Global Affective Computing Research in the Period 1997-2017:
A Bibliometric Analysis

ABSTRACT

Notable fallouts in marketing and financial market prediction have raised the interest by the scientific community and the business world in Affective Computing (AfC). Automatically recognizing and responding to a user's affective states, AfC shows a great potential to improve companies capabilities of customer relationship management. The aim of this study is to evaluate this filed of research during the last twenty years, identifying for one side its evolution, by the major publications, citations, journals, authors, productive countries, productive institutions, and collaboration patterns; and for another side, identifying its trends through the analysis of research hotspots, burst keywords and areas of research done so far. This bibliometric analysis is based on the science citation index expanded (SCI-E), from the Institute of Scientific Information Web-of-Science, which is now firmly established as an integral part of research evaluation methodology especially within the scientific and applied fields. The results show a significant 4.19 rate of growth in AfC, doubling the number of publications in 4.02 years time. This field of interest is paving the way for creativity and innovation, and provides opportunities for its greater development. The authors expect to contribute to the theory, supplying researchers with new tools and enabling practitioners to improve their marketing strategies, constantly interested in collecting and predicting the attitudes of the consumers toward their products, brands or services.

Keywords: Affective Computing, bibliometric analysis, Scientific outputs, Collaboration network, Research hotpots, Research trends.

1. Introduction

Affective Computing (AfC), is a computational system that aspires to respond to the affective states of the user, narrowing the communicative gap between the highly emotional human and the emotionally challenged computer (Calvo & D'Mello 2010). Its relevance can be seen in various scenarios in which there is a benefit from knowing information about user's emotions. This is the case of persuasive technologies, which aim to explore how to obtain behavioral changes (cognitive or emotional) in its users (Fogg, 1998; Torning & Oinas-Kukkonen, 2009), or to detect several affective states, such as frustration, inducing consumers to have appropriate positive responses (Kappor, Burleson, & Picard, 2007). Automatically recognizing and responding to a user's affective states during interactions with a computer enables companies to enhance the quality of the interaction. In this way, AfC shows a great potential to improve companies capabilities of customer relationship management in order to increase their marketing strategies, constantly interested in collecting and predicting the attitudes of the general public toward their products and brands (Rukavina et al. 2016).

Emotions are composed of behavioral, expressive, physiological, and subjective reactions, or feelings (Desmet, 2005), and influence the way a person appropriates a product and its use in the long term (Holbrook, 1986). Emotions modulate almost all modes of human communication (Picard, Vyzas and Healey, 2001), signaling when events are favourable or harmful (Frijda, 1986), playing an important role not only in successful and effective human-human communication, as well as in human's rational learning (Cambria, 2016). They may be monitored through several techniques, like computing systems (objective) and by asking users to self-report their own emotions (Lopatvoska & Arapakis, 2011). There have been relatively few attempts to develop applications in marketing specifically to support the evaluation of emotions using computer-based tools, namely through affective computing (AfC), which requires collaboration between brand researchers and skilled engineers and psychologists. The measurement of emotions is critical for commercial purposes (Lang, 2014).

We present a bibliometric analysis of research work done on AfC during 1997 till November 2017, using data from the science citation index expanded database (SCI-E), from Web-of-Science. To obtain a more accurate trajectory, we identify the most productive publications, authors, institutes, journals, countries (e.g. Sakai et al. 2011), citations (e.g. Wen and Huang 2012; Piryani et al. 2017), keywords distribution (e.g. Li et al. 2009; Mao et al. 2010; Wang et al. 2013), research hotspots, and areas of research (e.g. Zhou & Zhao 2015). The study's outcomes will provide researchers with all-around insights into the current state and will establish where further research is required. The analytical mapping can answer the following research questions about AfC:

- What are the main areas and documents of research?
- How research publications have grown over time?
- In which countries and institutions most of the research work has been done?
- What are the top publication sources?
- Who are the most productive and more cited authors?
- What are the collaboration of authors, countries and institutions?
- What are the hot issues and trends observed?

Bibliometric analysis is now firmly established as an integral part of research evaluation methodology especially within the scientific and applied fields (Ellegaard & Wallin, 2015). Following the same authors, the use of bibliometric methods is obviously driven by a need to evaluate scientific production and making the results available to policymakers, scientists or other stakeholders. Researchers become aware of the new trends, competing groups and possibilities for scientific cooperation (Barth, Haustein, & Scheidt, 2014).

Our paper identifies the course of development and analyze different aspects of AfC research. The results obtain a useful overview and understanding of this field from 1997 to the current state of art. To the best of our knowledge, this work is the first of its kind. The rest of the paper is organized as follows: Section 2 describes the material and methods used. Section 3 presents the analytical results and discussion. Finally, Section 4 concludes with a summary of the work, its usefulness and limitations.

2. Material and methods

The following dimensions were selected as a basis to measure the global research in AfC: publications, citations, journals, keywords, countries, authors, institutions, research areas, and trends. The underlying data originate in the tabulation of each dimension came from the online version of science citation index expanded the database, from the Institute of Scientific Information Web-of-Science database (WoS). The WoS is a leading and frequently used metric of scientific accomplishment in most fields of human creativity (Li et al. 2009). Since January 1997 until November 2017, there were 2,239 documents with keywords *affective computing*, in the topic field, distributed through 94 areas, where the top 14, corresponding to 87.2% of all AfC research are represented in Fig 1. The two major areas are Computer Science (37.2%) and Engineering (17.5%), totalizing 54.7% of all research.

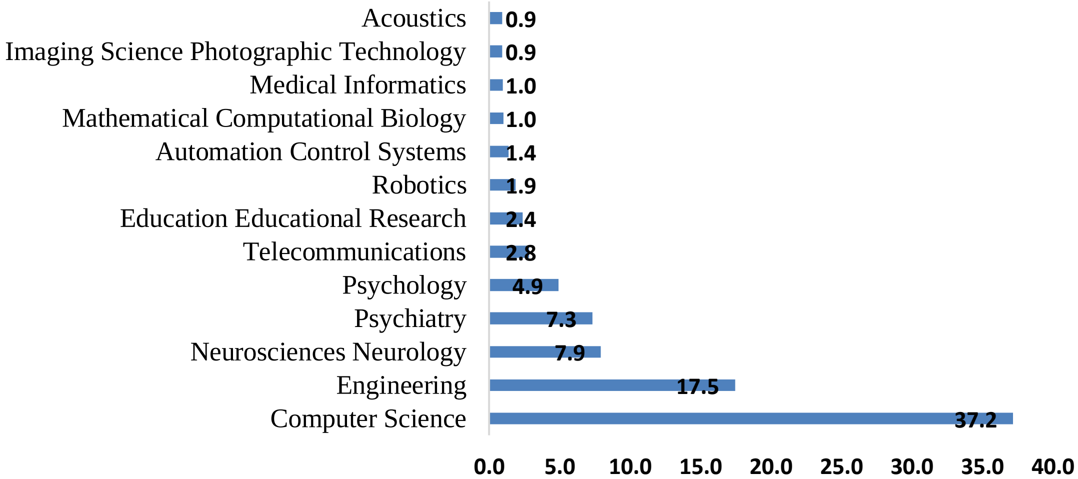


Fig.1: Percentage of research areas of Affective Computing extracted from SCI_E

Within the WoS references obtained, the focus of the present research is proceedings paper (48.97%) and articles (45.36%), which constitute 94.37% of the document type (Fig.2).

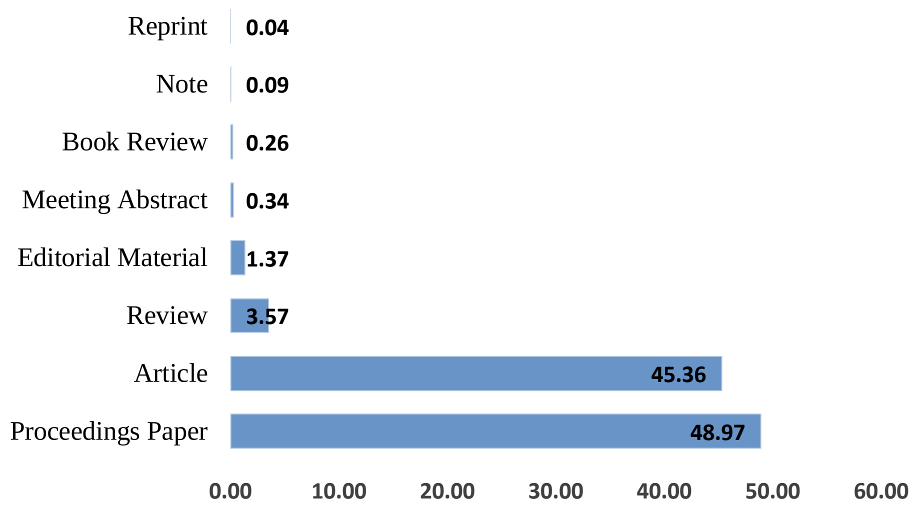


Fig.2: Document type extracted from Web-of-Science during 1997-2017 on Affective Computing

To provide more scientific and accurate information about our research, only documents with the search keywords in the front page were searched out for further analysis (Fu et al. 2012). The most cited documents should have at least a total of 100 citations in the surveyed period (Chuang et al. 2013), originating for the present research 94 highly cited documents. Similarly, amongst 5,922 authors in AfC, there are 48 authors highly cited.

The global scientific outputs were generated using CiteSpace (http://cluster.cis.drexel.edu/~cchen/citespace/), Carrot (http://search.carrotsearch.com/carrot2-webapp), CitNetExplorer (http://www.citnetexplorer.nl/), and Vosviewer (http://www.vosviewer.com/). The method to evaluate the global research in AfC is shown in Fig.3.

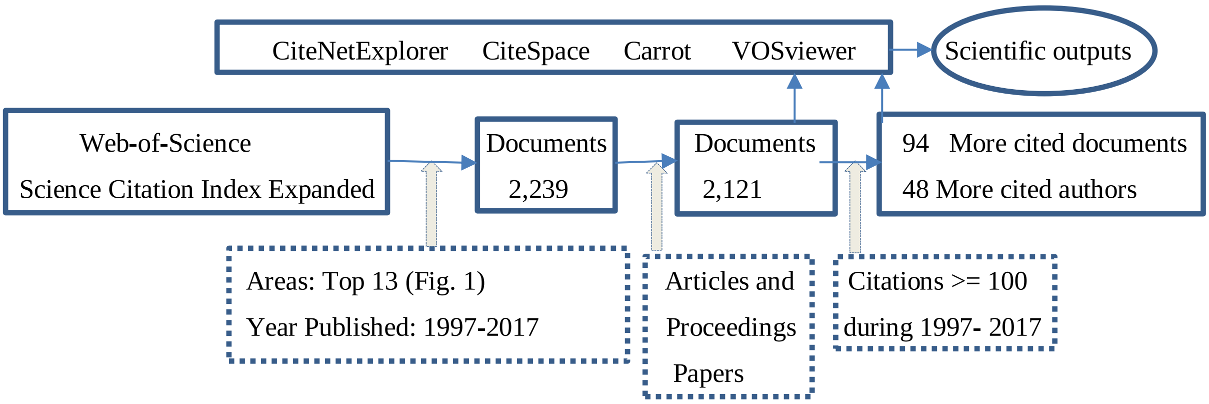


Fig.3: Method to evaluate the global research in Affective Computing

The scientific output includes publications, citations, journals, keywords, countries, authors, institutions, research areas, and trends. Collaboration and contributions of different countries and institutions were estimated by the affiliation of at least one author to the publication.

3. Results and Discussion

3.1 Year-wise publication and growth pattern

The analytical methodology used by the authors involve computing different indicators as defined in standard bibliometric literature. The main indicators include TP (total number of publications), TC (total number of citations), Average Citations Per Publication (ACPP), Relative Growth rate (RGR) and Doubling Time (DT), which measure the time required for the number of publications in a particular year to become double. ACPP is defined as: $ACPP = TC/TP$. According to Mahapatra (1985), the rate of growth with respect to time and doubling time are defined as follow, where Ni and Ni-1 are the number of publications in the years i and $i - 1$:

$$RGRi = \ln(N_i) - \ln(N_{i-1})$$

$$DTi = ln2/RGRi$$

The authors have computed the parameters RGRi, DTi and ACPP (Table 1). Over the past 20 years the average number of publications (101) and citations (1254.77), indicate that on average each publication was read 15.23 times. AfC has now emerged as is a wide research area, with applications into different domains.

The results show that RGR between 1999-2001 and 2004-2008 almost double to values in 2014 and 2016. The mean RGR and mean DT are also calculated for the all period. It can be seen that as RGR increases, DT decreases. The mean of RGT indicates that the relative rate of growth for the period is 4.19. A DT value of 4.02 indicates that the number of research publications is doubling in 4.02 years time, which is an indicator of some slow growth in amount of research work being done on this domain.

Table 1: Year-wise output and growth pattern.

Years	TP	Cumulative	TC	ACPP	RGR	DT
1997	32	32	347	10.84	0.00	0.00
1998	26	58	372	14.31	0.59	1.17
1999	16	74	447	27.94	0.24	2.85
2000	21	95	513	24.43	0.25	2.77
2001	24	119	540	22.50	0.23	3.08
2002	25	144	541	21.64	0.19	3.63
2003	30	174	645	21.50	0.19	3.66
2004	51	225	705	13.82	0.26	2.70
2005	54	279	746	13.81	0.22	3.22
2006	74	353	840	11.35	0.24	2.95
2007	96	449	1035	10.78	0.24	2.88
2008	117	566	1207	10.32	0.23	2.99
2009	108	674	1385	12.82	0.17	3.97
2010	109	783	1393	12.78	0.15	4.62
2011	141	924	1472	10.44	0.17	4.19
2012	150	1074	1656	11.04	0.15	4.61
2013	212	1286	2048	9.66	0.18	3.85
2014	162	1448	2084	12.86	0.12	5.84
2015	293	1741	2329	7.95	0.18	3.76
2016	268	2009	2868	10.70	0.14	4.84
2017	112	2121	3175	28.35	0.05	12.78
Mean	101	-	1254.77	15.23	4.19	4.02

Search results from SCI-E and from the authors (2017)

The number of published documents for each of the years 1997 to November 2017 are represented on a year-wise plot (Fig.4). This curve, with a 4.19 RGR, show a steep rise after 2014. The lesser number in 2017 is understandable since many of publications from 2017 are yet to be indexed in WoS database.

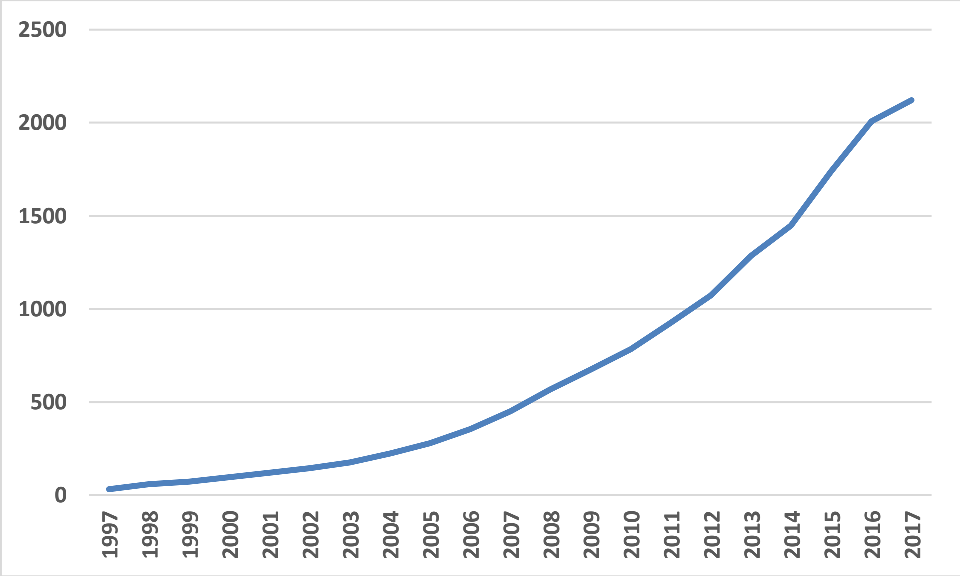


Fig.4: Year-wise publications in Affective Computing.
Search results from SCI-E

3.2 Country-wise distribution and international collaboration

The country-wise distribution of AfC research publications (e.g. Wang et al. 2012) during the full 20 years period, allow understanding the places where the research work was originated and progressed during the 1997-2017 period. Moreover, the metadata of publications records was analysed to extract those instances which contain authors from at least two different countries. VOSviewer was used to represent the collaboration between countries that have produced more than 5 documents. Amongst a total of 76 countries from SCI-E, there are 50 that have published more than 5 publications in this domain, during 1997-2017, which have been aggregated into 9 homogeneous clusters of research collaboration. Table 2 list those countries, analysed according to the total number of publications (TP), the total number of citations (TC), the average number of citations per publication (ACPP), the average mean year of publication (APY), and their links(LINKS), which represent the citations received and those given to other countries. It can also be seen the percentage of the collaboration of each cluster to the total publications (% TP), where the major cluster is 1, contribute in 27.2%, to the research development while the smallest one is cluster 9, contribute in 1.8%.

The most productive countries in AfC, with more than 100 publications (Chuang et al. 2013), are USA (509), Peoples R China (261), England (220), Germany (188), Netherlands (122), Italy (118), Spain (107) and Japan (103). Domination in the publication is not surprising from these mainstream countries since this pattern occurred in most scientific fields, showing a correlation between investigation and Gross Domestic Product (Zhou and Zhao 2015).

A strong core of research (TP) comes from the USA, followed by England, Netherlands and Germany. According to each cluster link strength, four groups with strong collaborations on this research occurs between the USA, Spain and Sweden; between England, Netherlands, Switzerland and South Korea; between Peoples R China and Japan; and between Italy, Greece, Portugal and Australia.

The proportion of citations per publication were also calculated. In the USA, each paper is on average cited 38.5 times, flowed by Switzerland with 31.9 times and Netherlands with 31.1 times.

Moreover, it can be observed that most of the initial papers also come from the USA, with the average year of 2008.1 for publications (APY), followed by Scotland with 2008.3 (APY). The more recent countries in the topic research, with an average year of publication 2015, are Chile and Colombia.

In general, a total of 82.9% research publications involve international collaboration. Only 13 of 76 countries work isolated in terms of AfC research. Table 2 identify the countries that have at least one international collaboration, and therefore the isolated countries are not represented.

Table 2: Country-wise Affective Computing contribution and international research collaboration.

Country (% TP)	TP	TC	ACPP	APY	LINKS	Country (% TP)	TP	TC	ACPP	APY	LINKS
Cluster 1 (27.2%)						Cluster 5 (9.9%)					
USA	509	19590	38.5	2008.1	49	Germany	188	2944	15.7	2010.3	41
Spain	107	569	5.3	2012.3	34	Singapore	35	398	11.4	2013.5	24
Sweden	30	456	15.2	2009.4	25	Scotland	32	906	28.3	2008.3	26
Finland	29	379	13.1	2011.3	18	Belgium	17	488	28.7	2004.4	15
Austria	28	417	14.9	2010.1	23	Cluster 6 (8.0%)					
Russia	12	22	1.8	2015.6	9	Canada	92	2279	24.8	2010.6	34
Slovenia	9	77	8.6	2014.3	19	Taiwan	63	295	4.7	2012.8	29
Chile	8	16	2.0	2015.1	5	Mexico	25	67	2.7	2012.5	16
Croatia	8	37	4.6	2012.4	10	Malaysia	22	74	3.4	2013.7	15
Czech Republic	6	9	1.5	2012.0	5	Iran	11	51	4.6	2013.7	10
Cluster 2 (17.2%)						Philippines	6	153	25.5	2010.8	15
England	220	5845	26.6	2010.2	48	Cluster 7 (5.5%)					
Netherlands	122	3798	31.1	2011.9	48	France	94	811	8.6	2012.0	30
Switzerland	57	1817	31.9	2011.4	42	Israel	20	587	29.4	2009.2	18
South Korea	37	633	17.1	2011.5	35	North Ireland	18	366	20.3	2013.6	29
Ireland	14	56	4.0	2013.2	6	Denmark	14	210	15.0		16
South Africa	8	132	16.5	2011.3	6	Malta	5	13	2.6	2013.4	12
Tunisia	8	22	2.8	2014.1	12	Cluster 8 (5.1%)					
Cluster 3 (13.7%)						Turkey	45	144	3.2	2013.4	16
Peoples R China	261	995	3.8	2011.9	37	Poland	28	133	4.8	2013.5	24
Japan	103	484	4.7	2009.9	24	Brazil	27	378	14.0	2011.1	20
Serbia	6	11	1.8	2011.8	5	Romania	24	22	0.9	2013.4	12
Thailand	6	19	3.2	2010.0	8	New Zealand	8	98	12.3	2008.6	10
Cluster 4 (11.4%)						Bangladesh	7	10	1.4	2014.4	11
Italy	118	1400	11.9	2011.3	33	Cluster 9 (1.8%)					
Australia	81	1299	16.0	2011.6	37	India	39	46	1.2	2014.2	30
Greece	54	433	8.0	2011.5	31	Wales	9	76	8.4	2013.7	7
Portugal	53	63	1.2	2012.1	19						
Bulgaria	7	6	0.9	2014.4	7						

Search results from SCI-E and VoSViewer

3.3 Institution Analysis

To understand the institution-level research output share and dynamics, the authors have tried to identify the highest cited institutions (citations >= 100) contributing significantly to AfC research, and the collaboration between them. Through SCI-E, were identified 1,825 institutions that have published scholarly publications related to this research. There are 68 highly cited institutions. However, only 61 institutions or 3.3% of the total, are connected to each other in the network. Table 3 list those institutions aggregated in 8 clusters of collaboration, all playing an important role in the research activities. The most productive collaboration comes from cluster 1, contributing with 25.8% of the total publications, until cluster 8, contributing with 6.1% of the total publications in AfC. There is the predominance of institutions of USA. MIT perform the best, with the highest number of publications (45) and citations (2349), followed by Univ Twente, with 36 TP and 1862 TC. This last university have the highest number of links with other institutions (42 LINKS). On the other hand, on ACPP indicator, Univ Wisconsin (167.5) and Massachusetts Gen Hosp (101.2) have the best performance.

Table 3: Most productive institutions on Affective Computing research.

Cluster (% TP)	TP	TC	ACPP	LINKS	Cluster (% TP)	TP	TC	ACPP	LINKS
Cluster 1 (25.8%)					Cluster 5 (9.15%)				
Univ Twente	36	1862	51.7	42	Duke Univ	13	923	71.0	2
Tech Univ Munich	30	626	20.9	21	Univ Penn	9	179	19.9	1
Univ Geneva	25	781	31.2	19	Mcgill Univ	8	187	23.4	5
Imperial Coll London	18	172	9.6	27	Univ Montreal	8	112	14.0	4
UCLl	17	132	7.8	4	Univ Michigan	7	270	38.6	2
Univ London Imperial Coll Sci Technol & Med	16	1344	84.0	21	Univ Heidelberg	6	234	39.0	1
Univ Nottingham	15	166	11.1	17	Univ Maryland	6	183	30.5	5
Queens Univ Belfast	12	290	24.2	22	Univ N Carolina	6	229	38.2	4
Univ Augsburg	12	295	24.6	4	Rensselaer Polytech Inst	5	143	28.6	3
Queen Mary Univ London	11	420	38.2	14					
					Cluster 6 (7.7%)				
Cluster 2 (21.1%)					Columbia Univ	14	176	12.6	8
MIT	45	2349	52.2	20	Univ Calif San Diego	11	378	34.4	3
Univ Cambridge	23	434	18.9	3	Univ Pisa	8	122	15.3	3
Nanyang Technol Univ	22	298	13.5	7	Shanghai Jiao Tong Univ	7	120	17.1	1
Univ Sydney	20	618	30.9	5	Nimh	6	481	80.2	2
Univ Illinois	14	1219	87.1	9	Washington Univ	6	273	45.5	4
Univ Stirling	13	358	27.5	8	Univ Iowa	5	164	32.8	2
Univ Memphis	12	690	57.5	2					
Univ Notre Dame	8	129	16.1	5	Cluster 7 (6.7%)				
					Univ Amsterdam	11	917	83.4	8
Cluster 3 (13.3%)					Univ Wisconsin	11	1843	167.5	3
Stanford Univ	23	1265	55.0	16	Univ New S Wales	9	366	40.7	1
Harvard Univ	20	1425	71.3	15	Leiden Univ	7	641	91.6	5
Univ Pittsburgh	19	1068	56.2	8	Univ Edinburgh	7	258	36.9	4
Univ Basel	8	167	20.9	4	Univ New Mexico	5	101	20.2	4
Univ Toronto	8	182	22.8	1					
Massachusetts Gen Hosp	6	607	101.2	9	Cluster 8 (6.1%)				
Emory Univ	5	327	65.4	3	Delft Univ Technol	22	473	21.5	11
Univ Oxford	5	315	63.0	2	Univ So Calif	12	325	27.1	4
Univ Texas	5	212	42.4	2	Univ Utrecht	6	174	29.0	5
					Psychometrix Associates Inc	5	208	41.6	3
Cluster 4 (10.1%)									
Univ British Columbia	15	358	23.9	5					
Univ Calif Los Angeles	13	236	18.2	9					
Chinese Acad Sci	12	112	9.3	3					
Tsinghua Univ	11	152	13.8	8					
Cornell Univ	9	497	55.2	2					
Huazhong Univ Sci & Technol	5	134	26.8	3					
Nyu	5	233	46.6	3					
yale univ	5	422	84.4	4					

Search results from SCI-E and VoSviewer

3.4 Leading Journals

Research articles on AfC appear in 1270 journals included in WoS. The 13 major journals are represented in Table 4. The journal impact fact (JIF), based on Science Citation Index (SCI), is defined as the yearly average number of citations to recent articles published in that journal, and is used as a proxy for the relative importance of a journal withing its field. Therefore, JIF based on 2016, is the number of citations received in that year, of articles published in that journal during the two preceding years, divided by the number of articles published in that journal during the two preceeding years:

$$JIF_{2016} = \frac{TC_{2015} + TC_{y2014}}{TP_{y2015} + TP_{y2014}}$$

Journals with higher impact factors are often deemed to be more important than those with lower ones. IEEE Transactions on Affective Computing, with JIF of 3.149 in 2016, published the largest number of high-quality papers in this domain, with 66 papers receiving 1709 citations in other publications. IEEE Transactions on Multimedia has the highest impact factor (3.509), while International Journal of Human-Computer Studies, has the lower impact factor (1.118) of these top journals. The International Journal of Human-Computer Studies have the highest ACPP value for the research publications.

Table 4: The most active 13 journals in Affective Computing research.

Source Titles	TP	TC	ACPP	Links	JIF
IEEE Transactions on Affective Computing	66	1709	25.9	34	3.149
International Journal of Human-Computer Studies	27	1814	67.2	25	1.118
Interacting with Computers	25	977	39.1	22	1.410
Multimedia Tools and Applications	13	27	2.1	10	1.530
Plos One	11	87	7.9	3	2.806
IEEE Transactions on Multimedia	8	231	28.9	10	3.509
Speech Communication	8	186	23.3	6	1.768
Image and Vision Computing	7	183	26.1	12	2.671
Computers in Human Behavior	6	75	12.5	8	3.435
Cognitive Computation	5	71	14.2	2	3.441
Cognitive Systems Research	5	110	22.0	3	1.182
IEEE Transactions on Autonomous Mental Development	5	25	5.0	3	1.638
Personal and Ubiquitous Computing	5	74	14.8	9	2.395

Search results from SCI-E

3.5 Most productive and most cited authors

High productive authors are those who produce a high amount of research publications during the given period. Similarly, high cited authors are those whose research work published during a given period is cited the most (Piryani, Madhavi & Singh 2017), corresponding to a minimum of 100 citations in the surveyed period (Chuang et al. 2013). Overall 5,922 authors have published scholarly publications related to AfC, and 48 or 0.8% of them are highly cited, contributing 20.5% to the TP. SCI-E and VOSviewer were used to represent these authors aggregated into homogenous clusters of research collaboration. Table 5 shows the highly productive 25 authors, which are aggregated into 4 clusters of co-collaboration, displayed by decreasing order of PT research. The top five more productive authors (according to TP) in AfC research are Schuller B, Pantic M, Picard RM, Cambria E, and Calvo RA. Pantic M, Picard RW, Huang TS and Zeng ZH, are the author more cited. Clearly, according to link strength, Schuller B, Pantic M., Cowie R. and Valstar M., stand up by their production and collaboration in AfC research.

Table 5: Co-authorship network of highly productive authors in Affective Computing.

Clusters	TP	TC	ACPP	Links	Clusters	TP	TC	ACPP	Links

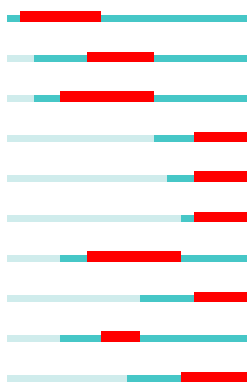
of Authors					of Authors				
Cluster 1					Cluster 2				
Schuller, B	38	513	13,5	247	Picard, RW	21	1785	85,0	86
Pantic, M	21	1887	89,9	275	Nijholt, A	12	389	32,4	33
Eyben, F	13	427	32,8	190	Pun, T	10	598	59,8	67
Bianchi-Berthouze, N	12	153	12,8	50	Andre, E	9	294	32,7	44
Cowie, R	12	306	25,5	110	Soleymani, M	8	597	74,6	77
Valstar, M	10	234	23,4	106	Chanel, G	7	146	20,9	42
Mckeown, G	7	322	46,0	84	Kim, J	7	276	39,4	24
Zhang, Y	7	136	19,4	6	Wilhelm, FH	7	166	23,7	10
Chen, M	5	138	27,6	13	Surakka, V	6	216	36,0	11
Li, Y	5	132	26,4	10	Lanata, A	5	101	20,2	19
					Scilingo, EP	5	101	20,2	19
					Valenza, G	5	101	20,2	19
Cluster 3					Cluster 4				
Cambria, E	18	430	23,9	111	Calvo, RA	15	466	31,1	58
Hussain, A	13	291	22,4	99	Huang, TS	10	1153	115,3	115
Poria, S	6	193	32,2	75	Zeng, ZH	8	1077	134,6	113
					D'Mello, S	7	491	70,1	59
					D'Mello, SK	5	266	53,2	77

Source SCI-E, CitNetExplorer and VOSviewer

Further, by using CiteSpace, it can be observed the top references with strongest burst citations in AfC research publication data obtained. Burst detection can identify documents emerging over time, having statistically significant fluctuations on the citation count, during a short period of time. The time interval is depicted as a blue line. The period time in which a document was found to have a burst is shown as a red line segment, indicating the beginning year and the ending year of the duration of the burst. The results give an idea about the initial research papers on AfC which are being cited often by researchers during recent times as well. As can be seen, many of these papers with strong bursts are published during the 1997-2003 period. This is easy to understand that since many of these works were the initial pioneering research works in the area, they have been cited a lot by later papers. The emerging references in AfC research with influence nearby 2017 are Calvo and D'Mello, Chang and Lin, Koelstra, and Kim and Elizabeth. Table 6 shows the top 13 documents, identified through the 20 years span, their authors, sources of publication, year of publication, and burst strength.

Table 6: Top 10 references with strongest citations burst in Affective Computing.

Authors	Source	Year	Strength	Begin	End	1997 - 2017
Picard	Affective Computing	1997	21.680	2000	2005	
Cowie et al.	IEEE Signal Proc Mag	2001	15.039	2005	2009	
Picard, Vyzas & Healey	IEEE T Pattern Anal	2001	14.436	2003	2009	
Calvo & D'Mello	IEEE T Affect Comput	2010	10.694	2013	2017	
Chang & Lin	ACM T Intel Syst Tec	2011	8.262	2013	2017	
Koelstra	IEEE T Affect Comput	2012	8.257	2013	2017	
Pantic & Rothkrantz	P IEEE	2003	8.175	2005	2011	
Zeng, Roisman & Huang	IEEE T Pattern Anal	2009	7.701	2013	2017	
Picard	Int J Hum-Comput St	2003	7.442	2006	2008	
Kim & André	IEEE T Pattern Anal	2008	5.698	2012	2017	



Source SCI-E and CiteSpace

3.6 Research Hotspots

There are 4,775 keywords identified by SCI-E in AfC research, where the top 34 keywords with at least 10 occurrences are analysed. The total number of keywords (TP), the average year of publication (APY), average number of citations (ANC), and links strength are shown in Table 7, which are displayed by APY.

Except for affective computing, which is the search word in the study, a keywords analysis revealed that the top five research hotspots of the study are: i) emotion/affect, pattern recognition and feature selection; ii) human-computer interaction (HCI), machine learning and intelligent tutoring systems; iii) sentiment analysis; iv) physiological signal processing; and v) and user interface.

Table 7: Research hotspots and trends of Affective Computing

Keywords	TP	APY	ANC	LINKS	Keywords	TP	APY	ANC	LINKS
affective computing	1025	2012.1	107.268	1059	feature extraction	15	2013.0	87.333	37
emotion recognition	368	2012.0	147.771	292	classification	15	2012.8	36.667	32
facial expression recognition	102	2013.5	5.907	57	skin conductance	15	2010.7	272.667	48
human-computer interaction	90	2012.4	22.500	131	emotion classification	14	2013.8	23.000	21
machine learning	54	2013.4	45.926	120	physiological computing	14	2013.3	202.143	26
sentiment analysis	38	2014.5	38.684	63	pervasive computing	14	2010.1	152.143	16
affect	38	2010.1	412.368	58	affect recognition	14	2009.7	257.143	31
intelligent tutoring systems	27	2013.6	74.074	44	speech	13	2012.8	200.769	40
pattern recognition	25	2009.5	8.720	58	data mining	13	2011.8	88.462	26
social signal processing	21	2013.4	108.095	25	cognition	13	2009.6	55.385	22
physiological signals	20	2014.4	20.400	48	user experience	12	2014.9	5.000	22
feature selection	20	2012.1	41.300	39	music	12	2013.8	69.167	33
human-robot interaction	20	2010.5	5.400	24	affective states	11	2012.3	359.091	17
artificial intelligence	19	2012.3	54.737	29	wearable computing	11	2011.8	56.364	8
ubiquitous computing	18	2011.9	8.500	16	facial expression analysis	11	2009.9	29.091	14
hci	17	2012.2	23.529	25	multimodal fusion	10	2014.1	13.300	23
sentic computing	16	2012.8	209.375	17	speech emotion recognition	10	2013.9	14.100	11
support vector machine	16	2012.4	4.250	21					

Source form SCI-E and Vosviewer

The visualization in a foam tree, through Carrot, offers an innovative non-rectangular tree map, where the size of each one represents the frequency of the topic (Fig. 5). Although there are some discrepancies between the frequencies obtained with VOSviewer and Carrot, the similarity between top keywords makes it a useful point of reference about the main trends (Chen et al., 2014) on AfC research. The discrepancy is explained by the difference in sources working on SCI-E and PubMed.

It can be seen that the core issue is emotions, including the dimensions of detection, expressions, feelings, moods, sentiments, technology, interactions, devices, machines. The pioneering paper in AfC of Rosaline Picard, the relevance of IEEE journals, Human-Computer Interaction (HCI), Affect Sensing, and Sentiment analysis (e.g.Youtub) are considered relevant areas of research in AfC.

Fig.5 Major topics in Affective Computing.

Results from PubMed extracted by Carrot

3.6.1 Emotion recognition. Emotions are central to several human processes, may enhance system effectiveness (Picard, 2003), and are identified in our bibliometric analysis as the central core of research in AfC. Emotion recognition depends on the way emotions are measured. Research in psychology consider three major approaches to affect modelling: categorical, dimensional and appraisal-based (Grandjean, Sander, & Scherer, 2008). The most commonly adopted in research on automatic measurement of human affect, is the categorical which considers the existence of a small number of basic emotions, hard-wired in our brain and recognised universally (Ekman & Friesen, 1975). However, this approach has been criticised by several researchers who consider that in everyday interactions people exhibit rather complex affective states, like embarrassment, thinking, depression, which can be expressed via several of anatomically possible facial and bodily expressions, audio or physiological signals (e.g. Russell, 1980). Hence, other researchers advocate the use of dimensional description of human affect, where affective states are not independent from one another; rather, they are related in a systematic manner (e.g., Grandjean, Sander, & Scherer, 2008). The more known applications in this approach are the Circumplex of Affect (Schweitzer & Garcia, 2010), and the 3D emotional space of pleasure/ displeasure, arousal/ nonarousal and dominance/submissiveness (Mehrabian, 1996), at times referred to as the PAD emotion space (Jia et al.,2010). The 3D dimension has been improved with the inclusion of expectation, defined as the degree of anticipating or being taken unaware (Fontaine et al., 2007), or by the inclusion of intensity, defined as how far a person is away from a state of pure, cool rationality (e.g., McKeown et al., 2010). Finally, the appraisal-based approach emotions are generated through continuous, recursive subjective evaluation of both our own internal state and the state of the outside world (relevant concerns/needs) (e.g. Fridja, 1986). The initial applications in this 3D approach was the componential models of emotion (Scherer et al., 2001), but did not have much success because it requires complex, multicomponent and sophisticated measurements of change. A standard cognitive appraisal model for emotions, known as OCC (Ortony, Clore, & Collins, 1988), and is the most used in affect synthesis in embodied conversational agent design (Bartneck, 2002). All these approaches explain the relevance and complexity of emotion recognition to be manage by humans and computers alike.

3.6.2. *Human-computer interaction (HCI), machine learning and intelligent tutoring systems.* This hotspot can be explained in human-centred computing, and AfC. Human-centred computing is a research field which aims at bridging the existing gaps between human science and computer science (Sebe, 2010), and is a reimagining of HCI in which some researchers consider that understanding people with their concerns and activities should be the first consideration in technology design (Bannon, 2011). Moreover, AfC is the research area that focuses on computing's relationship to emotions- how it influences them and is influenced by them (Picard, 1997). The interaction must become two-sided which can be accomplished if computers learn the emotions of its user, since humans have emotional experiences when interacting with their computers (Polzin & Waibel, 2000).
3.6.3. *Sentiment analysis.* Also known as opinion mining, is a computational method to extract emotional content of a written text and to classify this content according to a set of possible dimensions. It is gaining a lot of attention from industry and academia alike, due to the phenomena of Web 2.0, which led to an unprecedented increase in the amount of on-line content generated by regular users, rather than web-site owners or publishers (Thelwall, Wilkinson, & Uppal, 2010). The information contained in user-generated content could be of pivotal importance to firms and institutions, which need to identify whether a text is objective or subjective (ie, containing facts or opinions/emotions), and to determine its subjective polarity, identifying how positive/negative it is.
3.6.4 Physiological signal. Emotion recognition can be summarized into non-physiological and physiological signals. Non-physiological signals, includes text, facial expression, speech and gesture (Calvo & D'Mello, 2010). Physiological signals includes pupillary diameter, electroencephalography, electromyogram, and electrocardiogram, and are considered more effective and reliable, inspite of needing more expensive techniques (Soleymani, Pantic, & Pun 2012). The accuracy of human emotion recognition as been improved by utilizing advanced analysis methods and techniques including voice recognition (e.g.Wang, Chien & Moutinho, 2015), natural language processing, image processing and electroencephalography devices (Cambria, 2016).
3.6.5 User interface. A user interface is the representation of a system with which a user can interact (Jacko, 2012). As examples, we have natural user interface, which allows the user to interact using body language and gestures (Wigdor & Wixon, 2011); ubiquitous computing which is technology that "disappears" with the goal of designing computers that fit the human environment (Weiser, 1995), having high embeddedness and mobility, while pervasive computing has low mobility (Lyytinen & Yoo, 2002). Ubiquitous and pervasive technologies may be represented by different types of interfaces, like tangible user interfaces, which allow users to manipulate digital information and physically interact with it (Ishii, 2008).

3.7 Research Trends

To track the advancement of the collective knowledge of AfC, burst keywords are used as indicators of emerging trends with statistically significant fluctuations on the citation count, during a short period of time (Table 8). Prior to 2006, some topics with high frequency of burst were performance, avatar, pattern recognition, artificial psychology, and Human-Computer Interaction (HCI). Topics between 2007-2011 were biosignal, pervasive computing, affect, sentic computing and social signal processing. The trend in AfC research after 2011 until nowadays include music, facial expression recognition, support vector machine, meta-analysis, recognition, sentiment analysis, multimodal, context analysis, and brain computer interface.

The majority of models use standardized descriptions of emotions to be used in any context, where the most common standard approach is Russell's circumplex model of affect (Russell, 1980), possibly because it defines a large set of adjectives to categorize emotions, which allows flexibility and covering a large range of emotions. There are several factors that may affect the self-report of emotions using technology: the interface characteristics, as shape, design and interaction style may impact motor and cognitive processes (Lottridge & Chignell, 2009b); the users' own cognitive abilities and digital skills; the interest, enjoyment, and motivation to use an interface; and the user's context when is doing the experiment.

Table 8: Top keywords with strongest citation burst

Keywords	Strength	Begin	End	1997 - 2017
Performance	63.594	2004	2009	
Avatar	35.535	2005	2009	
Pattern Recognition	37.760	2006	2011	
Artificial Psychology	42.066	2006	2009	
Human-Computer Interaction	42.606	2006	2008	
Biosignal	33.218	2008	2010	
Pervasive Computing	33.218	2008	2010	
Affect	43.816	2009	2011	
Psychophysiology	43.283	2011	2012	
Sentic Computing	39.996	2011	2012	
Social Signal Processing	33.884	2011	2012	
Music	55.392	2012	2015	
Facial Expression Recognition	51.967	2013	2017	
Support Vector Machine	61.097	2013	2015	
Metaanalysis	73.601	2013	2014	
Recognition	45.218	2013	2014	
Sentiment Analysis	90.086	2014	2017	
Physiological Signal	61.356	2014	2017	
Machine Learning	64.062	2014	2016	
Multimodal	71.363	2015	2017	
Context Analysis	57.957	2015	2017	
Brain Computer Interface	44.032	2015	2017	

Source CSI-E and CiteSpace

4. Conclusions

This study has performed a comprehensive bibliometric analysis of research outputs in AfC published in SCI-E journals since 1997 until November 2017. The research publication dataset has been computationally analyzed to map the AfC research landscape during last 20 years. The bibliometric analysis helped in identify year-wise number and rate of growth of publications, types of authorship of papers on AfC, collaboration patterns in publications on AfC, most productive countries, institutions, journals, authors, citation patterns, research hotspots, burst keywords, and trends in publications during the period. The analysis has successfully provided an analytical account of progress of AfC from 1997 to state of art today, and a map of major areas of research and keywords.

This computational analysis provided the answer to various research questions stated in Section 1. First of all, year-wise growth pattern indicates that there is a significant rate of growth in research output on AfC, with the number of publications is doubling in 5.9 years time. The country-wise distribution of AfC research shows that AfC research is now geographical widespread, though USA and Spain still produce most of the research papers. In terms of international collaborative papers USA, England, Netherlands and Germany stand at the top, as well as the strongest collaboration link during the period. This study also identifies that the most productive institutions on AfC are MIT and Univ Twente, having the highest TP and TC, and Uni Wisconsin with the highest ACPP. The collaboration between authors indicates a greater globalization, with complex and articulated research networks where the distance has some interesting explanation but the main factor seems to be a positive correlation with the income of the countries. These networks could also be explained by the increased number of communication technologies, which allows more international collaboration and more share of ideas and workloads. The authors also observe that the top publications sources are IEEE Transactions on Affective Computing, with the highest TP; IEEE Transactions on Multimedia with the highest impact factor, and International Journal of Human-Computer Studies with the highest ACPP value for research publications. The analysis identifies Schuller B and Pantic M as the most productive authors, and Pantic M, Picard RW and Huang TS as the most cited authors. On authorship pattern, all highly productive authors have multi-author publications. The analysis further identifies that AfC publications are in a wide variety of hotspot areas. The analysis of keywords publications, citations, average year of publications and links strength, identifies as hotspots emotion recognition, human-computer centred, sentiment analysis, physiological signal processing, and user interface, which are further elaborates by burst detection algorithm. Burst detection shows that the focus of AfC research before 2006 was related to performance, pattern recognition and HCI. Between 2007 and 2011 the focus was directed at signal processing and affect detection. After 2011 was born a different focus directed to new applications, a research interest in sentiment analysis and meta-analysis, and the use of multimodal signals. Besides, the development of multimodal systems that includ the context appeared to be considered a necessary technological development to obtain a more precise and real recognition of emotions. The computationsl results present a first of its kind analytical view of the AfC research area. Researhers from the scientific community, marketing, and business world can benefit from these results. SCI-E analysis helped to understand that more AfC research output is based on the use of computer science, and the document type are mainly proceedings papers and articles. Overall, this paper presents a detailed analytical account of AfC research from 1997 until Novembre 2017 by computational analysis of research publication data in AfC. The paper helps in understanding the broad landscape of AfC research and presents results useful for researchers in the area. Bibliometric analysis has helped to characterize qualitatively and quantitatively the AfC research in terms of its development, hotspots, and trends of the investigation, supplying the researchers and marketers with new tools in this domain.

Our research spans 20 years of scientific literature. In order to create a representative corpus of documents for investigation, we set up the following profile in WoS: topic: “affective computing”, indexed SCI-Expanded; timespan 1997-Nov 2017. This profile, although not exhaustive, produces a comprehensive number of documents to have been analysed. If we had analysed the JIF based not only on the results obtained in 2016, as we did, but based on previous years, we could have followed tendencies in the change of impact of AfC journals over time. The data chosen is WoS which has the oldest and most comprehensive records of citation indexes, assumed to have a sufficient amount of high quality literature. Nevertheless, it doesn't necessarily index the totality of journals and then not all research of interest can be examined using this data (Li et al., 2010).

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