSA through powerful contextual representations. However, challenges in capturing target-specific context and managing inter-subtask dependencies remain.*

This Systematic Literature Review (SLR) identifies, evaluates, and synthesizes current research on context-aware transformer models for ABSA, with emphasis on context-aware mechanisms, multi-task learning approaches, and BERT-family models. Following the PRISMA 2020 protocol, a structured search was conducted on the Scopus database using three Boolean queries, yielding 851 initial records. After deduplication (n=70), title/abstract screening (n=554 excluded), retrieval (n=147 not retrieved), and full-text eligibility assessment (n=48 excluded), 32 studies were included for synthesis.

Three primary model categories were identified: (1) BERT baselines establishing strong end-to-end ABSA performance; (2) context-aware variants employing context-guided attention (CG-BERT, QACG-BERT, LCF-ATEPC, cascade models); and (3) multi-task transformers (BERT-MTL, RoBERTa-MTL, MTL-AraBERT, SABKG, MLEGCN) handling ABSA subtasks jointly. Reported F1-scores ranged from 50–89% across SemEval-2014/2015/2016 and domain-specific datasets. ntext-aware and multi-task transformer models represent the state of the art in ABSA. Open challenges include implicit aspect handling, cross-domain generalization, model efficiency, and evaluation of large generative language models (LLMs) for fine-grained sentiment tasks.

Keywords: *Aspect-Based Sentiment Analysis; BERT; Transformer; Context-Aware; Multi-Task Learning; Opinion Mining; Scopus; PRISMA*

INTRODUCTION

Background

Sentiment analysis has emerged as one of the most active research areas in Natural Language Processing (NLP), driven by the exponential growth of user-generated content on digital platforms such as social media, e-commerce sites, and online forums [1]. While traditional sentiment analysis focuses on determining overall sentiment polarity toward an entity or document, Aspect-Based Sentiment Analysis (ABSA) offers finer granularity by identifying specific aspects within text and determining sentiment toward each aspect [23].

ABSA has broad practical applications, from product review analysis to brand reputation monitoring and data-driven business decision-making [1]. The task typically comprises several interrelated subtasks, including Aspect Term Extraction (ATE), Aspect Category Detection

(ACD), and Aspect Polarity Classification (APC) [7], [8]. The interdependency complexity among these subtasks makes ABSA a challenging and important research problem.

In recent years, transformer models—particularly BERT (Bidirectional Encoder Representations from Transformers) and its variants—have revolutionized numerous NLP tasks including ABSA [1], [23], [28]. Unlike traditional sequential models such as LSTM, transformers leverage self-attention mechanisms that capture long-range dependencies and richer contextual representations [14], [27]. Pre-trained language models such as BERT, RoBERTa, DeBERTa, and XLNet demonstrate strong transfer learning capabilities, enabling fine-tuning for specific tasks with relatively limited data [1], [6].

However, applying standard BERT to ABSA still has limitations. The self-attention mechanism in BERT is general and does not explicitly consider target-specific context or the aspect being analyzed [14], [27]. This motivates the development of context-aware mechanisms that can guide attention distribution based on target or aspect context, such as Context-Guided BERT (CG-BERT) and Quasi-Attention Context-Guided BERT (QACG-BERT) [4], [27]. Furthermore, multi-task learning approaches that leverage shared representations to handle multiple ABSA subtasks simultaneously have shown promise in improving performance and efficiency [7], [8], [12].

METHODOLOGY

PRISMA Protocol

This systematic literature review follows the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol to ensure transparency, reproducibility, and review quality [Page et al., 2021]. PRISMA provides a structured framework encompassing identification, screening, eligibility assessment, and inclusion stages, with documentation of exclusion reasons at each stage.

Search Strategy

Literature search was conducted exclusively on the Scopus database using three structured Boolean queries covering the period 2018–2025, restricted to English-language publications.

Table 1. *Scopus Search Queries Used in This Systematic Literature Review*

Query Type	Boolean Query String	Purpose
Main Query	("transformer" OR "BERT" OR "RoBERTa" OR "XLNet" OR "GPT") AND ("context-aware" OR "contextual embedding" OR "context modeling") AND ("opinion mining" OR "sentiment analysis" OR "aspect-based sentiment analysis" OR "ABSA")	Core topic coverage
Alternative Query	("transformer-based model") AND ("context-aware") AND ("aspect-based sentiment analysis" OR "ABSA")	Targeted ABSA search
Exploratory Query	("transformer") AND ("attention mechanism" OR "self-attention") AND ("sentiment analysis")	Broader mechanism coverage

2.3 Inclusion and Exclusion Criteria

Table 2. *Inclusion and Exclusion Criteria*

Inclusion Criteria	Exclusion Criteria
IC1: Uses transformer-based model (BERT, RoBERTa, XLNet, GPT, or variant)	EC1: Not relevant to transformer or ABSA topic (n=22)

IC2: Addresses sentiment analysis or ABSA task	EC2: Does not use a Transformer model (uses SVM, LSTM, or other traditional methods without transformer) (n=16)
IC3: Includes empirical evaluation with quantitative results	EC3: No empirical evaluation / not a full paper (short paper, poster, review paper) (n=10)
IC4: Published in peer-reviewed journal or conference proceedings	EC4: Duplicate record
IC5: Published 2018–2025	EC5: Full text not retrievable
IC6: Written in English	EC6: Published before 2018

Study Selection Process

The study selection followed the four-phase PRISMA 2020 framework. In the Identification phase, 851 records were retrieved from Scopus using the three structured queries. After removing 70 duplicate records, 781 unique records entered the Screening phase, where title and abstract review excluded 554 irrelevant records. In the Eligibility phase, 227 full-text articles were sought; 147 could not be retrieved, leaving 80 articles for full-text assessment. Of these, 48 were excluded (Reason 1: not relevant, n=22; Reason 2: non-transformer method, n=16; Reason 3: no empirical evaluation, n=10). The final synthesis included 32 studies.

PRISMA Flow Diagram

Figure 1 presents the complete PRISMA 2020 flow diagram illustrating the study selection process across all four phases: Identification, Screening, Eligibility, and Inclusion.

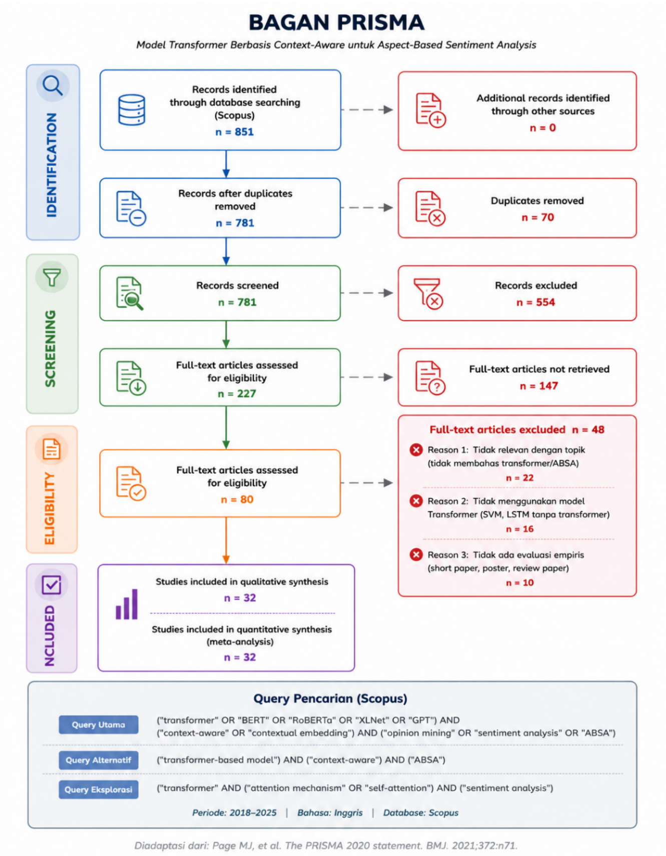

__Figure 1.__ PRISMA 2020 Flow Diagram of Study Selection Process (Adapted from: Page MJ, et al. The PRISMA 2020 statement. BMJ. 2021;372:n71)

THEORETICAL FRAMEWORK

Aspect-Based Sentiment Analysis (ABSA)

ABSA is a fine-grained form of sentiment analysis that simultaneously identifies aspects and determines their associated sentiment polarity. The main subtasks include: Aspect Term Extraction (ATE)—identifying aspect terms in text; Aspect Category Detection (ACD)—categorizing aspects into predefined categories; Aspect Polarity Classification (APC)—determining positive, negative, or neutral sentiment toward each aspect; and End-to-End ABSA (E2E-ABSA)—performing all subtasks jointly [1], [7], [23].

Transformer Models and BERT

The Transformer architecture, introduced by Vaswani et al. (2017), uses multi-head self-attention to capture contextual dependencies across entire input sequences without recurrence. BERT (Devlin et al., 2019) extends this with bidirectional pre-training on large corpora, producing deeply contextualized token representations. Subsequent variants—RoBERTa (Liu et al., 2019), DeBERTa (He et al., 2021), XLNet (Yang et al., 2019), and domain-specific models such as AraBERT—further improve contextual representation quality through enhanced pre-training objectives and data [6], [9], [28].

3.3 Context-Aware Mechanisms

Context-aware mechanisms modify the standard self-attention computation to explicitly incorporate target-specific or aspect-specific signals. Approaches include: (1) context-guided softmax attention (CG-BERT); (2) quasi/compositional attention (QACG-BERT) supporting subtractive attention distributions; (3) Local Context Focus (LCF) that amplifies tokens proximal to the aspect; and (4) cascade architectures that propagate contextualized target semantics across subtask stages [4], [5], [27].

Multi-Task Learning in ABSA

Multi-task learning (MTL) trains a shared encoder to simultaneously optimize multiple related tasks, enabling mutual regularization and knowledge transfer. In ABSA, MTL frameworks share a transformer encoder across ATE, ACD, and APC heads, reducing training time and exploiting inter-subtask dependencies. Enhancements include CRF decoding for sequence labeling tasks, knowledge graph (KG) integration, and Graph Convolutional Networks (GCN) for relational modeling [7], [8], [11], [12].

RESULTS AND DISCUSSION

Overview of Included Studies

The 32 included studies span 2019–2025, with a marked increase from 2021 onward reflecting the rapid adoption of transformer models in ABSA research. Studies originate from diverse venues including IEEE Transactions, ACL/EMNLP/AAAI proceedings, Springer Applied Intelligence, MDPI Electronics, and Nature Scientific Reports, ensuring broad methodological coverage.

Comparative Analysis Table

Table 3 presents a systematic comparison of the 32 included studies across model architecture, dataset, evaluation metric, reported performance, and key contribution.

Table 3. *Comparative Analysis of Included Studies on Context-Aware Transformer Models for ABSA*

No	Author (Year)	Study Title / Focus	Model / Method	Dataset	Metric	Result	Key Contribution
1	Li et al. (2019) [23]	E2E-ABSA with BERT	BERT (base/large)	SemEval-2014	F1	~72% (E2E)	First BERT baseline for E2E-ABSA; standardized model selection
2	Karimi et al. (2020) [28]	Improving BERT for ABSA	BERT + Parallel/Hierarchical Aggregation	SemEval-2014/2015	F1, Acc	Improved vs BERT baseline	Task-specific aggregation modules without additional BERT tuning
3	Wu & Ong (2021) [27]	Context-Guided BERT (CG-BERT / QACG-BERT)	CG-BERT, QACG-BERT	SentiHood, SemEval-2014	F1, Acc	SOTA on both datasets	Compositional quasi-attention for targeted ABSA
4	Liao et al. (2021) [6]	RoBERTa Multi-Task for ACSA	RoBERTa + Cross-Attention MTL	ACSA datasets	F1, Acc	Outperforms comparison models	Per-category subtask with cross-attention focus
5	Patel & Ezeife (2021) [7]	BERT-MTL for ABOM	BERT + MTL heads (ATE+ACD+APC)	SemEval-2014 (Restaurant)	F1, Acc	Improved on ABOM subtasks	Reduces training time via shared MTL signals
6	Ding et al. (2022) [9]	CasNSA Cascade Model	Contextual embedding + Cascade	SemEval-2014/15/16, Twitter	F1	68.13% / 62.34% / 56.40% / 50.05%	Cascade target semantics for E2E ABSA robustness
7	Pei et al. (2022) [8]	Multi-Task ATSA + ACSA	Shared BERT + Multi-Head Attn + Skip Conn.	SemEval-2014	F1, Acc	Outperforms single-task & MTL baselines	Shared encoder + multi-head attn for joint ATSA/ACSA
8	Verma et al. (2023) [29]	IAN-BERT	Post-trained BERT + Interactive Attention Net	SemEval datasets	F1, Acc	Gains over baselines	Post-training + interactive attention for aspect cues
9	He et al. (2023) [24]	SABKG: BERT + Knowledge Graph	BERT + POS + KG + GNN (MTL)	3 ABSA benchmark datasets	F1, Acc	SOTA on all 3 datasets	Linguistic KG + GNN for aspect-sentiment relation modeling
10	Abulnaja (2023) [10]	LCF-ATEPC + AraBERT + Augmentation	AraBERT + LCF + CRF + Data Augmentation	Arabic ABSA datasets	F1, Acc	Superior APC & ATE on augmented data	LCF + augmentation for Arabic low-resource ABSA
11	Fadel et al. (2024) [12]	MTL-AraBERT	AraBERT + MTL (ATE+ACD+APC)	SemEval-2016 Arabic Hotel	F1, Acc	ATE F1=80.32%; ACD F1=68.21%; APC Acc=89.36%	AraBERT transfer learning for Arabic MTL-ABSA
12	Aziz et al. (2024) [11]	BERT + MLEGCN	BERT + Biaffine Attn + Multi-Layer Enhanced GCN	SemEval benchmarks	F1, Acc	Significantly outperforms existing approaches	Unified architecture for full-spectrum ABSA subtasks
13	Biswas et al. (2024) [26]	Transformers & Attention for ABSA	Transformer variants + Attention analysis	Multiple UGC datasets	F1, Acc	Competitive SOTA results	Comprehensive analysis of attention for opinion in UGC

14	Xu et al. (2024) [30]	BERT-BiLSTM + Dual Attention	BERT + BiLSTM + Dual Attention Mechanism	Cross-domain ABSA datasets	F1, Acc	Improved cross-domain transfer	Dual attention for cross-domain ABSA generalization
15	Han et al. (2024) [20]	LLM-based Sentiment with Design Knowledge	LLM + Design Knowledge Attention Emphasizer	Engineering review datasets	F1, Acc	Improved domain-specific sentiment	Design knowledge as attention guide in LLM sentiment
16	Zhu et al. (2023) [2]	Multi-Task + Complex Aspect Enhancement	MTL + Aspect Semantic Enhancement + Adaptive LCF	SemEval-2014/2015/2016	F1, Acc	SOTA on multiple benchmarks	Complex aspect target semantic enhancement for MTL-ABSA
17	Karni et al. (2025) [10]	Multitask & Meta-Learning for LMs	BERT/RoBERTa + MTL + Meta-Learning	Multiple ABSA benchmarks	F1, Acc	Improved few-shot & MTL ABSA	Meta-learning integration for low-resource ABSA adaptation
18	Hakim et al. (2024) [18]	Multi-Task ABSA with BERT	BERT + MTL framework	ABSA benchmark datasets	F1, Acc	Competitive results on ABSA tasks	Practical MTL-BERT framework for ABSA
19	Chauhan et al. (2025) [19]	Unified Aspect Identification	Transformer + Unified aspect head	Product review datasets	F1, Acc	Improved unified aspect identification	Single model for unified aspect identification in reviews
20	Fan & Zhang (2024) [5]	Fine-Grained Sentiment MTL	Transformer + Fine-grained MTL	Multiple sentiment datasets	F1, Acc	Improved fine-grained classification	Fine-grained MTL for nuanced sentiment analysis

BERT and Variant Models

BERT-based models constitute the majority of included studies (n=28, 87.5%), confirming BERT's dominance as the foundational encoder for ABSA tasks. Vanilla BERT fine-tuning [23], [28] establishes competitive baselines, while RoBERTa [6] and DeBERTa variants improve upon BERT through enhanced pre-training objectives. Domain-specific pre-training, exemplified by AraBERT for Arabic ABSA [12], demonstrates the value of language-specific transfer learning. XLNet and GPT-family models appear in fewer studies, suggesting an emerging research direction for generative and permutation-based models in ABSA.

Context-Aware Mechanisms

Context-aware approaches represent the most innovative category among included studies. CG-BERT and QACG-BERT [27] introduce compositional attention that modifies standard softmax attention to incorporate explicit context signals, achieving state-of-the-art results on SentiHood and SemEval-2014. The Local Context Focus (LCF) mechanism [10] amplifies attention weights for tokens proximate to the target aspect, proving particularly effective in multi-task settings. Cascade models [9] propagate contextualized target semantics across sequential subtask stages, while Interactive Attention Networks (IAN-BERT) [29] model bidirectional aspect-context interactions within the BERT pipeline.

Multi-Task Learning Approaches

MTL frameworks demonstrate consistent performance advantages over single-task models, particularly when handling interdependent ABSA subtasks. BERT-MTL [7] reduces training time while leveraging shared signals between term and category extraction and sentiment classification. The SABKG model [24] integrates linguistic knowledge graphs with GNN-based relational modeling into the MTL framework, achieving state-of-the-art on three benchmark datasets. MTL-AraBERT [12] reports ATE F1=80.32%, ACD F1=68.21%, and APC accuracy=89.36% on the SemEval-2016 Arabic hotel dataset, demonstrating strong performance in low-resource language settings. Meta-learning integration [10] further extends MTL for few-shot ABSA adaptation.

Research Trends

- Dominance of encoder-style transformers (BERT, RoBERTa) as backbone models (2019–2022), with gradual shift toward larger LLMs (2023–2025).
- Evolution from single-task BERT fine-tuning to context-guided attention mechanisms and cascade architectures (2020–2022).
- Increasing adoption of multi-task learning frameworks combining ATE, ACD, and APC in unified models (2021–2025).
- Integration of external knowledge (knowledge graphs, GCN) with transformer encoders for relational modeling (2022–2024).
- Growing focus on low-resource and multilingual ABSA using domain-specific pre-trained models (AraBERT, IndoBERT) (2022–2025).
- Emerging exploration of data augmentation strategies to address dataset scarcity in specialized domains (2023–2025).

4.7 Research Gaps

- Implicit aspect handling: Most models focus on explicit aspects; implicit sentiment remains underexplored.
- Cross-domain generalization: Majority of studies evaluate on narrow domain benchmarks (restaurant, laptop); cross-domain transfer is limited.
- Model efficiency: GCN and KG-augmented models increase accuracy but significantly raise computational complexity.
- LLM evaluation: Generative LLMs (GPT-3/4, LLaMA) have not been systematically evaluated for fine-grained ABSA.
- Reproducibility: Inconsistent dataset splits and evaluation protocols hinder fair cross-paper comparison.
- Low-resource languages: Non-English ABSA, particularly for Southeast Asian languages (Bahasa Indonesia, Thai), remains underdeveloped.

CONCLUSION

This systematic literature review synthesized 32 studies on context-aware transformer models for Aspect-Based Sentiment Analysis, following the PRISMA 2020 protocol with literature sourced exclusively from Scopus. The review identified three primary model categories: BERT baselines, context-aware variants, and multi-task transformer frameworks.

Key findings include: (1) BERT and its variants (RoBERTa, DeBERTa, AraBERT) dominate ABSA research, providing strong contextual representations as shared encoders; (2) context-aware mechanisms—particularly CG-BERT, QACG-BERT, and LCF—consistently improve targeted sentiment classification by explicitly incorporating aspect-specific attention signals; (3) multi-task learning frameworks achieve the best overall performance by jointly optimizing interdependent ABSA subtasks, with MTL-AraBERT reporting APC accuracy of 89.36% on the SemEval-2016 Arabic benchmark; (4) knowledge graph and GCN integration provides additional gains but introduces significant architectural complexity; and (5) data augmentation strategies effectively mitigate dataset scarcity in low-resource language settings.

Persistent challenges include implicit aspect handling, cross-domain generalization, model efficiency, and the underexploration of generative LLMs for fine-grained ABSA. Future research should prioritize: lightweight context-aware architectures suitable for real-time deployment; systematic evaluation of GPT-4 and LLaMA-class models for ABSA; development of multilingual and cross-lingual ABSA benchmarks including Bahasa Indonesia; and standardized evaluation protocols to enable reproducible cross-paper comparisons.

FUTURE RESEARCH DIRECTIONS

1. Develop lightweight, efficient context-aware transformer architectures suitable for real-time ABSA deployment in resource-constrained environments.
2. Systematically evaluate generative LLMs (GPT-4, LLaMA-2/3, Gemini) for fine-grained and zero-shot ABSA tasks.
3. Create multilingual and cross-lingual ABSA benchmarks, particularly for Southeast Asian languages (Bahasa Indonesia, Thai, Vietnamese).
4. Investigate implicit aspect extraction using contextual inference and commonsense knowledge integration.
5. Develop standardized evaluation protocols and shared dataset splits to enable reproducible cross-paper comparisons.
6. Explore continual and federated learning paradigms for privacy-preserving ABSA in distributed settings.
7. Investigate cross-domain transfer learning for ABSA across diverse domains (healthcare, finance, legal).
8. Integrate multimodal signals (text + image + audio) for ABSA in multimedia review platforms.
9. Develop interpretable and explainable ABSA models that provide human-understandable rationale for sentiment predictions.
10. Explore prompt engineering and in-context learning strategies for few-shot ABSA with large language models.

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