Societal Transformation: AI and Big Data Journal
Vol: 3(2): 1-32,2025
DOI:10.20547/aibd.253201

ASPECT-BASED SENTIMENT ANALYSIS: TAXONOMY, RECENT TRENDS & FUTURE DIRECTIONS

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Abstract: With the expansion of online platforms, new rooms are opening to extract full insights from huge textual data. Aspect-Based Sentiment Analysis (ABSA) is rising as an essential Artificial Intelligence (AI) discipline that employs Natural Language Processing (NLP) to associate sentiments with specific attributes of entities. In this systematic review, we focused on ABSA studies published between 2020 and 2024, encompassing 66 primary research articles focusing on advancements in AI methodologies, including transformer-based models and generative AI techniques. The novel ABSA taxonomy developed in this study defines methodological categories and analyzes the use of commercial and domain-specific datasets. This research emphasizes the practical need for domain-specific datasets in ABSA. for domain domain-specific dataset for ABSA. It also reveals significant trends, including the growing acceptance of deep learning (DL), machine learning (ML), and LLM-based/ transformer models. This paper also highlights limitations in current research and provides actionable insights for advancing ABSA methodologies, such as encouraging the use of more robust generative models for ABSA tasks and outlining strategies for developing new domain-specific datasets. These contributions can be used as a reliable resource for academicians and researchers for reference in the domain of sentiment analysis.

Keywords: systematic literature review, ABSA task, ABSA datasets, ABSA trends, opinion term extraction, sentiment classification, aspect categorization, sentiment Analysis

Introduction

The explosion of internet avenues such as social platforms, e-commerce websites, blogs, and discussion forums over the past two decades has fundamentally shifted the paradigm of how individuals express opinions and share experiences. Analyzing this content enables businesses to gain valuable

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insights into customer preferences and improve their offerings accordingly [1].

Sentiment analysis is a very important downstream task in natural language processing (NLP) that extracts user's opinions from textual data and classifies them based on their polarity—positive, negative, [2]. Sentiment analysis primarily functions at varied levels of granularity. These levels include document-level analysis, sentence-level analysis, and aspect-level analysis [3] .The former two assume that a single entity or topic is discussed, they underperform in scenarios where opinions about multiple aspects or entities with wavering polarities coexist. Mitigating this drawback, ABSA allow fine grained insights by annotating sentiments with different entities [4].This detailed holds immense significance for unveiling about people preference and there likes or dislikes about specific attributes of a product, service, or event.

This survey systematically reviews ABSA literature, aiming to provide a comprehensive analysis of existing studies. It examines the methodologies, datasets, and most recent trends that influence ABSA research.

The research phase is carried out by searching over a varied number of databases for the years 2020 to 2024, and using a wider variety of search queries. As a result, 66 primary ABSA studies were retrieved. These studies were thoroughly analyzed based on the datasets used and the domains covered. In addition, a new classification taxonomy was proposed for the various techniques applied. These classifications were based on the ABSA task and the adopted approach. In contrast to previous surveys, this taxonomy incorporates the recent advancements in ABSA such as transformer-based and generative models and provides a deeper examination of domain-specific dataset challenges, which earlier reviews did not fully address.
The rest of the paper is organized as follows: The next section provides some background details on aspect-based sentiment analysis. The is followed with the summary of related work in the discipline. Section 4 discusses the methodology used for performing the systematic literature review. Section 5 presents the findings based on the systematic literature review. Section 6 discusses the limitations of primary studies. It also presents the avenues for future research. The paper ends with concluding remarks.

Background

Aspect-based sentiment analysis (ABSA)
Sentiment Analysis has been emerging as a novel domain of NLP. It assists an organization in determining their user's opinion[5]. Sentiment analysis focuses on extracting the people's opinion about a product or service [3] and classifies it into different sub-categories. These categories can be a positive ,negative or neutral. Alternatively, more levels of sentiments can be added [6]

. It is also be noted that sentiment analysis can be applied at three levels. It can be done at document level, sentence level or aspect level, as shown in figure 1.

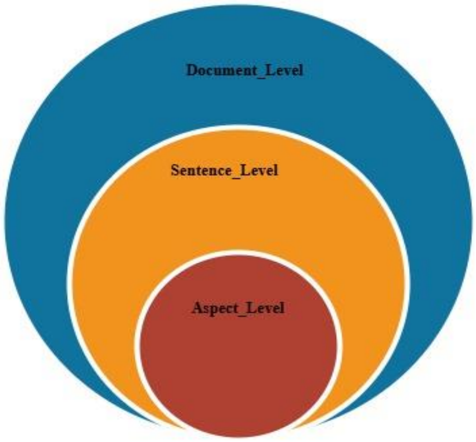

Figure 1: Sentiment Analysis at three levels

The highest level of SA is at document level, where entire document is analyzed and is categorized as belonging to positive or negative sentiment [7].At sentence level ,each sentence is evaluated individually and is categorized having a positive sentiment, neutral or negative sentiment [8]. However, as consumers/ users increasingly express their opinions on specific perspective/ features also called aspects of a item, product, or service instead of holistically doing a trial, the coarser levels often prove insufficient. These approaches fail to identify opinion targets or assign sentiment to specific targets [9] . This limitation has led to the emergence of fine-grained analysis. This type of analysis is performed at the aspect level. It is also termed as feature mining [10] .Aspect based sentiment is a detailed level sentiment analysis [11] where user's opinion about specific aspect of the entity is extracted [12] [13] [14] . ABSA give more useful insights about people's opinion on various aspects /Features.[15].

Aspect-Based Sentiment Analysis: Core elements

[3] discussed four primary elements of Aspect-Based Sentiment Analysis: opinion term [16], aspect category [17] [18] [19] and aspect polarity [20] as depicted in figure 2. The opinion term, or aspect term, refers to a specific term present in the given sentence. The aspect category corresponds to a predefined list of general terms, while aspect polarity indicates the polarity of the opinion/ sentiment related to the sentence.

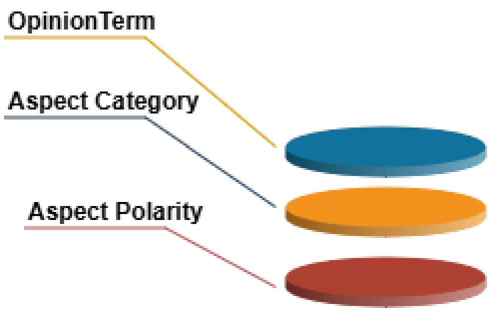

Figure 2: Core Elements of ABSA

Aspect-Based Sentiment Analysis's tasks

ABSA can be categorized as a single task [21] [22] or Multiple Task or Compound Task [23] [24] based on the desired output. For instance, opinion term extraction (OTE), which identifies all opinion terms within a sentence, is a single-task ABSA. Similarly, aspect category detection is another example of single-task ABSA. In contrast, tasks like pair extraction, which aim to identify aspect-opinion pairs [25],fall under multiple-task ABSA.

Figure 3. gives a higher-level outline of different ABSA tasks. The diagram also shows the representative methods for each task.

Table 1: Overview of the related work

Reference	**Objective**	**Review Type**	**Databases**
[26]	Explore the methods, datasets, and cover areas of the study on explicit aspect extraction for several languages.	Review	Science Direct
[27]	Analyze studies that deal with the limitations of the used technique, assessment metrics, covered domains, and implicit and explicit aspect extraction for several languages.	SLR	Science-Direct ,IEEE Xplore, Springer, Scopus, Web of Science,ACM

[15]	An overview of the most current ABSA developments that depicts the cutting-edge deep learning methods developed for target location	Survey	Google scholar,IEEE explore, semantic scholar
[28]	Systemic issues with datasets, research application domains, and solution methodologies.	SLR	Science Direct
[29]	Provides a new taxonomy for ABSA that highlights recent developments in compound ABSA tasks and arranges previous research along the axes of relevant sentiment aspects.	Survey	arXiv
[30]	Proposed a novel taxonomy is proposed that categorizes the ABSC models into three types: knowledge-based, machine learning, and hybrid models.	Survey	ACM
[31]	A thorough examination of Sentiment analysis with a major empshize on ABSA with machine learning and deep learning approaches	Survey	Science Direct

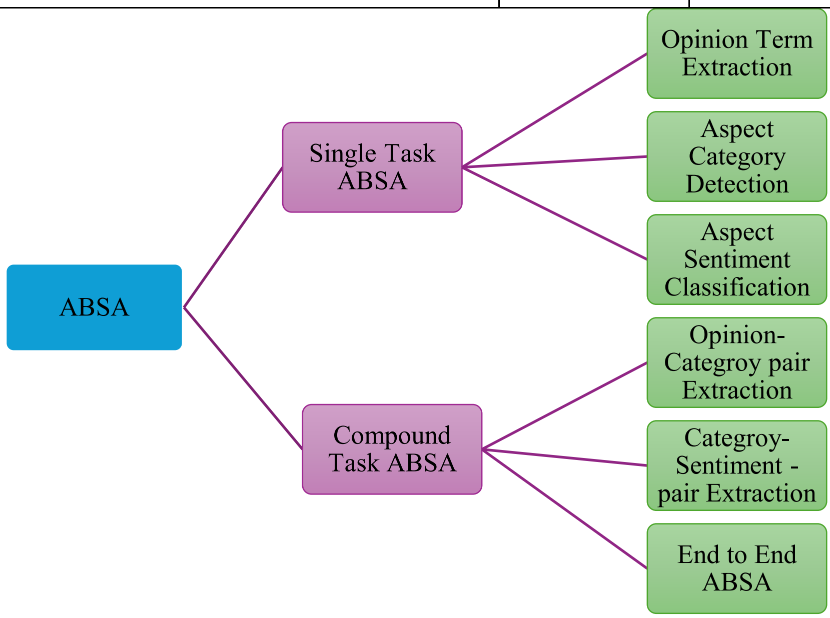

Figure 3: Taxonomy of ABSA Task

Related Work

The summary of the previous review papers is presented in the **Error! Reference source not found.**. These papers highlight various issues related to ABSA, including the techniques employed and the level of granularity considered. From the **Error! Reference source not found.**, it is evident that domain-specific dataset issues are rarely addressed. Additionally, most of the reviews primarily target a specific ABSA task. For instance, the authors in [26] [27] deliberated on aspect extraction.

To fill the gaps in earlier reviews, this research provides a holistic review of the literature on the said topic. The authors systematically analyze the papers searched on a search engine, using terminologies aligning with the domain of ABSA tasks. The keywords holistically cover different publications in the year 2020-2024.

The paper primarily analyzes 66 primary studies on aspect-based sentiment analysis. The next sections deliberate on the topic. It provides a detail account of various studies covering different sub-topics such as covered tasks, datasets, latest techniques and domains.

METHDOLOGY

This study aims to conduct a comprehensive systematic review of Aspect-Based Sentiment Analysis (ABSA), with a focus on its core subtasks and challenges, including the development of domain-specific datasets. The research seeks to uncover emerging trends and patterns within the ABSA field, providing valuable insights for researchers and professionals.

The review process followed the guidelines outlined by [32].The process begins with formulating the research question, followed by the identification of relevant studies in databases. The retrieved papers were then categorized based on inclusion and exclusion criteria. Lastly, studies that met the inclusion criteria were thoroughly reviewed to address the research question, as demonstrated in figure 4.

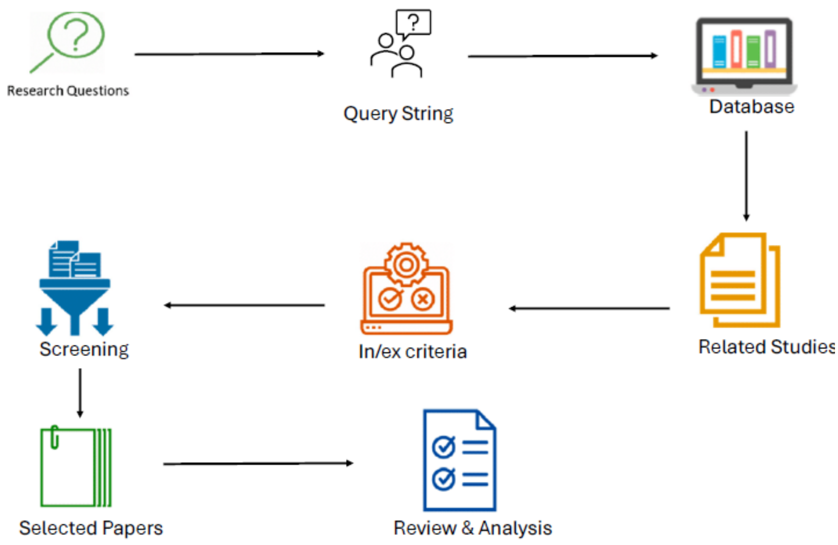

Figure 4: The flow of the search and selection process

Research Questions

We seek to address the research questions given.
RQ1: What proportion of ABSA research focuses on commercial Dataset and what proportion uses the domain specific Dataset? What are the challenges and considerations while constructing the domain specific dataset?
RQ2: What are the most effective ABSA subtasks addressed using the commercial and domain-specific datasets, and how often are these datasets utilized for comprehensive subtasks (combinations versus individual subtasks)?
RQ3: What is the trend of hybrid approaches for ABSA solution? To what extent do linguistic and traditional machine learning methods contribute to ABSA sub-Tasks?
RQ4: What is the trend of adopting Transformers and large language models (LLMs) for ABSA solutions? To what extent do these transformer-based models contribute to ABSA sub-tasks compared to traditional approaches?

Search Strategy and Selection Process Database

In order to carry out thorough research on relevant studies we employed [33] to extract the data citations .we searched 6 major databased Google Scholar and semantic scholar that are very well known to cover all major journals and conference of Computer science .The Details extracted are presented in Table 2.

Aspect based sentiment analysis has been referred to by various terminologies .For instance [11] used the term opinion mining while [3] and [34] employed the term "feature-based sentiment analysis". Similarly various terms are used for aspects like aspect term, opinion tern, target etc ([35] [36] [37] [38].Due to these variation of terms we used the keyword that are more generic and common across ABSA nomenclature. . Consequently, the term we used to construct our search strings are "aspect-based sentiment analysis ," "opinion term," 'aspect category', 'aspect sentiment classification', 'aspect extraction' among others.We used wild card (*) to extract all the words relevant to root word. Additionally, we employed Boolean operator AND OR to extract jointly.

Table 2.Search Setting used with search engines

Data Base Source	Study Count	Meta Data3	Publication Type	Publication Date
Google Scholar	700	ALL	Journals & Conference Papers	2020-2024
Semantic Scholar	225	ALL	Journals & Conference Papers	2020-2024
IEEE	89	ALL	Journals & Conference Papers	2020-2024
Science Direct	53	ALL	Journals & Conference Papers	2020-2024
ACM	18	ALL	Journals & Confernce Papers	2020-2024
Springer Link	15	ALL	Journals & Conference Papers	2020-2024

[3] Meta Data included Title, Abstract, Publication Year, URL, DOI,# of cities, Type of publications etc

Inclusion and exclusion

Table 3: Inclusion & Exclusion Criteria

Inclusion Criteria
The study must focus on any aspect of ABSA (Aspect-Based Sentiment Analysis), including its subtasks, datasets, or technologies. **The study must be published between 2020 and 2024.** **The study must be published in a peer-reviewed journal or conference proceedings.** **The study must be written in English.**
Exclusion Criteria
Studies not published in English. **Studies that are not survey papers or grey literature (e.g., non-peer-reviewed articles, technical reports, etc.).**

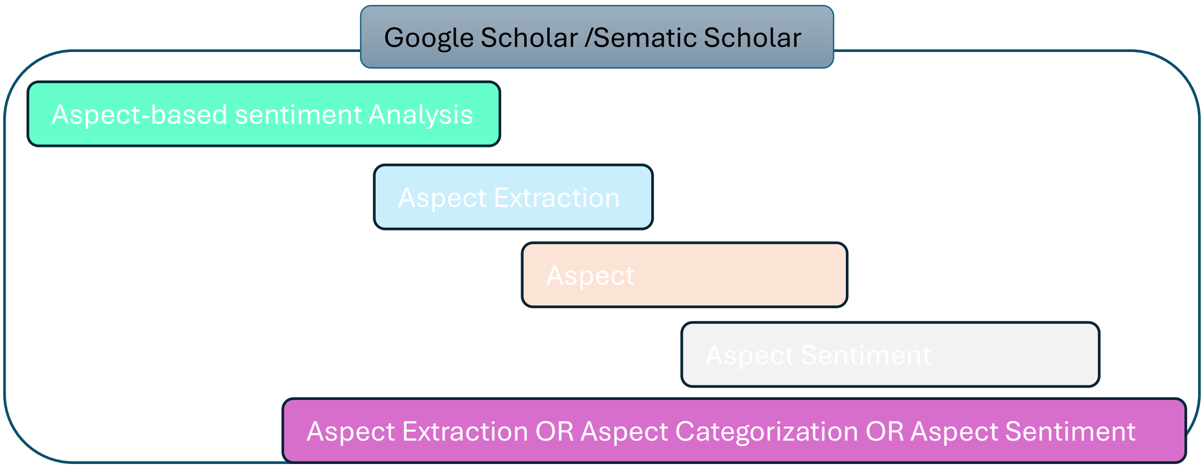

Figure 6: Query String used for searching across search engines

Quality Assessment Control

Once the duplicates are removed and the inclusion exclusion criteria are applied, a quality assessment was carried out to ensure the methodological reliability of the selected studies. This helps to verify that all papers included in the final synthesis met a minimum standard of research quality, transparency, and reproducibility.

Each study was assessed using five quality criteria adapted from [32] Table 4 summarizes the assessment framework applied in this review while few examples are added as appendix in Table 5.

Table 4:Quality Assessment Criteria

Criterion	Description	Assessment Scale
Relevance to Research Question	The study directly addresses at least one ABSA subtask such as Opinion Term Extraction (OTE), Aspect Category Detection (ACD), or Aspect Sentiment Classification (ASC).	Yes / Partial / No
Methodological soundness	The paper clearly explains its approach, algorithms, experimental setup, and evaluation strategy.	Yes / Partial / No
Data Set Transparency	The dataset used is explicitly stated, with details on domain, size, and source.	Yes / Partial / No
Result Completeness	The study provides sufficient quantitative results, including performance metrics and baselines for comparison.	Yes / Partial / No
Reproducibility	The methodology or resources (e.g., code, dataset, or workflow) are	Yes / Partial / No

	publicly available or described in detail for replication.	

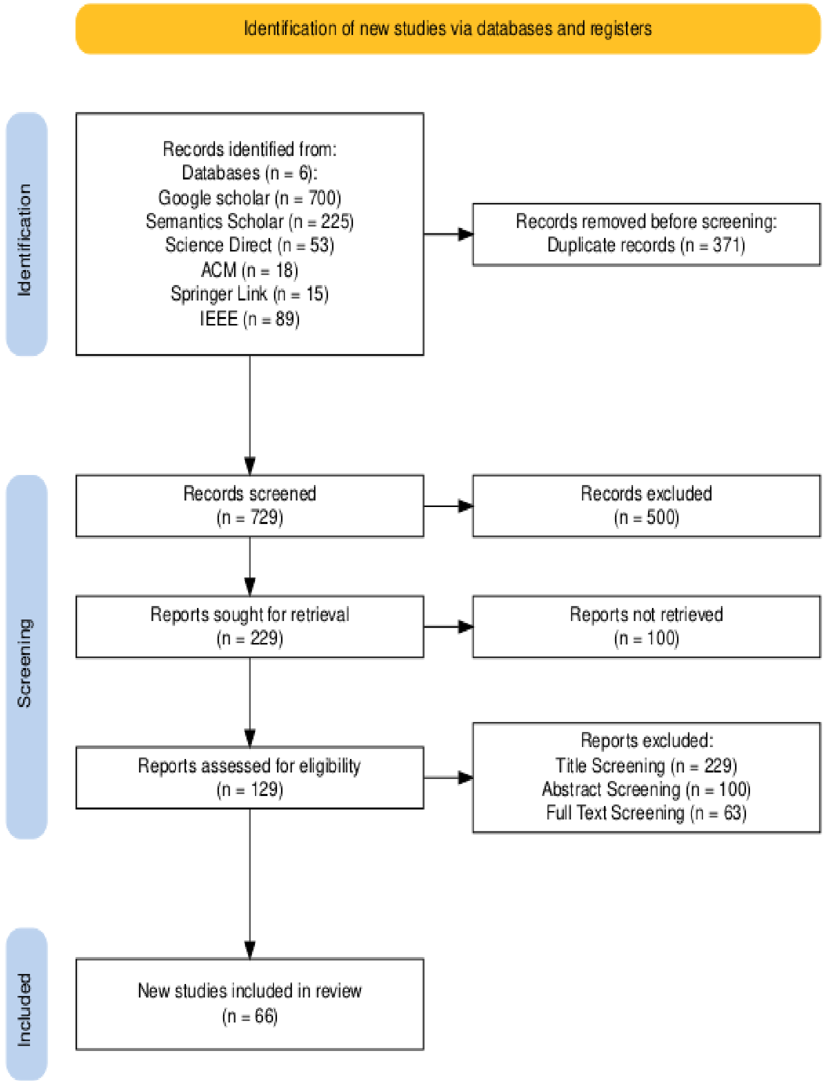

Figure 7: Prisma flow of the complete search and screening process

Table 5: Example of Quality Assessment Scoring for Selected Studies

Paper Reference	Methodological Soundness	Dataset Transparency	Result Completeness	Reproducibility
[39]	Yes	Yes	Yes	Yes
[40]	Yes	Yes	Yes	NO
[41]	Yes	Yes	Partial	No
[42]	Yes	Yes	Yes	Yes
[43]	Yes	Yes	Partial	NO

RESULT & DISCUSSION

This section highlights the findings of the systematic literature review (SLR), beginning with a summary of the primary studies selected for inclusion. It then delves into a detailed analysis of the extracted data, aiming to address predefined research questions.

Overview of included studies

After completing the selection process, we identified 66 studies.Figure 8 illustrates the distribution of the included primary studies by publication year, with over 62% of the papers published in 2023 and 2024. **Error! Reference s ource not found.** highlights the distribution of studies by publisher while **Error! Reference source not found.** shows the classification of the primary s tudies by publication format, categorizing them into three groups: conference papers, journal articles, and preprints (arXiv).

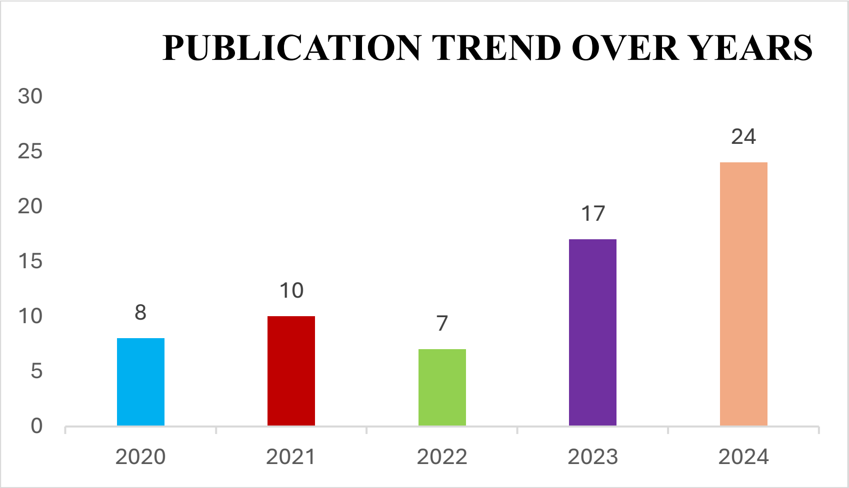

Figure 8: Publication Trend over Time

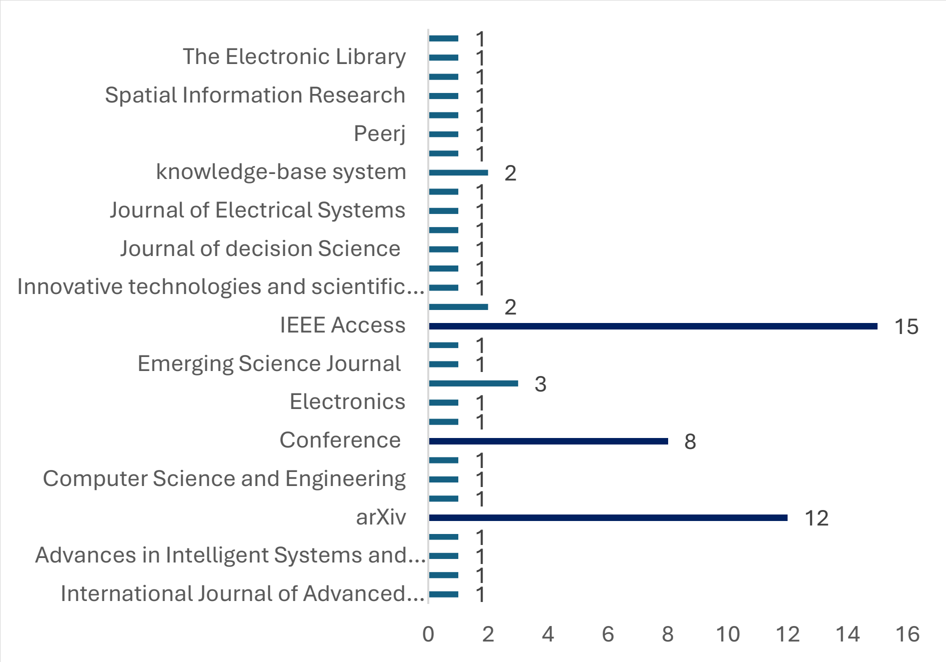

Figure 9: Distribution of ABSA studies by publisher

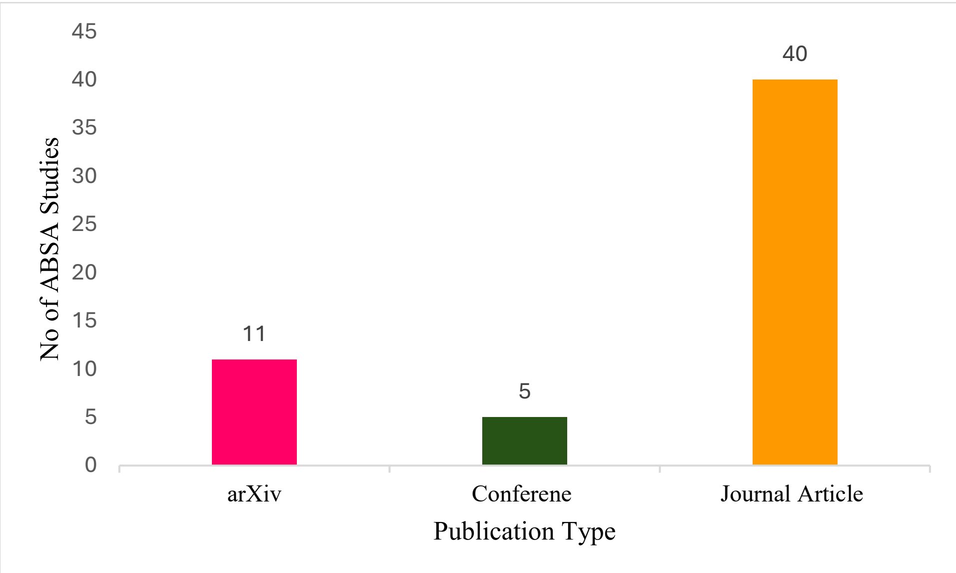

Figure 10: Distribution of ABSA Studies by publication type.

RQ1: What proportion of ABSA research focuses on domain-specific datasets? What are the challenges and considerations while constructing the domain-specific dataset?

To answer RQ1, we examined the distribution of reviewed studies by their dataset domains. From the 70 reviewed studies, we recorded 14 data sets domain categories.

Our results answer RQ1 by showing that:

1). The majority (61 %) of the reviewed studies targeted commercial domain as shown in Table 6 (42 % product, 10 % Hotel, 10% Restaurant). At this point we also examined that out of these 61% approximately 26 % studies used Samvel bench mark datasets
2). The domain-specific data sets were rare (39%) and miscellaneous, shown in Table 6. Out of these studies only two studies discussed the issue while constructing the domain specific dataset. The rest of studies doesn't specify the Datasets. Key results are presented in Table 7.

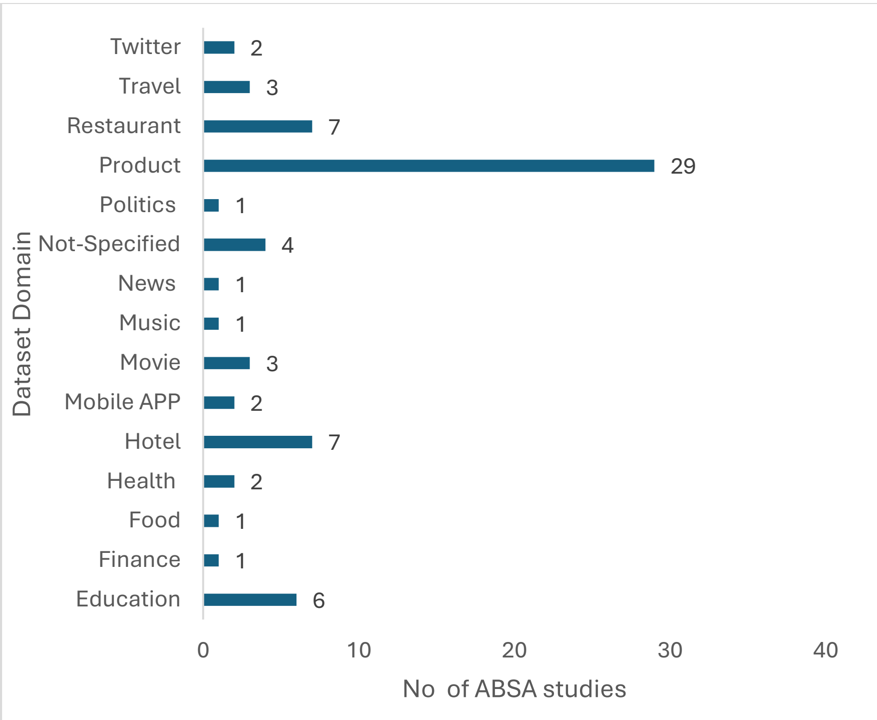

Figure 11: Domain-Wise Distribution of ABSA Studies

Table 6: Number of ABSA studies per dataset domain category

Dataset Domain	No of studies
Hotel	1
Education	6
Finance	1
Food	1
Health	2
Hotel	6
Mobile APP	2
Movie	3
Music	1
News	1
Not-Specified	4
Politics	1
Product	29
Restaurant	7
Travel	3
Twitter	2

RQ2: What are the most effective ABSA subtasks addressed using the commercial and domain-specific datasets, and how often are these datasets utilized for comprehensive subtasks (combinations versus individual subtasks)?

For RQ2, the first step involved examining the studies for three main ABSA task ‘ OTE’(opinion term extraction),ACD (Aspect Category detection) and ASC(Aspect Sentiment Classification) subtasks .As depicted in Figure12 ,OTE is most covered task ,with 67.8% of studies covering it followed by ASC at 36.9% .

In the second step, we analyzed 13 combinations of subtasks across the reviewed studies. As illustrated in Figure 13, approximately 41% of the studies focused on single-task ABSA, while 59% explored a combination of ABSA subtasks. Table **7** and .

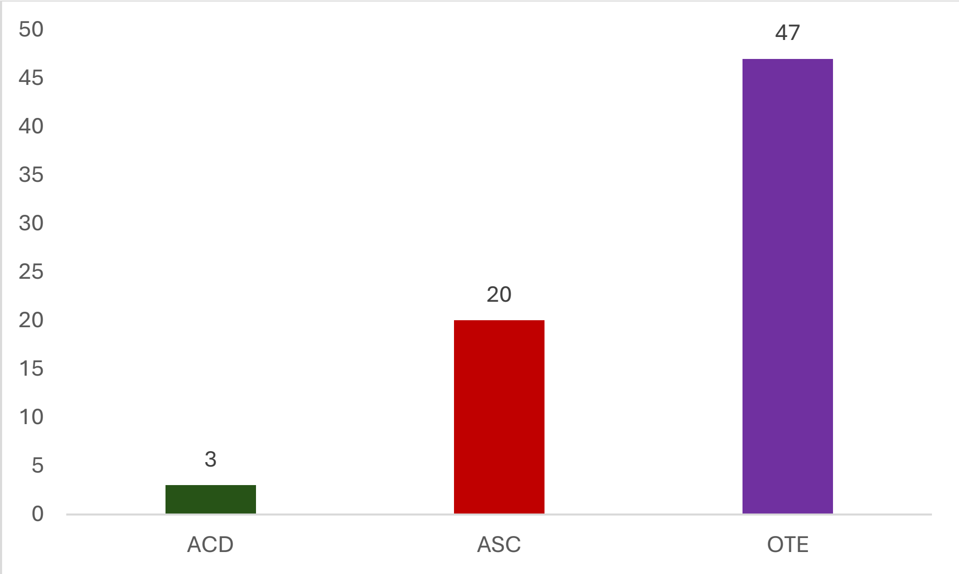

Figure 12: Number of Arabic ABSA studies that covered each ABSA task

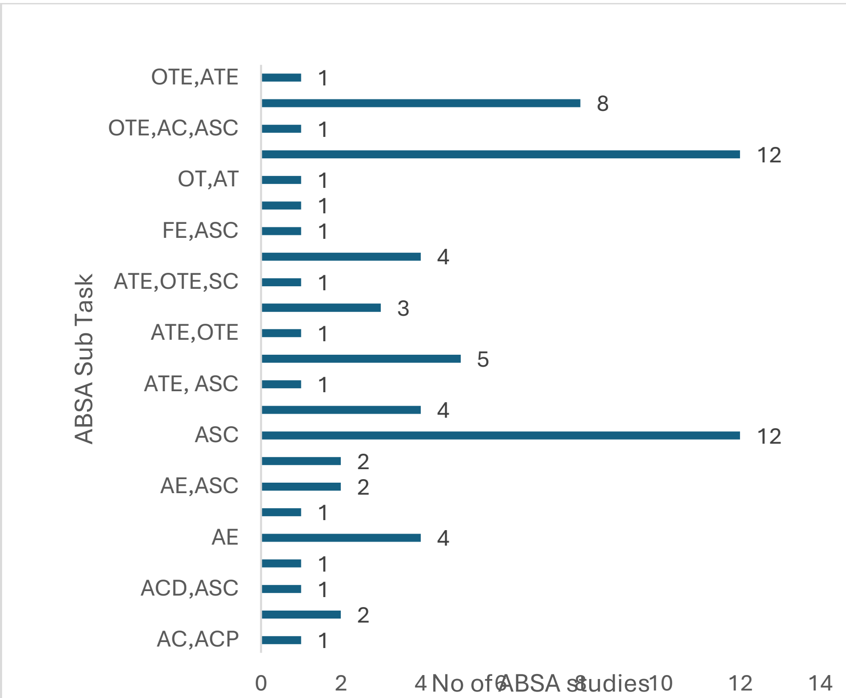

Figure 13: Number of studies on aspect based sentiment analysis in Arabic covering various ABSA subtask

Table 7:No of studies per ABSA Task

Paper Name	Domain	Dataset	Data Set Size	ABSA SubTask
[44]	Politics	Twitter dataset	NA	AE
[45]	Product	SemEval Datasets	2,000 sentences	SC
[46]	Restaurant	Semeval Datasets	1,818 sentences	SC
[47]	Hotel	Semeval Datasets	1,818 sentences	AE
[48]	Food	fine foods dataset	f 27,470 sentence-level quadruples	OATS
[48]	Education	Coursera course	17,092 review-level tuples	OATS
[49]	Not-Specified	Limited labeled dataset	NA	NA
[50]	Product	Semeval Datasets	3,045 sentences	AE
[51]	Movie	Twitter dataset	NA	ASC
[51]	Product	Product reviews dataset		ASC
[51]	Hotel	TripAdvisor dataset	2000 reviews	ASC
[52]	News	Humanly annotated dataset in economic and financial domains.	1400 sentences	ASC
[53]	Education	Student Feed back	10000 sentence	AE
[42]	Movie	IMDB Movie Dataset	3000 movie reviewes	AE
[20]	Product	Mobile review	NA	OTE
[54]	Restaurant	SemEval restaurant 2014 dataset	3,044 sentences	OTE
[54]	Product	SemEval restaurant 2014 dataset	3,044 sentences	ASC
[41]	Mobile APP	Domain specific government smart apps dataset	7000 mobile app reviews	ASC

[55]	Product	headphones and earphones Dataset	NA	OTE
[56]	Product	Semeval	3,045 sentences	OTE
[57]	Twitter	Social text	NA	ASC
[58]	Product	Pontiki dataset	3,045	OTE
[59]	Product	Semeval	3,045 sentences	ASC
[40]	Travel	Google Maps reviews.	16170 sentence	OTE
[60]	Hotel	Online Hotel and Product reviews		ASC
[61]	Product	Product customer reviews (crawled data)	NA	OTE
[62]	Product	Product reviews.	2226 tweets	ASC
[43]	Education	student comments about teachers.	2 million	ASC
[62]	Music	Free Kaggle Dataset	18,000 Spotify songs	AT
[63]	Restaurant	Semeval 2014	3,044 sentences	ASC
[64]	Not-Specified	NA	NA	AC
[65]	Product	website data set	NA	FE
[66]	Product	Semeval	3,044 sentences	ATSC
[39]	Restaurant	SemEval-2014 restaurant	3,844 reviews	AT
[67]	Product	SemEval14 benchmark dataset.	3,844 reviews	ACSP
[68]	Product	Six new datasets from five distinct domains.	2000 reviews	OAP
[68]	Education	Six new datasets from five distinct domains.	2000 reviews	OAP

[68]	Hotel	Six new datasets from five distinct domains.	2000 reviews	OAP
[69]	Product	Website Dataset	2,449 beauty Produc treviews	ATE
[70]	Hotel	Polish language dataset	4200 Document	ATE
[71]	Travel	TripAdvisor reviews	21390	KE
[72]	Product	SemEval	3,045 sentences	SP
[73]	Finance	SentiFin	10,753 news	SP
[74]	Twitter	Twitter dataset ProductDataset	8040 messages	FE
[73]	Product	Twitter dataset ProductDataset	8040 messages	FE

Table 8: No of studies per Compound Task of ABSA

Paper Name	Domain	Dataset	Data Set Size	ABSA SubTask
[75]	Education	Real World Data (Student Review Dataset)	105k reviews from Coursera MOOCs. 5989 students' feedback from traditional classroom settings.	AC,ACP
[76]	Product	SemEval	3,045	ATE,OTE,SC
[77]	Health	Covid vaccinations dataset Sentiment on Twitter dataset	NA	AE,SC
[78]	Product	Car reviews from Car Dekho		AE,SC
[79]	Restaurant	Yelp restaurant reviews for sentiment analysis. SemEval-2014 dataset for aspect extraction evaluation.	610,000 reviews, 3,041 English sentences	SA,AE
[80]	Movie	Movie reviews Sentihood data-sets	NA	AE,AC
[81]	Health	Covid 19 Tweets	2000	AT,SC
[82]	Product	Semeval	3,045	AC,ACP
[83]	Product	Consumer reviews from eBay	200 pre-processed shampoo reviews	OE,AE,OP
[84]	Hotel	reviews from booking.com	12,396 customer reviews from booking.com	AT,SP
[85]	Restaurant	SemEval datasets for ABSA subtasks.	1,315	ATE, ATSC
[86]	Product	Semeval	3,045	OT,AT
[84]	Hotel	online customer reviews	12,396 customer reviews	AE,SC
[87]	Mobile APP	App review	40000 review	OTE,AC,SC

RQ3: What is the trend of solo and hybrid approaches for ABSA solution? To what extent do linguistic and traditional machine learning methods contribute to ABSA sub-Tasks?

To examine the RQ3, we noticed that researchers used various approaches to perform ABSA task i.e. OTE, ACD and ASC. These approaches include frequency-based, rule-based, lexicon-based, machine learning, and a hybrid of different approaches as presented in Figure 14. In Addition, we classified machine learning techniques as traditional machine learning and deep learning. It is important to note deep learning itself refers to a subset of machine learning techniques that leverage artificial neural networks with multiple hidden layers[88].

ML Approaches

Around 32% of studies used traditional machine learning for OTE and 22% for ACD as shown in Figure 15 and Figure 16. Majority used Support Vector Machine (SVM; 10.14%) Other includes Decision Tree (DT 3.45%), Latent Dirichlet allocation (LDA; 1.72%), Logistic Regression (LR1.45%), Naïve Bayes (NB, 1.45) and KNN: 1.45%
Linguistic and statistical approaches

Researcher also used linguistic approaches for OTE, ACD and ASC. Figure 15 shows 25% of studies used the linguistic approaches to extract the opinion terms. 15 % out of 21 studies followed a rule based approach to extract opinion terms. In, 4% used lexicon based approaches, 4% used ontology based while 2% used frequency based. Figure 16 depicts that 22% of studies followed rule-based approach for category detection. Similarly, Figure 17 emphasize that for ASC task 13% studied utilized lexicon-based method while 7% followed rule-based approach.

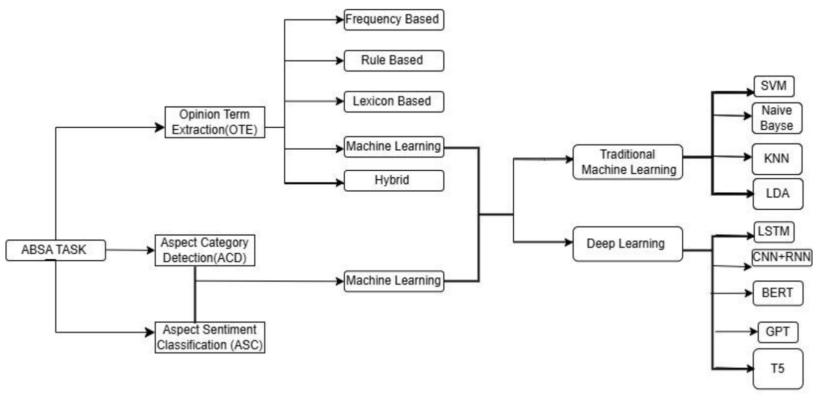

Figure 14: Taxonomy of ABSA Tasks with followed approach

DL Approaches

Approximately 17% of studies utilized deep learning models for opinion term extraction, 56% employed deep learning for aspect category detection, and 20% of studies reported improvement. As shown in Figure 18, 7 out 22 studies used Bidirectional LSTM, 6 used CNN, and 5 used LSTM while 4 % studies used LSTM with RNN.Additionaly 3 7% studies employed Transformer including BERT and Roberta. We have also discussed the relevant studies using the generative models for the ABSA task. Although the result suggests that this is a new domain which ABSA research community is exploring .17 % used Generative model like BART, T5 and ChatGPT for OTE while 33% used these for ASC as shown in Figure 19..

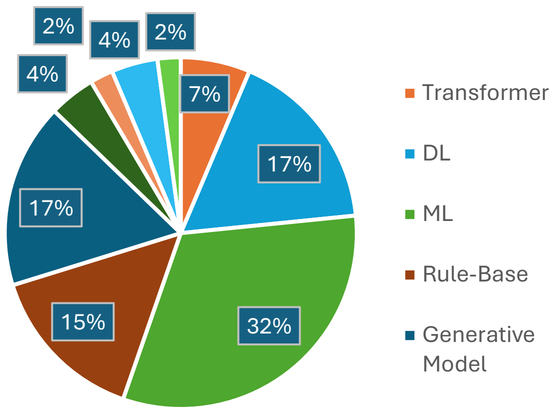

Figure 15: Distribution of various approaches employing ABSA for OTE

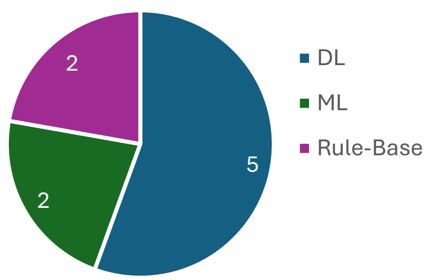

Figure 16: Distribution of various approaches employing ABSA for ACD

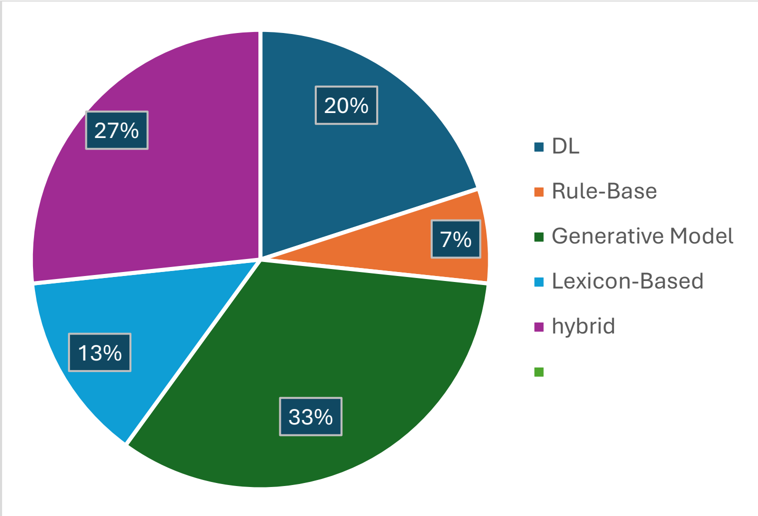

Figure 17: Distribution of employed approaches by ABS A studies for ASC

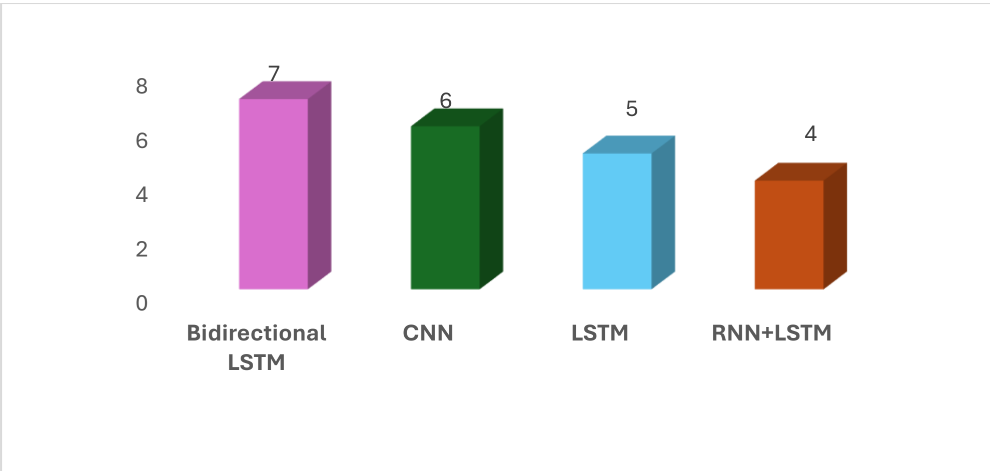

Figure 18: Commonly used deep learning techniques for OTE

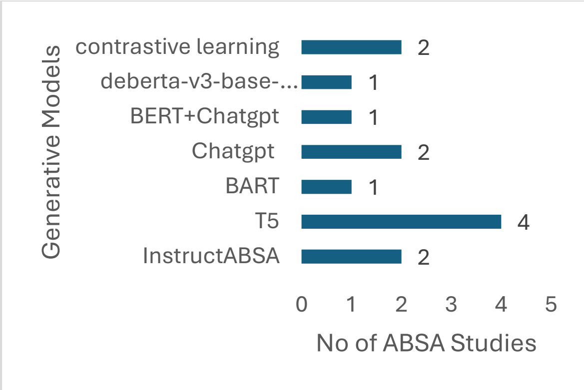

Figure 19: Commonly used Generative Models for ABSA task

Limitation

Despite doing a comprehensive study on aspect-based sentiment analysis, there are various limitations associated with the study. Firstly, the systematic literature review was focused on those studies that were published from 2020 to 2024. So, if future studies are done on new research papers, it can change the analysis and conclusions presented in this study. Secondly, the systematic review results are very sensitive to keywords employed for searching papers, as well as the database considered during searching. Specifically, at the time screening based on title, the research process is based on the search key terms used and filtering is based on the title.
This may result in inclusion or exclusion of certain studies. To cater this to some extent, the authors manually examined the bibliographic portion of the included studies and the referred review articles. Lastly, the study only considered works that are published in English and therefore not considering those relevant studies that have been published in other languages. It is also worth mentioning that the missing values in the considered studies may slightly introduce bias into the analysis and the interpretation/ conclusion of the results may slightly vary based on the context.

Conclusion

This research has provided a systematic review of ABSA literature that has ben published between 2020 and 2024. Overall, 70 studies were considered that are extracted from various databases. These databases include Google scholar and semantic scholar with ensuring that these papers address various ABSA tasks. A thorough analysis was done using a systematic process applied to the extracted studies. The research phase considers multiple factors that affect performance on aspect-based sentiment analysis. These factors include datasets, domains and miscellaneous approaches. In addition, the issues and limitations applied on the present study is also discussed. On the basis of these limitations, new research avenues were also recommended. This research provides ample information on existing approaches and resources for Arabic ABSA. This helps relevant researchers to contribute further to this field.

References

[1] S. Hudson and K. Thal, "The Impact of Social Media on the Consumer Decision Process: Implications for Tourism Marketing," J. Travel Tour. Mark., vol. 30, no. 1–2, pp. 156–160, Jan. 2013, doi: 10.1080/10548408.2013.751276.

[2] J. Jabbar, I. Urooj, W. JunSheng, and N. Azeem, "Real-time Sentiment Analysis On E-Commerce Application," in 2019 IEEE 16th International Conference on Networking, Sensing and Control (ICNSC), Banff, AB, Canada: IEEE, May 2019, pp. 391–396. doi: 10.1109/ICNSC.2019.8743331.

[3] B. Liu, Sentiment Analysis and Opinion Mining. in Synthesis Lectures on Human Language Technologies. Cham: Springer International Publishing, 2012. doi: 10.1007/978-3-031-02145-9.

[4] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androutsopoulos, and S. Manandhar, "SemEval-2014 Task 4: Aspect Based Sentiment Analysis," in Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), Dublin, Ireland: Association for Computational Linguistics, 2014, pp. 27–35. doi: 10.3115/v1/S14-2004.

[5] M. Wankhade, A. C. S. Rao, and C. Kulkarni, "A survey on sentiment analysis methods, applications, and challenges," Artif. Intell. Rev., vol. 55, no. 7, pp. 5731–5780, Oct. 2022, doi: 10.1007/s10462-022-10144-1.

[6] M. Tubishat, N. Idris, and M. A. M. Abushariah, "Implicit aspect extraction in sentiment analysis: Review, taxonomy, oppportunities, and open challenges," Inf. Process. Manag., vol. 54, no. 4, pp. 545–563, Jul. 2018, doi: 10.1016/j.ipm.2018.03.008.

[7] S. Hamed, M. Ezzat, and H. Hefny, "A Review of Sentiment Analysis Techniques," Int. J. Comput. Appl., vol. 176, no. 37, pp. 20–24, Jul. 2020, doi: 10.5120/ijca2020920480.

[8] W. Zhang, Y. Deng, B. Liu, S. J. Pan, and L. Bing, "Sentiment Analysis in the Era of Large Language Models: A Reality Check," May 24, 2023, arXiv: arXiv:2305.15005. Accessed: Sep. 27, 2024. [Online]. Available: http://arxiv.org/abs/2305.15005

[9] V. Ganganwar and R. Rajalakshmi, "Implicit Aspect Extraction for Sentiment Analysis: A Survey of Recent Approaches," Procedia Comput. Sci., vol. 165, pp. 485–491, 2019, doi: 10.1016/j.procs.2020.01.010.

[10] B. Liu and L. Zhang, "A Survey of Opinion Mining and Sentiment Analysis," in Mining Text Data, C. C. Aggarwal and C. Zhai, Eds., Boston, MA: Springer US, 2012, pp. 415–463. doi: 10.1007/978-1-4614-3223-4_13.

[11] M. Hu and B. Liu, "Mining and summarizing customer reviews," in Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, Seattle WA USA: ACM, Aug. 2004, pp. 168–177. doi: 10.1145/1014052.1014073.
[12] S. Poria, N. Ofek, A. Gelbukh, A. Hussain, and L. Rokach, "Dependency Tree-Based Rules for Concept-Level Aspect-Based Sentiment Analysis," in Semantic Web Evaluation Challenge, vol. 475, V. Presutti, M. Stankovic, E. Cambria, I. Cantador, A. Di Iorio, T. Di Noia, C. Lange, D. Reforgiato Recupero, and A. Tordai, Eds., in Communications in Computer and Information Science, vol. 475. , Cham: Springer International Publishing, 2014, pp. 41–47. doi: 10.1007/978-3-319-12024-9_5.
[13] K. W. Trisna and H. J. Jie, "Deep Learning Approach for Aspect-Based Sentiment Classification: A Comparative Review," Appl. Artif. Intell., vol. 36, no. 1, p. 2014186, Dec. 2022, doi: 10.1080/08839514.2021.2014186.
[14] G. Brauwers and F. Frasincar, "A Survey on Aspect-Based Sentiment Classification," ACM Comput. Surv., vol. 55, no. 4, pp. 1–37, Apr. 2023, doi: 10.1145/3503044.
[15] A. Nazir, Y. Rao, L. Wu, and L. Sun, "Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey," IEEE Trans. Affect. Comput., vol. 13, no. 2, pp. 845–863, Apr. 2022, doi: 10.1109/TAFFC.2020.2970399.
[16] C. Ojha, M. Venugopalan, and D. Gupta, "A rule based approach for aspect extraction in hindi reviews," J. Intell. Fuzzy Syst., vol. 41, no. 5, pp. 5477–5485, Nov. 2021, doi: 10.3233/JIFS-189869.
[17] T. G. Md. Shad Akhtar Asif Ekbal, "Multi-task learning for aspect term extraction and aspect sentiment classification," vol. 398, 2020, doi: 10.1016/j.neucom.2020.02.093.
[18] N. I. JZ Maitama A. Abdi…, "Aspect extraction in sentiment analysis based on emotional affect using supervised approach," 2021.
[19] L. Luo et al., "Unsupervised Neural Aspect Extraction with Sememes," in Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, Macao, China: International Joint Conferences on Artificial Intelligence Organization, Aug. 2019, pp. 5123–5129. doi: 10.24963/ijcai.2019/712.
[20] Y. M. GS Chauhan, "Domsent: Domain-specific aspect term extraction in aspect-based sentiment analysis," 2020, doi: 10.1007/978-981-13-8406-6_11.
[21] Y. Li, C. Wang, Y. Lin, Y. Lin, and L. Chang, "Span-based relational graph transformer network for aspect–opinion pair extraction," Knowl. Inf. Syst., vol. 64, no. 5, pp. 1305–1322, May 2022, doi: 10.1007/s10115-022-01675-8.
[22] H. Huan, Z. He, Y. Xie, and Z. Guo, "A Multi-Task Dual-Encoder Framework for Aspect Sentiment Triplet Extraction," IEEE Access, vol. 10, pp. 103187–103199, 2022, doi: 10.1109/ACCESS.2022.3210180.
[23] S. Chen, J. Liu, Y. Wang, W. Zhang, and Z. Chi, "Synchronous Double-channel Recurrent Network for Aspect-Opinion Pair Extraction," in

Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Online: Association for Computational Linguistics, 2020, pp. 6515–6524. doi: 10.18653/v1/2020.acl-main.582.
[24] H. Zhao, L. Huang, R. Zhang, Q. Lu, and H. Xue, “SpanMlt: A Span-based Multi-Task Learning Framework for Pair-wise Aspect and Opinion Terms Extraction,” in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Online: Association for Computational Linguistics, 2020, pp. 3239–3248. doi: 10.18653/v1/2020.acl-main.296.
[25] S. Li, Y. Zhang, Y. Lan, H. Zhao, and G. Zhao, “From Implicit to Explicit: A Simple Generative Method for Aspect-Category-Opinion-Sentiment Quadruple Extraction,” in 2023 International Joint Conference on Neural Networks (IJCNN), Gold Coast, Australia: IEEE, Jun. 2023, pp. 1–8. doi: 10.1109/IJCNN54540.2023.10191098.
[26] B. Dalila, A. Mohamed, and H. Bendjanna, “A review of recent aspect extraction techniques for opinion mining systems,” in 2018 2nd International Conference on Natural Language and Speech Processing (ICNLSP), Algiers: IEEE, Apr. 2018, pp. 1–6. doi: 10.1109/ICNLSP.2018.8374382.
[27] J. Z. Maitama, N. Idris, A. Abdi, L. Shuib, and R. Fauzi, “A Systematic Review on Implicit and Explicit Aspect Extraction in Sentiment Analysis,” IEEE Access, vol. 8, pp. 194166–194191, 2020, doi: 10.1109/ACCESS.2020.3031217.
[28] Y. C. Hua, P. Denny, J. Wicker, and K. Taskova, “A systematic review of aspect-based sentiment analysis: domains, methods, and trends,” Artif. Intell. Rev., vol. 57, no. 11, p. 296, Sep. 2024, doi: 10.1007/s10462-024-10906-z.
[29] W. Zhang, X. Li, Y. Deng, L. Bing, and W. Lam, “A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges,” 2022, doi: 10.48550/ARXIV.2203.01054.
[30] G. Brauwers and F. Frasincar, “A Survey on Aspect-Based Sentiment Classification,” ACM Comput. Surv., vol. 55, no. 4, pp. 1–37, Apr. 2023, doi: 10.1145/3503044.
[31] D. Kumar, A. Gupta, V. K. Gupta, and A. Gupta, “Aspect-Based Sentiment Analysis using Machine Learning and Deep Learning Approaches,” Int. J. Recent Innov. Trends Comput. Commun., vol. 11, no. 5s, pp. 118–138, May 2023, doi: 10.17762/ijritcc.v11i5s.6636.
[32] B. Kitchenham, O. Pearl Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman, “Systematic literature reviews in software engineering – A systematic literature review,” Inf. Softw. Technol., vol. 51, no. 1, pp. 7–15, Jan. 2009, doi: 10.1016/j.infsof.2008.09.009.
[33] A.-W. Harzing -, “Publish or Perish,” Harzing.com. Accessed: Nov. 27, 2024. [Online]. Available: https://harzing.com/resources/publish-or-perish
[34] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androutsopoulos, and S. Manandhar, “SemEval-2014 Task 4: Aspect Based

Sentiment Analysis," in Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), Dublin, Ireland: Association for Computational Linguistics, 2014, pp. 27–35. doi: 10.3115/v1/S14-2004.
[35] S. Poria, E. Cambria, L.-W. Ku, C. Gui, and A. Gelbukh, "A Rule-Based Approach to Aspect Extraction from Product Reviews," in Proceedings of the Second Workshop on Natural Language Processing for Social Media (SocialNLP), Dublin, Ireland: Association for Computational Linguistics and Dublin City University, 2014, pp. 28–37. doi: 10.3115/v1/W14-5905.
[36] I. M. A Ndoni M. Street, "Aspect Detection Enhancement for Aspect Based Sentiment Analysis," 2021.
[37] H. Cai, R. Xia, and J. Yu, "Aspect-Category-Opinion-Sentiment Quadruple Extraction with Implicit Aspects and Opinions," in Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), Online: Association for Computational Linguistics, 2021, pp. 340–350. doi: 10.18653/v1/2021.acl-long.29.
[38] R. Agerri and G. Rigau, "Language Independent Sequence Labelling for Opinion Target Extraction," Artif. Intell., vol. 268, pp. 85–95, Mar. 2019, doi: 10.1016/j.artint.2018.12.002.
[39] M. M. Azman Busst, K. S. M. Anbananthen, S. Kannan, and R. Kannan, "Extracting Explicit and Implicit Aspects Using Deep Learning," Emerg. Sci. J., vol. 8, no. 1, pp. 61–76, Feb. 2024, doi: 10.28991/ESJ-2024-08-01-05.
[40] M. S. M. Alaydaa, J. Li, and K. Jinkins, "Aspect based sentimental analysis for travellers' reviews," Aug. 01, 2023, arXiv: arXiv:2308.02548. doi: 10.48550/arXiv.2308.02548.
[41] O. Alqaryouti, N. Siyam, A. Abdel Monem, and K. Shaalan, "Aspect-based sentiment analysis using smart government review data," Appl. Comput. Inform., vol. 20, no. 1/2, pp. 142–161, Jan. 2024, doi: 10.1016/j.aci.2019.11.003.
[42] P. S. I AnetteRegina, "An Approach To Aspect-Based Sentiment Analysis Of Movie Reviews Using Supervised Machine Learning," 2024.
[43] N. N. A Bhowmik, "Evaluating Teachers' Performance through Aspect-Based Sentiment Analysis," 2024.
[44] K. K. K Ananthajothi R. Prabha, "Explicit and implicit oriented Aspect-Based Sentiment Analysis with optimal feature selection and deep learning for demonetization in India," 2022.
[45] Q. C. Y Wang J. Shen, B. Hou, M. Ahmed…, "Aspect-level sentiment analysis based on gradual machine learning," 2021.
[46] A. A. A Alhadlaq, "Distilroberta2gnn: a new hybrid deep learning approach for aspect-based sentiment analysis," 2024.
[47] A. S. M Kuppusamy, "A novel hybrid deep learning model for aspect based sentiment analysis," 2023, doi: 10.1002/cpe.7538.
[48] S. U. S. Chebolu, F. Dernoncourt, N. Lipka, and T. Solorio, "OATS: Opinion Aspect Target Sentiment Quadruple Extraction Dataset for Aspect-

Based Sentiment Analysis," Mar. 06, 2024, arXiv: arXiv:2309.13297. doi: 10.48550/arXiv.2309.13297.
[49] S. J. K Sarathchandra, "An Aspect Based Sentiment Analysis Model Applicable for a Domain with a Small Labeled Data Set," 2024.
[50] S. S. N Lakshmidevi, "A Hybrid Enhancing Aspect-Based Sentiment Analysis with BERT for Aspect Extraction and Diverse ML Classifiers," 2023.
[51] S. R. T Khan, "RMDEASD: Integrating Rule Mining and Deep Learning for Enhanced Aspect-Based Sentiment Analysis Across Diverse Domains," 2024.
[52] L. B. S Consoli S. Manzan, "Fine-grained, aspect-based sentiment analysis on economic and financial lexicon," 2022.
[53] S. S. J Melba Rosalind, "Predicting students' satisfaction towards online courses using aspect-based sentiment analysis," 2022, doi: 10.1007/978-3-031-11633-9_3.
[54] A. M. D Jayakody K. Isuranda…, "Instruct-DeBERTa: A Hybrid Approach for Aspect-based Sentiment Analysis on Textual Reviews," 2024.
[55] Y. Prakash and D. K. Sharma, "Aspect Based Sentiment Analysis for Amazon Data Products using PAM," in 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India: IEEE, Mar. 2023, pp. 1–5. doi: 10.1109/ISCON57294.2023.10112193.
[56] R. S. G Negi O. Zayed, P. Buitelaar, "A Hybrid Approach To Aspect Based Sentiment Analysis Using Transfer Learning," 2024.
[57] A. K. AN Nawathe VM Thakare…, "Aspect-based sentiment analysis for social media text using NLP and Deep Learning," 2023.
[58] C. F. R Sarno, "Aspect-based sentiment analysis: natural language understanding for implicit review.," 2024.
[59] Y. Z. Z Li C. Zhang, Q. Zhang, Z. Wei, "Learning implicit sentiment in aspect-based sentiment analysis with supervised contrastive pre-training," 2021.
[60] H. S. Lakmisagar and M. S. Sumathi, "Design and implementation of aspect Based Sentiment Analysis of Hotel Reviews," in 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India: IEEE, Aug. 2021, pp. 303–309. doi: 10.1109/RTEICT52294.2021.9573897.
[61] R. T. N Nandal J. Pruthi, "Machine learning based aspect level sentiment analysis for Amazon products," 2020, doi: 10.1007/s41324-020-00320-2.
[62] D. Asuquo, K. Attai, P. Usip, U. George, and F. Osang, "Aspect-Based Sentiment Classification of Online Product Reviews Using Hybrid Lexicon-Machine Learning Approach," in Applied Machine Learning and Data Analytics, vol. 2047, M. A. Jabbar, S. Tiwari, F. Ortiz-Rodríguez, S. Groppe, and T. Bano Rehman, Eds., in Communications in Computer and Information Science, vol. 2047. , Cham: Springer Nature Switzerland, 2024, pp. 124–143. doi: 10.1007/978-3-031-55486-5_10.

[63] P. F. Simmering and P. Huoviala, “Large language models for aspect-based sentiment analysis,” Oct. 27, 2023, arXiv: arXiv:2310.18025. doi: 10.48550/arXiv.2310.18025.

[64] B. Z. W Liao X. Yin, P. Wei, “An improved aspect-category sentiment analysis model for text sentiment analysis based on RoBERTa,” 2021, doi: 10.1007/s10489-020-01964-1.

[65] N. P. Arthamevia, Adiwijaya, and M. D. Purbolaksono, “Aspect-Based Sentiment Analysis in Beauty Product Reviews Using TF-IDF and SVM Algorithm,” in 2021 9th International Conference on Information and Communication Technology (ICoICT), Yogyakarta, Indonesia: IEEE, Aug. 2021, pp. 197–201. doi: 10.1109/ICoICT52021.2021.9527489.

[66] J. Huang, Y. Cui, J. Liu, and M. Liu, “Supervised and Few-Shot Learning for Aspect-Based Sentiment Analysis of Instruction Prompt,” Electronics, vol. 13, no. 10, p. 1924, May 2024, doi: 10.3390/electronics13101924.

[67] A. Kumar, V. Dahiya, and A. Sharan, “ACP: A Deep Learning Approach for Aspect-category Sentiment Polarity Detection,” in Machine Intelligence and Soft Computing, vol. 1280, D. Bhattacharyya and N. Thirupathi Rao, Eds., in Advances in Intelligent Systems and Computing, vol. 1280. , Singapore: Springer Singapore, 2021, pp. 163–176. doi: 10.1007/978-981-15-9516-5_14.

[68] S. U. S. Chebolu, F. Dernoncourt, N. Lipka, and T. Solorio, “ROAST: Review-level Opinion Aspect Sentiment Target Joint Detection for ABSA,” Jul. 18, 2024, arXiv: arXiv:2405.20274. doi: 10.48550/arXiv.2405.20274.

[69] K. E. D. Fauzan Lukmanul Hakim, “Aspect Based Sentiment Analysis of Beauty Products Using Neighbor Weighted K-Nearest Neighbor,” 2024, doi: 10.34010/komputa.v13i1.9437.

[70] Aleksander Wawer, “Few-Shot Methods for Aspect-Level Sentiment Analysis,” 2024, doi: 10.3390/info15110664.

[71] I. Nawawi, K. F. Ilmawan, M. R. Maarif, and M. Syafrudin, “Exploring Tourist Experience through Online Reviews Using Aspect-Based Sentiment Analysis with Zero-Shot Learning for Hospitality Service Enhancement,” Information, vol. 15, no. 8, p. 499, Aug. 2024, doi: 10.3390/info15080499.

[72] A. V. AK Singh, “An efficient method for aspect based sentiment analysis using spacy and vader,” 2021.

[73] V. Ivanenko, “Enhancing aspect-based financial sentiment analysis through contrastive learning,” Innov. Technol. Sci. Solut. Ind., no. 3(25), pp. 138–147, Sep. 2023, doi: 10.30837/ITSSI.2023.25.138.

[74] F. A. Devendra Kumar, “Opinion Extraction using Hybrid Learning Algorithm with Feature Set Optimization Approach,” 2024, doi: 10.52783/jes.3694.

[75] A. I. Z Kastrati A. Kurti, “Weakly supervised framework for aspect-based sentiment analysis on students’ reviews of MOOCs,” 2020.

[76] M. S. S Sharma, "A robust approach for aspect-based sentiment analysis using deep learning and domain ontologies," 2024, doi: 10.1108/EL-05-2023-0105.
[77] D. Kumar, A. Gupta, V. K. Gupta, and A. Gupta, "Aspect-Based Sentiment Analysis using Machine Learning and Deep Learning Approaches," Int. J. Recent Innov. Trends Comput. Commun., vol. 11, no. 5s, pp. 118–138, May 2023, doi: 10.17762/ijritcc.v11i5s.6636.
[78] A. Khan, T. Fatima, T. Aman, and T. Ahmad, "A Multi-Model Approach to Aspect-Based Sentiment Analysis of Car Reviews," in Proceedings of the Cognitive Models and Artificial Intelligence Conference, İstanbul Turkiye: ACM, May 2024, pp. 1–8. doi: 10.1145/3660853.3660854.
[79] N. A. ES Alamoudi, "Sentiment classification and aspect-based sentiment analysis on yelp reviews using deep learning and word embeddings," 2021, doi: 10.1080/12460125.2020.1864106.
[80] S. G. W Ansar A. Chakrabarti…, "An efficient methodology for aspect-based sentiment analysis using BERT through refined aspect extraction," 2021.
[81] M. A. KT Shahriar IH Sarker, "Aspect Based Sentiment Analysis of COVID-19 Tweets Using Blending Ensemble of Deep Learning Models," 2022, doi: 10.1007/978-3-031-34619-4_31.
[82] S. S. Rachmad Abdullah R. Sarno, "Aspect Based Sentiment Analysis for Explicit and Implicit Aspects in Restaurant Review using Grammatical Rules, Hybrid Approach, and SentiCircle," vol. 14, 2021, doi: 10.22266/IJIES2021.1031.27.
[83] S. T. M Kothalawala, "Aspect-based sentiment analysis on hair care product reviews," 2020.
[84] E. K. İA Özen, "Aspect-based sentiment analysis on online customer reviews: a case study of technology-supported hotels," 2023, doi: 10.1108/JHTT-12-2020-0319.
[85] L. Cabello and U. Akujuobi, "It is Simple Sometimes: A Study On Improving Aspect-Based Sentiment Analysis Performance," Jun. 06, 2024, arXiv: arXiv:2405.20703. doi: 10.48550/arXiv.2405.20703.
[86] P. R. JK Prathi MV Gopalachari, "Real-time aspect-based sentiment analysis on consumer reviews," 2020, doi: 10.1007/978-981-15-1097-7_67.
[87] A. Maroof, S. Wasi, S. I. Jami, and M. S. Siddiqui, "Aspect-Based Sentiment Analysis for Service Industry," IEEE Access, vol. 12, pp. 109702–109713, 2024, doi: 10.1109/ACCESS.2024.3440357.
[88] K. Pasupa and W. Sunhem, "A comparison between shallow and deep architecture classifiers on small dataset," in 2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE), Yogyakarta, Indonesia: IEEE, Oct. 2016, pp. 1–6. doi: 10.1109/ICITEED.2016.7863293.