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A Systematic Mapping Study of the Empirical Explicit Aspect Extractions in Sentiment Analysis

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ABSTRACT Aspect-based sentiment analysis (ABSA) is described as one of the most vibrant research areas over the last decade. However, due to the exponential increase in aspect-based sentiment researches, there is a massive interest in advanced explicit aspect extraction (EAE) techniques. This interest brings about a huge amount of literature in the EAE domain. This study aims to investigate and identify the existing approaches, techniques, types of research, quantity of publications, publication trends and demographics shaping the EAE research domain in the last decade (2009 - 2019). Accordingly, an evidence-based systematic methodology was adopted to effectively capture all the relevant studies. The main findings revealed that, 1) there is considerable and continuous rise of EAE research activities around different parts of the globe in the last five years, particularly Asia, Middle-East, and European countries; 2) EAE research has been very limited among African countries which need to be addressed due its role on business intelligence as well as semantic values; 3) three research facets were highlighted based on this study, i.e. solution research, validation research, and evaluation research, in which solution research gets the highest attention; and finally 4) the EAE challenges, as well as feasible future recommendations, were highlighted in this study.

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

I. INTRODUCTION

Online communication is becoming an inevitable necessity among people. The increase in social media connectivity as well as its acceptance has helped people to receive and disseminate information to others more quickly. There exists a particular type of information that deals with opinions, emotions, evaluations, attitudes, as well as feelings [1]. Online interactions has currently changed the traditional purchasing approaches, as well as social events. Nowadays, customers often check for online reviews about services or products they wish to buy [2]. Authorities also track online comments and sentiments on social events to improve their policies and security-related services. Looking at the exponential accumulation of the sentiment oriented information, demand for more studies on aspect-based sentiment analysis (ABSA) is paramount.

The application of sentiment analysis could be seen in different aspects of life, such as business where consumers' preferences are accessed through online opinions gathering [3]. An average human reader normally undergoes difficulties in detecting relevant information, not to mention the extraction or analysis of their associated sentiment. Thus, a review on sentiment oriented studies is needed due to the exponential increase in the online platforms containing useful information. Generally, the rationale behind sentiment analysis (SA) is to determine a sentiment polarity expressed in a given statement, i.e either negative, positive or neutral sentiment [4], [5].

Even though many researchers highlight the significance of analyzing peoples' opinion especially towards products [6], sentence and document-level analysis cannot determine the precise sentiment expressed. Thus, aspect-level analysis is introduced to achieve a fine-grained SA and focused on three tasks, namely: aspects extraction, category detection, and sentiment polarity [7]–[10]. It has been revealed that in every sentiment expression, there is one or more aspect term. Among all the sub-levels of SA, ABSA captured the attention of more researchers over the last decade [1], [2]. However, analyzing as well as extracting these aspects, remain

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the most crucial and vital task of the ABSA [8]. The area further increases the ability of the existing SA approach at semantic-level with a fine-grained result [11], this is in addition to efforts on identifying the desired aspects [12]. It is found that aspect is the level that processes multi-text feature-capability [13]. Several works have been published in SA research domain, ranging from quality criteria-based, renewable energy, and public opinions [14], [15], etc.

In view of the growing interest of the research community towards ABSA over the last decade, [8] conducted a comparative analysis, as well as a survey that focused on various aspect extraction techniques. Also, [16] reveals the effective role of topic modelling technique in aspect categorization and extraction, by reviewing topic modelling approaches with the aim of providing assessment and comparisons among the approaches. The study by [17] deliberated on semantically oriented concept-centric SA at aspect level, while [18] focuses on comparing and presenting recent developments in deep learning techniques in general as well as that of ABSA. Meanwhile, [19] presents a comprehensive review that described various studies specifically for implicit aspect extraction. The findings of their study revealed that implicit aspect consists of various aspects that can be explored independently and offered vital opportunities to the research community.

However, looking at the entire highlighted survey studies, systematic mapping studies are non-existence in this research domain. Our systematic mapping study was primarily conducted to bridge the gap by analyzing relevant literature extensively over the last decade (2009-2019). This is to assist new and veteran researchers in comprehending new trends involving the most or less utilized explicit aspect extraction (EAE) techniques, most utilized datasets, distribution of the contribution and research facets, the most influential publication venues (proceedings and Journals), most commonly used evaluation metrics, as well as the research challenges associated to the domain. Our contribution primarily lies in the detailed synthesis and analysis of the studies concerning aspect extraction in sentiment analysis. To ensure proper enclosure of all the relevant studies, we deployed an evidence-based systematic mapping methodology to ensure state-of-the-art literature coverage through an unbiased evaluation and selection process, which is lacking in the existing survey studies. The study was initiated with the systematic mapping protocol construction, which comprises of a search strategy, selection process, data extraction, inclusion and exclusion criteria, as well as strategies for the data synthesis. We further investigates the general research demographics, productivity and trends modelling the landscape of the research domain.

To elaborate detail, this paper is structured into 6 sections. Section 2 discussed the research methods in detail, which includes study selection procedure, research questions, and inclusion and exclusion criteria. In Section 3 and 4, anaylsis and discussions were presented respectively. Section 5 discussed the research's threats to validity comprehensively. Finally, we concluded our findings in Section 6.

II. RESEARCH METHOD

A systematic mapping study is basically conducted to offer an overview of a research domain by means of classifying contributions according to their categories [20]. These studies primarily explore current literature to examine the boundaries of multiple topics, research trends, publication venues, and frequency of publications in a related research area of interest. Systematic Literature Reviews (SLR) and Systematic mapping studies have many characteristics in common, such as study selection procedures and evidence-based searching. However, a systematic mapping studies consist of different kind of objectives in addition to its unique approach towards data analysis. An SLR deals with evaluation, identification, interpretation, and reporting tasks of available research that is relevant to a particular area of interest [21], while systematic mapping studies mainly focus on shaping a research area. Thus, our systematic mapping study primarily follows the guidelines proposed by Kitchenham and Charters [21] and Petersen *et al.* [20].

According to the systematic mapping studies guidelines [20], a systematic mapping process basically involves seven essential phases as shown in Figure 1. The first phase consist of the research questions (RQs) description, which is referred to as the primary activity. The second phase is where we provide adequate and appropriate strategy for searching the primary studies. The third phase involves screening of the literature identified to detect the related studies, while the fourth phase is essential as a point where the classification scheme is designed to familiarize the structure of the research focus. The fifth is the data extraction phase, and the sixth is the construction of systematic maps. The last phase involves the result and discussion of the study.

A. RESEARCH QUESTIONS

This study aimed at investigating and offering a fine-grained description of the present state of EAE research. Therefore, our focus is on what and how EAE researchers mostly investigates, what is the focus of EAE researchers, how has EAE research evolved over the last decade, as well as the methodology that EAE researchers utilized in providing reasonable solutions. However, the formulated RQs in this study were enthused from other influential ABSA studies such as [8], [19], [22], [23]. Equally, we observed the importance of a well-defined research question and its influence on researches of this nature. Table 1 presents the research questions.

B. LITERATURE SEARCH PROCESS

Seven electronic databases were considered as data sources for this study which are, Web of Science (WoS), ACM Digital Library, Springer Links, IEEE Xplore, Science Direct, Scopus, and Dblp. We did not consider Google Scholar due to its low precision as well as overlapping results compared

TABLE 1. Research questions.

RQ#	Research Questions	Objectives
RQ1	What types of approaches involved in EAE in SA?	To identify the types of EAE approaches in SA.
RQ2	What EAE techniques are commonly used in the previous works?	To investigate the commonly used EAE techniques in SA
RQ3	What are the research facet used in EAE and what contribution facet did EAE studies provide?	To explore the research facets (i.e validation, philosophical, evaluation, experience, demos/tools, Solution) and contribution facets (i.e framework, technique/method, Model, evaluation/comparison, and tool).
RQ4	What kind of datasets are commonly used in EAE?	To determine the various types of datasets used in EAE research.
RQ5	What types of evaluation metrics are mostly employed by EAE researchers?	To investigate the most employed metrics for evaluating EAE techniques in SA research domain.
RQ6	What are the demographic features of the relevant researches?	To determine the distribution of EAE studies geographically, highly cited studies, publication trends, publication venues, and influential studies (Proceedings and Journals) in EAE research domain.

FIGURE 1. The systematic mapping process.

to other databases. Additionally, there is no provision of advanced search options in the Google Scholar database which is needed for a more accurate search of relevant primary selected studies (PSS).

The formulation of search terms is important for an effective retrieval of the relevant studies. In this regards, Kitchenham *et al.* [24] has suggested a population, intervention, comparison and outcome (PICO) viewpoints. The viewpoints have been providing essential guide to several researchers conducting SLRs. At this point, we outlined the relevant terms for the population, intervention, and outcome as:

Population: Aspect, Features.

Intervention: Technique, Algorithm, Method, Approach, Framework, Model, System.

Comparison: Sentiment, Opinion.

Outcome: Extraction, Detection, Identification.

Going by the PICO structure, we formulated a generic string to ensure consistency in the search amongst the multiple databases. *Generic search string: ((“aspect” OR “aspect features”) AND (“extraction” OR “detection” OR “identification” OR “opinion” OR “explicit”) OR (“technique” OR “algorithm” OR “method” OR “approach” OR “framework” OR “model” OR “system”) AND (“sentiment” OR “sentiment analysis”)).* The fact that databases have dissimilar interfaces for normal command search and advanced search activities, our search strings were cautiously keyed in a form that suits each of the seven databases for optimal detection of all the relevant studies. Table 2 presents our search process involving initial and final results, as well as the amount of studies obtained from each database.

C. DATA EXTRACTION AND VETTING

For an efficient data selection, we started by cleaning and integrating the results obtained from any identified duplicate based on the study’s author, year, and title. Microsoft Excel was then used to identify and eliminate the duplicates. The studies obtained were equally distributed among two of our research team members. The full text of the studies were downloaded and shared among our researchers. In this study, a snowballing procedure was further conducted to ensure optimal selection of the desired studies.

We employed the vetting procedure proposed by [25], to ensure that each article undergoes an in-depth screening and to determine its relevancy. In addition, each researcher read the article carefully to check whether the article is qualified enough to be considered based on our inclusion and exclusion criteria described in Table 3. After the initial vetting, another researcher reviewed the selected study for verification. In some cases, only the most experienced member of our research team gave decision on the exclusion or inclusion of a study, as there are varieties of primary studies involving diverse methods in EAE domain. Finally, studies that were deemed irrelevant to be in the final list of the studies are excluded.

D. INCLUSION AND EXCLUSION CRITERIA

In order to answer the research questions highlighted in this systematic study, and to determine the potentially related

TABLE 2. Study selection process.

Database ID	Database	Initial Search Result	Relevant Screened Result	Final Selected Studies Based on Inclusion/Exclusion Criteria
DB1	Web of Science	490	124	23 (94-71 duplicates)
DB2	Scopus	1,882	310	26
DB3	ACM	2,647	511	21
DB4	Science Direct	938	270	18
DB5	Springer Link	160	99	14
DB6	IEEE Xplore	515	147	20
DB7	DBLP	442	97	11

TABLE 3. Inclusion and exclusion criteria.

	Inclusion Criteria
ICC1	Peer-reviewed Journal articles and conference proceedings
ICC2	Articles that focus on EAE methods as well as techniques, and provides a significant contribution to the EAE literature
ICC3	Articles with focus on aspect extraction, detection or identification in SA as a fundamental topic
ICC4	Inclusion of the most recent study where there exist several studies on the same theme
ICC5	Articles published over the last decade (2009 - 2019)
	Exclusion Criteria
ECC1	Studies in languages other than English
ECC2	Aspect extraction in the context other than sentiment analysis
ECC3	Studies on implicit aspect extraction
ECC4	Studies without validation of proposed approaches/techniques
ECC5	Work in progress

studies from the data source, an inclusion and exclusion criteria were employed. These criteria were utilized in the retrieval of all the selected studies across the entire phases involved in the study selection procedure. The inclusion criteria (ICC), and exclusion criteria (ECC) employed in this study are presented in Table 3.

E. CLASSIFICATION SCHEME

A classification structure was developed according to Petersen *et al.* [20] guidelines. Based on the 133 finalized studies, we examined the titles, keywords, abstracts, research methods, contribution/research facet, and research focus. In addition, publication outlets that involves geographic distribution (continent and country), publication year, publication fora, and journal/proceedings affiliations were examined. In some cases, we had to read the entire study comprehensively in order to determine the various characteristics involved in the study for classification. We document the characteristics identified in each study on a data extraction form illustrated in Figure 2.

The first classification deals with classifying the PSS into various research approaches and techniques employed. The three major research approaches employed in this empirical EAE are supervised, semi-supervised and unsupervised approaches. Subsequently, the classification was extended to the identification of the commonly used techniques, datasets domains, commonly used data sources, commonly used evaluation metrics and the most influential language domains employed in our PSS.

The second classification was inspired by [20] which involves classification and exploration of the selected studies based on the current types of research approaches. According to [20], research facets consist of evaluation research, philosophical paper, validation research, experience report, solution proposal and opinion papers. In view of the nature of our empirical study, only validation, solution, and evaluation research facets were considered for this study. The third classification focus on contribution facet, which mainly comprised of various contributions proposed by the selected studies. Based on our knowledge of ABSA and inspiration from other aspect extraction studies such as [8] and [19], we classified our contribution facets into algorithm, comparison/evaluation, architecture, tool/system, framework, model, and method/approaches. Also, our contribution facets classification as well as the 'lesson learned' which eventually entails the set of outcomes obtained in this study as inspired from [25], [26] were presented as framework, model, guidelines, theory, lesson learned, tools and advice. These contribution facets are in line with the guidelines proposed by [27].

Finally, we highlighted where EAE studies were mostly published by investigating our PSS publication fora, publication dates, geographical distributions, and citation counts.

III. ANALYSIS

In this section, the research questions were answered by analysing the results obtained from our PSS data.

A. WHAT TYPES OF APPROACHES INVOLVED IN EAE IN SENTIMENT ANALYSIS?

This study reported the degree to which different approaches are applied. Four approaches are involved in the EAE,

<table>
<tr><td colspan="9">Study Data Extraction and Eligibility</td></tr>
<tr><td>Study ID (Surname of first author and year e.g Bailey 2019)</td><td colspan="8"></td></tr>
<tr><td rowspan="2">Demographic features/publication fora</td><td>Journa l paper</td><td>Journal name</td><td>Proceedings</td><td>Conference organizers</td><td>Publication citation</td><td>Country</td><td>Author's name</td><td>Institution</td><td>Year</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Study Approach</td><td colspan="3">Machine Learning (ML)</td><td colspan="3">Non-machines learning (NML)</td><td colspan="3">Both ML and NML</td></tr>
<tr><td>Supervised</td><td>Semi-supervised</td><td>unsupervised</td><td colspan="3"></td><td colspan="3"></td></tr>
<tr><td>Dataset Used</td><td colspan="9"></td></tr>
<tr><td rowspan="2">Evaluation Metrics</td><td>Precision</td><td>Recall</td><td>F-measure</td><td>Accuracy</td><td colspan="5">Others</td></tr>
<tr><td></td><td></td><td></td><td></td><td colspan="5"></td></tr>
<tr><td rowspan="2">Validation</td><td colspan="2">Experimental</td><td>Comparison with Others</td><td colspan="3">Expert Validation</td><td colspan="3">None</td></tr>
<tr><td colspan="2"></td><td></td><td colspan="3"></td><td colspan="3"></td></tr>
<tr><td rowspan="2">Contribution</td><td>Method</td><td>Comparison</td><td>Technique</td><td>Model</td><td>Algorithm</td><td>System</td><td>Tool</td><td>Framework</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Decision</td><td colspan="3">Include</td><td colspan="6">Exclude</td></tr>
<tr><td colspan="3"></td><td colspan="6"></td></tr>
<tr><td>Reason for Exclusion</td><td colspan="9"></td></tr>
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FIGURE 2. Data extraction form.

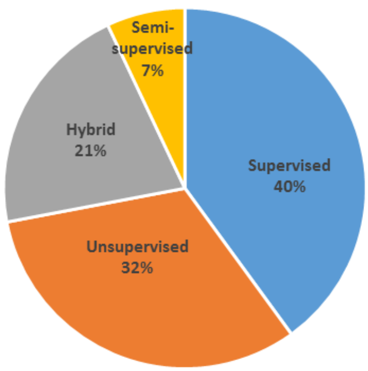

FIGURE 3. Explicit aspect extraction approaches with frequencies.

namely supervised, unsupervised, semi-supervised, and hybrid. Meanwhile, hybrid approach refers to a situation whereby two or more approaches are combined in a single work. According to the frequency distribution presented in Figure 3, 40% of the entire papers used supervised approach, followed by unsupervised with 32%. This implies that supervised approach is more prepared for EAE probably due to the complex and ambiguous nature of the aspect identification. At the moment it requires proper labelling for effective machine recognition. Although some researchers prefer to use semi-supervised approach with 7%, but the 21% frequency made it clear that hybrid approach is more relevant to the researchers because they are more concerned with getting optimal performance in recent years through hybridizing approaches.

B. WHAT EAE TECHNIQUES ARE COMMONLY USED IN THE PREVIOUS WORKS?

In view of our selected studies analysis, 24 prominent EAE techniques were found as depicted in Table 4 with their references. According to the result presented in Figure 4, 26% of the papers used hybrid-based technique, followed by neural networks (NN) (where NN also includes: recursive neural networks (RNN), convolutional nueral networks (CNN), and long short term memory (LSTM)), and conditional random field (CRF) with 15% and 9% respectively. On the other hand, techniques that have less contribution includes topic modelling and NLP-based (refers to *Named Entity Recognition*, being the most basic and essential NLP-based technique for the extraction of entities in text) that have 3% each, graph-based, Latent Dirichlet Allocation (LDA), and statistical-based 2% each, while expert-based and clustering have 1% each. Lastly, 8 papers are considered miscellaneous which contributed 6% of the total techniques involved. These papers used distinct EAE techniques that are not part of the frequently used techniques listed in Figure 4, because they were applied only once. Papers characterized as miscellaneous consist of techniques such as backpropagation, decision tree, bootstrapping, boltzmann machine, hierarchical-based, lexicon-based, bipartite networks, and ontology-based techniques.

Hybrid aspect extraction techniques as presented in Table 4 refers to a technique that combines two or more aspect extraction techniques together to ensure efficient aspect identification task. From our PSS, we have seen a huge rise in the utilization of hybrid techniques over the last decade. This revealed that 26% of the entire PSS techniques relied on hybrid-techniques. However, regardless of the prevailing utilization of neural networks technique, it has been observed that CRF-technique is still gaining more attention from aspect-based research community. From 2009 - present, we observed 133 papers, out of which 33 are based on hybrid technique, whereas NN and CRF-based techniques have 21 and 12 papers, respectively. Table 4 shows the reference of these techniques with years.

TABLE 4. Prominent EAE techniques with frequencies and references.

S/N	Techniques	Frequency	References
1.	Hybrid	33	[11, 28-59]
2.	NN	21	[23, 42, 60-78]
3.	CRF	12	[79-90]
4.	Semantic-based	9	[11, 91-97]
5.	Rule-based	8	[22, 98-104]
6.	Dependency Parsing	6	[105-110]
7.	SVM	6	[111-116]
8.	Pattern-based	5	[117-121]
9	Frequency-based	4	[122-125]
10.	Topic Modeling	4	[51, 126-128] ,
11.	NLP-based	4	[129-132]
12.	Graph-based	3	[133-135]
13.	LDA	3	[136-138]
14.	Statistical-based	3	[139-141]
15.	Expert-based	2	[142, 143]
16.	Clustering	2	[144, 145]
17.	Back Propagation	1	[146]
18.	Decision Tree	1	[147]
19.	Bootstrapping	1	[148]
20.	Boltzmann Machine	1	[149]
21.	Hierarchical-based	1	[150]
22.	Lexicon-based	1	[151]
23.	Bipartite Networks	1	[152]
24.	Ontology-based	1	[153]

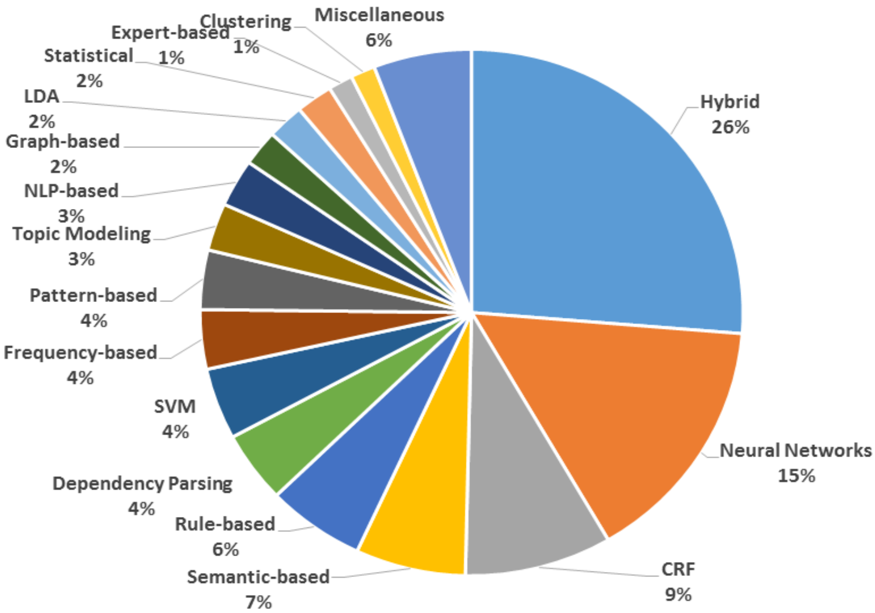

FIGURE 4. Distribution of prominent EAE techniques.

C. WHAT ARE THE RESEARCH FACET USED IN EAE AND WHAT CONTRIBUTION FACET DID (EAE) STUDIES PROVIDE?

The PSS could be described more in terms of contribution facet and research facet. Meanwhile, contribution facet are classified into Method/Approach, Model, Framework, Architecture, Tool/System, Evaluation/Comparison, and Algorithm as shown in Figure 5. In this study, *method/approach* are concerned with solving a specific issue or a well-defined research question on a particular objective and aims. An example of the papers focusing on method/approach could be seen in these references: [11], [23], [35], [51], [57], [60], [88], [89], [100], [118], [127], [128], [135], [152]. In comparison, *model* refers to a situation when a model-based approach is utilized, studies that employed *models* are [46], [48]–[50], [63], [70], [71], [75], [116], [126], [136], [146], [150]. In addition to *method/approach* and *model*, some aspect-based researchers presents a *framework*

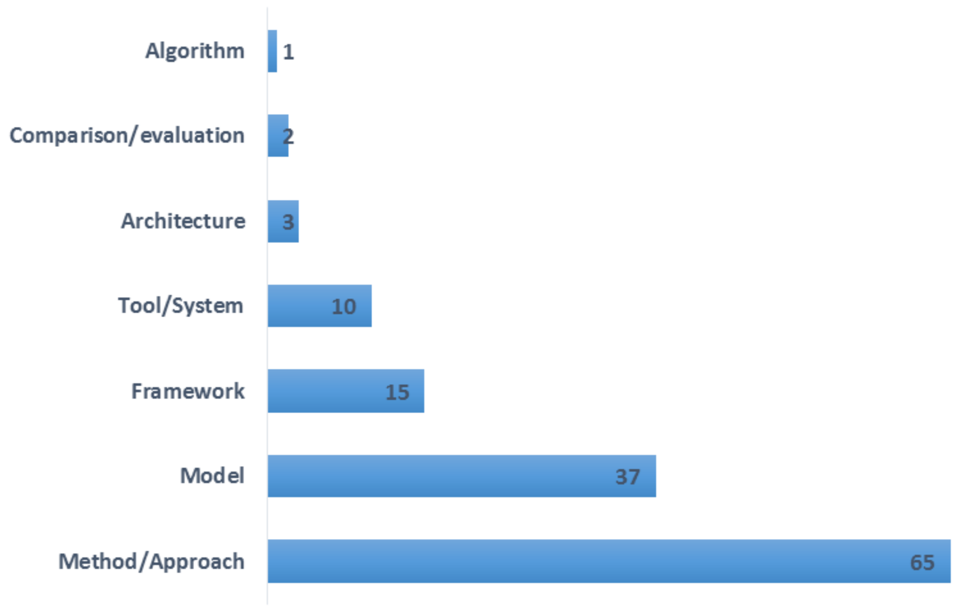

FIGURE 5. Contribution facet distribution.

as the main contribution, some of these studies includes: [59], [92], [94], [96], [109], [110], [113], [123]. Although their names were used interchangeably, *tool/system* are presented as the major contribution of some papers as shown by: [58], [79], [122], [129], [131]. For example, [131] proposed an open-source *tool* titled ABSA Toolkit that primarily analysed sentiments associated to aspects, while [79] presents an aspect-based hierarchical system which is considered as a fine-grained sentiment analysis system in edge computing. Some authors tend to unveil *architecture* for EAE among which are [43], [66]. *Comparison or Evaluation* refers to the PSS evaluating other approaches, systems, methods or, models etc. specifically evaluating the performance of the studies in aspect-based sentiment analysis context. An example of *comparison/evaluation* is given in [33], [73] where [73] conducted a comparative-study based on word embedding, sentic-features and POS-tag for Thai sentiment analysis using deep learning techniques. Moreover, there exists studies that proposed *architecture* and could be seen in [43], [66]. Finally, *algorithm* is normally a set of rules proposed to solve aspect extraction related problems and only one study [91] proposed *algorithm* as its contribution.

In this study, the analysis of contribution facet results has disclosed that contribution facet of *method/approach* is the highest with 49%. On the contrary, *algorithm* contribution facet appeared to be 1%, which makes it the least studied with just 1 paper in our PSS. Figure 5 demonstrates the contribution facets distribution with their number of papers.

This systematic mapping study further pursues the exploration of various research facets in the aspect extraction research context. These research facets are classified as evaluation research, solution research, and validation research. Evaluation research is about implementing techniques in order to produce a performance evaluation of a technique. Such research facet category reveals the usability of the proposed technique as well as its strengths and limitations. The examples of evaluation research could be found in [11], [86], [101], [128]. Solution research offers a solution to problems that can either be a substantially extension of the current approach or just a novel one. Similarly, example of solution research could be found in [36] which proposed a supervised and unsupervised approach for aspect category detection in sentiment analysis using co-occurrence. Finally, validation research usually introduced a novel techniques that have neither been fully implemented nor evaluated. The examples of validation research are demonstrated in [82], [109], [122].

Analysis of the PSS based on research facets revealed that most of those studies were carried out using a solution research approach with (70%) of the entire studies. However, the number of studies with focus on evaluation research are considerably insignificant (20%). While validation research is found to attract the least studies with (10%). This justifies the fact that most of the current researches on EAE focuses on novel solution proposals as well as experiments conducted in a well-ordered environment. This entails the need for more validation and evaluation researches that can help in evaluating how effective new aspect extraction solutions really are. A bubble map in Figure 6 presents the research facets distribution against the EAE techniques. Meanwhile, the first

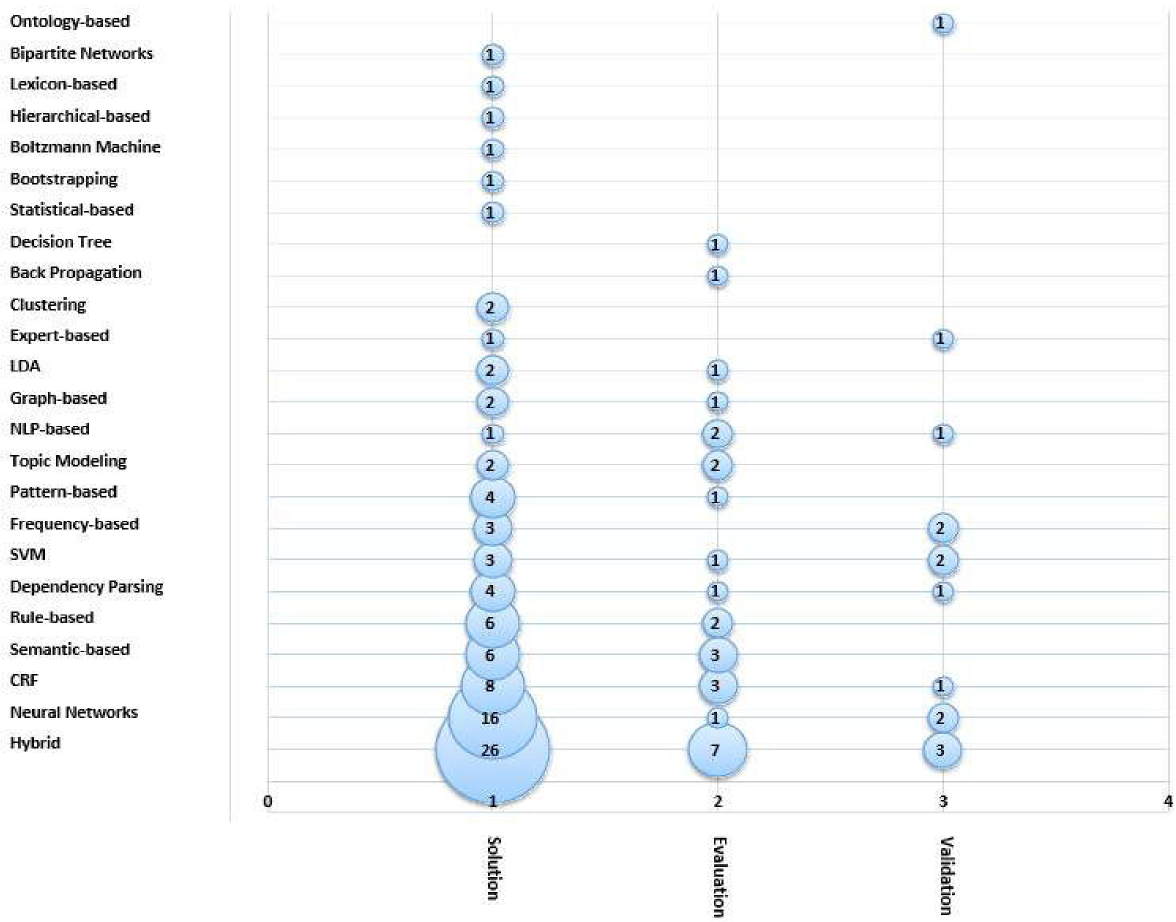

FIGURE 6. **Bubble plot for research facet of EAE techniques.**

column represents solution research, second column represents evaluation research, whereas last column represents validation research papers.

D. WHAT KIND OF DATASETS DOMAINS ARE COMMONLY USED IN (EAE)?

According to our analysis, 18 different types of data domains are involved in this study which are referred to as single data domains. The term single data domain means a situation where only one type of domain is used in a study. The result obtained revealed that among single data domains, product reviews data are the most commonly used in EAE research area (see Table 5). It is further discovered that the 5 most utilized datasets (i.e datasets with the highest number of papers) are profit-oriented datasets namely: Product Reviews (15), Restaurant Reviews (13), Electronic Reviews (11), Hotel Reviews (9) and Customer Reviews (6). We found that most of these data domains are publicly available for the researchers and contain huge datasets of different patterns that could lead to multiple research findings. However, the least frequently used data domains are Automobile Reviews, Hate Crime Corpus, Children Tales, Train Ticket Reviews, Online Skin Care Reviews, Document Reviews, and Online TV Reviews. Each of these data domains is used by only one study. This less utilization of those data is mainly due to the fact that they involved specialized datasets with limited demand and interest among researchers.

Apart from single data domains, there exists a multiple data domain, which refers to a situation where multiple data domains are combined in an EAE oriented study. According to the result presented in Table 6, majority of the studies used multiple data domains. This could be observed from the number of papers that uses Restaurant and Laptop reviews with 27 papers, which turn out to almost double the papers used by the most frequently used single data domain. Even though both single and multiple data domains are active among researchers, we further learned that *Restaurant* + *Laptop* reviews have the highest usage among the entire data domains. This is basically due to its multi-pattern coverage as well as open accessibility that made it easy to conduct and evaluate researches.

Figures 7A – 7E below presents analysis of the datasets employed over the last 5 years (2015 – 2019). In 2015, we discover that out of all the datasets, *Customer*, *Electronic* and *News Headline* Reviews are used the most with 2 studies utilizing them each. Book and Digital Camera Reviews are

TABLE 5. Single data domains.

SN	Data Domains Used	Number of Papers	Reference
1.	Product Reviews	15	[11, 23, 31, 46, 54, 67, 81, 82, 85, 103, 106, 134, 135, 137]
2.	Restaurant Reviews	13	[33, 38, 58, 99, 101, 118, 121, 124, 125, 130, 148]
3.	Electronic Reviews	11	[33, 38, 58, 99, 101, 118, 121, 124, 125, 130, 148]
4.	Hotel Reviews	9	[37, 42, 97, 113, 122, 136, 143, 146]
5.	Customer Reviews	6	[55, 59, 75, 98, 139, 147]
6.	Social Media Reviews	4	[94, 112, 127, 129]
7.	News Headlines	4	[47, 49, 60, 90]
8.	Mobile Reviews	3	[92, 96, 138]
9.	Digital Camera Reviews	3	[40, 115, 117]
10.	Movie Reviews	3	[102, 108, 114]
11.	Book Reviews	2	[111, 142]
12	Automobile Reviews	1	[74]
13.	Hate Crime Corpus	1	[57]
14.	Children Tales	1	[73]
15.	Train Ticket Reviews	1	[41]
16.	Online Skin Care Reviews	1	[56]
17.	Document Reviews	1	[64]
18.	Online TV Reviews	1	[144]

TABLE 6. Multiple data domains.

S/N	Data Domains Used	Number of Papers	Reference
1.	Restaurant + Laptop	27	[22, 28, 29, 32, 39, 45, 48, 52, 61-63, 66, 68, 70, 72, 76, 79, 80, 83, 88, 89, 93, 105, 107, 110, 132, 150-152]
2.	Restaurant + Laptop + Hotel + Product	5	[43, 71, 128, 131, 133]
3.	Restaurant + Hotel	3	[34, 53, 109]
4.	Product + Hotel	2	[104, 120]
5.	Restaurant + Electronic	2	[50, 91]
6.	Camera + Hotel	2	[51, 52]
7.	Clothes + Hotel	1	[116]
8.	Restaurant + Movie	1	[145]
9.	Electronic + Movie	1	[100]
10.	Restaurant + Cricket Game	1	[65]
11.	Laptop + Mobile	1	[126]

the remaining datasets used in 2015 with 1 study each. In 2016, product reviews and Restaurant reviews were discovered to be the most active datasets utilized by 5 and 4 studies respectively. As 2016 marks the beginning of the exponential increase in researchers' interest in EAE, more studies make used of *Hotel*, *News Headlines*, *Digital Camera*, and *Electronic* reviews consisting of studies that almost doubled that of 2015. In 2017, we observed the rapid increase in the utilization of *Restaurant* reviews. This is primarily because restaurant dataset accumulates on daily bases, as dealing with restaurant is inevitably part of humans' life, so as its reviews. Also, free SemEval restaurant review dataset became known to researchers in 2017. However, from 2018 – 2019, we have seen that *Product* reviews are the most utilized dataset due to fact that the current trend in sentiment analysis unveils the industrial values of ABSA to attain customer satisfaction. In 2019 we can see that the utilization of the dataset has decreased generally, it is primarily because many papers in the year are yet to be published.

1) THE MOST INFLUENTIAL LANGUAGES

From our selected studies, 17 language domains were involved, where 6 languages are considered the most influential due to the fact that they were used multiple times. These languages were applied in 120 out of 133 analysed papers in the study. Figure 8 shows that English language has the highest frequency with 88% among the influential language domains, followed by Chinese with 8 papers. Despite the multi-utilization status, Hindi and Vietnamese languages have less influence. The remaining 12 languages are considered least influential as they were found to be employed once throughout this study, which are German, Thai, Spanish, Dutch, Basque, Catalan, French, Russian, Turkish, Korean, Bangla, and Czech.

2) THE MOST INFLUENTIAL DATA SOURCES

According to our studies, 48 different data sources were identified, 13 of which were used multiple times by different papers totalling to 138 precisely. On the other hand, 35 data sources are used by a single study each, which includes: LABR, OpeNER Sentiment Corpora, Google App Store, TanSongBo, SINA Blog, GermEval-2017, Big Data and Computational Intelligence Competition (BDCI2018), JD.com, Internet Movie Database (IMDb), Kaggle, Wikipedia, Ebay.in, VLSP-2018, Opinimine Corpus, Youtube, Al-Arabiya, Donanim Haber, Github.com, CNN, Aljazeera, Zomato, OpenTable.com, Jeeran.com, Naver, Immdb.com, large movie reviews, Cornell sentiment Polarity,

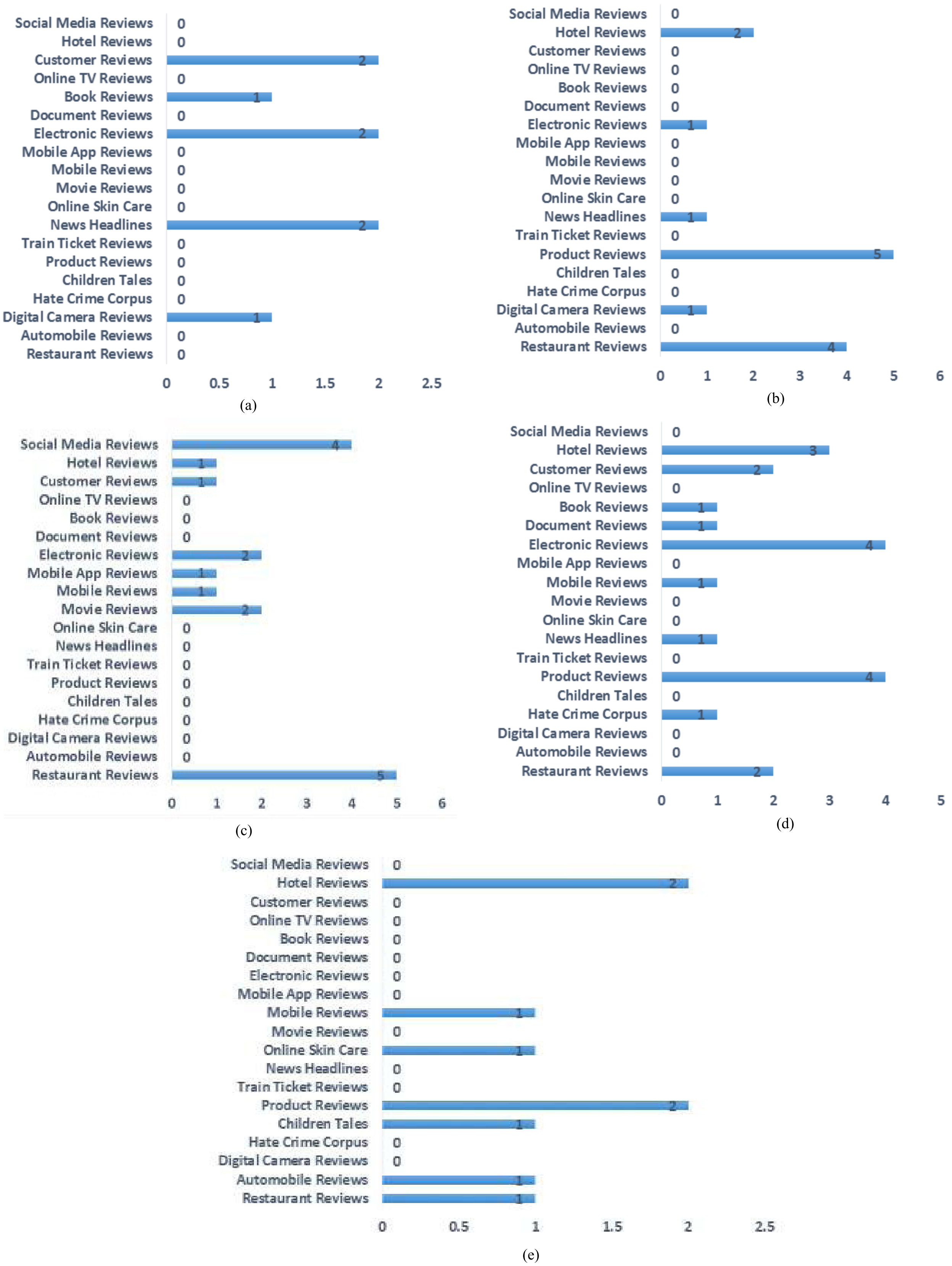

FIGURE 7. **(a) 2015. (b) 2016. (c) 2017. (d) 2018. (e) 2019.**

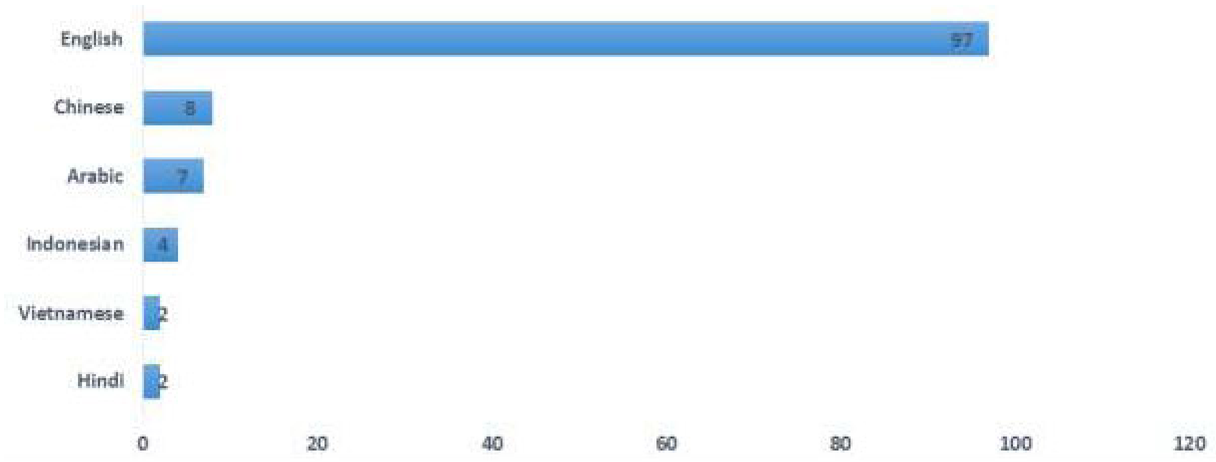

FIGURE 8. Most influential languages.

TABLE 7. Most influential data sources.

S/N	Data Sources	Data Sources Link	Number of Use
1.	SemEval-2014	http://metashare.ilsp.gr:8080/repository/browse/semeval-2014-absa-restaurant-reviews	29
2.	Amazon	Amazon.com	27
3.	SemEval-2016	http://metashare.ilsp.gr:8080/repository/browse/semeval-2016-absa-restaurant-reviews	12
4.	Online Market Places	https://crazylister.com/blog/online-marketplaces-ecommerce/	12
5.	Trip Advisor	TripAdvisor.com	11
6.	Twitter	Twitter.com	11
7.	SemEval-2015	http://metashare.ilsp.gr:8080/repository/browse/semeval-2015-absa-restaurant-reviews	8
8.	Yelp	Yelp.com	7
9.	C|net	C|net.com	6
10.	Citysearch New York	www.citysearch.com	3
11.	Booking.com	https://www.booking.com/	2
12.	Newegg.com	Newegg.com	2
13.	FBS Customer Review Data	Cs.uk.edu/liub/FBS/CustomerReviewData	2
14.	SenticNet	http://sentic.net/babelsenticnet.zip	2
15.	Sentihood Dataset	http://github.com/senticnet/concept-parser	2

Bollywoodhungama, COAE-2008, it168.com, ZOL, Internet Movie Database, epinions.com, BBC Bengali service and DailyProthomALO. In summary, the 48 different data sources were used by our selected studies 167 times, and 13 of these data sources consist of 83% of our selected studies which is why they were tagged "most influential data sources". This is primarily because they were mostly made publicly available and accessible to other researchers in this domain. Whereas, the remaining 35 data sources obtained just 17% of the total used and were named "Less influential data sources" as shown in Figure 9.

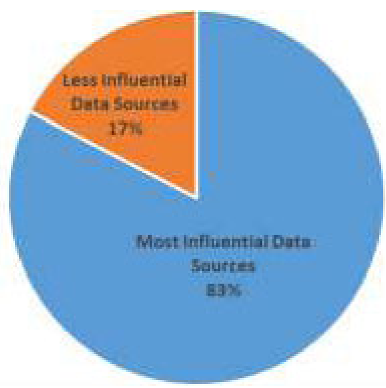

FIGURE 9. Distribution of data sources influence.

Table 7 presents the most influential data sources in EAE with their corresponding links. The result revealed that SemEval-2014 is the most frequently used data source with 29 papers, followed by Amazon with 27 papers. Though Amazon achieved the second most influential data source with insignificant difference with SemEval-2014, it is also the only standard product firm with global recognition that stood to be among the most influential EAE data sources. However, what makes SemEval unique is the fact that we found three different SemEval datasets in this study happened to be among the most influential data sources and makes almost 40% of all the influential sources namely: Semeval-2014, Semeval-2015, and Semeval-2016 (see Table 7). This is primarily due to its reliability, accessibility, and sentimental nature. In addition, these SemEval data are generated, structured, and provided annually for sentiment oriented researches through a well-organized sentiment symposium that involves experts in the field [154]–[156]. On the other

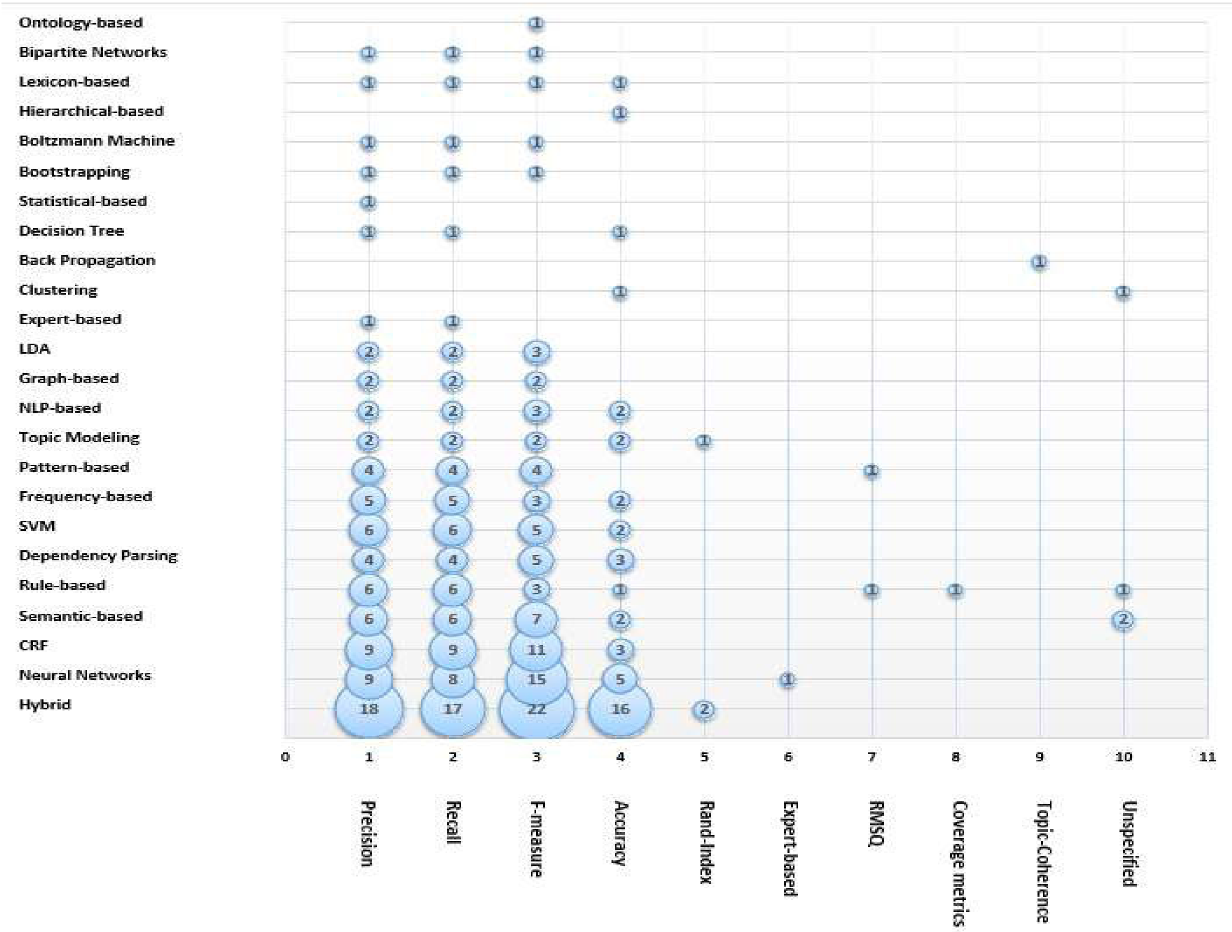

FIGURE 10. Evaluation metrics utilized.

hand, Booking.com, Newegg.com, FBS Customer Reviews, SenticNet and Sentihood dataset are the most influential data utilized by the least number of studies of 2 each, simply due to their limited patterns, as well as limited access of the data by researchers.

E. WHICH EVALUATION METRICS ARE MOSTLY USED BY EAE RESEARCHERS?

To determine the most utilized evaluation metrics in the subject's literature, a comprehensive analysis of the PSS was conducted. Figure 10 presents the entire evaluation metrics identified in relation to the EAE techniques used. A total of 10 metrics were identified consisting of F-measure, Precision and Recall with 85, 81 and 78 number of usage respectively as the 3 most utilized metrics on EAE. Also the 3 most used EAE techniques in relation to the top metrics are hybrid-based technique, Neural Network-based technique, and CRF technique. On the other hands, Topic Coherence, Coverage, and Root Mean Square (RMSQ) metrics are categorized as less essential metrics, because they are the least employed with only 1 study each. However, 4 studies comprising of Clustering, Rule-based as well as 2 Semantic-based techniques were exempted in our analysis due to lack of a clearly defined metrics used for evaluating their studies.

F. WHAT ARE THE DEMOGRAPHIC FEATURES OF THE RELEVANT RESEARCHES?

In response to this research question, we examined 6 classes of our PSS: publication fora, publication trend that is instrumental in publishing the most represented studies (Proceedings and Journals), most influential proceedings, most influential journals, most represented countries, and the most active institution in EAE research field.

1) WHAT ARE THE PUBLICATION TREND?

From the year (2009 – 2019), 133 publications were found from the literature in accordance with our methodology (see Section 3). Figure 11 presents the evolution of the publication in EAE research domain. Generally, the research activity in EAE appeared active and progressive. Although sentiment analysis has been a well-known and vibrant area in the last decades, EAE started significantly in 2010. Meanwhile from 2010 – 2012 research activity was observed to be linear, with an increasing number of publications as a result of calls for

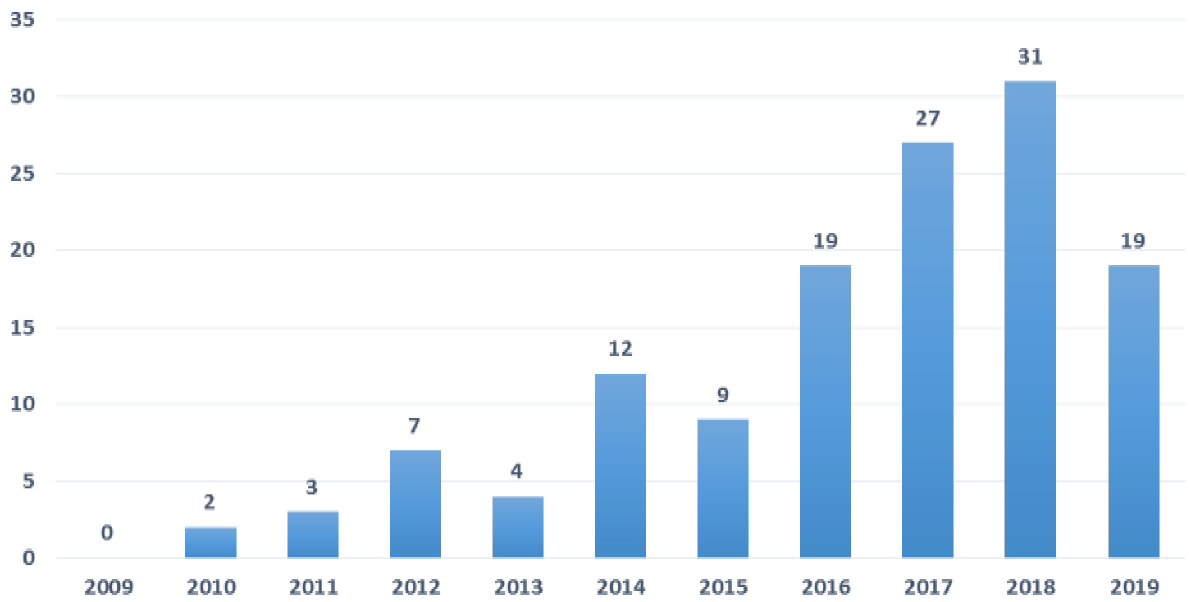

FIGURE 11. Publication per year.

participation in fine-gained SA techniques which eventually became popular [136], [154]. However, in 2013, there was a slight decrease in the research activities. One possible justification of this is that, researchers were cynical about the acceptability or recognition of ABSA globally. From 2014, there was a tremendous increase in research activity in the field of ABSA, even though it is newly introduced. The research activities in EAE increases considerably due to giant efforts to boost and make aspect-based research activities much easier. This could obviously be justified considering existence of the most represented proceeding (i.e *International Workshop on Semantic Evaluation (SemEval))* with a specific focus on ABSA. The workshop took place in 2014, which mark the beginning of a dedicated ABSA task by sentiment evaluation workshops (i.e SemEval-2014). It aimed at fostering research activities in ABSA domain, example [157] extensively highlights significance of the field.

Even though we noticed a little publication declined in 2015, this was due to the fact that there was decrease in researchers' participation in our leading proceedings (i.e SemEval) from 163 submissions in 2014 [154] to 96 in 2015 [155]. The year 2016, 2017, and 2018 witnessed consistent research activities with a considerable increase in the PSS of 19, 27, and 31 publications respectively. The main reason for the rise in this research activities is that 73% of the most represented journal in EAE publication (i.e *Knowledge Based System*) were found within the range of 2016 – 2018. Also, the incorporation of the 7 additional languages namely: *Arabic, Dutch, Chinese, French, Turkish, Russian, and Spanish* in SemEval-2016 [156] as well as making them easily accessible helped significantly in attracting more researchers, which leads to the publication of highly influential articles in EAE such as [8], [14], [16], [17], [19]. Moreover, in 2019, there were 19 publications, even though a little less than the preceding year, but it was considered impressive. The key reason for the decrease is linked to the fact that we cannot make strong and valid conclusion for the year 2019 because our research covers only part of the year as more papers are yet to get published. Generally, in spite the result of the studies on EAE, the research activity continue to upsurge and the area demonstrates stable growth, predominantly within the last 5 years. Figure 11 shows the distribution of EAE publication trends over the years.

2) WHICH PUBLICATION FORA HAVE PUBLISHED RELEVANT STUDIES?

In this study, we covered 25 journals, 54 conference proceedings, 2 symposium proceedings, 6 workshop proceedings, and 2 book chapters. Figure 12 shows that most of the PSS were extracted from conference proceedings (72), trailed by journal articles (45), workshop proceedings (11), book chapters (3), and lastly symposium proceedings (2).

With regards to the publication venues in which EAE studies were published, Table 8 presents the top 7 most represented journals. The *Journal of Knowledge Based System* as well as *Journal of Information Science* were the top contributors among the entire journals involved with 10 and 6 publications respectively.

Similarly, this study described conference, book chapter, workshop and symposium as proceedings. Table 9 shows the top 15 most represented proceedings. Therefore, the *International Workshop on Semantic Evaluation (SemEval)*, and *IEEE International Conference on Data Mining* Workshops were shown as the top contributors among the proceedings with 9 and 6 publications respectively.

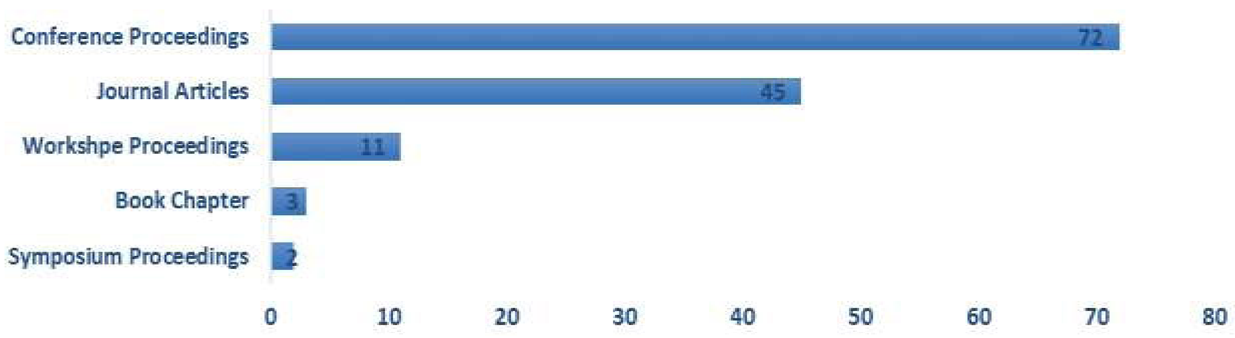

FIGURE 12. Publication channel.

TABLE 8. Most represented journals.

S/N	Title	Number of Papers
1.	Knowledge Based System	10
2.	Journal of Information Science	6
3.	Information Processing and Management	5
4.	Computation and Language	5
5.	International Journal of Machine Learning and Cybernetics	4
6.	IEEE Transactions Audio, Speech, and Language Processing	4
7.	IEEE Transactions on Cybernetics	3

TABLE 9. Most represented proceedings.

S/N	Title	Number of Papers
1.	International Workshop on Semantic Evaluation (SemEval)	9
2.	IEEE International Conference on Data Mining Workshops	6
3.	AAAI Conference on Artificial Intelligence	3
4.	ACM International Conference on Information and Knowledge Management	3
5.	IEEE International Conference on Advanced Informatics: Concept, Theory and Application (ICAICTA)	3
6.	IEEE International Conference on Information Retrieval and Knowledge Management	3
7.	International Conference on Computational Linguistics	2
8.	Annual Meetings of the Association for Computational Linguistics	2
9.	International Conference on Intelligent Text Processing and Computational Linguistics	2
10.	IEEE International Conference on Neural Networks (IJCNN)	2
11.	IEEE International Conference on Asian Languages Processing (IALP)	2
12.	IEEE International Conference on Computing communication Control and Automation (ICCUBEA)	2
13.	Pacific – Asian Conference on Knowledge Discover and Data Mining	2
14.	Joint Conference on Empirical Methods in Natural Language Processing	2
15	IEEE Symposium Series on Computational Intelligence (SSCI)	2

3) WHAT ARE THE CITATION IMPACT?

Ordinarily, one of the major factors that greatly influenced citations is the duration of the publication, and perhaps publishing paper earlier entails more citations. According to our study, it has been observed that the proceedings tend to have more citations compared to journal articles. This is obviously due to the rate at which proceedings are published is much higher than journal articles, and the publication time is also less. Citation counts of the entire selected study were extracted from Google Scholar, which is subject to change at any moment. Google Scholar provides a reliable measure of the number of times a paper is cited. We identified 10 journal articles as the most influential studies in EAE as presented in Table 10. It was found that 3 studies appeared as the top most influential with more than 100 [23], [108], [127], 5 articles obtained over 60 citations and 2 articles with more than 40 citations each [48], [51], [52], [71], [114], [128], [158]. On the other hand, 10 most influential proceedings were similarly identified, where we have identified 7 proceedings with more than 100 citations each [22], [35], [45], [50], [112], [133], [136], and 3 proceedings with over 40 citations each [11], [69], [159]. Table 11 provides a list of the most influential EAE proceedings based on the citation count.

4) WHAT IS THE GEOGRAPHICAL DISTRIBUTION OF THE SELECTED STUDIES?

According to our selected studies, 40 unique counties were involved in EAE research. China with 32 publications is the most active country in EAE research, followed by India with 17, and Malaysia with 8 publications. We also found that Singapore, Spain and Indonesia have 7 publications

TABLE 10. Most influential EAE journals articles.

S/N	Journal Title	Citation Count
1.	Aspect extraction for opinion mining with a deep convolutional neural network [23]	317
2.	Aspect-based sentiment analysis of movie reviews on discussion boards [108]	238
3.	Multi-aspect sentiment analysis for Chinese online social reviews based on topic modeling and HowNet lexicon [127]	174
4.	Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier [114]	97
5.	A hierarchical model of reviews for aspect-based sentiment analysis [71]	86
6.	Recursive neural conditional random fields for aspect-based sentiment analysis [48]	74
7.	W2VLDA: Almost Unsupervised System for Aspect Based Sentiment Analysis [158]	63
8.	Product aspect extraction supervised with online domain knowledge [51]	61
9.	Incorporating appraisal expression patterns into topic modeling for aspect and sentiment word identification [128]	47
10.	Feature selection and ensemble construction: A two-step method for aspect based sentiment analysis [52]	44

TABLE 11. Most influential EAE proceeding papers.

S/N	Proceeding Title	Citation Count
1.	Aspect and sentiment unification model for online review analysis [50]	702
2.	Towards an integrated pipeline for aspect-based sentiment analysis in various domains [112]	411
3.	Aspect extraction through semi-supervised modeling [136]	292
4.	NRC-Canada-2014: Detecting aspects and sentiment in customer reviews [45]	237
5.	Multi-aspect sentiment analysis with topic models [35]	175
6.	A rule-based approach to aspect extraction from product reviews [22]	162
7.	Opinion target extraction using word-based translation model [133]	100
8.	An unsupervised neural attention model for aspect extraction [69]	88
9.	Improving opinion aspect extraction using semantic similarity and aspect associations [11]	54
10.	Human Annotated Arabic Dataset of Book Reviews for Aspect Based Sentiment Analysis [159]	46

each. Whereas Netherland, Vietnam and Jordan have 5 publications each. Germany is the list active country with 4 relevant studies. Generally, with regards to continent, Asia appeared to be the most active continent in EAE research consisting of 60% of the entire countries involved, followed by Europe with 30% of the countries, and finally, the list among the most active continents is Middle East whereby only Jordan succeeded in being among the most active countries in EAE research as well as the only country from the Arabian Peninsula with 10% coverage. There are countries with more than one publications but less than the most active countries, they includes: *Korea, Pakistan, Sri Lanka,* and *USA*, they published 3 studies each, while *Italy, Brazil, Poland, Ireland, UK,* and *Iran* published 2 studies each. The remaining 12 countries that contributed to the EAE researches published 1 paper each. Surprisingly, there is no African country with EAE publications. Table 12 shows the most active countries in EAE research.

TABLE 12. Most active countries in (EAE) research.

S/N	Countries	Number of Papers
1.	China	32
2.	India	17
3.	Malaysia	8
4.	Singapore	7
5.	Spain	7
6.	Indonesia	7
7.	Netherland	5
8.	Vietnam	5
9.	Jordan	5
10.	Germany	4

Based on our selected studies, we were able to identify 10 unique institutions and tagged them as the most active institutions in EAE researches around the world. All the 10 top institutions were discovered to be academic-oriented institutions. *University Sains Malaysia* has the highest number of publications with 6 papers, followed by *Bandung Institute of Technology, Bandung Indonesia*, *Erasmus University Rotterdam, Netherlands*, and *Jordan University of Science and Technology* with 5 publications each. Although the last 3 Institutions on this list of the most active institutions are Chinese Institutions. However, Chinese is the only country with 3 different institutions on the novel list of the most active institutions in EAE research, namely *Tsinghua University Beijing China*, *Peking University Beijing China*, and *Southeast University China* with 3 publications each. Table 13 displays the most active institutions in EAE research with respect to the number of their publications.

IV. DISCUSSION

In this study, we adopted Petersen's systematic mapping study as our principal guideline to provide an overview of the current empirical studies in ABSA. Additionally, this study also considered kitchenham's systematic literature review as the secondary guideline to enrich the results and ensure comprehensiveness of the study. This section is structured into 2 parts. The first part presents the major findings of this study comprehensively. The second part highlights some of

TABLE 13. Most active institution in (EAE) research.

S/N	Institutions	Number of Papers
1.	University Sains Malaysia	6
2.	Bandung Institute of Technology, Bandung Indonesia	5
3.	Erasmus University Rotterdam, Netherlands	5
4.	Jordan University of Science and Technology	5
5.	Indian Institute of Technology Patna (IIT Patna)	4
6.	Nanyang Technology University, Singapore	4
7.	Ho Chi Minh City University of Science, Vietnam	4
8.	Peking University Beijing, China	3
9.	Tsinghua University Beijing, China	3
10.	Southeast University China	3

the key challenges identified from the PSS, and offer possible recommendations for future research direction. Moreover, research challenges mentioned in the literature were also highlighted.

A. MAJOR FINDINGS

The major aim of this study is to examine the present research activities in EAE. In doing so, 133 papers were carefully chosen to be the primary studies of this study in accordance with the methodology adopted for analysis. The major findings of our proposed study are presented as follows.

EAE research domain has been gaining more attention from the sentiment analysis community since 2014, with a growing publications that lead to an average of 10 publications from a reputable proceedings and journals every year. According to our PSS, it has been discovered that about 34% of the published papers were in a journals, whereas 66% papers published in proceedings consisting of symposiums, workshops, book chapters and conferences. Considering the publication consistency as well as the increasing attention from the research community, we have confidence that EAE research domain would probably gain even more attention in the near future due to its semantic values as well as effect on business intelligence.

The most commonly used EAE technique is hybrid-based technique as used in 26% of the PSS. However, we have witnessed growing activities in both NN and CRF based techniques. An additional observation was the growing number of miscellaneous studies, with 6% out of the entire selected studies. However, we discovered that Hybrid-based technique is consistently gaining more attention particularly in the last 5 years, in which 60% of the selected studies depends on the Hybrid technique between (2014 – 2019). It could be predicted that there would be even more works on Hybrid-based techniques in years to come.

Based on our primary studies, it has been identified that the top publication fora are *Knowledge Based System* and *Journal of Information Science* with 10 and 6 articles respectively. This does not come as a surprise, considering the fact that they are among the most highly regarded journals in SA context. They have been publishing key research papers that shaped ABSA research direction. As for proceedings, *International Workshop on Semantic Evaluation (SemEval)* has made a significant contribution with highest publications of 9 papers, followed by *IEEE International Conference on Data Mining Workshops* with 6 papers.

Considering the increasing activity in EAE researches in the last five years, 8% of the primary studies has more than 100 citation. Looking at countries with large publications, our studies have revealed that 24% of the selected studies were published in China, whereas 13% of the entire studies were from India. Nevertheless, countries like Malaysia (8), Singapore (7), Spain (7), Indonesia (7), Netherland (5), Vietnam (5), Jordan (5) and Germany (4) are the top publishing countries identified. It is also observed that Asian countries are the most active nations in EAE research consisting of 60% of the publications from the entire countries involved, followed by Europe with 30%. The only country from Arabian Peninsula (Middle East) countries that is found on the list of the top most active countries in EAE is Jordan, with 10% of the publications. It was further revealed that despite the research effort from different parts of the world on EAE, there have been limited studies from African counties. Therefore, there is need for future researches to investigate and address these barriers, inorder to facilitate even EAE researches in all parts of the world.

Our study revealed that all the contributing institutions are academic-oriented. *University Sains Malaysia* has the largest number of publications of (6), then followed by *Bandung Institute of Technology Bandung Indonesia*, *Erasmus University Rotterdam Netherlands*, and *Jordan University of Science and Technology* with (5) publications each. It was further discovered that even though (3) Chinese Institutions are the least among top most active institutions, they were revealed as the only multiple institutions from the same country that appeared among the most active institutions in EAE area. This could be as a result of Chinese commitment to any research domain that requires keen attention, with aim of making the world a better place.

The study shows that the datasets can be categorized into single data domains and multiple data domains. Single data domains are utilized by 62% of the PSS and referred to as the most frequently used data domains. On the other hand, multiple data domains consist of 38% of the publications. The result obtained revealed that among the single data domains, *product reviews* data are the most commonly used data in

EAE research area. It is further discovered that 5 datasets with the highest number of studies are profit-oriented datasets due to their semantic value and effect on business intelligence namely: Product Reviews (15), Restaurant Reviews (13), Electronic Reviews (11), Hotel Reviews (9) and Customer Reviews (6) (i.e they are mostly used for business purposes). Another reason for the frequent utilization of these data domains is the fact that they were made publicly available, and contains huge datasets of different patterns that could lead to multiple research findings. However, we observed that the possible reason for the least utilized data domains such as Automobile Reviews, Hate Crime Corpus, Children Tales, Train Ticket Reviews, Online Skin Care Reviews, Document Reviews, and Online TV Reviews is because they consist of a specialized datasets with limited research interest. On the other hand, our study revealed that majority of researchers used multiple data domains in a study which entails more optimal performance. This could be linked to the 32 number of studies that utilizes Restaurant + Laptop reviews, which turn out to almost doubled the studies used by the most frequently used single data domain. Even though both single and multiple data domains are active among researchers, we noticed that Restaurant + Laptop reviews have the highest usage basically due to its multi-pattern coverage and open accessibility that made it easy to conduct and evaluate researches.

Our study also found that English Language is the most utilized among the publications with 73%, followed by Chinese and Arabic with 6% and 5% respectively. This shows a wide merging as well as dominance of English language domain in relation to other languages involved in EAE studies, primarily due to its global standard and popularity. With regards to the most influential data source, we found that *SemEval-2014* is the most frequently used data source with 22% among the entire studies, followed by *Amazon* with 20% studies. Though Amazon achieved the second most influential data source with insignificant difference compared to *SemEval-2014*, it is also the only standard profit-oriented organization that stood to be among the most influential EAE data sources. This might probably be due to its global recognition, and huge number of subscribers globally. On the other hand, what makes *SemEval* unique is the fact that we found that three different *SemEval* datasets in this study happened to be among the most influential data sources and makes almost 40% of all the influential sources namely: *SemEval-2014*, *Semeval-2015*, and *Semeval-2016* (see Table 7). This is primarily due to its reliability, accessibility, and sentimental nature. Also, these *SemEval* data are generated, structured, and provided annually for sentiment oriented researches through a well-organized sentiment symposium that involves experts in the field [154]–[156].

Analysis of our PSS in relation to research facets shows that most of the PSS were *solution research* with 70% of the entire studies making the highest, followed by *evaluation research* which is considerably smaller than the former with 20%, and finally *validation research* with 10%. With regards to contribution facet, our studies revealed that *method/Approach* has 65 studies with 49%, followed by *model* with 28%, *framework* with 11%, *tool/system* with 8%, *architecture* 2%, *comparison/evaluation* 1.5%, and lastly *algorithm* with 1%.

On evaluation metrics, the study revealed that out of the 10 metrics identified, *F-measure* is the most utilized evaluation metrics which is used in 85 studies, followed by *precision* with 81, and *recall* used by 78 studies. However, 3% of our PSS comprising of *Clustering*, *Rule-based* as well as 2 *Semantic-based* techniques were exempted in this analysis due to lack of a clearly defined metric utilized for evaluation, hence, we were unable to comprehend the evaluation metric applied in their study.

B. IDENTIFIED RESEARCH CHALLENGES AND DIRECTION FOR FUTURE WORK

After a comprehensive analysis of the entire PSS, we highlighted a few research challenges in EAE research domain that needs to be addressed by the research community. Future recommendations were also identified to offer a proper guidance to researchers on feasible future directions. We discovered that *SemEval* dataset have been the most utilized dataset in EAE research domain over the last 5 years. However, excessive utilization of *SemEval* has limits the diversification as well as competitiveness in terms of datasets with a diverse patterns that can accommodate all forms of researches beyond what is been offered by *SemEval* dataset. Therefore, more open sources datasets that can compete with *SemEval* are recommend in the future.

Despite the considerable increase in EAE research activities from different parts of the world, it was revealed that EAE research has been very limited among African countries. This is evident considering the fact that none of our PSS came from African nations. Therefore, there is need for future research that will investigate and address this barrier, to improve participation in EAE researches in this part of the world.

The EAE research appears to have more bearing on problem solving, this was evident in the huge amount of the *solution papers* consisting of (70%) of the entire PSS, followed by evaluation papers with (20%). However, there were significantly less *validation researches* (10%) in the literature. Thus, this should be considered as major challenge in EAE research domain. Hence, more validation research are desired in EAE research domain in the future.

Our studies have shown that 3% of the PSS which comprises of 1 Clustering, 1 Rule-based as well as 2 Semantic-based techniques were not included in the evaluation metrics analysis due to the lack of a clearly defined *metric* utilized for their evaluations. This is a major limitation, as future research, there is need to investigate the reasons behind researchers' failure to explicitly state their metrics.

The EAE domain is dominantly academic-centric as 70% of the PSS were carried out by academic institutions. Although there exists few industrial centric studies with influential sentiment oriented data sources such as *Amazon.com*, *Booking.com*, and *Trip Advisor* this significantly boost EAE domain. However, our study revealed less industrial focus by EAE researchers despite its role in business intelligence and prosperity. Therefore, it is recommended that focus should be given more on EAE researches with industrial considerations.

Moreover, it has been discovered that there is a wide merging as well as dominance of English Language domain in relation to other Languages involved in EAE studies. This was evident in the frequency of studies conducted in those languages, as *English* language have the highest frequency of 88% among the selected studies, followed by *Chinese* with 6%. This challenge have consistently been highlighted in the literature, as could be seen in both [8], [19]. Hence incorporation of more language domains other than English should be considered in future research.

V. THREATS TO VALIDITY

To achieve an extensive analysis of the results obtained in this study, it is deemed to be considerate of the limitations involved. The major threats to this systematic mapping studies's validity includes, study selection bias, data extraction bias, and data classification bias. We discussed the threats outlined extensively in this section.

A. STUDY SELECTION BIAS

To reduce researchers' bias in relation to the literature selection process, an essential ICC and ECC were prepared. Different researchers may express dissimilar opinion on the ICC/ECC, hence, the literature selection outcomes of each researcher may likely differ. In order to minimize this bias, we conduct a trial selection to make sure that there is an agreement among the researchers on the understanding of the literature selection criteria. The possible mismanagement of duplicates in the study is yet another threat that might have alter our results. We have identified and examined four different cases of potential duplications in order to check whether the studies are similar. Meanwhile, the researcher that handles the search process gives the final decision on the literature selection. When there is a disagreement between the two researchers, they resolve it based on productive discussion until a solid agreement is achieved. The most senior researcher then review the final selected literature.

Additionally, to make sure that all potential studies in EAE have been captured, a thorough search on seven foremost digital libraries were conducted. A collection of additional studies from other databases (Web of Science and Google Scholar) were also added using snowballing technique to avoid excluding any relevant literature by the advanced search feature of the databases. Also, as publication titles may affect the literature search coverage, an effective inclusion strategy of the studies was introduced using backward reference searched to ensure more optimal results.

B. DATA EXTRACTION BIAS

In view of the data extraction, the process may involves bias that may likely affect the classification and analysis of the selected studies' results. In order to tackle these biases, the extraction of the data entities in our study were properly discussed amongst all the researchers involved, and agreement on the definition of each data entity was reached. A pilot data extraction, detection and selection were carried out, in which consensus was reached on the data results' disagreements outlined. Thus, the entities extracted were observed by two researchers where 27 disagreements were duly deliberated and resolved. These procedures are taken to mitigate the data extraction bias, which can leads to an improved and more reliable data extraction entities.

C. DATA CLASSIFICATION BIAS

Looking at the PSS, majority of the studies shows limited description of the kind of information needed to be identified as data entities. Consequently, some of these information were inferred during the data classification. For instance, in an event where dependency-parsing technique is used as either unsupervised, semi-supervised or supervised approach for aspect extractions in difference studies. Inadequate information to the readers explaining the nature of the intances may lead to bias. In this situation, our study determines the technique of such studies based on their experimental setup. Hence, with such practice, the potential bias could effectively be mitigated.

VI. CONCLUSION

Aspect-based sentiment analysis (ABSA) domain have been given more attention in recent years. Recently, aspect extraction has become one of the most essential area of SA to conduct useful researches. Though many studies were conducted in the last decade, yet the existing literatures are unable to provide a fine-grained overview of EAE research domain. This study reported a systematic mapping that provides summary of the existing researches in EAE over the last decade (2009 - 2019). The study examined frequently utilized research techniques, approaches, data domains, language domains, publication fora, journals/proceedings affiliations, research/contribution facet, and evaluation metrics in EAE.

The primary objective of this study is to apply systematic mapping method to equip the ABSA research community with detailed knowledge of the entire research trends, productivity, and demographics modelling the landscape of EAE domain. These was successfully achieved through answering all the research questions identified in this study. We also highlight numerous prospective opportunities, so that both novice and veteran researchers can conduct more impactful studies in the research domain.

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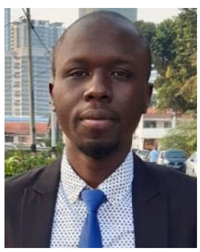

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