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Opinion Mining, Sentiment Analysis and Emotion Understanding in Advertising: A Bibliometric Analysis

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ABSTRACT In the last decade, the advertising industry has experienced a quantum leap, powered by recent advances in neuroscience, a large investment in artificial intelligence, and a high degree of consumer expertise. Within this context, opinion mining, sentiment analysis, and emotion understanding bring us closer to one of the most sought-after objectives of advertising: to offer relevant ads at scale. The importance of studies about opinion mining, sentiment analysis, and emotion understanding in advertising has been rising exponentially over the last years. The peak of this new situation has been the interest of the research community in studying the relationship between such innovations and the spread of smart and contextual advertising. This article analyzes those works that address the relationship between sentiment analysis, opinion mining, and emotion understanding in advertising. The main objective is to clarify the current state of these studies, explore issues, methods, findings, themes, and gaps as well as to define their significance within the current convergence advertising research scenario. To reach such objectives, a bibliometric analysis was conducted, retrieving and analyzing 919 research works published between 2010 and 2019 based on results from Web of Science (WoS).

INDEX TERMS Advertising research, bibliometrics, communication, consumer behavior, emotion understanding, opinion mining, science mapping analysis, SciMAT, sentiment analysis, VOSviewer, Web of Science (WoS).

I. INTRODUCTION

The combination of technology, data, and creativity is today the driving force in the advertising landscape. Personalized advertising, ongoing data privacy concerns, shifting stakeholder power, and data-based targeting are converging to disrupt the future of advertising [1]. The way advertisers reach their consumers is evolving at lightning speed and consumers are moving away from traditional channels and platforms to digital media ecosystems. For an industry that requires the attention and interaction of consumers, it is essential to understand the consumer behavior and the complexities of the target audience [2].

Sentiment Analysis, opinion mining and emotion understanding are an interdisciplinary multimodal field of study gathering between neuroscience [3]–[7], and computer science and artificial intelligence [8]–[10] that analyzes people's attitudes, appraisals, evaluations, sentiments, opinions, and emotions to entities such as organizations, services, products, individuals, issues, events topics and their attributes [11].

The use of sentiment analysis, opinion mining and emotion understanding may be very useful as a real-time feedback loop for advertising effectiveness and might be able to predict advertising results, as well as to find and measure consumer

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opinions and attitudes towards their brand, products, services, and campaigns [12], [13].

A series of recent studies have indicated that analyzing brand sentiment provides an outstanding source of data that demonstrates the different perceptions they can qualify KPIs [14], identify influencers for the brand [15], define the brand's reputation [16], improve the consumer experience [17], determine the future of marketing strategies [18], generate leads and improve marketing campaigns and product messaging [19], [20]. Brands such as The Walt Disney Co. rely on sentiment analysis and emotion understanding to activate soundtracks when parents read stories aloud to their children or Coca-Cola, that uses opinion mining to reinvent the way consumers interact with products through smartphones [21]–[24].

Diverse industry protagonists such as media companies, digital platform businesses, agencies, advertisers, independent researchers, and consumers are aware of the urgent need to implement digital advertising transformation strategies to create a fundamentally different business that can generate sustainable profitability in the face of this disruption [25]. This consumer behavior specialization is trying to take a step further [26], leading scientists and scholars to work on responses with a high level of personalization and emotional understanding [27], fostering a sensitive connection with the consumer which is leading to increased brand recall, positive brand associations and brand awareness [28], [29].

However, some key questions and notions are still not discussed in the literature about this topic. We do not the key themes and how they evolve through the time [30], [31], patterns, trends, and methodologies recently used in the advertising environment to respond to consumer demands. Besides, we do not know the recent scientific results on the needs of the advertising market as well as future developments in intelligent advertising [32]. In this article, we conducted a bibliometric analysis [33]–[35], a system that analyzes citations and discusses scientific works published in a specific area of knowledge. Review the literature allow us to discover important patterns and variables relevant to the object of study, to establish the context of the topic or problem, to synthesize and acquire a new perspective, to relate ideas and theories to their applications, to distinguish the research that has been carried out and future lines of research, to identify main methodologies and research techniques as well as to place the research in a historical context to demonstrate familiarity with the latest developments [36], [37].

This bibliometric analysis aims to answer the following research questions:

- RQ1. What are the key themes, incoming or outgoing topics, citation patterns, prolific authors, organizations, countries, journals, and publications detected in sentiment analysis, opinion mining, and emotion understanding in the advertising ecosystems?
- RQ2. What are the thematic areas and cluster networks in sentiment analysis, opinion mining, and emotion understanding in the communication landscape?
- RQ3. What are the trends, methodologies, research gaps, and main future lines of research about the studies already carried out?

For better clarification of the results, a thematic cluster network and strategic diagrams by periods are used to categorize the detected topics or themes. Furthermore, we develop a performance analysis using different basic bibliometric indicators (number of received citations, number of published documents, etc.,) as well as H-Index.

This paper is organized as follows: Section 2 explains our review materials, methodology approach, and query design. In Section 3 we provide a bibliometric analysis of opinion mining, sentiment analysis and emotion understanding in advertising and Section 4 contains the discussion, conclusion and briefly accomplishes and sketches out an agenda for future research.

II. MATERIALS AND METHODS

The bibliometric mapping was conducted based on scientific publications related to opinion mining, sentiment analysis, and emotion understanding in advertising. The source of information was the Web of Science (WoS) database. The WoS, owned by Clarivate Analytics, is a collection of databases of bibliographic references and citations from periodicals that collect information from 1900 to the present. The choice of the WoS database was determined by the fact that it contains the most accurate and reliable research information and offers a high number of analysis tools to process it [38].

In this study, we obtained research publications indexed in WoS on opinion mining, sentiment analysis, and emotion understanding in advertising for a significantly large period of years (2010-2019), which covers almost the whole period of large scientific production in this field. Key-terms and phrases associated with emotion understanding, sentiment analysis, and opinion mining were utilized in the subject search in combination with advertising/marketing. The specific search strings were formulated according to the search logic of the WoS database. Table 1 illustrates the query design, this query selects the publications according to the inclusion and exclusion criteria used, and the indexes, timespan, and date of the data download.

To perform the review, we have used the following tools for the analysis of scientific production:

VOSviewer version 1.6.15, a software tool for constructing and visualizing bibliometric networks (including individual publications, researchers, journals); being those constructed based on co-authorship relations, co-citation, bibliographic coupling, citation and co-occurrence networks of important terms extracted from a body of scientific literature [39].

VOSviewer was used to obtain citation based-networks, analyze bibliometric networks, and create visualization maps based on network data of countries/regions, authors, organizations, sources, and documents. VOSviewer uses different techniques such as the network layout and network clustering (layout and clustering results can be fine-tuned using various

TABLE 1. Details of dataset.

Source/Index	Period	Query to extract data	No. of documents retrieved	Date of Download
Web of Science Core Collection: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCISSH, BKCI-S, BKCI-SSH, ESCI.	2010-2019	(((((((TS = ((("Sentiment Analysis") OR ("Sentiment of Images") OR ("Sentiment Classification") OR ("Opinion Mining") OR ("Opinion Classification") OR ("Image Sentiment") OR ("Image Emotion") OR ("Emotion Understanding") OR ("Image Processing") OR ("Image Recognition") OR ("Mining sentiment") OR ("Visual Content") OR ("Visual Attention") OR ("Object Recognition") OR ("Object Detection") OR ("Image Classification") OR ("Affect Analysis") OR ("Affective Computing")) AND (Advert* OR "Marketing"))))))))) AND LANGUAGE: (English OR Spanish) AND DOCUMENT TYPES: (Article OR Book Chapter OR Proceedings Paper OR Review)	919	02.05.2020

parameters) and natural language processing techniques (Relevant and non-relevant terms can be distinguished algorithmically). VOSviewer Analysis Configuration we followed:

1) Unit of analysis: Organizations, Authors, Countries/Regions, Sources and Documents
2) Kind of network: Citation Analysis (the relatedness of items is determined based on the number of times they cite each other)
3) Cluster network design: Network Visualization and Density Visualization (provides a quick overview of the main areas/relationships in a bibliometric network).

SciMAT version 1.1.04 (Science Mapping Analysis Software Tool), is an open-source science mapping software tool that incorporates methods, algorithms, and measures for all the steps in science mapping workflow, from preprocessing to the visualization of the results [30], [31]. SciMAT was used to study the evolution of key themes over time and the identification of developing or decreasing topics. ScIMAT Analysis Configuration we followed:

1) Unit of analysis: Words (authorRole = true, sourceRole = true, addedRole = false)
2) Kind of network: Co-occurrence
3) Normalization measure: Equivalence index
4) Cluster algorithm: Centers simples
5) Max cluster size: 12
6) Min cluster size: 3
7) Evolution measure: Inclusion index
8) Overlapping measure: Jaccard index

III. RESULTS

A. DISTRIBUTION OF PUBLICATIONS BY YEAR AND RECORD COUNT (2010-2019)

The distribution of publications during the period 2010-2019 is shown in Figure 1. During the first lustrum (2010-2014) of the study, sustained growth of publications (n = 214, 23.28%) is observed while in the second lustrum (2015-2019) it is detected that opinion mining, sentiment analysis and emotion understanding in advertising has suffered an exponential growth in the number of publications (n = 705, 76.71%).

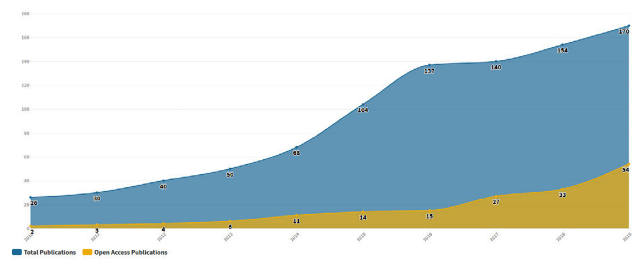

FIGURE 1. Distribution of publications by year and record count.

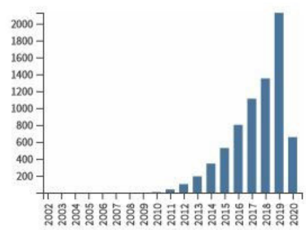

FIGURE 2. Sum of times cited by year.

B. CITATION REPORT AND RECORD COUNT

In Table 2 is shown the Citation Report and the Record Count. The total publications retrieved (919) combined a sum of 7263 times cited (Figure 2), making an average of 7,9 citations per paper. The H-index is the same as 40, which means that 40 studies have received at least 40 citations. The H-Index is often used to quantify an individual's research output [40]. An extension of the H-Index to identify the highly cited papers called H-Classics can be viewed in [38], and consequently, in that case, H-Classics identifies 50 highly cited papers.

TABLE 2. Citation report and record count.

Citation Report	
Results found	919
Sum of Times Cited	7263
Average citation per item	7,9
H-Index	40

FIGURE 3. Document types in web of science.

C. DOCUMENT TYPES AND RECORD COUNT

In Figure 3 is shown the total average % of 919 document types in Web Of Science: The largest collection of Article (485 records, 52.77%), followed by Proceedings Paper (392 records, 42.65%) Review (44 records, 4.78%), Book Chapter (28 records, 3.04%), Early Access (2 records, 0.21%) and by the end Editorial Material (1 record, 0.10%).

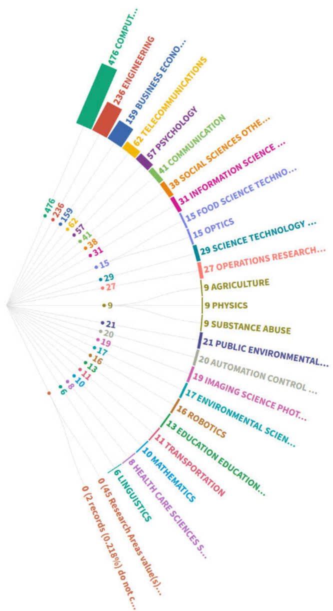

FIGURE 4. Research areas and record count in web of science categories.

D. WEB OF SCIENCE CATEGORIES/RESEARCH AREAS AND RECORD COUNT

Figure 4 shows the Web of Science Research Areas. Among the Top 10 most representative categories in opinion mining, sentiment analysis and emotion understanding in advertising we find the following: Computer Science (476 registers and 51.75% of 919 works), Engineering (236 registers and 25.68% of 919 works), Business Economics (159 registers and 17.30% of 919 works), Telecommunications (62 registers and 6.74% of 919 works), Psychology (57 registers and 6.20% of 919 works), Communication (41 registers and 4.46% of 919 works), Social Sciences (38 registers and 4.13% of 919 works), Information Science and Library Science (31 registers and 3.37% of 919 works) and Science Technology and Other Topics (29 registers and 3.15% of 919 works).

E. PERFORMANCE INDICATORS FOR ORGANIZATIONS AND RECORD COUNT

Table 3 presents the Performance Indicators for Organizations and Record Count, a Top 25 selection of the most high-ranking universities along with several records; two indicators of global university ranking according to the 2019 Quacquarelli Symonds (QS) World University Rankings and 2019 Academic Ranking of World Universities (ARWU) that allow us to measure the relative position in which we find the most influential institutions in sentiment analysis, opinion mining and emotion understanding in advertising.

The relatedness of items is based on the number of times they cite each other. A minimum number of documents of an organization (5) and a minimum number of citations of an organization (5). The number of citations of an organization equals the total number of citations the documents of the organization have received in Web of Science. Of the 1146 organizations, 26 meet the threshold.

Within the first 10 universities, 40% are in the United States, followed by institutions in The Netherlands (1), Singapore (1), Hong Kong (1), Denmark (1), South Korea (1) and United Kingdom (1). Further down the rankings are other institutions in China, Malaysia, Austria, Italy, The Netherlands, Taiwan, South Korea, China, Australia, Malaysia, and Italy. The first institution in the ranking in terms of citation is the City University of Hong Kong with a total of 8 documents published about sentiment analysis, opinion mining, and emotion understanding in advertising, where 8 of these studies have received 321 citations.

According to the relative position of the university ranking, 1st ranked is the City University of Hong Kong with a total of 8 publications and 321 citations, located within the first 201-300 (ARWU2019) and 55 (QS 2019), followed by 2nd ranked Nanyang Technological University, with a total of 10 articles published, of which 10 have been cited at least 305 times, 3rd ranked is the Copenhagen Business School, with 5 papers published and a ratio of 216 citations. Only 8 of the Top 25 university rankings are in the Top 100 ranking according to ARWU: Nanyang Technological University, University of California, San Diego, University of Florida, University of Minnesota, Aarhus University, Cornell University, University of Maryland and the National University of Singapore.

Of these, 5 universities are in the United States while only 9 are part of the Top 100 according to QS: City University of Hong Kong, Nanyang Technological University, University of California San Diego, University of Nottingham,

TABLE 3. Performance indicators for organizations and record count.

	Organization	Country	Documents	Citations	Total link strength	ARWU 2019	QS 2019
1.	City University of Hong Kong	China	8	321	8	201-300	55
2.	Nanyang Technological University	Singapore	10	305	7	73	12
3.	Copenhagen Business School	Denmark	5	216	0	701-800	-
4.	University of Georgia	USA	9	183	12	201-300	431
5.	University of California, San Diego	USA	7	161	2	18	41
6.	University of Arizona	USA	6	110	2	101-150	246
7.	University of Nottingham	UK	7	105	0	101-150	82
8.	Korea Advanced Institute of Science and Technology	South Korea	6	102	8	201-300	40
9.	University of Amsterdam	The Netherlands	7	99	12	101-150	57
10.	University of Florida	USA	9	76	2	95	180
11.	University of Minnesota	USA	6	58	3	41	156
12.	University of Science and Technology of China	China	5	50	1	101-150	98
13.	Sun Yat-sen University	China	5	46	2	801-900	295
14.	Aarhus University	Denmark	6	42	1	60	141
15.	Cornell University	USA	8	40	1	13	14
16.	University of Maryland	USA	6	39	0	46	126
17.	Michigan State University	USA	5	36	1	101-150	141
18.	University of Malaya	Malaysia	6	31	4	301-400	87
19.	National Cheng Kung University	Taiwan	5	28	0	301-400	234
20.	University of Vienna	Austria	5	28	3	151-200	175
21.	Chinese Academy of Sciences	China	9	27	1	-	-
22.	National University of Singapore	Singapore	7	26	0	67	11
23.	Radboud Universiteit Nijmegen	The Netherlands	5	22	1	101-150	204
24.	Politecnico di Milano	Italy	5	21	3	201-300	156
25.	Beihang University	China	5	19	6	201-300	491

Korea Advanced Institute of Science and Technology, University of Amsterdam, University of Science and Technology of China, Cornell University, University of Malaya and National University of Singapore.

F. PERFORMANCE INDICATORS FOR AUTHORS AND RECORD COUNT

The Performance Indicators for Authors and Record Count can be seen in Table 4, which presents a Top 25 ranking of the most commanding authors in opinion mining, sentiment analysis, and emotion understanding in advertising in terms of the number of documents/citations. The relatedness of items is based on the number of times they cite each other. The minimum number of documents of an author (3) and the minimum number of citations of an author (1). The number of citations of a country equals the total number of citations the documents of the country have received in Web of Science. Of the 2853 authors, 41 meet the threshold.

G. PERFORMANCE INDICATORS FOR COUNTRIES/REGIONS AND RECORD COUNT

The Performance Indicators for Countries/Regions can be seen in Table 5, which presents a Top 25 ranking of the most leading countries/regions in opinion mining, sentiment analysis, and emotion understanding in advertising in terms of the number of documents/citations. The relatedness of items is based on the number of times they cite each other (Figure 5). The minimum number of documents of a country (10) and the minimum number of citations of a country (1). The number of citations of a country equals the total number

TABLE 4. Performance indicators for authors and record count.

	Author	Documents	Citations	Total link strength
1.	Cambria, Erik	8	329	8
2.	Poria, Soujanya	3	214	5
3.	Wojdynski, Bartosz	5	156	14
4.	Ahn, Jae-Hyeon	3	75	5
5.	Boerman, Sophie c.	3	70	9
6.	Bang, Hyejin	4	45	13
7.	Scott, Noel	4	23	3
8.	Holmberg, Nils	3	22	6
9.	Sandberg, Helena	3	22	6
10.	Dragoni, Mauro	4	15	3
11.	Niu, Jianwei	3	15	3
12.	Kim, Annice	3	13	2
13.	Nonnemaker, James	3	13	2
14.	Recupero, Diego Reforgiato	3	13	4
15.	Lee, Kun Chang	3	12	2
16.	Yao, Zhong	3	8	7
17.	Khachatryan, Hayk	3	7	1
18.	Rihn, Alicia	3	7	1
19.	Gomez, Mauro	3	4	18
20.	Poveda, Jonatan	3	4	18
21.	Tous, Ruben	3	4	18
22.	Wust, Otto	3	4	18
23.	Kincl, Tomas	3	3	4
24.	Novak, Michal	4	3	4
25.	Pribil, Jiri	3	3	4

TABLE 5. Performance indicators for countries/regions.

	Country	Documents	Citations	Total link strength
1.	USA	206	2804	177
2.	Italy	55	883	42
3.	China	117	829	79
4.	Australia	44	489	53
5.	England	52	465	48
6.	France	21	460	27
7.	Spain	53	375	26
8.	Singapore	24	371	30
9.	The Netherlands	24	335	70
10.	India	82	288	22
11.	Taiwan	41	287	40
12.	Germany	45	279	32
13.	Canada	21	271	21
14.	Denmark	12	265	15
15.	South Korea	28	182	38
16.	Japan	25	137	8
17.	Iran	17	130	9
18.	Greece	11	112	11
19.	Sweden	11	80	15
20.	Malaysia	14	54	18
21.	Thailand	12	53	4
22.	Pakistan	17	33	14
23.	Austria	14	30	6
24.	Indonesia	15	28	3
25.	Saudi Arabia	14	16	14

of citations the documents of the country have received in Web of Science. Of the 88 countries, 27 meet the threshold.

The first place is occupied by the USA (206 documents and 2804 citations), followed by Italy (55 documents and 883 citations), China (117 documents and 829 citations), Australia (44 documents and 489 citations) and by the end, England (52 documents and 465 citations).

H. PERFORMANCE INDICATORS FOR JOURNALS AND RECORD COUNT

The Performance Indicators for Journals might be seen in Table 6, which presents a Top 10 ranking of the most important sources in opinion mining, sentiment analysis, and emotion understanding in advertising in terms of the number of documents/citations. The relatedness of items is based on the number of times they cite each other. The minimum number of documents of a source (6) and the minimum number of citations of a source (1). The number of citations of a country equals the total number of citations the documents of the source have received in Web of Science. Of the 687 sources, 10 meet the threshold.

As shown in Table 6, the most cited journals in opinion mining, sentiment analysis, and emotion understanding in advertising have a clear focus on communication and marketing, artificial intelligence, computational neuroscience, or psychology among others. Being the 1st ranked Expert Systems with Applications (with 11 documents and a sum

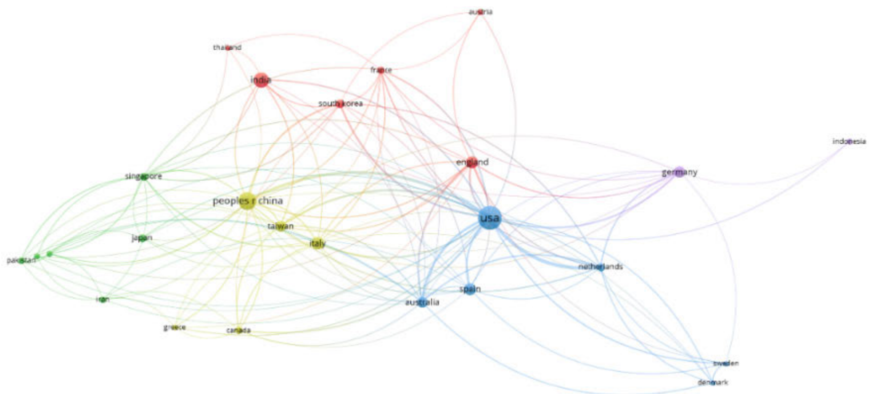

FIGURE 5. Citation analysis (countries/regions) in network visualization [39].

TABLE 6. Performance indicators for journals.

	Source	Documents	Citations	Total link strength
1.	Expert Systems with Applications	11	482	2
2.	Decision Support Systems	8	458	2
3.	Neurocomputing	6	112	0
4.	Computers in Human Behavior	8	110	1
5.	Psychology & Marketing	7	79	0
6.	Frontiers in Psychology	7	75	0
7.	Multimedia Tools and Applications	7	51	1
8.	PLOS ONE	6	39	1
9.	Sustainability	7	8	1
10.	International Journal of Advanced Computer Science and Applications	6	5	0

of 482 citations), 2nd ranked Decision Support Systems (8 documents and a sum of 458 citations), 3rd ranked Neurocomputing (with 6 documents and a sum of 112 citations), 4th ranked Computers in Human Behavior (with 8 documents and a sum of 110 citations) and 5th ranked Psychology and Marketing (with 7 documents and a sum of 79 citations) are the most cited journals in sentiment analysis, opinion mining and emotion understanding in advertising. The first, second and third are usually regarded as the three most influential sources in artificial intelligence and technology, while the fourth and fifth journals show its clear thematic connection (psychology, human behavior, and marketing).

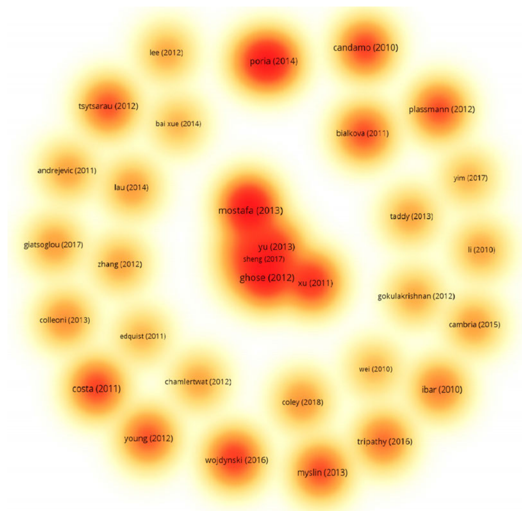

FIGURE 6. Citation analysis (documents) in density visualization [39].

I. PERFORMANCE INDICATORS FOR PUBLICATIONS IN DENSITY VISUALIZATION

Performance Indicators for Publications through Citation Analysis in item density visualization is shown in Figure 6. Relatedness of items is determined based on the number of times they cite each other (Units of analysis: documents). Of the 919 documents, 40 meets the threshold and a minimum number of citations of a document are shown (40). Some of the 49 works of the network are not connected and the largest set of connected items consists of 9 items (the figure shows all the items). In the item density visualization, items are represented by their label in a similar way as in the network visualization and the overlay visualization. Each point in the item density visualization has a color that indicates the density of items at that point. Only in the center of Figure 6 a recent citation network established by the authors can be appreciated: Mostafa (2013), Yu (2013), Sheng (2017), Ghose (2012), and Xu (2011).

The results reveal that there is only citation pattern connectivity's in recent works where there has been a research study about social networks and text mining for consumer brand sentiment, mining comparative opinions from customer reviews for competitive intelligence, ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content, the impact of social and conventional media on firm equity value (a sentiment analysis approach), and multidisciplinary perspective of big data in management research (research review).

J. PERIOD VIEW AND LONGITUDINAL RESULTS 2010-2019: STRATEGIC DIAGRAM AND PERFORMANCE MEASURES (WORDS ANALYSIS)

A total of 919 web of science papers were collected, of which 916 could be used, as there were 3 that could not be included in the study due to indexing and export errors in a format not supported by SciMAT. The analysis has been divided into two consecutive lustrums (2010-2014 | 2015-2019). There are 214 documents understudy in the first subperiod and 702 documents in the second subperiod.

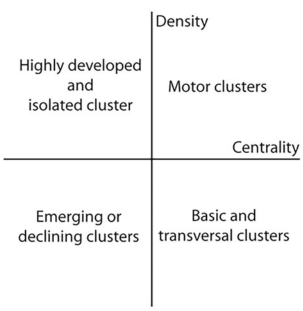

FIGURE 7. The strategic diagram based on Callon's density and centrality measures.

The resulting strategic diagrams (Figure 9 and 10) shows the detected clusters of each period in a two-dimensional space and categorizes them according to their Callon's density and centrality measures. The strategic diagram is divided into 4 quadrants shown in Figure 7 (upper-right quadrant defines motor clusters, upper-left quadrant defines highly developed and isolated clusters, lower-left quadrant defines emerging or declining clusters and lower-right quadrant defines basic and transversal clusters).

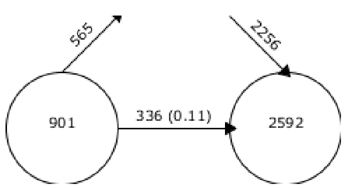

FIGURE 8. Overlap fractions (incoming and outcoming keywords between successive subperiods).

Figure 8 shows the stability measures across the two consecutive periods. The circles represent the subperiods (2) and their number of associated keywords (901 and 2592 respectively). The horizontal arrow represents the number of keywords shared by both periods (336) and, in parentheses, the Similarity Index between them is shown (0.11). The upper-incoming arrow represents the number of new keywords in period 2 (565), and the upper-outcoming arrow represents the keywords that are present in period 1 but not in period 2 (2256).

1) SUBPERIOD VIEW 2010-2014: STRATEGIC DIAGRAM AND PERFORMANCE MEASURES (WORDS ANALYSIS)

The subperiod (2010-2014) shows quantitative measures based on the number of documents and qualitative or impact measures based on the number of received citations/average citations of the documents and bibliometric indices such as the H-Index (Table 7 and Figure 9). We analyzed the two quadrants that we consider fundamental and most interesting for the development of the discipline: upper-right and lower-left.

TABLE 7. Performance measures for the themes of the subperiod 2010–2014.

Theme Name	Number of Documents	H-Index	Average of Citations	Number of Citations
WORD-OF-MOUTH	14	11	60.43	846
VISUAL-ATTENTION	29	13	20.9	606
CLASSIFICATION	12	5	33.83	406
VALENCE	3	3	47.67	143

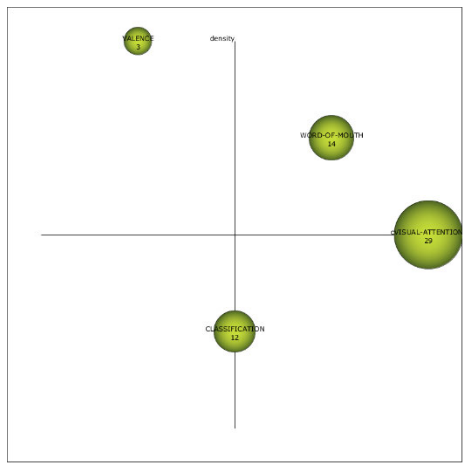

FIGURE 9. Strategic diagrams for the subperiod 2010–2014 (documents count).

In the first subperiod of study (2010-2014), we witness the birth of the inter-discipline object of the study. Sentiment analysis, opinion mining, and emotion understanding in advertising is not very developed and there are still no emerging trends or representative thematic groups.

We observe that the motor themes quadrant with the greatest number of works is focused on different clusters:

WORD-OF-MOUTH with studies in social networks text mining for consumer brand sentiments, design of ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content, and deciphering word-of-mouth in social media through text-based metrics of consumer reviews.

VISUAL-ATTENTION cluster with studies in effects of advertising billboards during simulated driving, the influence of selective attention, and inattention to products on subsequent choice and eye movements when viewing advertisements among others.

In emerging or declining themes quadrant, we find CLASSIFICATION cluster with studies in predicting consumer sentiments from the online text, sentiment-oriented contextual advertising, and emotional polarity analysis of consumers' airline service tweets.

2) SUBPERIOD VIEW 2015-2019: STRATEGIC DIAGRAM, PERFORMANCE MEASURES, EMERGING OR DECLINING CLUSTERS AND MOTOR CLUSTER NETWORKS ANALYSIS (WORDS ANALYSIS)

The subperiod (2015-2019) shows quantitative measures based on the number of documents and qualitative or impact measures based on the number of received citations/average citations of the documents and bibliometric indices such as the H-Index (Table 8 and Figure 10).

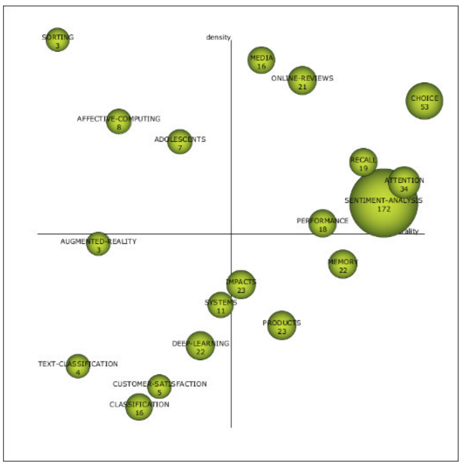

FIGURE 10. Strategic diagrams for the subperiod 2015–2019 (documents count).

During the second subperiod (2015-2019), we observed the fast development of research in sentiment analysis, emotion recognition, and opinion mining in advertising. This is the period in which the greatest scientific production exists, where we find considerably defined and powerful clusters divided into quadrants.

The results show that in motor themes quadrant (Figure 10 and Figure 11), we found a large cluster amount of research in:

MEDIA cluster with studies about Facebook as a destination marketing tool, eye-tracking technique to understand the effects of brand placement disclosure types in television programs, social media metrics, and analytics in marketing-s3m and Facebook social engagement for national tourism organizations.

TABLE 8. Performance measures for the themes of the subperiod 2015–2019.

Theme Name	Number of Documents	H-Index	Average of Citations	Number of Citations
SENTIMENT-ANALYSIS	172	15	4.73	814
CHOICE	53	12	7.66	406
IMPACTS	23	8	9.78	225
MEDIA	16	6	13.56	217
PRODUCTS	23	7	7.43	171
ATTENTION	34	7	4.76	162
ONLINE-REVIEWS	21	6	6.9	145
SYSTEMS	11	4	12.36	136
RECALL	19	6	6.89	131
CLASSIFICATION	16	5	6.62	106
MEMORY	22	6	4.59	101
PERFORMANCE	18	5	4.28	77
DEEP-LEARNING	22	4	3.45	76
AFFECTIVE-COMPUTING	8	4	6.88	55
CUSTOMER-SATISFACTION	5	2	8.2	41
ADOLESCENTS	7	3	5.43	38
TEXT-CLASSIFICATION	4	2	1.5	6
SORTING	3	2	1.67	5
AUGMENTED-REALITY	3	1	1	3

ONLINE-REVIEWS cluster with studies in consumer sentiment in an online community environment, the study of the power of the "like" button and the impact in social media, social media analytics in extracting and visualizing Hilton Hotel ratings and reviews from TripAdvisor and assessment consumers' satisfaction and expectations through online opinions and reviews.

CHOICE cluster with studies in first fixation and total fixation duration in consumer choice and visual attention toward tourism photographs with the text through an eye-tracking study.

RECALL cluster with studies in creativity, attention, and the memory for brands in outdoor advertising and effects of personalized banner ads on visual attention and recognition memory.

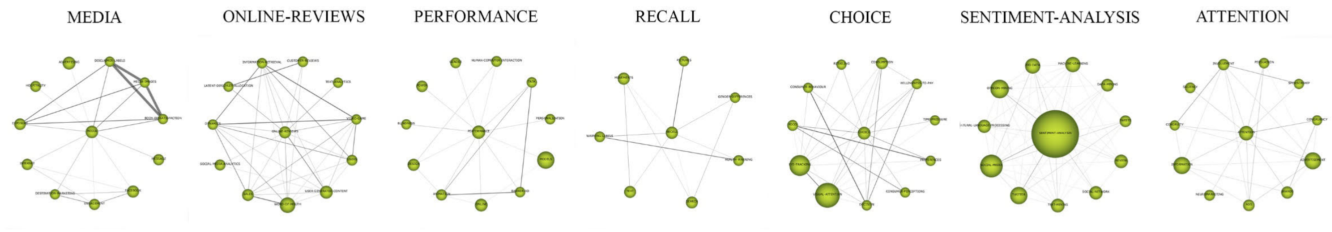

FIGURE 11. **Subperiod 2015-2019 thematic area (motor clusters).**

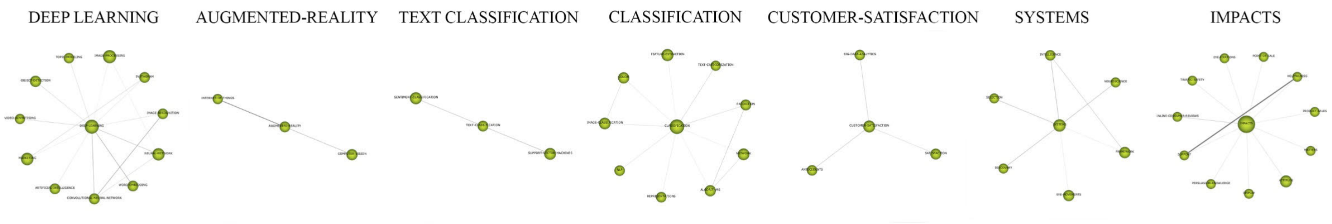

FIGURE 12. **Subperiod 2015-2019 thematic area (emerging or declining clusters).**

ATTENTION cluster with studies in visual attention and responses to personalized advertising based on task cognitive demand, advertising effectiveness in travel 2.0 websites, and distraction effects of contextual advertising on online news processing through an eye-tracking study.

SENTIMENT-ANALYSIS cluster with studies in novel social media competitive analytics framework with sentiment benchmarks and business intelligence in online customer textual reviews.

PERFORMANCE cluster with studies in attention allocation and memory effects when multiscreen, content composition, and slot position in personalized banner ads, and how they influence visual attention in online shoppers.

In emerging or declining themes quadrant (Figure 10 and Figure 12) we found the following:

DEEP-LEARNING cluster with studies in Sitcom-star-based clothing retrieval for video advertising with deep learning, inbound e-marketing using neural network-based visual and phonetic user experience analytics and automated curation of brand-related social media images.

SYSTEMS cluster with studies in credibility ranking of users in big social data incorporating semantic analysis and temporal factor.

IMPACTS cluster with studies in seeking attention through an eye-tracking study of in-store merchandise displays.

CUSTOMER-SATISFACTION cluster with studies in enhancing hotel guest experience.

CLASSIFICATION cluster with studies in the analysis of geolocated Airbnb rental images in cities and predicting purchase intention according to fan page user's sentiment.

TEXT CLASSIFICATION cluster with studies in recurrent neural networks for short text and sentiment classification and novel frameworks to detect unqualified restaurant reviews.

AUGMENTED-REALITY cluster with studies in application and scope analysis of augmented reality in marketing using image processing technique and scalable mobile image recognition for real-time video annotation among others.

We note that the CLASSIFICATION cluster has been maintained in both the first and second subperiods.

Thematic networks (Figures 11 and 12) are labeled using the name of the most significant keyword in the associated theme usually identified by the most central keyword of the theme).

K. CITATION CLASSICS IN OPINION MINING, SENTIMENT ANALYSIS AND EMOTION UNDERSTANDING IN ADVERTISING

Based on the result of the query, a selection of publications was performed based on the H-Classics, considered an indicator that reflects the quality of the research and its impact [38], [41], [42]. The H-Index provided by WoS encompasses all the instances of citing articles successfully linked to the cited reference. In this case, we selected the publications that have obtained at least H-Index 40 citations during the period 2010-2019, considering them the most relevant research publications in the field. The Citation Classics can be seen in Table 9, which presents a ranking of the most significant documents in terms of H-Classics.

The selection of studies is done according to their Rank, Title, Author, Publication Year (PY), Source Title, Special Issue (SI), Total Citation (TC), Average citation/year (AY), and Citation Timespan.

Themes in the upper-right quadrant (Motor Clusters). Themes that are well developed and important for the structuring of a research field (Figure 11).

TABLE 9. Citation classics and relatedness of items is determined based on the number of times they are cited (publications).

Rank	Title	Authors	PY	Source Title	SI	TC	AY	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	CT
1.	More than words: Social networks' text mining for consumer brand sentiments	Mostafa et al.	2013	EXPERT SYSTEMS WITH APPLICATIONS		200	25	0	0	0	2	19	23	32	33	40	43	
2.	Designing Ranking Systems for Hotels on Travel Search Engines by Mining User-Generated and Crowdsourced Content	Ghose et al.	2012	MARKETING SCIENCE	SI	196	21,78	0	0	1	3	22	16	33	32	36	45	
3.	Understanding Transit Scenes: A Survey on Human Behavior-Recognition Algorithms	Candamo et al.	2010	IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS		146	13,27	2	4	16	23	21	16	14	12	19	17	
4.	Shape Analysis of Agricultural Products: A Review of Recent Research Advances and Potential Application to Computer Vision	Costa et al.	2011	FOOD AND BIOPROCESS TECHNOLOGY		145	14,5	0	3	9	14	21	27	23	16	14	14	
5.	Sentic patterns: Dependency-based rules for concept-level sentiment analysis	Poria et al.	2014	KNOWLEDGE-BASED SYSTEMS	SI	138	19,71	0	0	0	0	10	23	27	27	22	26	
6.	The impact of social and conventional media on firm equity value: A sentiment analysis approach	Yu et al.	2013	DECISION SUPPORT SYSTEMS	SI	134	16,75	0	0	0	0	6	18	21	32	21	25	
7.	Branding the brain: A critical review and outlook	Plassmann et al.	2012	JOURNAL OF CONSUMER PSYCHOLOGY	SI	132	14,67	0	0	2	8	12	16	17	21	24	24	
8.	Using Twitter to Examine Smoking Behavior and Perceptions of Emerging Tobacco Products	Myslin et al.	2013	JOURNAL OF MEDICAL INTERNET RESEARCH		131	16,38	0	0	0	3	7	22	26	34	21	13	
9.	Survey on mining subjective data on the web	Tsytsarau, Mikalai; Palpanas, Themis	2012	DATA MINING AND KNOWLEDGE DISCOVERY	SI	126	14	0	0	4	4	11	15	25	26	19	19	
10.	Affective News: The Automated Coding of Sentiment in Political Texts	Young, Lori; Soroka, Stuart	2012	POLITICAL COMMUNICATION		124	13,78	0	0	1	4	6	13	9	20	25	38	
11.	Mining comparative opinions from customer reviews for Competitive Intelligence	Xu et al.	2011	DECISION SUPPORT SYSTEMS	SI	123	12,3	0	2	3	7	15	16	23	15	13	22	
12.	Going Native: Effects of Disclosure Position and Language on the Recognition and Evaluation of Online Native Advertising	Wojdynski, Bartosz W.; Evans, Nathaniel J.	2016	JOURNAL OF ADVERTISING		111	22,2	0	0	0	0	0	0	9	9	21	54	
13.	Classification of sentiment reviews using n-gram machine learning approach	Tripathy et al.	2016	EXPERT SYSTEMS WITH APPLICATIONS		99	19,8	0	0	0	0	0	2	1	22	23	42	
14.	Facebook as a destination marketing tool: Evidence from Italian regional Destination Management Organizations	Mariani et al.	2016	TOURISM MANAGEMENT		88	17,6	0	0	0	0	0	0	4	13	27	37	
15.	Predicting consumer sentiments from online text	Bai, Xue	2011	DECISION SUPPORT SYSTEMS	SI	88	8,8	0	1	7	6	11	10	12	15	12	12	
16.	H-ATLAS: PACS imaging for the Science Demonstration Phase	Ibar et al.	2010	MONTHLY NOTICES OF THE ROYAL ASTRONOMICAL SOCIETY		87	7,91	0	12	12	17	9	13	13	3	5	3	
17.	An efficient methodology for assessing attention to and effect of nutrition information displayed front-of-pack	Bialkova et al.	2011	FOOD QUALITY AND PREFERENCE		80	8	0	1	4	11	6	9	12	12	11	11	
18.	Cross-Domain Sentiment Classification Using a Sentiment Sensitive Thesaurus	Bollegala et al.	2013	IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING		78	9,75	0	0	0	1	3	16	9	19	13	13	
19.	Sentiment Data Flow Analysis by Means of Dynamic Linguistic Patterns	Poria et al.	2015	IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE		76	12,67	0	0	0	0	0	3	21	29	9	13	
20.	CSR communication strategies for organizational legitimacy in social media	Colleoni, Elanor	2013	CORPORATE COMMUNICATIONS	SI	71	8,88	0	0	0	3	1	7	8	11	13	21	
21.	Machine Learning in Computer-Aided Synthesis Planning	Coley et al.	2018	ACCOUNTS OF CHEMICAL RESEARCH		67	22,33	0	0	0	0	0	0	0	0	4	51	
22.	A novel social media competitive analytics framework with sentiment benchmarks	He et al.	2015	INFORMATION & MANAGEMENT	SI	65	10,83	0	0	0	0	0	3	11	20	10	14	
23.	Social analytics: Learning fuzzy product ontologies for aspect-oriented sentiment analysis	Lau et al.	2014	DECISION SUPPORT SYSTEMS	SI	61	8,71	0	0	0	0	0	6	8	16	13	14	
24.	Sentiment analysis leveraging emotions and word embeddings	Giatsoglou et al.	2017	EXPERT SYSTEMS WITH APPLICATIONS		59	14,75	0	0	0	0	0	0	0	5	19	26	
25.	An ELM-based model for affective analogical reasoning	Cambria et al.	2015	NEUROCOMPUTING		59	9,83	0	0	0	0	0	10	13	16	12	6	
26.	THE WORK THAT AFFECTIVE ECONOMICS DOES	Andrejevic et al.	2011	CULTURAL STUDIES	SI	55	5,5	0	0	3	8	5	8	11	7	7	5	
27.	Multinomial Inverse Regression for Text Analysis	Taddy et al.	2013	JOURNAL OF THE AMERICAN STATISTICAL ASSOCIATION		53	6,63	0	0	0	1	3	4	10	8	12	12	
28.	Deciphering Word-of-Mouth in Social Media: Text-Based Metrics of Consumer Reviews	Zhang et al.	2012	ACM TRANSACTIONS ON MANAGEMENT INFORMATION SYSTEMS		53	5,89	0	0	2	8	2	3	10	11	7	9	
29.	Discovering Consumer Insight from Twitter via Sentiment Analysis	Chamlertwat et al.	2012	JOURNAL OF UNIVERSAL COMPUTER SCIENCE		53	5,89	0	0	0	0	8	7	11	12	7	6	
30.	Identifying influential reviewers for word-of-mouth marketing	Li et al.	2010	ELECTRONIC COMMERCE RESEARCH AND APPLICATIONS		53	4,82	1	2	5	5	10	10	9	3	2	6	
31.	Do you like what you see? The role of first fixation and total fixation duration in consumer choice	van der Laan et al.	2015	FOOD QUALITY AND PREFERENCE		52	8,67	0	0	0	0	0	5	9	6	13	16	
32.	Using Eye Tracking to Understand the Effects of Brand Placement Disclosure Types in Television Programs	Boerman et al.	2015	JOURNAL OF ADVERTISING		51	8,5	0	0	0	0	0	0	9	6	10	16	
33.	Attention to Banner Ads and Their Effectiveness: An Eye-Tracking Approach	Lee, JooWon; Ahn, Jae-Hyeon	2012	INTERNATIONAL JOURNAL OF ELECTRONIC COMMERCE		50	5,56	0	0	0	0	4	4	12	8	11	8	
34.	Opinion Mining and Sentiment Analysis on a Twitter Data Stream	Gokulakrishnan et al.	2012	INTERNATIONAL CONFERENCE ON ADVANCES IN ICT FOR EMERGING REGIONS		50	5,56	0	0	0	1	6	7	9	8	11	8	
35.	A multidisciplinary perspective of big data in management research	Sheng et al.	2017	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS		45	11,25	0	0	0	0	0	0	0	1	13	23	
36.	Is Augmented Reality Technology an Effective Tool for E-commerce? An Interactivity and Vividness Perspective	Yim et al.	2017	JOURNAL OF INTERACTIVE MARKETING		42	10,5	0	0	0	0	0	0	0	1	10	23	
37.	A Study on Sentiment Computing and Classification of Sina Weibo with Word2vec	Xue et al.	2014	2014 IEEE INTERNATIONAL CONGRESS ON BIG DATA		42	6	0	0	0	0	1	1	7	10	9	11	
38.	Effects of advertising billboards during simulated driving	Edquist et al.	2011	APPLIED ERGONOMICS	SI	42	4,2	0	0	2	2	2	2	5	10	4	12	
39.	Understanding what concerns consumers: a semantic approach to product feature extraction from consumer reviews	Wei et al.	2010	INFORMATION SYSTEMS AND E-BUSINESS MANAGEMENT	SI	42	3,82	2	1	2	2	9	7	8	2	5	4	
40.	Measuring and Managing Consumer Sentiment in an Online Community Environment	Homburg et al.	2015	JOURNAL OF MARKETING RESEARCH		41	6,83	0	0	0	0	0	0	3	8	9	15	
			2012		13	3408	11,5955	0,125	0,65	1,825	3,325	5,75	8,55	12,1	13,975	14,4	19,425	

Themes in the lower-right quadrant (Emerging or Declining Clusters). Themes that are important for a research field but are not developed. So, this quadrant group transversal and general, basic themes (Figure 12).

The results of 40 Times-Cited documents reveal that 12 studies have been cited at least 100 times and 34 studies that have been cited at least 50 times. The year mode is 2012 with a total of 8 publications. There are 13 of the 40 publications that correspond to scientific works published in Special Issues.

The sum of the total citation of 40 Times-Cited documents is 3408 citations and the Citation Average/Year is 11,59 citations. Different journals repeated with different publications in the top 40 Times-Cited: Expert Systems with Applications (3 publications), Decision Support Systems (4 publications), Journal of Advertising (2 publications), and Food Quality and Preference (2 publications).

The 1st Ranked publication with 200 citations is the work of Mohamed M. Mostafa, a journal article published in August 2013 in Expert Systems with Applications ''More than words: Social networks' text mining for consumer brand sentiments''. The study uses text mining techniques to investigate hidden patterns in consumers' attitudes towards global brands.

IV. DISCUSSION AND CONCLUSION

Opinion mining, sentiment analysis, and emotion understanding are nowadays fundamental in any business development strategy, playing a big role in the advertising research ecosystem by helping companies to deliver tailored marketing messages based on business goals, rethinking the entire strategy and personalizing the marketing messages to cater to the target audience. The complexity of the study of sentiment analysis and emotion recognition leads us to approach the study of this inter-discipline from a threefold perspective: the study of the synergies between computer vision, natural language processing, and neuroscience in advertising. This bibliometric analysis explored the factors most likely to influence how today's advertising players will vie for relevance and market share and offers diverse visions for the future.

The bibliometric analysis allows us to highlight the following remarkable findings:

Are collected 919 publications in opinion mining, sentiment analysis, and emotion understanding in advertising were identified in the period 2010–2019, with citation counts ranging from 317 to 4772. The results suggest that most of the research carried out is developed during the second lustrum 2015-2019 (n = 705, 76.71%). The total publications retrieved combined a sum of 7263 times cited, making an average of 7,9 citations per paper. The H-index is the same as 40 (based on the study and methodology of H-Classics).

The largest collection of publications in Web of Science is Article Document Type (485 records, 52.77%) followed by Proceedings Paper Document Type (392 records, 42.65%).

The most representative Categories/Research areas in Web of Science in opinion mining, sentiment analysis and emotion understanding in advertising are the following: Computer Science (476 registers and 51.75% of 919 works), Engineering (236 registers and 25.68% of 919 works) and Business Economics (159 registers and 17.30% of 919 works).

The City University of Hong Kong (China) with a total of 8 publications and 321 citations, located within the first 201-300 (ARWU2019) and 55 (QS 2019) and Nanyang Technological University (Singapore) within the 73 positions (ARWU2019) and 12 (QS 2019), with a total of 10 articles published, of which 10 have been cited at least 305 times are the main institutional contributors in the discipline in terms of citation/documents.

The most prolific authors with the highest citation impact in terms of documents/citation are Professor Cambria, from Nanyang Technological University (Singapore), and professor Poria, from the Singapore University of Technology and Design (Singapore).

The most important journals in terms of the number of documents/citations in opinion mining, sentiment analysis, and emotion understanding in advertising are Expert Systems with Applications (11 documents and 482 citations) and Decision Support Systems (8 documents and 458 citations).

The hegemony and predominance of the USA in research on sentiment analysis and opinion mining in advertising are remarkable. Its production represents a third part of the total amount of publications with 206 documents and 2804 citations. Followed by Italy with 55 documents and 883 citations and Peoples R. China with 117 documents and 829 citations. It is paradoxical how Italy is in the second position with half as many articles as China and with a similar number of citations. This denotes the scarce Italian production but of great quality and sum citation impact.

The results reveal that there is only citation pattern connectivity's in recent works where there has been a research study about social networks and text mining for consumer brand sentiment, mining comparative opinions from customer reviews for competitive intelligence, ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content among others.

During the first subperiod of study (2010-2014), we observed the birth of the inter-discipline object of the study. The field is not very developed at that time and there are still no emerging trends or representative thematic groups.

During the second subperiod (2015-2019) we observed the fast development of research in sentiment analysis, emotion recognition, and opinion mining in advertising. It is the period, the greatest scientific production happens, where we find significantly defined and powerful clusters divided into quadrants. Focusing the study on the two quadrants that we consider fundamental for the study and development of the discipline:

The motor themes focused on studies in Facebook as a destination marketing tool, eye-tracking technique to understand the effects of brand placement disclosure types in television programs, studies in consumer sentiment in an online community environment, studies of the power of the "like" button and the impact in social media, social media analytics in extracting and visualizing ratings and reviews from TripAdvisor, assessment consumers' satisfaction and expectations through online opinions and reviews, first fixation and total fixation duration in consumer choice, visual attention toward tourism photographs with the text through an eye-tracking study, attention and the memory for brands in outdoor advertising, effects of personalized banner ads on visual attention and recognition memory, content composition and slot position in personalized banner ads, and how they influence visual attention in online shoppers among others.

The emerging or declining themes are focused on studies in clothing retrieval for video advertising with a deep learning, inbound e-marketing using neural network-based visual and phonetic user experience analytics, automated curation of brand-related social media images, studies in seeking attention through an eye-tracking study of in-store merchandise displays, studies in the analysis of geolocated Airbnb rental images in cities, predicting purchase intention according to fan page users sentiment, studies in recurrent neural networks for short text and sentiment classification, novel frameworks to detect unqualified restaurant reviews and by the end, studies in application and scope analysis of augmented reality in marketing using image processing technique and scalable mobile image recognition for real-time video annotation among others.

We note that the CLASSIFICATION cluster has been maintained in both the first and second subperiods.

The findings of 40 Times-Cited documents (H-Classics) reveal that 12 studies have been cited at least 100 times and 34 studies that have been cited at least 50 times. The year 2012 was the most productive period with a total of 8 publications. The 1st Ranked publication with 200 citations is the work of Mohamed M. Mostafa, a journal article published in August 2013 in Expert Systems with Applications ''More than words: Social networks' text mining for consumer brand sentiments''.

It is worth mentioning the practical application of the present study as it provides potentially relevant information to help understand the past, present, and future scientific structure of opinion mining, sentiment analysis, and emotion understanding in the advertising and marketing field that could help its upcoming research development.

For future research lines, it would be interesting to analyze the literature through alternative metrics, explore visual features and patterns and its effects on moving ads images, develop alternative indexes to measure and analyze online reviews in electronic commerce, as well as develop ontologies that allow us to better structure the knowledge in the field of visual communication and marketing to raise new models of expert systems or decision support systems in the advertising ecosystem.

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