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A Systematic Review on Implicit and Explicit Aspect Extraction in Sentiment Analysis

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ABSTRACT Aspect-based sentiment analysis (ABSA) is currently among the most vigorous areas in natural language processing (NLP). Individuals, private and government institutions are increasingly using media sources for decision making. In the last decade, aspect extraction has been the most essential phase of sentiment analysis (SA) to conduct an abridged sentiment classification. However, previous studies on sentiment analysis mostly focused on explicit aspects extraction with limited work on implicit aspects. To the best of our knowledge, this is the first systematic review that covers implicit, explicit, and the combination of both implicit and explicit aspect extractions. Therefore, this systematic review has been conducted to, 1) identify techniques used for extracting implicit, explicit, or both implicit and explicit aspects; 2) analyze the various evaluation metrics, data domains, and languages involved in the implicit and explicit aspect extraction in sentiment analysis from years 2008 to 2019; 3) identify the key challenges associated with the techniques based on the result of a comprehensive comparative analysis; and finally, 4) highlight the feasible opportunities for future research directions. This review can be used to assist novice and prominent researchers to understand the concept of both implicit and explicit aspect extractions in aspect-based sentiment analysis domain.

INDEX TERMS Aspect-based sentiment analysis, aspect extraction, explicit aspect, feature extraction, implicit aspect.

I. INTRODUCTION

The explosive magnification of social media on the Internet has helped people not only to receive information on the networks but also in the generation of information to others. Online interaction is becoming more real, in which people can discuss and give information about individual or topic on social networks such as Twitter, forums, Facebook, Instagram, etc. There is a special kind of information which is opinions, evaluations, feelings, and attitudes [1]. This information comes implicitly from the users or customers when they discuss the services or products they have used, or about the social events they have witnessed in their lives. Online interaction also changes the traditional purchasing behaviors, as well as social studies. Customers often search for online reviews about various products or services that they intend to buy [2]. Authorities also search online to find information about people's comments on social events. With this trend, there are more studies on automatic analysis and synthesis of information on product reviews collected from social media.

Nowadays, individuals, private and governmental organizations are progressively utilizing the contents in those platforms for decision-making [1]. The application of opinion mining/sentiment analysis (SA) is in diverse fields such as for business, the consumers' satisfaction and expectations are accessed through online opinions [3]. In the event where one intends to purchase a product, he/she does no longer need to ask friends or family members for opinions, simply because there exist numerous user reviews publicly available on the Web in relation to the products. Organizations may no longer need to conduct surveys or any opinion polls to collect open opinions because there is an availability of

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such information in public domains. However, tracking and monitoring sentiment-oriented sites on the Web as well as purifying the information that is involved in them remains a powerful task due to the rapid increase in the diverse platforms. A site usually contains a huge amount of sentiment text that cannot be easily decrypted. An average human reader usually undergoes difficulties in identifying relevant sites, extraction as well as a summarization of the sentiment in them. Therefore, a review on sentiment related issues is thus needed.

SA is all about the analysis of people's opinions, evaluations, appraisals, attitudes as well as emotions towards different entities involving products, services, individuals, organizations, issues, topics, events and their attributes [1]. It is an influential area of studies with very wide coverage, in the industrial domain, the term *sentiment analysis* has been used more frequently, but in academic settings, the terms *sentiment analysis* and *opinion mining* are frequently employed, which fundamentally refers to a similar meaning in the field of study [1].

Generally, SA is being investigated based on three ranks, namely: document, sentence, and aspect [1]. Document-level SA job is to classify whether a whole opinion document expresses a positive or negative sentiment [4], [5]. The task of sentence-level involves determining whether each sentence expresses a positive, negative, or neutral opinion [1].

Although researchers emphasized the importance of analyzing peoples' opinion, particularly towards products [6], document and sentence-level analysis cannot determine what precisely people like or dislike. However, the aspect level analysis is used to achieve a fine-grained SA by handling three sub-problems such as aspects extraction from reviews text, identification of the entity referred to by the aspect, and the opinion or sentiment polarity classification towards the aspect [7]. Aspect level is usually called *feature level, opinion mining, as well as a summarization* of product, service, or entity [7]–[10]. The product of the aspect level SA task is eventually summarized and visualized [9], and the features extracted can either be explicit or implicit. This feature is said to be explicit if it is stated clearly in the sentence, otherwise, it is referred to as implicit [7].

It is equally observed that the entire sentiment for a particular product or topic consists of the aspect's sentiments, and in turn, each aspect has its sentiments expressed in related sentences composed from their words. Among the three sub-levels of the SA, ABSA has fascinated many researchers through the last decade [1], [2]. However, investigation, as well as extraction of these aspects, is the most vital and crucial task of the ABSA [9]. Aside from efforts to recommend the desired aspects [11], the area also boosts the capability of the traditional SA approaches at semantic level with finer-grained result capable of representing multiple text features [12], [13]. As for the modern machine learning approaches, in the last few years, deep learning techniques appeared to be another promising solution to NLP related challenges, which makes its deployment more often among sentiment-based researchers. In view of this, [14] reviewed the state-of-the-art studies that have used deep learning to address sentiment analysis problems, such as sentiment polarity. As several studies proposed the used of different deep learning techniques in SA, [15] applied word embedding and TF-IDF, [16]–[18] applied deep learning for sentiment classification, whereas [13], [19] employed deep learning for ABSA and identified it among the most promising approaches in machine learning.

The fact that most of the existing studies gave much emphasis to explicit aspect extraction alone is not enough, because SA is incomplete without considering the implicit due to its contribution to the meaning of the content. It has been discovered that most of the text documents come with an associated implicit aspect, for example, according to Xu *et al.* [20], 30% of the Chinese reviews contains implicit aspect elements. To bridge this research gap, this study provides a review of techniques that focuses on either implicit, explicit, or combination of both implicit and explicit aspect extraction from 4 different perspectives, considering their significance and contributions to the meaning of a text.

The first perspective is the identification of techniques used for extracting either implicit, explicit or both implicit and explicit aspects; second is the analysis of the various evaluation metrics, data domains, and languages involved from 2008 to 2019; and the third is the identification of the key challenges associated with the techniques based on the result of a comprehensive comparative analysis and fourth is the highlight feasible opportunities for future research directions. This can assist novice and veteran researchers to understand those perspectives in relation to either implicit, explicit or both implicit and explicit aspect in aspect-based sentiment analysis domain.

Several types of reviews have been published in the field of SA and ABSA, including those that used quality criteria followed by recent studies in SA field [21], as well as those for public opinions and renewable energy [22]. However, none of the reviews focused on the techniques used for either implicit, explicit or both implicit and explicit aspect extraction in SA at the same time. Consequently, this systematic literature review (SLR) was conducted to achieve a better understanding of the current state-of-the-art in implicit and explicit aspect extraction. Therefore, the aim of this study is to perform a systematic review of aspect extraction in order to:

1. identify the techniques used for extracting implicit, explicit, or both implicit and explicit aspects in SA,
2. analyze the various evaluation metrics, data domains, and languages involved in implicit and explicit aspect extraction in SA,
3. highlight various aspect extraction techniques with their associated challenges, and
4. highlight feasible opportunities for future research directions.

This review was conducted based on Kitchenham's procedures for performing systematic reviews Kitchenham, *et al.* [23]. The remaining sections of the paper have been structured as follows. Summary of the related works is discussed in Section 2. The methodology of this study is described in Section 3. Section 4 presents an analysis of the results of the review based on the synthesis of the evidence. In Section 5 and 6, the discussion and threats to validity were described respectively. Finally, Section 7 gives concluding remarks of the study.

II. RELATED WORKS

In the occasion of conducting the review, we also stumbled other reviews that are closely related to the ABSA in SA, namely aspect-level SA, feature extraction in SA, opinion types in SA, aspect extraction in SA, and implicit aspect extraction in SA. Specifically, Schouten and Frasincar [24], conducted a thorough overview of the current state-of-the-art, revealing the enormous achievements that have been recorded in finding all the targets. These targets can either be an entity, or some aspect of it, as well as the equivalent sentiment. The survey focuses on ABSA, in which the aim is to identify and aggregate opinion or sentiment on entities stated within documents or aspects of them. This work differs from ours because it aimed at finding sentiments on entities mentioned within the documents, while our work focused more on the approaches used in extracting aspects at both implicit and explicit levels. Important findings from this review show that aspect-level SA provides in-depth sentiment information, which can be beneficial in different kind of applications domains. Current solutions are classified based on whether they offer a method for detecting aspects, analyzing sentiment or both. Moreover, an analysis based on the type of algorithm employed is also given. Finally, semantically rich concept-centric aspect-level SA was deliberated in the survey and recognized as one of the most reliable future research direction (also known as an implicit aspect). However, a systematic classification of implicit based approaches and report on the correlation with the explicit based techniques is still missing, a gap that the current SLR is aiming to fill.

Rana and Cheah [9] conducted an extensive comparative analysis and survey that focused on different aspect extraction techniques. Apart from elaborating the performance of a given technique, the survey also serves as a guide to the readers on how to compare the accuracy with different state-of-the-art and most recent approaches. More than 60 techniques are being summarized and classified based on their complexity and nature, but only those studies whose results were presented are included in the study. The findings from the comparative analysis revealed the significance of different approaches and the impact of deploying different techniques on different language datasets in diverse domains. However, the claims made in the studies lacked weight due to the inability to include the existing techniques for implicit aspects extraction in the comparison as well as the analysis. That is why we aim to consider the existing approaches related to both implicit and explicit aspect extractions.

The fact that SA has been attracted by researchers in recent years with aspect level SA being attracted the most. Rana, *et al.* [25] reviewed topic modeling in the field of SA and successfully offered extensive comparative assessments of various approaches. The review demonstrated the effectiveness of topic modeling in aspect extraction as well as categorization. The work further highlights that even though, a number of approaches have not given much attention to grouping synonyms such as maximum entropy seeded sentiment (ME-SAS), but mostly used LDA-based techniques for aspect extraction and groping of the aspects simultaneously. Although this review emphasizes the significance of topic modeling for aspect extraction in SA, several other explicit and implicit based approaches for SA were not included, which shows that many findings were greatly missing. Therefore in our proposed SLR, we conduct a review with comparative analysis systematically among 35 both implicit and explicit aspect extraction approaches, including the topic modeling based (LDA) approach.

The fact that aspects have an important role in SA and its extraction is now becoming an active area of research. Hu and Liu [7] discussed the current techniques as well as the approaches for feature extraction in SA and opinion mining. A systematic literature review process was embraced for identifying areas vigorously focused by researchers by highlighting the addressed areas with further research opportunity to researchers. The author also uncovered the most and least frequently used feature selection techniques to identify research gaps for future direction. Finally, it was concluded that feature space decrease, redundancy removal together with assessing the performance of hybrid oriented methods of feature selection could be the future direction of the domain to the contemporary researchers in the field of feature extraction in SA. However, the review only includes research papers as well as doctoral thesis published, while ours is a systematic literature review that specifically focused on implicit and explicit aspects extraction research papers. In another effort, as SA is threatened by technical challenges involving extraction of essential information from social media platforms as well as the transformation of mined data into useful information. In view of this, [26] proposes fuzzy ontology-oriented sentiment analysis and semantic web rule language (SWRL), [27] used ontology and latent Dirichlet allocation, whereas [28] claimed that the current ontology-based techniques could not extract distorted reviews, rather proposes a new extraction and opinion mining system based on type-2 fuzzy ontology named ‘‘T2FOBOMIE’’ to retrieve and extract the targeted aspect features from reviews.

In [29], a review that aimed to provide description of various studies conducted on implicit aspect extraction was presented. The findings indicated that implicit aspect poses many aspects which can be explored and redeemed vital opportunities for the researchers. The review involves the analysis and review of 45 papers on implicit aspects which spans from 2005 to 2016. On the other hand, Maitama *et al.* [30] focus on investigating the techniques, approaches, types of research, publication trends, quantity of publications as well as demographics of explicit aspect extraction-based studies in the last decade (2008 - 2019) through an evidence-centred systematic mapping methodology.

Even though the related studies discussed in this section yielded good information to the SA community concerning different issues in aspect extraction. However, none of the related studies investigated both implicit and explicit aspect extraction-based techniques and further identified the key challenges associated with the techniques based on the result of a comprehensive comparative analysis. The comparative analysis was conducted based on the direct correlation between the implicit, explicit, and combination of both implicit and explicit aspects on the basis of techniques, dataset and evaluation metrics. Furthermore, none of the existing approaches keeps track and highlights the most prominent challenges associated with ABSA studies at individual and generic levels. A better understanding of the available approaches can be beneficial to researchers in identifying what is available and what needed to be done in future researches that can be useful to various industries and agencies for adoption. Thus, our SLR aims at contributing not only to the building of knowledge through researchers but also to the general stakeholders in SA domain.

III. REVIEW METHODOLOGY

This segment presents the process involved in conducting the SLR. Kitchenham *et al.* [23], in their study, defined systemic review as the process of identifying as well as interpreting all available research proof with the target of answering a well-defined research question. SLR introduced a more systematic approach to synthesize the research proof with inclusion as well as exclusion criteria to provide the borders of evidence to be incorporated in the review. The guidelines on performing SLR were used in this work to identify research gaps in the existing researches and draw a conclusion based on our research questions. The review was conducted in three major phases, as indicated in Fig. 1, and each phase is discussed in the following sections.

A. PLANNING REVIEW (PHASE 1)

In this planning phase, the objectives of the review were clearly identified in conjunction with the following events that described every stage in detail.

1) IDENTIFYING THE NEED FOR THE REVIEW

In Phase 1, we discovered that there was no systematic review that covers implicit and explicit aspect extraction techniques. The explosive number of papers on aspects in SA across various disciplines (that includes governmental and private agencies, product, mobile devices, laptop, hotel reviews, and many others) is adequate evidence that aspect extraction in SA had been a pressing issue in the last decade [31]. Hence, we recognize the need for conducting this review based on the results from the past studies that exploited the aspect extraction.

2) FORMULATING THE RESEARCH QUESTIONS

In line with our research focus, the RQs derived in this study were inspired by other essential ABSA studies such as [9], [29], [30]. Similarly, we perceived the importance of well-formulated research questions on survey oriented researches in proving proper guidance. Keeping in mind the need to ensure that all the derived questions were duly answered at the end of the study. As an essential activity of phase 1, we outlined the following research questions to be the focus of this review:

(a) What techniques have been used for extracting both implicit and explicit aspects in SA?
(b) How can various evaluation metrics, data domains, and languages involved in both implicit and explicit aspect extraction be analyzed?
(c) What are the aspect extraction techniques with their associated challenges?
(d) How could feasible opportunities be highlighted for future research directions?

3) IDENTIFICATION OF RELEVANT ONLINE DATABASES

In reaction to the aforementioned queries, we selected the online databases that span the majority of journals as well as conference papers published within computer science field in order to discover relevant studies for the review (Activity 3, Phase 1). We recognized the online databases itemized as relevant for computer science-based research: ACM, DBLP, IEEE Xplore, Science-Direct, Springer-Link, Scopus, and Web of Science. Setting an opening as well as the closing date for a review is one of the strategies of this systematic review, as described in the study by Stapić, *et al.* [32]. Many researchers reported that the area had been identified as one of the most vibrant fields of research in the last decade [9], therefore, 2008 was selected as the opening date of the review and covers associated papers published from then until 2019. The searches were narrowed to journal and conference proceedings that were published within the above period.

B. CONDUCTING THE SYSTEMATIC REVIEW (PHASE 2)

In earlier studies, several terms have been used for ABSA, such as aspect-feature, aspect extraction, and aspect detection. Similarly, different terms and synonyms have been used for the aspect extraction techniques, including approaches, methods, and algorithms in order to capture the maximum relevant studies. Kitchenham, *et al.* [23] applied structured questions to define search strings that will be used in the online databases. To construct the search strings, we make use of the Boolean OR to include substitutes and alternative words. The Boolean AND was used to link the foremost terms from population, intervention, and context. Hence, comprehensive search strings were derived as (1.) *((“implicit” OR “explicit”) AND (“aspect extraction”) OR (“aspect detection”) OR (“aspect feature”) OR (“opinion target”) OR (“aspect”) AND (“sentiment analysis”)),*

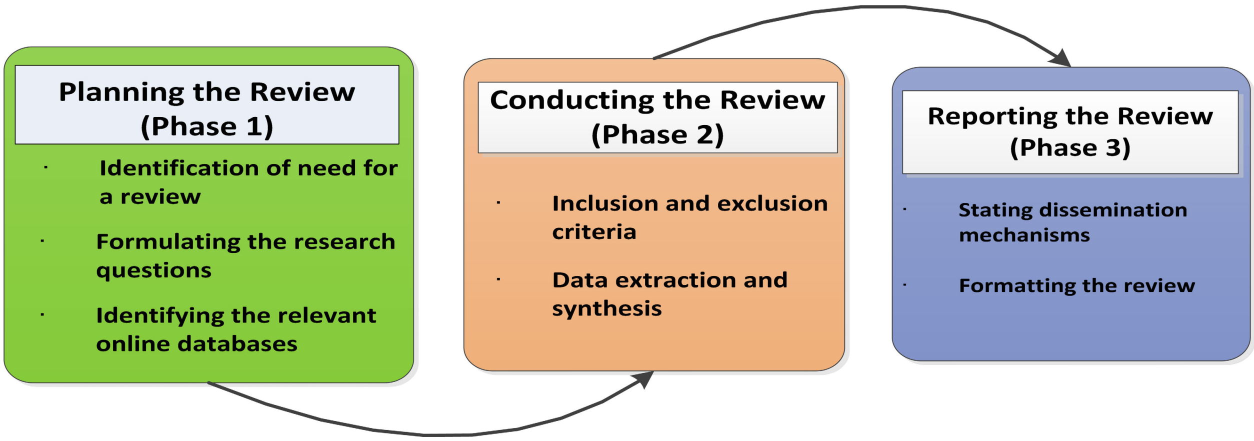

FIGURE 1. Systematic literature review phases with activities.

and (2.) *((“implicit” OR “explicit”) AND (“aspect feature”) OR (“aspect extraction”) OR (“aspect detection”) OR (“aspect”) AND (“sentiment analysis”) AND (“approach” OR “technique” OR “method” OR “algorithm”)).*

As indicated, 2 search strings were used in this SLR, where the 1st string was used for Web of Science database. Meanwhile, the 2nd string was used for all the remaining databases involved in this study. In total, we have explored through seven databases that comprised Computer Sciences related articles in order to retrieve as much research papers as possible. Google Scholar was not considered in this study due to its overlapping results as well as the low precision results constrains compared to other databases. Additionally, Google Scholar does not have an advanced search option, which is required for more accurate and precise retrieval of relevant PSS. Table 1 presents the search procedure involving the initial and final results, as well as the number of studies obtained from each database.

1) INCLUSION AND THE EXCLUSION CRITERIA

In the event of this review, we outlined some standards or criteria on which studies can be included as well as those that need to be excluded. A contesting article is carefully selected as one of the PSS if it satisfies at least one of the inclusion criteria. Likewise, excluded if fulfilled any of the exclusion criteria.

Our major inclusion criteria targets are to include all articles describing either implicit, explicit or combination of both implicit and explicit aspect extraction techniques in SA. Whereas, the key exclusion criteria consist of articles that have nothing to do with either implicit or explicit aspect extraction techniques in SA. Additionally, the articles that satisfied any of those criteria itemized below were also excluded.

- Articles describing aspects or feature (extraction, detection, algorithm, method or approaches) that are not based on SA, non-related feature extractions such as feature extraction techniques for reuse in software product lines [33], or any article on aspect-based SA that does not include or cover any aspect extraction techniques. Generally, any research work on aspect or feature (algorithm, systems, technique, approach, method, extraction or tool) in SA, but does not include aspect or feature extraction, detection or identification were barred from our SLR. Furthermore, several articles that stated feature extractions were found but were excluded as it related to image processing, pattern recognition as well as software product lines.
- Articles unfolding the concepts of aspects in SA and appear in abridged papers, work in progress papers, as well as a model proposal for aspects in SA that are not empirically authenticated were also excluded.
- Review articles (tertiary studies) associated with the topic that are basically considered as secondary studies are not counted as primary selected studies (PSS) of this SLR.
- Papers that are not written in English are also excluded.

2) DATA EXTRACTION AND SYNTHESIS

Extraction of the data plan is structured to precisely record the facts acquired by the researchers after the primary studies [34]. We begin by cleaning the results obtained from any identified duplicate through the study’s abstract, introduction and conclusion. In the initial assessment, the inclusion together with the exclusion criteria, were also applied to remove irrelevant studies according to the screening of the titles as well as the abstracts. When the titles, abstracts, and conclusions were not enough to determine the relevancy of the paper. We then refer to the full text. Considering the outlined criteria, 94 articles were carefully chosen for ultimate review in order to reveal answers to the questions identified. Majority of these articles (i.e. 87) were retrieved from the seven databases, while the remaining were obtained using a snowballing procedure to ensure optimal selection of all the desired studies.

The fact that ABSA appeared to be among the most attractive area of interest by many researchers, various terms were

TABLE 1. Study selection procedure.

S/N	Database	Preliminary Search Result	Screened Result	Selected Studies in line with Inclusion/Exclusion Criteria
1.	Web of Science	475	111	17 (73-56 duplicates)
2.	Scopus	1,882	290	20
3.	ACM	2,647	412	13
4.	Science Direct	938	147	10
5.	Springer Link	160	77	9
6.	IEEE Xplore	515	115	11
7.	DBLP	417	91	7

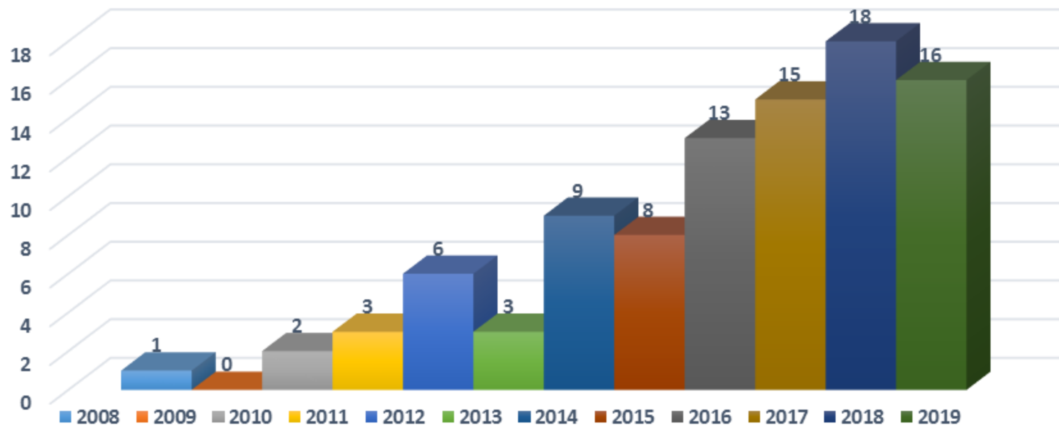

FIGURE 2. Distribution of the Extracted Articles from 2008 to 2019.

used in the existing study to report on aspect extraction in SA. Thus, we cannot determine a precise definition of aspect or features extraction. Moreover, in the event of reviewing limited papers, we have discovered that some studies did not use the term "aspects" but used "features" while for the term "approach", some used techniques, method, or algorithm, etc. Hence, in this review, we adopted the used of "aspect extraction" term with a focus on both implicit and explicit by considering a search string with broader coverage to ensure wider retrieval of more relevant articles. Figure 2 shows the distribution of the papers based on years.

IV. ANALYSIS

In this section, we presented the results of this systematic literature review and discussed them in order to respond to the questions presented in Section 1 (Phase 3: reporting the systematic review). The result is divided into four parts and presented in accordance with the flow of our proposed research questions. We have also presented the comparison and analysis of aspect extraction on the bases of techniques, approaches, evaluation metrics, data domains, and languages. The results of the comparison are for both implicit and explicit aspect extraction.

A. WHAT TECHNIQUES HAVE BEEN USED FOR EXTRACTING BOTH IMPLICIT AND EXPLICIT ASPECTS IN SA?

Part 1 of the result section focuses mainly on the general overview and result presentation of techniques used for aspect

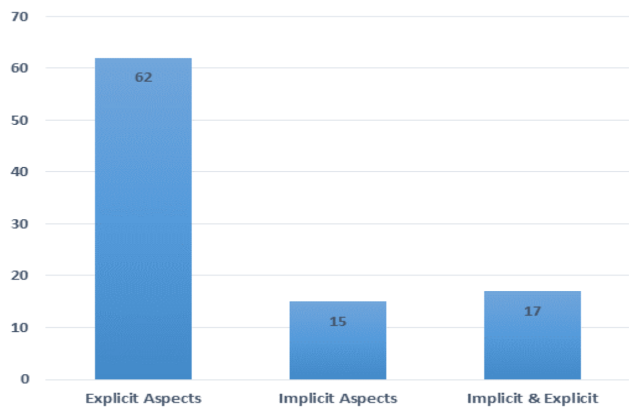

FIGURE 3. Distribution of the Articles at each phase of the SLR.

extraction. References of the researches that proposed the techniques are duly presented as well. Fig. 3 shows the distribution of the articles at each phase of the conducted SLR.

1) ASPECT EXTRACTION TECHNIQUES OVERVIEW

Extraction of implicit and explicit aspects from different online reviews turns to be the major task in ABSA. In this study, we tried to classify both implicit and explicit aspect extraction techniques into three main approaches i.e. supervised, semi-supervised and unsupervised. The abridge description of all the three classes has been presented in tabular form in this section. We presented the technique names, approaches used, and reference of the paper in which they are applied in Tables 4, 5 and 6 for explicit aspects, implicit aspects and combination of implicit and explicit aspects respectively. Detail description of the techniques, as well as the challenges associated with them, could be seen under subsection C of this section.

a: UNSUPERVISED ASPECT EXTRACTION TECHNIQUES

Unsupervised techniques are techniques that deploy the unsupervised approach concept and are widely employed by the researchers for the task of extracting various aspects from reviews. A technique is said to be unsupervised when it uses unannotated data to extract implicit or explicit aspects. In other words, it does not require training. These techniques are used on different kind of data domains which are of different language domains. Some examples of the unsupervised techniques are *statistical* [35], [36] for explicit aspect extractions, *topic modeling* [37], [38] for implicit aspects and *dependency parsing* [39], [40] for a combined implicit and explicit aspects.

b: SEMI-SUPERVISED ASPECT EXTRACTION TECHNIQUES

Semi-supervised techniques are those that used semi-supervised approach concept to extract aspects from reviews. The concept is all about the utilization of both unlabeled and labeled data to extract both implicit and explicit aspects. Semi-supervised techniques use algorithms that require training in a certain limited context. Example of the semi-supervised techniques is, *Recurrent Neural Network (RNN)* in [41], [42] for explicit aspects, *semantic-based* in [43] for implicit aspects, and *lexicon-based* [44], [45] for a combined implicit and explicit aspects.

c: SUPERVISED ASPECT EXTRACTION TECHNIQUES

Supervised techniques are those that applied the concept of supervised approach to extract aspects from reviews. The concept used labeled data to extract both implicit and explicit aspects. In other words, supervised techniques use algorithms that require training. Examples of the supervised techniques are, *Conditional Random Field (CRF)* [46], [47] for explicit aspects, *Hierarchy* [48] for implicit aspects, and *long short term memory* [49] for a combined implicit and explicit aspects.

2) EXPLICIT ASPECT EXTRACTION TECHNIQUES

The explicit aspect extraction techniques in this systematic review imply to the techniques used for the extraction of only explicit aspects. A total of 32 techniques were identified, which were applied in 62 different articles, as presented in Table 2.

This review also reported the rate at which the approaches are used based on the 3 groups of the aspect extractions, be it implicit, explicit or both. In this regards, considering the result obtained in Table 2, 45% of the total papers on explicit aspect extraction relied on an unsupervised approach. Supervised and semi-supervised approaches are 42% and 13% respectively. This indicates that the unsupervised approach can be recognized as the most commonly used approach for explicit aspect extraction among the existing studies. This is due to the fact that the unsupervised approaches do not require dataset annotation as well as training. In addition, the cost of using the unsupervised approach is less and much faster compared to other approaches. Even though the supervised approach is second to unsupervised in term of usage, yet, the difference is not much compared to the semi-supervised approach. This shows that the supervised approach is also effective in explicit aspect extraction.

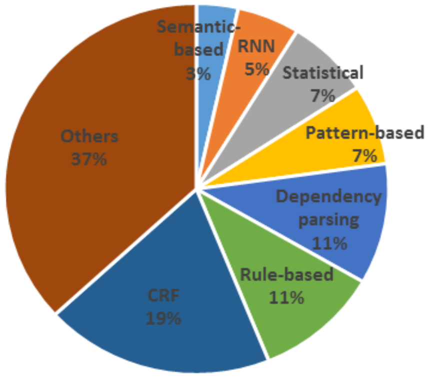

FIGURE 4. Most commonly used techniques for explicit aspect extraction.

The fact that explicit aspect extraction involves up to 32 different techniques in different studies, we went further to elaborate more on the techniques that are commonly used and vice versa. We identified seven (7) different techniques that were used in at least 3 papers in Fig. 4 with their corresponding frequencies, while the remaining 25 are regards as less commonly used techniques. Considering the results obtained, 19% of the total papers on explicit aspect extraction relied on CRF, 11% on dependency parsing, 11% on rule-based, 7% on pattern-based, 7% on statistical technique, 5% on RNN, 3% on semantic-based, while the 26 papers applied the remaining techniques for the explicit aspect extraction which translates to the 37%. This revealed that CRF could be considered as the most commonly used technique for explicit aspect extraction among researchers, in which it almost doubled dependency parsing and rule-based that appeared second most frequently used techniques. This is as a result of the fact that CRF can perform competitively and shows good result even with a lesser set of features. Besides not having a strict independence assumption, CRF can also accommodate any context information, and its feature design is flexible.

3) IMPLICIT ASPECT EXTRACTION TECHNIQUES

The implicit aspect extraction techniques refers to the techniques used for the extraction of only implicit aspects. In this study, we presented the result of the implicit-based aspect extraction techniques in Table 3.

In addition, the result in Table 3 also showed even distribution among semi-supervised and unsupervised, which entails equality in the use of the machine learning approaches by

TABLE 2. Explicit aspect extraction techniques.

S/N	Techniques	Approaches	References
1.	Backpropagation	Supervised	[50]; [51]
2.	Conditional Random Field (CRF)	Supervised	[46]; [47]; [52]; [53]; [54]; [55]; [56]; [57]; [58]; [59], [60]
3.	Distributional Vector Representations	Supervised	[61]
4.	Support Vector Machine (SVM)	Supervised	[62]
5.	Iterative decision tree	Supervised	[63]
6.	Gini Index	Supervised	[64]
7.	Recurrent Neural Network (RNN)	Supervised	[64]
8.	Boltzmann Machines	Supervised	[65]
9.	Hierarchy	Unsupervised	[66]
10.	Dictionary-based	Supervised	[67]
11.	Semantic-based	Supervised	[68]
12.	Lexicon-based	Semi-supervised	[69]
13.	Bipartite network	Semi-supervised	[70]
14.	Dependency Parsing	Unsupervised	[71]; [72]; [73]; [12]
15.	Clustering	Unsupervised	[74]
16.	Statistical	Unsupervised	[35]; [36]; [75]
17.	Rule-based	Unsupervised	[76]; [77]; [78]; [79]; [80]; [81]
18.	Bag of words	Unsupervised	[82]
19.	Pattern-based	Unsupervised	[83]; [84]; [85]; [86]
20.	Word alignment-based	Unsupervised	[87]
21.	Dependency Parsing	Supervised	[88]
22.	Frequency-based	Unsupervised	[89]
23.	Bootstrapping	Unsupervised	[90]
24.	LDA	Unsupervised	[91]
25.	NLP based	Unsupervised	[92]; [93]
26.	Human annotated	Unsupervised	[94]
27.	semantic-based	Semi-supervised	[95]
28.	Naive Bayes	Supervised	[96]
29.	Recurrent Neural Network (RNN)	Semi-supervised	[41]; [42]
30.	Dependency parsing	Semi-supervised	[97]
31.	Statistical	Semi-supervised	[98]
32.	Topic Modeling	Semi-supervised	[99]
33.	Graph-based	Unsupervised	[100]
34	Convolutional Neural Networks (CNN)	Supervised	[101]; [102]
35	Long Short Term Memory (LSTM)	Supervised	[103]

TABLE 3. Implicit aspect extraction techniques.

S/N	Implicit Aspect Techniques	Approaches	References
1.	Co-occurrence	Supervised	[104]
2.	Semantic-based	Semi-supervised	[43]
3.	Ontology	Unsupervised	[105]
4.	CRF	Supervised	[106]
5.	SVM	Supervised	[20]
6	CNN	Supervised	[104]
7	Hierarchy	Supervised	[48]
8	Lexicon-based	Supervised	[107]
9	Matrix Factorization	Supervised	[108]
10	Semantic-based	Unsupervised	[109]
11	Topic modeling	Unsupervised	[37]; [38]
12	LSTM	Semi-supervised	[110]
13	CNN	Semi-supervised	[111]
14	Lexicon-based	Semi-supervised	[112]

the techniques involved. Meanwhile, according to the result, the supervised approach is more needed than the others. It could be observed that 15 studies focused on pure implicit aspect extraction using 11 different techniques such as co-occurrence, semantic-based, ontology, CRF, SVM, LSTM, Hierarchy, CNN, Lexicon-based, Matrix Factorization, and Topic modeling with the supervised, semi-supervised and unsupervised approaches involved. This shows that there exist limited works targeting purely implicit aspect extraction, which is due to the fact that current researchers focused more on the explicit aspects. Meanwhile, the implicit aspect is not fully explored despite being one of the demanding concepts in some areas associated with the explicit aspects extraction such as emotional affects. Secondly, the fact that implicit aspect extraction is considered as the latest aspect extraction area that is ambiguous in nature and is more semantic than explicit. That is why the majority of studies do recommend implicit as a feasible future direction. Researchers are mostly at the investigation stage of implicit aspects, and most of the techniques used are on trial based, by involving all the 3 approaches (supervised with 46%, semi-supervised 27%, and unsupervised 27%) for the task.

TABLE 4. Implicit and explicit aspect extraction techniques.

S/N	Implicit and Explicit Aspect Techniques	Approaches	References
1.	Conditional Random Field (CRF)	Supervised	[113]; [114]
2.	Recurrent Neural Network (RNN)	Semi-supervised	[115]
3.	Hierarchy	Supervised	[115]
4.	Lexicon-based	Semi-supervised	[44]; [45]
5.	Double Propagation	Semi-supervised	[116]
6.	Dependency Parsing	Unsupervised	[39], [40]
7.	Clustering	Semi-supervised	[117]
8.	Rule-based	Unsupervised	[118]; [119]
9	LSTM	Supervised	[49]; [120]
10	Syntactic-based	Supervised	[121]
11	Pattern-based	Semi-supervised	[122]
12	Frequency-based	Semi-supervised	[123]

4) IMPLICIT AND EXPLICIT ASPECT EXTRACTION TECHNIQUES

The result presented in this part is about techniques used for a combined implicit and explicit aspects extraction. The implicit and explicit aspect extraction techniques in this context mean the process of extracting the combined implicit and explicit aspects by a single technique in the same paper as depicted in Table 4.

Table 4 further presents the distributions of the approaches used for both implicit and explicit aspect extraction techniques. All the techniques were classified based on the three approaches as unsupervised, supervised, and semi-supervised, with frequencies of 24%, 35% and 41% respectively. Majority of the works relied on semi-supervised approach, which virtually doubled the use of unsupervised. The reason is that the task involved in the extraction of both implicit and explicit aspects in some cases requires data annotations, especially the implicit aspects due to the ambiguity and semantic nature inherent in it. This entails the frequent deployment of the semi-supervised approach, which falls amongst unsupervised learning (without any labeled training data) and supervised learning (with entirely labeled training data). Several machine-learning researchers have already established that the application of unlabeled data, in conjunction with a little amount of labeled data, can yield a significant improvement in learning accuracy over unsupervised learning (where no data is labeled), but without the time and costs required for supervised learning (where the entire data is labeled).

The result presented in Fig. 5 showed that Conditional Random Field, Lexicon-based, Dependency Parsing, Rule-based, and LSTM are the most commonly used techniques with 62% frequencies for the combined implicit and explicit aspect extraction. This shows that in addition to the feature design flexibility of these techniques, researchers also made use of their strict independence assumptions advantage to accommodate any context information for the combined implicit and explicit aspect extraction task.

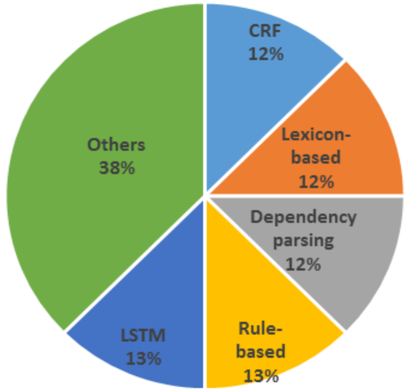

FIGURE 5. Most commonly used techniques for implicit and explicit aspect extraction.

B. HOW CAN VARIOUS EVALUATION METRICS, DATA DOMAINS, AND LANGUAGES INVOLVED IN BOTH IMPLICIT AND EXPLICIT ASPECT EXTRACTION BE ANALYZED?

This part (part 2) is divided into 3 segments based on the proposed question and the results were presented extensively. The first segment focused on the evaluation metrics overview and its analysis, followed by the data domain, and lastly the languages used for aspect extraction.

1) EVALUATION METRICS OVERVIEW

Evaluation metrics are subset of performance evaluation which are primarily used to measure the quality of machine learning or statistical models. Literally, a metric evaluates the quality of a system by comparing system's output (predicted result) with the actual result. A system presenting better prediction is deemed to yield a greater metric score, the tuning module gives the system parameter the maximum score. For the period of tuning, it is imperative for us to understand the fundamental definition of the metric, is to ensure that it aligned with the main system's prediction goal. Although training and preparing a machine learning system is an essential step in the machine learning channel, it is equally important to ensure that performance of the trained system is measured. Improper evaluation of a proposed model or system using different metrics can lead to a problem when the potential system is deployed on the unobserved dataset, thus can result in deprived predictions. There are different types of metrics for the tasks involving classification, ranking, regression, topic modeling, clustering, confusion matrix, logarithmic loss, etc. However, the most prominent metrics as far as this study is concerned are those related to the field of information retrieval, entity recognition, natural language processing and machine learning, namely: precision, recall, F1-Score of F-measure, and Accuracy.

Note the keys below:

TP = **True Positives**
FP = **False Positives**
TN = **True Negative**
FN = **False Negative**

a: PRECISION

Precision is defined as the ratio of system generated results with the aim of correctly predicting positive observations (i.e **True Positives**) to the system's overall predicted positive observations, comprising of the incorrect (i.e **False Positives**) and the correct (i.e **True Positives**) predictions.

Also, in classification context, precision is referred to as the number of items correctly labeled as belonging to the positive class (i.e **True Positives**) divided by the entire labeled elements belonging to the positive class (i.e. the sum of both the false positives and the true positives that belong to the whole class).

$$\textit{Formula; Precision} = (TP)/(TP + FP)$$

b: RECALL

Recall is defined as the ratio of system generated results which appropriately predicted positive observations (i.e **True Positives**) to the entire observations involved in the actual malignant class (i.e **Actual Positives**).

Recall is further regarded as a binary classification metric that measures how the number of the successfully predicted positive labels amid all the positive labels. In other words, it is the ratio between the number of correct positive answers (i.e **True Positive**) and the sum of wrongly negatively labeled answers (i.e **False Negative**) and correct positive answers (i.e **True Positive**).

$$\textit{Formula}; \textit{Recall} = (TP)/(TP + FN)$$

c: ACCURACY

Accuracy is defined as a ratio of the correctly predicted samples (i.e both **True Negatives** + **True Positives**) to the entire number of samples. It is also referred to as the most instinctive performance measure as well as a ratio that correctly predicts observation to the total observations.

It may be assumed that having high accuracy entails the most optimal model. Certainly, accuracy is a great performance measure, but if only there exist a symmetric data where values of false negatives and false positive are nearly identical. Thus, looking at other parameters for evaluating the performance of a given model is highly essential. In summary, accuracy is all about how well a given model performs. In other words, it can tell us whether a model is being trained properly and how it may perform holistically.

$$\textit{Formula}; \textit{Accuracy} = TP + TN/TP + FP + FN + TN$$

d: F1-SCORE

F1-score or F-Measure is defined as the weighted average of *recall* and *precision*. Thus, this score is made to take both false negatives and false positives into account. Even though F-measure is not easily understood as accuracy, but it is more useful than accuracy, especially when it involves uneven class distribution. It is revealed that accuracy works best if false negatives and false positives have the same cost. However, in a situation where the cost of false negatives and false positives are quite different, it is better to look at both *recall* and *precision* (which apparently means f1-score).

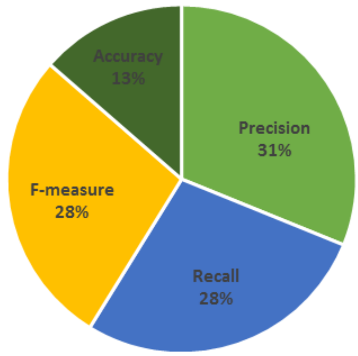

FIGURE 6. Distribution of evaluation metrics used in aspect extraction.

F1-score provides a means of combining both *recall* and *precision* into a single measure that captures both properties. Also, neither recall nor precision gives an absolute result. This is evident in the fact that an excellent precision could be reached with terrible recall or terrible precision with excellent recall. Thus, F1-score is the variant most often deployed when learning from the imbalanced dataset. The fact that F1-Score is the weighted average (or harmonic mean) of recall and precision, the scores takes both **False Negatives** and **False Positives** into account to provide a balance between recall and precision.

$$\textit{Formula}; \textit{F-Measure} = (2 * \textit{Precision} * \textit{Recall}) /(\textit{Precision} + \textit{Recall})$$

2) EVALUATION METRICS ANALYSIS

This segment focused on evaluation metrics used for aspect extraction (consist of implicit, explicit and the combination of implicit and explicit based aspect extractions). The result showed that precision, recall, F-measure as well as accuracy are the 4 major evaluation metrics used in the aspect extraction. We presented the rate at which each of the metrics is used at both single (1 metric for evaluation) or combined levels (2 or more different metrics for the evaluation). The frequencies of these metrics among the 94 PSS is presented in Fig. 6 with 31%, 28%, 28%, and 13% representing precision, recall, f-measure, and accuracy, respectively. It is obvious that the majority of the papers relied on these 4 metrics for evaluation. Simply because most of the reviewed papers proposed a model, and once a model is built, the most important question that arises is how good is the model? Thus, evaluating a model is the most imperative mission in the data science associated researches, which delineates how good the predictions are. The use of frequencies of the precision, recall, as well as F-measure, are relatively the same because they contribute much in determining how good a model has performed compared to the accuracy. It also helps in realizing that accuracy is not the be-all and end-all model metric to use when selecting the best model.

The evaluation result is extended by presenting frequencies of all the combined evaluation metrics that involved precision

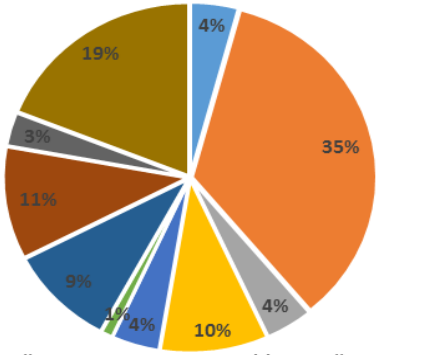

FIGURE 7. Distribution of both single and combined evaluation metrics in aspect extraction.

and recall; precision, recall, and f-measure; precision and f-measure, etc., and frequencies of the single used metrics such as f-measure only, or precision only, or accuracy only, etc. for the aspect extraction. According to the result presented in Fig. 7, it can be ascertained that combining precision, recall, and f-measure as evaluation metrics for implicit and explicit aspect extraction helps in achieving optimal performance of the models among the entire 94 PSS.

3) DATA DOMAIN

The result of data domains used for explicit, implicit, and the combination of implicit and explicit were presented in this segment. The entire data domain considered in the segment were within the range of 2008 to 2019. In this study, we classified the data domains into two classes, namely: single and multiple data domains. Single data domains refer to one data domain used in a paper e.g. product review, restaurant review, laptop review, etc., while multiple data domains mean the use of two or more data domains in a paper such as a restaurant and a laptop reviews (Restaurant + Laptop), camera and hotel reviews (Camera + Hotel), etc.

The data domains result presented in Fig. 8 are purely used for explicit aspect extraction. The result also showed that 20 different data domains were involved in the explicit aspect extraction. There exists 13 single data domains, 8 multiple domain data, and unspecified domain data. Among the multiple domain data, are the combination of *restaurant & laptop,* and *restaurant & movies* are the only domains used by two and above papers with frequencies of 23 and 2 (frequency in this context stand for the number of papers that used the data domain) respectively. On the other hand, 7 single data domains were used by two or more different papers. They are product (11), customer (9), restaurant (8), hotel (8), social media network (4), movies (3) and camera (2). The remaining data domains were used only once from 2008 to 2019. According to the result in Fig. 8 and the distribution of data domains' years presented in Table 5, it shows that the combination of the *restaurant + laptop* reviews can be considered as the most frequently used data domain for explicit aspect extraction, followed by *product + customer* reviews. However, based on the analysis of the distribution of their years, the use of *restaurant + laptops* is mostly between 2014-2019, this is probably due to the fact that 2014 was the year in which *SemEval-2014* was conducted with the provision of *restaurant + laptop* dataset for SA tasks. On the other hand, *product + customer* reviews mostly span 2015 and above, because *SemEval-2015* was also conducted and involved the collection of more documents and serve as a continuation of *SemEval-2014 with* specific targets on ABSA.

Results for data domains used for implicit aspect extraction, frequency and years were shown in Fig. 9. It consists of six (8) data domains, namely smart-apps (1), hate-crime (1), electronic + restaurant (1), customer (3), restaurant (3), restaurant + product (3), mobile (2), restaurant + laptop (4) and product (6). The *product reviews* has the highest frequency of 6 in the years 2018, 2017 three times, 2015 and 2013; followed by *restaurant + laptop* in the years 2019, 2018, 2017, 2016, and 2014. While electronic-devices & restaurant, hate-crimes, and smart-app reviews have the least frequency of 1 each in 2019, 2018 and 2019 respectively. It is clear from the figure that *product* reviews datasets are most frequently used data for implicit aspect extraction, while the distribution of the years shows that works are consistently increasing in the area, which entails an increase in researchers' interest towards the area.

The data domains used for the combined implicit and explicit aspect extractions, frequency and years are shown in Fig. 10. It also consists of 9 sets of data, namely product (8), restaurant + laptop (6), hotel (2), restaurant (1), TV online (1), cosmetics (1), hotel + mobile (1), hate-crime (1), restaurant + hotel (1), customer (1) and unspecified (1). The result further showed that *product reviews* has the highest frequency of 8 in the year 2019 twice, 2018 twice, 2017 twice, 2015 and 2013; followed by *restaurant + laptop reviews* in the years 2019 twice, 2018, 2017, 2016, and 2014. The *hotel reviews* got a frequency of 2 in 2018 and 2017, while the remaining data domains each got the least frequency of 1. It appeared that most of the researchers focused mostly on *product review* for the combined implicit and explicit aspect extraction. This is due to the fact that the product domain contains more than one product with different patterns of reviews. Hence, this larger coverage, diverse as well as multiple review patterns makes it suitable for both implicit and explicit aspect extraction.

This segment focus on presenting the result of the multiple and single data domains usage for the aspect extractions. In this study, a total of 77 single and multiple different data domains were used in the 94 PSS from 2008 to 2019. However, Fig. 11 showed that single data domain usage obtained 63% of the total frequency for the aspect extractions, while multiple data domains obtained 37%. Thus, the indication is that single data domains can be considered as the most frequently used domains for aspect extraction. This could be an effort to maximize the optimality of the extraction in the domain considered.

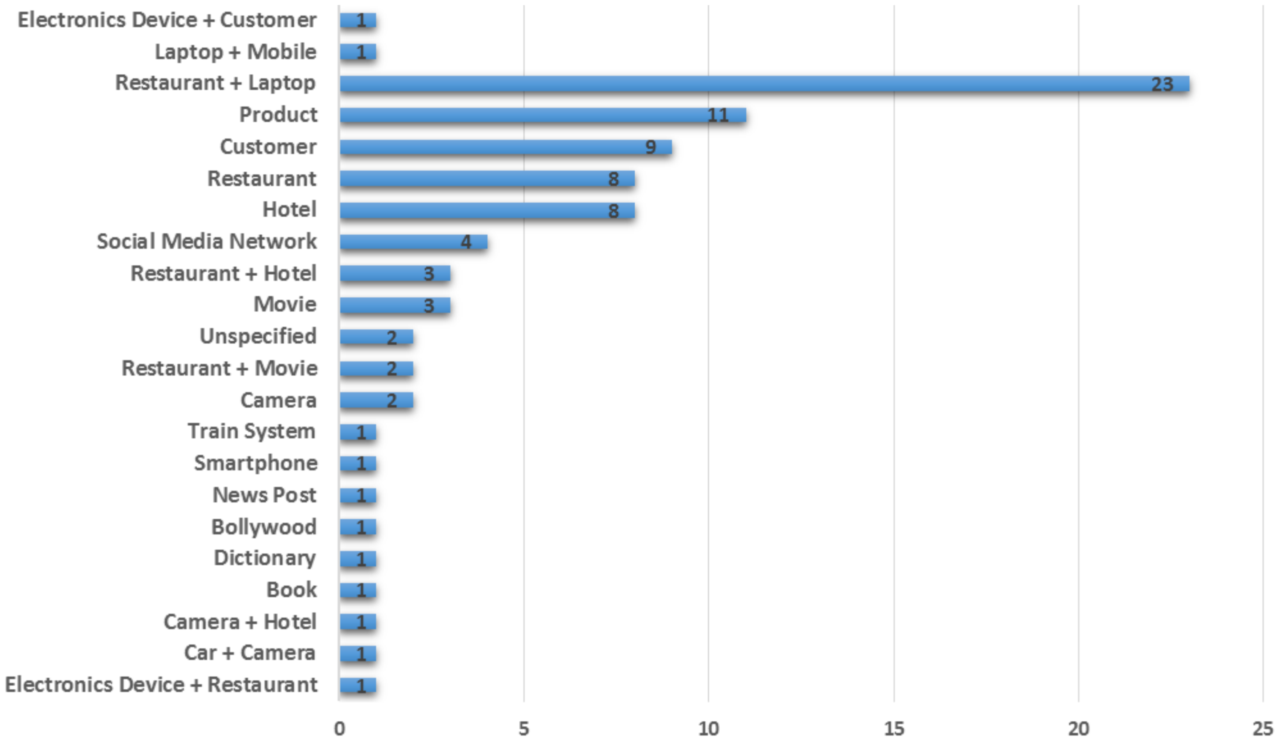

FIGURE 8. Distribution of data domains used for explicit aspect extractions with frequencies.

TABLE 5. Explicit aspect extraction data domains with years.

S/N	Data Domains	Years
1.	Electronics-device + Restaurant	2011(1)
2.	Train system	2011(1)
3.	Car + Camera	2013(1)
4.	Camera + Hotel	2014(1)
5.	Book	2015(1)
6.	Dictionary	2015(1)
7.	Bollywood	2017(1)
8.	News post	2016(1)
9.	Smartphone	2017(1)
10.	Laptop + Mobile	2018(1)
11.	Electronic-device + Customer	2019(1)
12.	Restaurant + Movie	2017(1); 2016(1)
13.	Camera	2017(1); 2013(1)
14.	Unspecified	2013(1); 2012(1)
15.	Movie	2017(2); 2010(1)
16.	Social media network	2017(3); 2015(1)
17.	Restaurant + Hotel	2017(1); 2014(1); 2012(1)
18.	Product	2019(2); 2018(2); 2017(4), 2016(2); 2015(3)
19	Restaurant + Laptop	2019(1); 2018(3); 2017(3); 2016(4); 2014(7)
20.	Hotel	2019(1); 2017(2); 2017(1); 2016(2); 2012(1); 2008(1)
21.	Restaurant	2019(1); 2018(1); 2017(2); 2016(2); 2012(1); 2011(1)
22.	Customer	2019(2); 2018(3); 2017(5); 2016(1); 2013(1); 2012(1)

4) LANGUAGE DOMAIN

The third segment of this study focused on language used for implicit, explicit and both implicit and explicit based aspect extractions in Fig. 12. We categorized the languages into 12 forms with their frequencies in this segment as: Arabic (13), Chines (29), Czech and English (1), Dutch (1), English (82), Hindi (2), Indonesian (2), Language dependent (1), Multilingual (3), Spanish (1), Turkish (2) and Vietnam (1). English is used 14 times for implicit, 53 times for explicit and 15 times for both implicit and explicit aspect extractions. All the purely implicit aspect extraction articles are published in English language domain. As for the explicit aspects, 11 languages are involved (i.e. almost all languages except Turkish), while 5 languages were used to extract both

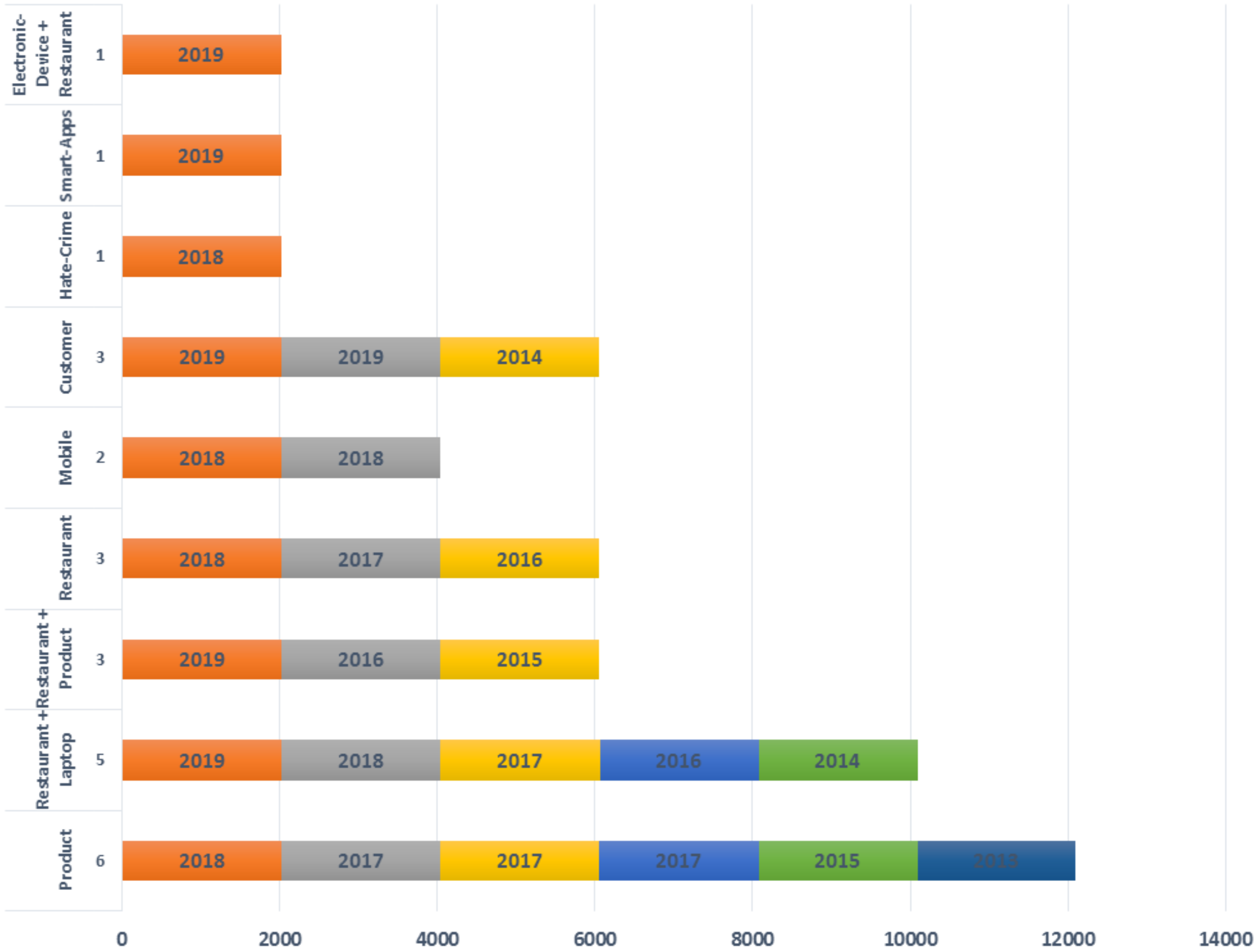

FIGURE 9. Distribution of data domains used for implicit aspect extractions with frequencies and years.

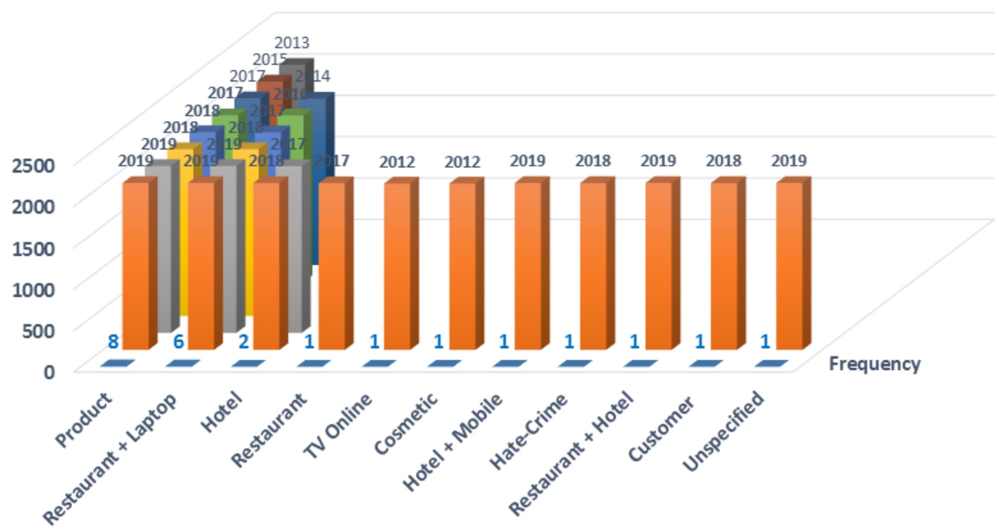

FIGURE 10. Distribution of data domains used for the combined implicit and explicit aspect extractions with frequencies.

implicit and explicit aspect in different papers. The result showed that English is the most frequently used language domain for aspect extraction, and researchers mostly relied on it in handling all the 3 tasks (i.e. implicit, explicit and

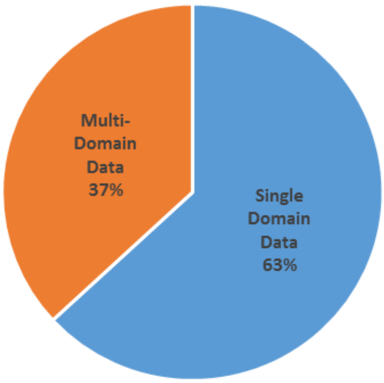

FIGURE 11. Distribution for the use of multiple and single data domains in aspect extraction.

both implicit and explicit). We also found that explicit aspect extraction has the highest languages because most of the studies focused on explicit in the last decade as the earliest task of ABSA. The fact that researchers are currently exploring explicit in relation to implicit could be the reason that leads to the emergence of the combined implicit and explicit aspects as second to explicit languages. While none of the languages was used for purely implicit aspect extraction but mostly recommended as future work.

We further present the detailed results of the most commonly used aspect extraction languages according to years. Figure 13 revealed that the English language is the most widely used language, which was deployed in almost all the years involved in this study (i.e. ten times). It could be observed that in 2019, there were 16 publications in English, even though a little less than 2018 with 21 but an impressive increment in the English-based studies has been recorded consistently since 2014. The primary justification for the reduction in 2019 is due to the fact that significant studies in the year are yet to get published. In general, this revealed that research activity continues to increase, and the area demonstrates stable growth, predominantly over the last 5 years. Although there is a vast gap between frequencies of using English with that of Chinese as the second most frequently used language (see Fig. 13), but the graph representing the annual utilization of the language goes in the same proportion.

On the other hand, we also found that Dutch, English + Chinese, English + Czech, English + Persian, Language-dependent, Spanish, and Vietnam are the least employed language domains in this study, as they were used once each among the PSS see Fig. 14. Meanwhile, the key findings here is that apart from English and Chinese languages, it has been observed that all the remaining languages identified were mostly used after SemEval-2016 on ABSA (i.e. between 2016 - 2019), which is a continuation of SemEval-2014 and SemEva-2015 tasks that provided 19 and 20 testing datasets for 8 different languages such as, English, Arabic, Chinese, Dutch, French, Russian, Spanish and Turkish. This shows that SemEval-2016 effectively contributes to increasing languages participation in ABSA tasks through the incorporation of the 8 more languages.

C. WHAT ARE THE ASPECT EXTRACTION TECHNIQUES WITH THEIR ASSOCIATED CHALLENGES?

To answer this research question, an extensive investigative study was conducted on the PSS with key focus on their technical parts to have vital revelations about the techniques with their associated challenges. The techniques and their associated limitations were discussed based on explicit, implicit, as well as combined explicit and implicit aspects.

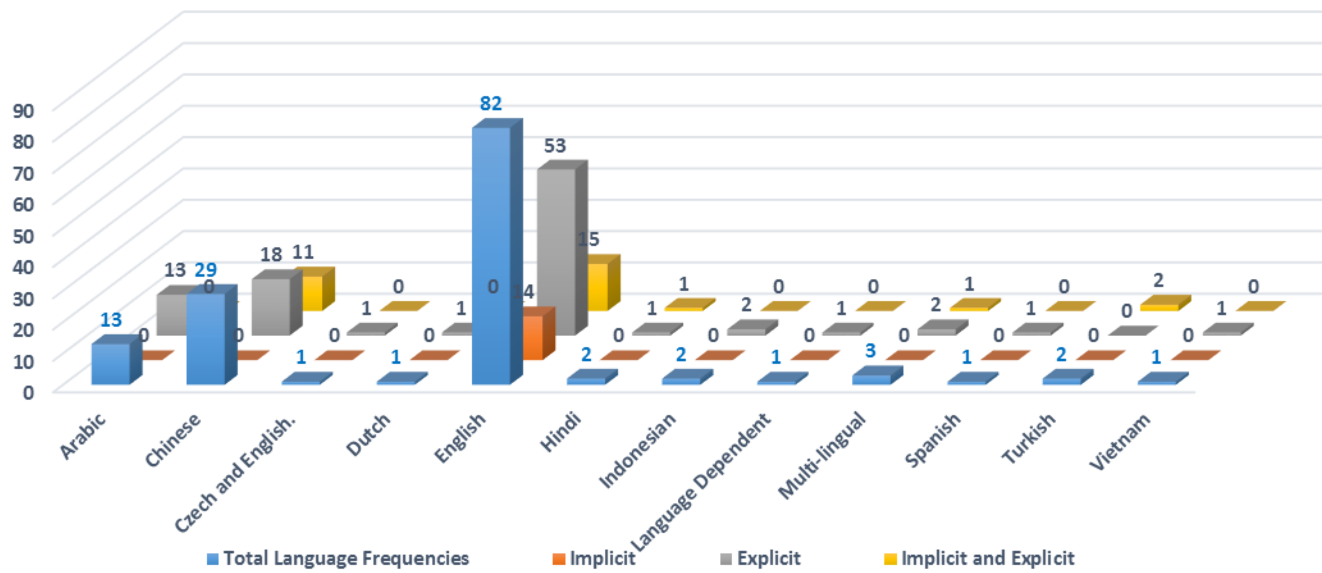

FIGURE 12. Distribution of languages used for implicit and explicit aspect extraction.

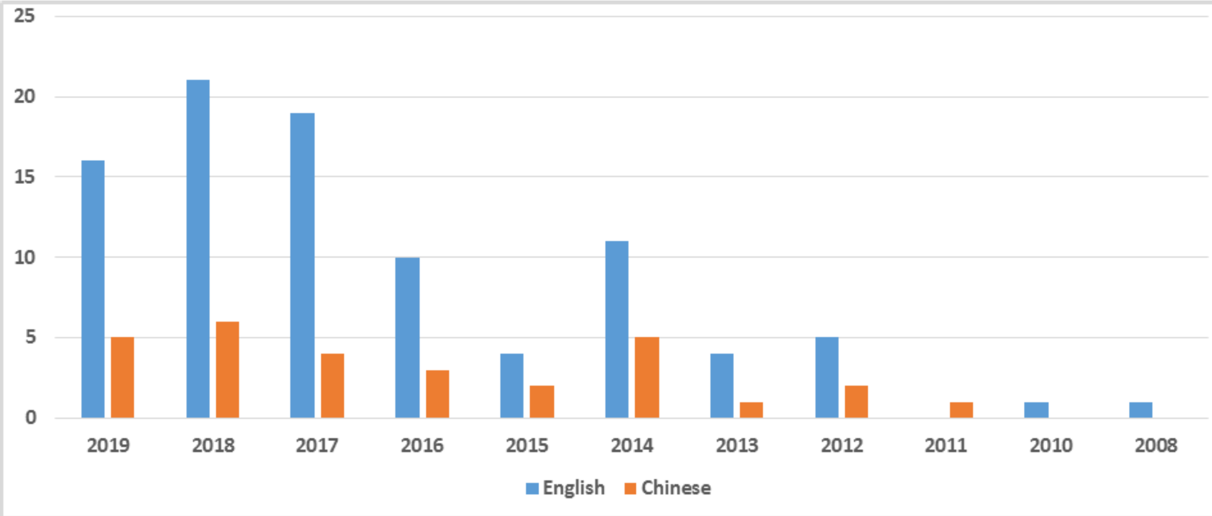

FIGURE 13. Distribution of the most commonly used languages for aspect extraction.

FIGURE 14. Distribution of the less utilized languages for aspect extraction.

1) EXPLICIT ASPECT EXTRACTION TECHNIQUES WITH THEIR ASSOCIATED LIMITATIONS

a: CONDITIONAL RANDOM FIELD (CRF)

Conditional Random Fields (CRF) are fundamentally a process of combining the advantages of graphical modeling and discriminative classification, which combines the ability to efficiently model multivariate outputs with the capacity of leveraging a large number of input features for prediction. Being the prominent techniques in both explicit and implicit aspect extraction, a significant number of researchers relied on the CRF for the aspect extraction and eventually led to reasonable performances [124]. Despite its promising nature, CRF possesses some limitations which were highlighted according to the articles.

Nasim and Haider [46] proposed an open-source oriented framework for summarizing and analyzing customer reviews. This framework contributed in circumventing document-level SA using CRF, by effectively tracking people's sentiment towards different products. However, it suffers the drawback of the limited dataset which affects the strength of the research findings. Due to the ineffective approach to detect emotional related conversations, Mohammad, *et al.* [47] introduced a novel approach for evaluating news affect using ABSA. The findings unveils the applicability of using ABSA on different types of news like sports, politics, and technology for analysis. Although the research enriches ABSA domain with emotional affects, it could not cover the emotional classes such as joy, disgust, sadness etc in their analysis. In another effort to minimize the effect of weak semantic vector representation for SA in paragraph, sentences and phrases, [52] used CRF for the extraction of opinion target expressions. However, its drawback comes from the polarity identification approach, which lacks the capacity of handling the positive, negative, and neutral polarity categories. Gojali and Khodra [53] proposed the utilization of CRF based technique for the extraction of aspect sentiment pair as well as the aspect rating computation for each group. The effort contributes significantly to addressing difficulties undergone in identifying relevant information from a large number of reviews available. Nevertheless, the limitation of the proposed work was tagged as insufficient features were selected and consequently affects the accuracy of the model. The fact that nowadays customers heavily relied on product user's comment to make decision, and insufficient amount of data set in the field to conduct impactful researches. In another study, Akhtar *et al.* [54] proposed a benchmark of the annotated dataset in Hindi, which was made publicly available for further research contributions. The work further presents the idea of using CRF for aspect term extraction with an impressive result. Yet, it suffers a problem of multi-word aspect terms which entails missing lots of aspects due to unreliable future selection. This, in turn, reduces the recall value. While De Clercq *et al.* [55] presents and integrated ABSA approach for the three subtasks on Dutch, namely aspect term extraction, aspect category extraction and polarity classification. Although the CRF based approach leads to a promising result, it still could not cover large dataset that involves other domains. Considering the recent difficulties in extracting aspect related opinions from the noisy and unstructured dataset, [56], [57] proposed a novel approach to extract aspect terms and its associated sentiment using CRF and different set features. Both the former and latter researches lack a reliable set of features that can effectively extract all types of aspect terms involved, not to talk of an effective classification of their sentiments. Hamdan *et al.* [58] proposed CRF based technique that focuses on determining the aspect terms existing in each sentence. The result obtained in the end shows that the techniques are effective in detecting aspect term and its polarity as well as the aspect categories and their polarity. However, it was found that the technique lacks the ability to handle such tasks in another domain due to dataset limitations. In their effort [100] applied graph-based technique for a precise extraction of opinion targets, but the approach demonstrated limited pattern coverage, hence a wider useful feature selective is required. While [59] and [60] used CFR to extract the opinion targets in both cross and single domain setting, and all the 3 techniques also suffers limited feature selection constraints.

b: STATISTICAL-BASED TECHNIQUES

Statistical is sometimes refers to as frequency-based technique which basically focuses on extracting the frequent aspects from reviews and eventually determine their opinion words. An aspect is said to be frequent when most of the users are interested in expressing their opinions about it. For this reason, [35], [36] used statistical unsupervised approach to tackle ABSA, which tries to eliminate relational crisis involving aspects and subjective phases in reviews. While the proposed approaches outperform the existing models on explicit aspect prediction, they both suffer from subjectivity, relevance, as well as relational detections. Also, [75] presented a joint model of text and aspect ratings for extracting text to be displayed in sentiment summaries, but could not handle end-to-end summarization tasks. On its side, [98] used semi-supervised statistical modeling for effective extraction of aspects and clustering. However, the approach could not handle semantic oriented aspects.

c: DEPENDENCY PARSING

In another effort, [71]–[73] used unsupervised dependency parsing to address difficulties of reading entire reviews by most of the consumers, while [118], [125], [126] combines dependency with commonsense reasoning for the tasks, and [12] try to improve aspect extraction task at a syntactic level using dependency parsing. Some researches unveil an improved performance in explicit aspect extraction, however, [71], [72] lacks the ability to extract all pairs of aspects and opinions, while [73] does not include sentiment classification. In another effort, [88], [97] proposed the use of supervised and semi-supervised dependency parsing. It is observed that the former presents a novel approach for fine-grained analysis that could determine both sentiment strength and sentiment orientation of the reviewer towards different aspects of a given movie, but the approach does not capture single reader's preference. While the latter proposed an embedded representation learning framework and the first of its kind that based on fusion relation for aspect extraction, but focuses mainly on the object-attribute pair's extraction.

d: RULE-BASED

Besides, [76], [77] proposed an approach that identifies the explicit aspects together with its polarity using rule-based techniques from movie and customer reviews respectively. Also, [78] deployed rule-based approach for extracting both objective and subjective aspects from customer reviews. Meanwhile, the pattern demonstrated low recall for objective aspect extraction. While both results demonstrated appreciable capability in the identification of both single and multi-word aspects, their limitations lie on the inability to identify more complex and refined syntactic as well as semantic relations among the aspects. Furthermore, [80] and [81] proposed two automatic rule set selection methods to aspect identification in opinion mining, but the former could not handle the aspects-based semantic relations, while the latter could not recognize aspects associated with parallel clauses as well as exclamation opinion sentences. Whereas [79] use chunk-level linguistic rules for extracting nominal phrase chunks and regards them as candidate opinion targets and aspects.

e: PATTERN-BASED

Considering the unsatisfactory performance of the existing ABSA approaches, [83] applied a pattern-based approach to extract aspects that are objective in nature, however, the study does not give concern to subjectivity context despite its importance. Moreover, [85] apply the syntactic pattern to detect aspects from reviews that are unstructured in nature. However, it lacks semantic oriented powers due to total reliance on patterns. While [84] also used the sequential pattern-based technique for explicit extraction of aspects, but focuses only on the aspect pruning and neglect advantages of diverse feature selection for wider aspect coverage. [86] applied sequential pattern mining method to explore the associations among opinions and aspects that leads to an interesting results of explicit aspects on electronic products. Although the sequential patterns could be used in detecting objection sentences, subjective aspect detection remain challenging to the approach.

f: RECURRENT NEURAL NETWORK (RNN)

The fact that Neural Network (NN) based techniques were used by researchers in many ways for aspect extraction tasks [127]–[129]. Manek *et al.* [64] deployed RNN to extracts aspects in large movie reviews, but the approach could not handle the task semantic, sarcastic and emotional levels. Also, [42] proposed RNN approach that focuses on coherent aspect discovery. Although it succeeded in improving the coherence significantly, it is semantically weak. While [41] propose a RNN-based model for identifying aspects through the distributional vectors. This leads to a stronger result, but does not includes multinomial word distributions.

g: CONVOLUTIONAL NEURAL NETWORKS (CNN)

References [101] and [102] suggest the use of 7 deep convolutional neural networks to tag each word in opinionated sentences as either non-aspect or aspect word. While the latter further modifies the basic CNN model by permitting the dense layers to represent complex non-linear relationships between the output layer and the selected features, both approaches lack effective feature selection technique.

h: LONG SHORT TERM MEMORY (LSTM)

In consideration of the limitations associated with the traditional sentiment analysis approaches particularly when it comes to analyzing reviews with different products' aspects, [103] proposed implementation of bidirectional LSTM neural network with character-level embedding features for aspect-based sentiment analysis on Arabic Hotel reviews. This approach faced flexibility constraints despite the improvement of 39% for the aspect-OTEs extraction task.

i: SEMANTIC-BASED

Also [68], [95] employed semantic-based techniques, due to difficulties in effectively extracting the right aspects as a result of the exponential accumulation of online textual contents. They both achieved reasonable performance at the semantic level of the contents, but have limited aspect patterns coverage at both syntactic and semantic levels of NLP. Furthermore, [99] presents topic modeling-based aspect extraction model from regrouped reviews, but could not handle conceptual knowledge for aspect hierarchy recognition.

j: NLP-BASED

[92], [93] exploits NLP-based resources mainly *named entity recognition* that includes a stop words list, linguistic knowledge base, sentiment lexicons, and general-purpose natural language processing library for aspect extraction. The approaches are weak in terms of semantic based extraction, as it gives much emphasis to the syntactic level of the NLP.

2) IMPLICIT ASPECT EXTRACTION TECHNIQUES WITH THEIR ASSOCIATED LIMITATIONS

a: CO-OCCURRENCE

In recognition of the fact that it is unrealistic to read all the online reviews, let alone talk of comprehending their meaning within a short period of time, hence the need for the ABSA. Feng *et al.* [104] used Co-occurrence technique for implicit oriented aspect identification in English and Chinese languages, by considering the topic and the matching degree of aspects, sentiment words, as well as human language habit of being the major aspect factors. However, the limitation of the study is that it could not cover diverse domains as such limited to only mobile phone reviews. Also, some aspect terms and their sentiments were not effectively detected due to the limitation of the features selected.

b: SEMANTIC-BASED

Furthermore, [43] applied a semantic-based technique for implicit aspect extraction in consumer reviews. The research employed word sense disambiguation and utilized the word semantic relations in the text to yield a wider semantic context for extracting the implicit aspect. It has been discovered that the proposed approach could not appropriately harmonize synset and semantic relations within the WordNet, which could have leads to an improved sentence representation. In [109], Naïve Bayes (NB) classifier was used with five distinct subsets of synonym and definition words for implicit aspect identification in Sentiment Analysis. The result obtained indicated that reliable term frequency does not support NB classifier, which is based on the absence/presence of both noisy and reliable terms, hence the need for more effective features.

c: ONTOLOGY-BASED

On the other hand, [105] proposed an ontology-based technique for aspect extraction in product review summarization. The approach succeeded in eliminating the earlier problems of lexicon-based sentiment scoring. However, it still could not handle some important patterns or features such as nouns, verbs, as well as sentiment phrases which are believed to have substantial sentiment impact.

d: CONDITIONAL RANDOM FIELD (CRF)

Also, considering the fact that earlier studies have tireless concern on explicit aspects while implicit are ignored in spite its contribution to a clearer understanding of the reviews, [106] proposed a novel approach for extracting implicit oriented aspects using CRF, but insufficient feature were selected in the study.

e: SUPPORT VECTOR MACHINE (SVM)

Xu *et al.* [20] developed a model for implicit aspect identification in Chinese-based product reviews using Support Vector Machine (SVM). Nevertheless, the approach is subjected to insufficient features that could effectively handle dependencies and semantic patterns.

f: TOPIC MODELING

Based on the fact that existing models felt to provide justifications for an aspect being criticized or praised, [37] proposed a topic modeling approach that utilized linguistic associations for prominent implicit aspect terms identification. However, it works better on limited data domains. While [38] incorporates product descriptions to the contemporary sentiment topic model for the aspect extraction. The limitation of the study has to do with difficulty in capturing aspects related to different domains, as well as emotion-related data.

g: CONVOLUTIONAL NEURAL NETWORKS (CNN)

It has been found that in so many cases, the current machine learning techniques for sentiment analysis fail to extract implicit aspects and thus might not be very useful. For this reason [111] suggest the use of CNN to tag each aspect in the opinionated sentences. The study was able to combine a deep learning approach with a set of rules to improve the performance of sentiment scoring as well as aspect detection methods. However, the approach suffered low recall value constrain in all the domains, which entails missing some valid aspect terms. [104] used CNN to develop a novel approach for identifying implicit aspect by taking the two key factors of the aspects as a topic and the match degree of sentiment and aspects words, as well as the human language habit. The limitation of the approach observed in the study is the fact that it mainly focused on mobile phone reviews which resulted in the inability to correctly identify significant amount of aspect or sentiment words.

h: LONG SHORT TERM MEMORY (LSTM)

Augustyniak, *et al.* [110] used a bidirectional LSTM to detect aspect terms using char and word embedding. The approach revealed that combining character-based representations with word embedding makes neural architecture even more powerful and entails better achievement, yet it face challenge of small available corpora or limited datasets.

i: HIERARCHY

Gupta, *et al.* [48] proposed a novel approach for explicit based aspect extraction using Hierarchy technique, ordered weighted average operator was used in identifying the feature hierarchy for the implicit aspect on customer reviews. Although the study consider overlapping of features in two different segments using domain's feature hierarchy, but it has shown weak aspect classification task.

j: MATRIX FACTORIZATION

Xu, *et al.* [108] used Matrix Factorization for implicit aspect identification, the approach first clusters product aspects by combining the co-occurrence information with intra-relations of opinion and aspect words, which can improve the performance of aspect clustering. It is observed that the sentiment orientation of the implicit aspects were not duly explored by the technique which requires attention.

k: LEXICON-BASED

As most of the existing supervised studies require labeled datasets to train their models for each domain involved, and training a model is difficult without first extracting the domain specific aspects. For this reason [112] applied lexicon-based technique for the aspect extraction on smart apps reviews. The approach leverage domain independent parameters to describe the connections between aspects terms and their associated opinion expressions. Even though the model can utilize minimum data required to capture the aspect oriented sentiment, but stressful in identifying the appropriate feature for optimal extraction. Author [107] used lexicon-based approach that is based on term-weighting scheme and WordNet semantic relations, to improve training data crime implicit aspect sentences detection as well as crime implicit aspect extraction.

3) IMPLICIT AND EXPLICIT ASPECT EXTRACTION TECHNIQUES WITH THEIR ASSOCIATED LIMITATIONS

a: CONDITIONAL RANDOM FIELD (CRF)

In another development, [113], [114] employs a CRF-based technique for both implicit and explicit aspect identification. The findings of both approaches are significantly impactful but suffer some drawbacks, in which the former is unable to recognize many aspect features and the latter is only limited to Basque and Catalan languages.

b: HIERARCHY

More so, [115] applied hierarchy-based technique for aspect-level sentiment classification, but could not handle special patterns such as comparative sentiments.

c: LEXICON-BASED

Kama, *et al.* [44] used lexicon-based technique to extract aspect. However, it lacks the ability to includes aspect-sentiment pairs that belong to co-reference resolution, comparative sentences, as well as irony detection. In another development, the lexicon-based technique is also applied by [45] through the use of whale optimization algorithm (WOA) for chosen the desired dependency patterns from the list of hand-craft patterns with the help of web-based similarity to detect explicit aspects. As for the implicit, the study suggests a hybrid approach that relied on the use of dictionary-based, corpus co-occurrence, and web-based similarity.

d: DOUBLE PROPAGATION

More so, [116] used double propagation on Chinese reviews but lacked diverse features to handle all forms of the aspects.

e: DEPENDENCY PARSING

Also, Poria, *et al.* [39] used unsupervised dependency parsing techniques to extract aspects concepts and identify associated sentiments. However, the system could not adequately handle adjectives that are often employed to modify aspects in the sentimental text. [40] proposed its explicit and implicit aspect extraction approach that consists of set of rules for sentiment word identification and principal component analysis (PCA) to select sentiment word features, as well as sentiment classification using SVM. The study improves the accuracy performance in relation to the existing approaches, but it works on a limited datasets in detecting peoples' sentiment towards specific issues.

f: CLUSTERING TECHNIQUE

On the other hand, [117] applied a semi-supervised clustering technique for aspect and sentiment identification. Meanwhile, the proposed method is only limited to the Chinese language.

g: RULED-BASED

While [118] proposed ruled-based approach for both implicit and explicit aspect extraction using dependency tree as well as common sense knowledge. However, the approach is still weak in detecting complex aspects, therefore, more rules are needed. In [119] features are extracted from the remaining sentences with POS Tags and N-Grams to train the classifiers. The limitation constraint found in the approach is scalability issue.

h: LONG SHORT TERM MEMORY (LSTM)

In [49], LSTM was used for both explicit and implicit aspect detection. This approach first extracts the aspects' representative words from the corpus, which are considered as aspects' hints. It then computes the aggregation of hints and the output of LSTM via an attention mechanism on SemEval benchmark datasets. The approach is still weak subjectively as per as implicit aspects are concerned. Also, in [120] a multi-task Neural Networks learning framework was applied to capture the relations between the two tasks implicitly, and then offer a global inference method that explicitly modeled numerous syntactic constraints among aspect and opinion term identified to uncover their *inter task* and *intra-task* relationship. The approach has shown much reliance on dependency parse trees which contributed in its limited aspect detection capacity.

i: SYNTACTIC-BASED

In consideration of the fact that limited studies relied on syntactic features to derive sentiment, [121] employed syntactic-based technique for both implicit and explicit aspect extraction. At first, the approach detects the most repeated bigrams and trigrams in the corpus, followed by POS tagging to retain aspect descriptions and opinion words. Although domain specific knowledge and pre-existing lexicons are used to label all the adverbs and adjectives, but it is weak in detecting attribute-exhaustive topics as well as classifying short text.

j: PATTERN-BASED

[122] proposed a novel pattern oriented approach for both explicit and implicit aspect extraction by mining the patterns to generate rules among opinion and aspect words using sequential patterns. The approach observed to be unique, especially in utilizing knowledge from WWW to find the implicit aspects and a grouped synonyms, but it could not be applied to multiple domains as well as real-life reviews.

k: FREQUENCY-BASED

Karagoz, *et al.* [123] proposed semi-supervised framework capable of extracting both implicit and explicit aspects in Turkish. It first extracts the candidates from words that correspond to the aspect's topics, the matched sentiment words with the aspects in the text. However, it demonstrates an aspect sentiment matching constraints in addition to the language domain restriction.

4) MAPPING OF CHALLENGES ASSOCIATED WITH ASPECT EXTRACTION TECHNIQUES

Generally, it has been discovered that the common challenges associated with aspect extraction techniques in SA could be summarized and categorized into 3 classes presented in Table 6.

V. DISCUSSION

This study adopted Kitchenham's systematic review as our secondary guideline to enhance the results and ensure extensiveness as well as the completeness of the study. We then structured the section into 2 subparts. The presentation of the

TABLE 6. Common challenges associated with aspect extraction techniques.

S/N	Common Challenges Classes	References
1.	Ineffective and inefficient feature selections which excludes vital textual patterns, categories, and features that plays significant role in aspect and sentiment identification tasks, hence reduces the aspect extraction coverage and efficiency of the approached proposed.	[47], [52], [53], [54], [56], [57], [75], [113], [115], [44], [116], [39], [71], [72], [88], [97], [84], [41], [68], [95], [105], [20], [106], [118], [99], [12], [78] [100], [59], [60], [48], [112], [109], [107], [80], [101], [102], [103], [79], [103], [130]
2.	Limited dataset which consequently affects strength of the research findings.	[46], [55], [58], [104], [114], [117], [111], [104], [37], [119], [40], [122], [110], [38], [131], [132]
3.	Suffers low subjectivity as well as semantic oriented performance.	[35], [36], [98], [73], [76], [77], [83], [64], [43], [42], [85], [92], [108], [45], [49], [121], [123], [120], [86], [81], [93], [133]

major research findings was comprehensively done in the first part, while the future research directions where highlighted on the second part.

A. MAJOR DISCOVERIES

ABSA research domain has been attracting considerable attention from the sentiment analysis research community since 2014, with rising publications that reached an average of 13 publications from credible journals and proceedings every year. Based on our PSS, we observed that about 31% of the publications were journal papers, whereas 69% of the publications are made up of proceedings. In view of the consistent increase in publications from the research community over the last 5 years, we are evidently confident that ABSA research domain would perhaps attract additional attention in the coming years considering its potentials in business intelligence as well as semantic values.

Considering the results obtained, 19% of the total papers focused on explicit aspect relied on CRF. This revealed that CRF can be considered as the most commonly used technique for explicit aspect extraction among researchers, in which it almost doubled dependency parsing and rule-based that appeared second most frequently used techniques. This is as a result of the fact that CRF can perform competitively and shows good result even with a lesser set of features. Besides not having a strict independence assumption, CRF can also accommodate any context information, and its feature design is flexible. Additionally, in regards to the result obtained in Table 2, where 45% of the total papers on explicit aspect extraction relied on an unsupervised approach. Whereas supervised and semi-supervised approaches attained 42% and 13% respectively. This indicates that the unsupervised approach can be recognized as the most commonly used approach for explicit aspect extraction among the existing explicit aspect extraction studies. Meanwhile, the achievement is evidently due to the fact that the unsupervised approaches do not require dataset annotation as well as training. In addition, the cost of using the unsupervised approach is less and much faster compared to other approaches.

It could be observed that 15 studies focused on pure implicit aspect extraction using 11 different techniques such as co-occurrence, semantic-based, ontology, CRF, SVM, LSTM, Hierarchy, CNN, Lexicon-based, Matrix Factorization, and Topic modeling. This shows that there exist limited works targeting purely implicit aspect extraction, which is due to the fact that current researchers focused more on the explicit aspects. Meanwhile, implicit aspect is not fully explored despite being one of the demanding concepts in some areas associated with the explicit aspects extraction such as emotional affects. Secondly, the fact that implicit aspect extraction is considered as the latest aspect extraction area that is ambiguous in nature and is more semantic than explicit. That is why the majority of studies do recommend implicit as a feasible future direction. Researchers are mostly at the investigation stage of implicit aspects, and most of the techniques used are on trial based, by involving all the 3 approaches (supervised with 46%, semi-supervised 27%, and unsupervised 27%) for the task.

The result presented in Fig. 5 showed that Conditional Random Field, Lexicon-based, Dependency Parsing, Rule based, and LSTM are the most commonly used techniques with 62% frequencies for the combined implicit and explicit aspect extraction. This shows that in addition to the feature design flexibility of these techniques, researchers also made use of their strict independence assumptions advantage to accommodate any context information for the combined implicit and explicit aspect extraction task. We further found that the majority of the works for the combined aspects relied on semi-supervised approach which virtually doubled the use of unsupervised. The reason is that the task involved in the extraction of both implicit and explicit aspects in some cases requires data annotations, especially the implicit aspects due to the ambiguity and semantic nature inherent in it. This entails the frequent deployment of the semi-supervised approach. Several machine-learning researchers have already established that the application of unlabeled data, in conjunction with a little amount of labeled data, can yield a significant improvement in learning accuracy over unsupervised learning (where no data is labeled), but without the time and costs required for supervised learning (where the entire data is labeled or annotated).

Generally, and technically wise, we discovered that CRF is the most frequently applied techniques for explicit aspect extraction, and the combined implicit and explicit aspect extraction task with stronger performances. On the other hand, the fact that researchers are mostly at the investigative stage as per implicit aspects and most of the techniques applied are on trial based, thus the performance of their techniques are still unpredictable and dynamic.

Our analysis also showed that combination of precision, recall together with f-measure on the same study as metric for implicit, explicit or the combined implicit and explicit aspect extraction helps in achieving optimal performance of the models. Thus, the researchers evidently relied on those metrics with 35% utilization among the entire PSS.

More so, the study revealed that the datasets can further be classified into *Multi-Domain data* and *Single-Domain* data. According to our result, *Single-Domain* data are applied by 63% of the PSS and tagged as the most commonly used domains data. Whereas, *Multiple-Domain* covers 37% of the PSS (example *product reviews* is *Single-Domain* data and *restaurant* + *laptop* reviews are *Multi-Domain* data). With regards to datasets, *restaurant* + *laptop* reviews can be considered as the most frequently used data domain for pure explicit aspect extraction studies with 24% utilization frequency. We further observed that the use of *restaurant* + *laptops* is mostly between 2014-2019, which is probably due to the fact that 2014 was the year in which *SemEval-2014* was conducted and *restaurant* + *laptop* was among dataset provided for the ABSA tasks. Whereas, the result shows that *product* reviews are most frequently used for pure implicit as well as combined implicit and explicit aspect with 27% and 33% among PSS that targeted implicit and combined implicit and explicit respectively. Summarily, product reviews are dominantly used among the 3 PSS categories i.e implicit, explicit or combined implicit and explicit aspect extractions. This is due to the fact that the product domain contains more than one product with different patterns of reviews that were publicly available. Hence, this larger coverage, diverse as well as multiple review patterns makes it suitable for both implicit and explicit aspect extraction at a single time. It also emphasizes the contributions of some prominent online microblogs, social networks, and cloud service providers such as Amazon.com, C|net.com, Twitter, Facebook etc. in providing open source dataset to researchers. Meanwhile, the distribution of the years shows that works are consistently increasing in this area, which entails an increase in researchers' interest in the last decade with a major outbreak in 2014 to date.

The review also showed that apart from English and Chines languages, all the remaining languages identified were mostly used after SemEval-2016 on ABSA (i.e. between 2016 - 2019). The study also attest that English Language Domain is the most employed among the PSS with 71%, followed by Chinese 23%, and remaining less utilized Languages 6%. This shows that SemEval-2016 effectively contributed to the increase in language participation on ABSA tasks through the incorporation of the 8 different languages namely: English, Arabic, Chinese, Dutch, French, Russian, Spanish and Turkish via credible sentiment symposium involving experts in that field. In general, our study revealed that research activity continues to increase and the area demonstrates stable growth, predominantly over the last 5 years. Although there is a very wide gap between frequencies of using English with that of Chinese as the second most frequently used language (see Fig. 14), but the graph representing the annual utilization of the language goes in the same proportion.

Finally, it has been discovered that the key challenges associated with aspect extraction techniques are: (1) Ineffective and inefficient feature selections which exclude vital textual patterns, categories, and features that play a significant role in aspect and sentiment identification tasks, hence reduces the aspect extraction coverage and efficiency of the approaches proposed. (2) A limited dataset which affects the strength of the research findings. (3) Most of the approaches suffer low subjectivity as well as semantic oriented performance.

In view of our primary selected studies, we found that the top influential publication fora is *Knowledge-Based Systems*, which published 3 papers that are among the 5 most influential papers with a citation count of 407, 291, and 205 in [91], [101], and [126] respectively. This has to do with the fact that *Knowledge-Based Systems* is among the highly respected journals in Sentiment Analysis domain. It has been publishing significant research papers that shaped ABSA research direction. As for proceedings, *Proceedings of Association for Computational Linguistics* has made a significant contribution with the highest number of publications among the 5 most influential proceeding papers. The papers attracted citation counts of 688, 465 and 339 for [59], [75], and [98] respectively. It is also revealed that research activities in ABSA have been increasing over the last five years as 15% of our entire PSS has more than 100 citations.

B. HIGHLIGHT FOR FUTURE RESEARCH DIRECTIONS

We carefully studied the findings, results and discussions involved in this SLR. In the end, we were able to identify and highlight the following as feasible opportunities for future research directions:

1. Although efforts were made in explicit aspects extraction in the last decade, some areas such as subjectivity, objectivity as well as emotional effects associated with the aspects require consideration.
2. As good features selection plays a significant role in aspect and sentiment identification tasks in machine learning approaches and vice versa, this should be given special attention in future researches to ensure that the right features are always selected for optimal performance.
3. It has also been observed that additional attention is needed on implicit aspect extraction, considering its contributions to the meaning of textual contents.
4. The effects of *SemEval* on both data domains and languages changed the traditional perception of researchers on difficulties in accessing public data domains and more language inclusion by providing them with enabling environment to conduct more researches in the area of ABSA. Thus, more workshops and conferences that provide datasets in languages other than English should also be investigated in future research.

VI. FUTURE THREATS TO VALIDITY

To achieve a comprehensive analysis of the results obtained from this study, the limitations involved on the review must be considered. The key threats to this SLR's validity are study selection bias, data extraction bias, and data synthesis bias. These threats are discussed extensively in this section.

A. STUDY SELECTION BIAS

In order to minimize bias by researchers in relation to the study selection process, a well-defined inclusion and exclusion criteria (IC/EC) were formulated. Researchers may have a different perception on the IC/EC, hence, the study selection results of each researcher are likely to differ. To reduce this bias, a pilot selection was conducted to ensure that a consensus is reached among the researchers on the comprehension of the study selection criteria. The potential mismanagement of duplications is another threat that may have altered our results. Four cases of potential duplication were thoroughly examined to reveal whether they are the same study. Additionally, the final decision to select a study is given by the two researchers who handle the search process. Therefore, any disagreement emerged between the two researchers will be resolved between them through feasible discussion until a concrete agreement is achieved. The remaining researchers will then review the final selected studies. In this SLR, only peer-reviewed studies were considered. However, there is a tendency of missing some important non-peer-reviewed study on ABSA.

Moreover, to ensure that all prospective studies in ABSA have been covered, an extensive search on seven foremost digital libraries was conducted. A manual collection of studies from other databases (Web of Science and Google Scholar) were also added in the preliminary phase to avoid excluding any of the relevant studies due to the automatic advanced search limitations that can emerge from the ambiguous terms. Additionally, different publication titles may affect the automatic search coverage. To ensure effective inclusion of relevant studies, backward reference searched was also conducted. However, this study may suffer from timeline restrictions, which may cause bias because we try to consider the most recent studies. The rationale behind the timeline restriction is that the potential studies on the ABSA are revealed to have started around 2009.

B. DATA EXTRACTION BIAS

As for data extraction, this process may involves bias which may consequently affect the analysis and classification of the selected studies' results. To minimize this biases, the data entities extracted in this study were thoroughly discussed among the researchers and agreement on the meaning of each entity was reached. In addition, a pilot data identification, selection and extraction were carried out among the researchers in which consensus was reached on the data results' disagreements highlighted. Hence, the data entities extracted were observed by two researchers where 29 disagreements were deliberated and resolved. These measures are taken to mitigate bias, which will eventually leads to an improved accuracy of the extracted data entities.

C. DATA SYNTHESIS BIAS

Looking at the selected studies, most of the studies gives limited description of information needed to be extracted as data entities. As a result, some information about data entities had to be inferred during the data synthesis. For example, a study may use dependency-parsing technique which could be characterized as either supervised, semi-supervised or unsupervised approach for aspect extractions, with limited information to the readers. In this situation, we give the final conclusion on the category of the approach of such studies based on the nature of their experimental setup. Hence, potential bias and ambiguities can be reduced or mitigated.

VII. CONCLUSION

Aspect-based sentiment analysis (ABSA) has been revealed to be one of the most vigorous areas in NLP. In the last decade, aspect extraction has become the most essential phase of SA to conduct an abridged sentiment classification. Although many studies conducted mostly focused on explicit aspects, yet there are limited reviews that cover implicit, explicit, or combination of both implicit and explicit aspect extractions. Therefore, this systematic review has been conducted to identify techniques used for extracting implicit, explicit, or combination of both from perspective of supervised, semi-supervised and unsupervised approaches. Comparative analysis of various evaluation metrics, data domains, and languages involved in the implicit and explicit aspect extraction has been carried out from the year 2008 to 2019. Almost 100 research papers were reviewed, summarized and categorized systematically by adopting Kitchenham's systematic literature review procedure, in order to highlight the prominent challenges associated with the aspect extraction techniques based on the results of comprehensive comparative analysis. Considering the large number of papers involved, the significant findings obtained from the review are presented on the basis of approaches, techniques, evaluation metrics, data domains, languages and prominent challenges.

The main aim of this study is to use systematic literature methodology to furnish the aspect based sentiment analysis research community with an in-depth knowledge of the implicit and explicit aspect extraction domain. Our aim was achieved by means of answering the research questions highlighted. We finally identified feasible future research directions that can be beneficial to both veteran and novice researchers in conducting useful studies related to ABSA research domain.

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