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Affective computing at the edge: A bibliometric analysis of the period 1995-2020

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Abstract

Affective computing is one of the most dynamic, interdisciplinary researched topics that draw on computer sciences, engineering, psychology, physiology, and neuroscience to computationally model, track, and classify emotions and affective states. This field is the foundation of the fast-growing USD 20 billion emotional A.I. industry that transforms the way we live and work. Its applications range from music playlists compiling algorithms, drowsiness-detecting car engine, tone-sensing via texts, or micro-targeting algorithms for political ads. We deploy bibliometric analysis on a dataset of 1,646 Web-of-Science-indexed academic articles from 1995 to 2020 to track the development of the field: its growth rate, major players, major collaborative networks, and thematic evolution. The annual growth rate of scientific production is 12.5%. There is an exponential growth of scientific publications in this field, as the number of publication output in 2016-2020 alone far outstrips that in the previous 20 years (860 vs. 786). While the U.S. dominates the field both in research output and citation from 1995-2015, China emerges as a major player as research published by corresponding authors from China overtake the USA as most cited in 2016-2020. Surprisingly, Japan was missing in the top 10 countries measured by both output and citation. Our analysis also identifies two major collaborative networks: the “Asia Pacific cluster” of the USA., China, Singapore, Japan; the “European” cluster of Germany, the U.K., and the Netherlands. Finally, the thematic analysis reveals a growing academic interest in further fine-tuning computational techniques related to affective computing, as well as a decline of interest in using affective computing to detect and study mental illnesses such as depression and bipolar disorders. From these observations of the historical data, we speculate on the future trends of this dynamic research field.

Keywords: affective computing; emotional A.I.; bibliometric analysis; thematic evolution; machine intelligence

Introduction

Affective computing is a growing multidisciplinary field that draws on computer sciences, technology and engineering, psychology, physiology, and even neuroscience. The term was coined by Rosalind Picard in 1995 to mean “computing that relates to, arises from, and deliberately influences emotion” (Calvo et al., 2015, p. 13). As human lives become increasingly assisted and even dominated by technologies, there is an inevitable need to better understand the role of *human affect* in human-computer interactions. Emotional artificial intelligence (A.I.) and empathic media, i.e., media technologies that have an increasing capacity to sense, track, classify human emotions and affects (McStay, 2018), are the most recent developments of affective computing. These emotion-sensing technologies make up a growing global industry of USD 20 billion (Telford, 2019), which will transform the way we live and work.

Even though emotional A.I. and affective computing technologies have not reached technological maturity, their commercial applications have already become pervasive in many aspects of our daily life. In the context of the workplace, multinational corporations such as *Softbank*, *IBM*, *Unilever* are using emotional analytics to predict whether or not a job candidate will become a successful future employee. To tackle workplace harassment, the U.S. company, *Spot*, markets an A.I. chatbot that uses natural language processing tools to identify patterns and problems associated with harassment (Fouriezos, 2019). The Voice recognition algorithm of companies such as that of *Empath* in Japan or *Cogito* in Boston is

being used by call center managers worldwide to monitor an employee's moods in real-time. Amazon's research and development department, Lab126, is currently developing a voice-activated, wrist wearable bio-sensor. Besides providing managers with micro-second productivity updates of employees in Fulfillment Center worldwide, the company claims that it can be used in the workplace to detect depression, anxiety and even early signs of mental illness (Graziosi, 2020; Lecher, 2019).

In the context of education, algorithms that mine psycho data to provide psycho-metrics of students are increasingly deployed to provide feedback about the level of engagement for educators, with an aspiration of molding the behaviors and even affective states of the learners in the direction of "positive" feeling. For example, *ClassDojo*, a mobile application, currently allows millions of teachers to give positive points for desired students' behaviors on a smartphone while giving a lesson. In this vein, emotional A.I. and affective computing technologies have enabled an instantiation of psychological governance in education (Williamson, 2017, 2021). In the context of our daily life, Spotify can suggest playlists by sensing a person's mood (Ratliff, 2016), or Amazon's home assistant, Alexa, can detect through voice analytics the emotional state of its users, or Grammarly's algorithm can identify emotional tenor in texts (Richardson, 2020). Honda and Softbank have co-created the 'Emotion Engine', which detects if a driver is drowsy, distracted, or stressed as a response to the spike in elderly drivers' accidents (Dery, 2018). Our interactions on any digital platform are also increasingly mediated, even arguably, dominated by algorithms that track our affective states. One of the controversial examples is the deceptive and coercive, one can argue, micro-targeting political ads exposed in the famous Cambridge Analytica case (Bakir, 2020).

Such increasing influence of affective computing technologies in every walk of life prompts our investigation into the history of the field using bibliometric analysis. As one of the most actively researched topics, the number of research articles on "affective computing" is increasing rapidly, making it virtually implausible to be updated with every publication (Tao & Tan, 2005). Thus, we deploy bibliometric analysis on a dataset of 1,646 Web-of-Science-indexed academic articles from 1995-2020 to track the field growth rate, major players, major collaborative networks, and thematic evolution. The bibliometric approach is a widely used method to provide a broad overview of a given field, for example, A.I. applications in medicine (Tran et al., 2019), interdisciplinary robotics research (Michalec et al., 2021), global evolution of digital marketing communication (Kim et al., 2019), conversational agents and chatbots (Io & Lee, 2017), etc.

Materials and Method

We searched for the keyword "affective computing" in the Web of Science database for the period from 1995 (i.e., when Rosalind Picard first coined the term) to 2020. The purpose is to look for English-language publications on the topic, whether they are journal articles, books, book chapters, review articles, or editorial materials. The search query, conducted on March 17, 2021, is as follows.

Step	Query	Results
1	TOPIC: (affective computing) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=1995-2020	3,532
2	TOPIC:	3,465

	(affective computing) Refined by: LANGUAGES: (ENGLISH) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=1995-2020	
3	TOPIC: (affective computing) Refined by: LANGUAGES: (ENGLISH) AND [excluding] DOCUMENT TYPES: (PROCEEDINGS PAPER OR MEETING ABSTRACT OR NOTE OR BOOK REVIEW OR REPRINT OR EARLY ACCESS) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=1995-2020	1,657
4	After manually screening and removing articles published in 2021 and duplicate articles	1,646

The results yield a total of 1,657 items. Early access materials formally published in 2021 are excluded, resulting in the final list of 1,646 items. The open-source *bibliometrix* package in R, developed by Aria and Cuccurullo (2017), is used to conduct the bibliometric analysis. The package's web interface app, *biblioshiny*, enables users to perform analysis at three levels of analysis, namely sources, authors, and documents, as well as to map the structures of knowledge in conceptual, intellectual and social terms.

Results

Affective computing at a glance

The overall annual growth rate of scientific production is 12.5%. Figure 1 illustrates the annual scientific production. The two red dash lines serve as markers for each decade to be examined in detail. Specifically, the three periods are: from 1995 to 2005, from 2005 to 2015, and from 2015 to 2020.

Figure 1: Annual scientific production on "affective computing", 1995-2020 (Source: Web of Science)

Table 1 presents the main statistics of the publications on “affective computing” for 25 years, from 1995 to 2020.

Table 1: Descriptive statistics of research on “affective computing” in 1995-2020 (Source: Web of Science)

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	1995:2020
Sources (Journals, Books, etc.)	697
Documents	1646
Average years from publication	7.06
Average citations per documents	31.03
Average citations per year per doc	3.134
References	66375
DOCUMENT TYPES	
article	1431
article; book chapter	57
editorial material	45
editorial material; book chapter	2
review	110
review; book chapter	1
DOCUMENT CONTENTS	
Keywords Plus (ID)	3161
Author’s Keywords (DE)	4588
AUTHORS	
Authors	5201
Author Appearances	6564
Authors of single-authored documents	128
Authors of multi-authored documents	5073
AUTHORS COLLABORATION	
Single-authored documents	160
Documents per Author	0.316
Authors per Document	3.16
Co-Authors per Documents	3.99
Collaboration Index	3.41

In terms of authorship, the raw data show that the documents were written by a total of 5,201 unique authors, with the ratio of documents per author at 0.316. Of the documents, approximately 9.7% were written by a single author, while the remaining were written by multiple authors. A ratio of 3.16 for authors per document means that a paper on “affective computing” was written on average by 3.16 authors. Given that publications in which the number of authors is larger than usual can skew the metrics, the co-authors per document, which is 3.99 here, takes into account the number of times an author appears in the whole set of documents. Both measures suggest that, on average, three to four authors were involved in one publication on “affective computing” during the 1995-2020 period. A collaboration index

of 3.41, measured by dividing the total number of authors of multi-authored documents by the total number of multi-authored documents, confirms the aforementioned findings.

Table 2: Top ten countries with the highest count of publications and citations

	Country	Total articles	%		Country	Total Citations	%	Average Article Citations
1	USA	304	18.63	1	USA	17,932	27.02	58.987
2	CHINA	225	13.79	2	UNITED KINGDOM	4,872	7.34	38.976
3	UNITED KINGDOM	125	7.66	3	GERMANY	3,782	5.70	35.346
4	GERMANY	107	6.56	4	CHINA	3,077	4.64	13.676
5	SPAIN	77	4.72	5	NETHERLANDS	2,841	4.28	46.574
6	ITALY	74	4.54	6	CANADA	2,429	3.66	49.571
7	NETHERLANDS	61	3.74	7	AUSTRALIA	2,094	3.15	44.553
8	CANADA	49	3.00	8	SWITZERLAND	1,528	2.30	49.29
9	AUSTRALIA	47	2.88	9	SINGAPORE	1,515	2.28	54.107
10	INDIA	43	2.63	10	ITALY	1,404	2.12	18.973

Table 2 lists the ten countries that have published the most on “affective computing” in the analyzed period and those that record the highest count of citations. The country is determined based on the country affiliation of the corresponding author. The USA topped both lists, accounting for 18% of the total research output and 27% of the total citations. This speaks volumes to its position as the pioneering destination for research on affective computing. China came second to the USA in terms of publications but trailed behind the United Kingdom and Germany in terms of citations.

Meanwhile, Spain and India were present in the top ten most productive countries but missing in the top ten most-cited countries—the two positions taken by Switzerland and Singapore. Overall, the rise of China, Singapore and India as the only non-Western countries on the lists suggests that the shifting of research destinations away from the once Western concentration. Table 3 breaks down the scientific output of the top ten most productive countries over the three periods from 1995 to 2020.

Table 3: Changes in scientific output on “affective computing” of the top ten countries in three periods

Country	Period					
	1995-2005		2006-2015		2016-2020	
USA	77	43.75%	123	20.36%	104	12.22%
UNITED KINGDOM	0	0%	73	12.08%	152	17.86%
GERMANY	26	14.77%	45	7.45%	54	6.34%
CHINA	15	8.52%	44	7.28%	48	5.64%
NETHERLANDS	5	2.84%	23	3.81%	41	4.82%

CANADA	4	2.27%	36	5.96%	34	3.99%
AUSTRALIA	3	1.71%	38	6.29%	20	2.35%
SWITZERLAND	10	5.68%	19	3.15%	20	2.35%
SINGAPORE	4	2.27%	23	3.81%	20	2.35%
ITALY	0	0%	2	0.33%	41	4.82%
Total publications	181		605		860	

As can be seen, in the first decade in which research on affective computing was at its nascent stage, the United States was the major player, accounting for nearly 44% of the total output, whereas China and India were absent. This all changed in the next two periods: China overtook the United Kingdom as the second most productive in 2006-2015 and later also surpassed the USA as the most productive in 2016-2020.

Table 4 provides further empirical evidence for the emergence of China and India in 2006-2015 as two influential research hubs on affective computing. Research articles published by China were increasingly cited worldwide in the recent decade, allowing the country to overtake the USA as the most cited in the 2016-2020 period.

Table 4: Changes in scientific citations on “affective computing” of the top ten countries in three periods

Country	Period					
	1995-2005		2006-2015		2016-2020	
USA	8733	57.38%	8238	30.42%	961	12.22%
UNITED KINGDOM	1368	8.99%	2758	10.18%	746	9.49%
GERMANY	779	5.12%	2282	8.43%	721	9.17%
CHINA	0	0%	1867	6.89%	1210	15.39%
NETHERLANDS	497	3.27%	2189	8.08%	155	1.97%
CANADA	1284	8.44%	972	3.59%	173	2.20%
AUSTRALIA	356	2.34%	1454	5.37%	284	3.61%
SWITZERLAND	2	0.01%	1353	5.00%	173	2.20%
SINGAPORE	0	0%	529	1.95%	986	12.54%
ITALY	94	0.62%	1139	4.21%	171	2.17%
Total citations	15,219		27,083		7,863	

Japan was missing in both lists over the whole period.

Collaboration networks

Given that researchers do not work alone and increasingly collaborate outside their home institutions as well as home countries, it is also important to examine the networks of country collaboration.

Table 5: Publications by single-country and multiple-country collaboration in the top ten most productive countries

Country	Articles	Single-country	Multiple-country	Percentage of Multiple-country
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		publications	publications	publications
USA	304	249	55	18.1%
CHINA	225	154	71	31.6%
UNITED KINGDOM	125	86	39	31.2%
GERMANY	107	64	43	40.2%
SPAIN	77	54	23	29.9%
ITALY	74	57	17	23%
NETHERLANDS	61	40	21	34.4%
CANADA	49	42	7	14.3%
AUSTRALIA	47	31	16	34%
INDIA	43	39	4	9.3%

Table 5 shows that Germany has the highest rate of multiple-country publications in the top ten most productive countries while India has the lowest. This means German authors have many works published with international collaborators, as opposed to Indian authors who tend to publish among themselves. China, the United Kingdom, the Netherlands, and Spain followed Germany in terms of internationally collaborated publications. By comparison, the USA has a relatively moderate rate of multiple-country publications, indicating that American authors largely work together.

Figure 2: Networks of co-authored publications by countries

Figure 2 provides a visualization of the collaboration network by countries, in which the bigger the text is, the more co-authored publications the country has. The networks bring attention to three clusters of countries on affective computing research. Two measures of importance in network analysis are: (i) betweenness centrality, which measures the number of shortest paths that a node bridges between other nodes, and (ii) closeness centrality, which takes into account the shortest paths between all nodes. Here, the United Kingdom scores the highest in both measures (42.88 and 0.043, respectively), followed closely by the USA (39.15 and 0.041).

The USA and China are the two biggest nodes in the first hub of five countries, while the United Kingdom and Germany are the two biggest nodes in another hub of nine countries. What can be interpreted from Figure 2 is the rise of scientific output in China and Singapore, as shown in Table 2, is

also linked closely to the increased collaboration with authors from the USA. The transfer of knowledge is taking place from the more established to the newly emerging. Meanwhile, the third cluster, with the exception of Canada, consists of all European countries, with Italy and Spain having a higher count of publication output.

Table 6: Top ten most productive affiliations and their countries

Affiliations	Country	Articles	%
STANFORD UNIV.	USA	46	2.79%
UNIV. GENEVA	SWITZERLAND	46	2.79%
NANYANG TECHNOLOGY UNIV.	SINGAPORE	43	2.61%
HEFEI UNIV TECHNOLOGY	CHINA	36	2.19%
VANDERBILT UNIV.	USA	30	1.82%
IMPERIAL COLLEGE LONDON	UNITED KINGDOM	29	1.76%
UNIV. PISA	ITALY	29	1.76%
MIT MEDIA LAB	USA	28	1.70%
UNIV. PITTSBURGH	USA	28	1.70%
UNIV. WISCONSIN	USA	26	1.58%

The fact that the USA is the most productive country is indeed backed up by the output of the five most prolific U.S. institutions in the world's top ten (Table 6).

Figure 3: Collaboration networks of top 15 institutions on affective computing research

Thematic analysis and evolution

The conceptual analysis function of bibliometrix allows users to screen all topics and keywords, through which the most important topics and trend topics can be identified. In this section, we probe the conceptual structure that emerges in 30 years of affective computing research. The bibliometrix software package represents terms that appear together in a document, such as words in titles, abstracts, and

keywords of an article as a term co-occurrence network. Our analysis focuses on the top 50 author keywords, with a minimum appearance in 3 articles.

The co-word analysis allows finding subgroups of highly related terms, which can be represented graphically as four typologies of themes, defined by Cahlik (2000) as follows:

- The upper-right quadrant, characterized by high centrality and high density, implies themes in this quadrant are well-developed central and important for the overall research field.
- The lower-right quadrant, characterized by high centrality and low density, implies themes in this quadrant are important for certain research domains and concern topics and transverse to different research areas.
- The upper-left quadrant, characterized by low centrality and low density, implies weakly developed and marginal themes.
- The lower-left quadrant, characterized by low centrality and high density, implies well-developed themes, but they tend to be isolated.

It is important to note that, in network analysis, centrality is to measure the number of times a node lies on the shortest path between other nodes, which implies its importance in the network. Density is the measure of how many connections a node has. For more technical explanations and applications, see Kolaczyk and Csárdi (2014) and Ho et al. (2017).

Table 7: A summary of total publications and author's keywords in three periods

Period	Total articles	%	Author's keywords	Average keywords per document
1995-2005	181	10.99	453	2.50
2006-2015	605	36.76	1943	3.21
2016-2020	860	52.25	2859	3.24

Figure 4: Thematic mapping, 1995-2005

Figure 5: Thematic mapping, 2006-2015

Figure 6: Thematic mapping, 2016-2020

Figures 4, 5, and 6 provide visualizations of the research themes' evolution in the field of affective computing. Over the course of 25 years, “affective computing” moves from the upper-right to the lower-right quadrant. In other words, it moves from being the core, well-developed theme to become the basic and transversal theme. This suggests the increasing interest in affective computing from other research domains (the transversal quality, characterized by high centrality and low density).

In the 2005-2015 period (Figure 5), we have “depression” characterized by low density and low centrality, while in the previous ten years, depression and bipolar disorder were basic themes. Such tendency suggests the declining interest in applications of affective computing in studying or detecting mental illnesses such as depression or bipolar disorder.

The “computing” theme becomes an emerging theme in the period 2015-2020. We looked at finer details of words that co-occur with “computing” and find keywords such as “computational modeling,” “features selection,” and “emotion classification.” This implies a growing interest of the academic community to further fine-tune and improve computational techniques for better performance of affective computing algorithms.

Discussion and conclusion

Employing bibliometric analysis on a dataset of 1,646 Web-of-Science-indexed academic articles during 1995-2020, we have been able to identify major developments in the field over the past 25 years. In terms of growth rate, the annual growth rate of scientific production related to affective computing is 12.5%. There is an exponential growth of scientific publications in this field, as the number of publication output in 2016-2020 alone far outstrips that in the previous 20 years (860 vs. 786). With the current increase in

commercial and even political interests in affective computing's applications, the exponential growth trend will likely to continue into the future.

The thematic analysis reveals a growing academic interest in further fine-tuning computational techniques related to affective computing and a decline of interest in using affective computing to detect and study mental illnesses such as depression and bipolar disorders. In the future, the growing appreciation of the "Bayesian brain" perspective in the theoretical study of emotions and affects (Barrett, 2017b; Hoemann et al., 2019) will likely to create a new thematic shift in the field of affective computing. In this newly emerged "*theory of constructed emotion*" (Barrett, 2017a), emotions are considered as abstract categories constructed from past experiences to represent the bodily sensations and feelings mentally. The brain constructs such mental representations as a way to predict the body's needs and external environment so that it could allocate resources to move the body in a cost-efficient manner. Such *constructivist* understanding of how the brain generates emotions and affects is radically different from the *classical, essentialist* view of emotion, championed by the psychologist Paul Ekman (Ekman, 1999), which underlies the development of affective computing so far. When the *theory of constructed emotion* is operationalized and built into computational models to study emotion, it is likely that there will be a major thematic shift in affective computing research.

In terms of major global players, while the U.S. dominates the field both in research output and citation from 1995-2015, China emerges as a major player as research published by corresponding authors from China overtake the U.S. as most cited in 2016-2020. Surprisingly, Japan was missing in the top 10 countries measured by both output and citation. Our analysis also identifies two major collaborative networks: the "Asia Pacific cluster" of USA, China, Singapore, Japan; the "European" cluster of Germany, the U.K., and the Netherlands. The cross-cultural diversity of the Asia Pacific cluster might bring about a new wave of studies on the cross-cultural differences in emotionality and their implications for affective computing techniques. Moreover, as technologies move across national and cultural borders, it is likely that researchers will find various cultural differences in the way people express and infer emotions (Gendron et al., 2018), which will expose the short-comings of the current generation of techniques. Here, the academic and commercial interests align and point to the direction of more cross-cultural and multinational research collaborations in the field. Perhaps, one of the most under-researched areas of research in affective computing field is *emotion acculturation*, i.e., how people learn and unlearn a new mode of emotional expression and inference when they encounter a new culture (De Leersnyder et al., 2011), and how people add and mix new cultural values, then adapt emotionally to their transformed set of core values (Vuong et al., 2018; Vuong et al., 2020; Vuong, 2016). This is likely because of the hype of the *basic emotions* thesis posited by Paul Ekman (1999). As our understanding of the emotion acculturation process will grow at all levels: neuroscientific, individual, interpersonal, and societal, one would expect the next generations of affective computing research, born out of the growing trend of interdisciplinary, multinational collaborations, will produce better fine-tuned computational models that simulate such emotional acculturation process. This will likely be a major thematic change in the coming decades.

Finally, we would like to end this article with the following thought from David Deutsch, the father of quantum computing. When philosophizing about the nature of understanding, he puts forward the following rule of thumb: "*If you can't program it, you haven't understood it*" (Deutsch, 2011). The literature on AI is replete with discussions on a "*singularity*" (Eden et al., 2012; Kurzweil, 2005) or an "*intelligence explosion*" (Muehlhauser & Salamon, 2012), where human engineers not only capable of endowing the next level of machine intelligence with the ability to detect emotion, but also to understand

emotion enough to program the capacity for feeling in machines. With the intense upward trajectory of affective computing research output our analysis has shown, how long until we arrive at a singularity of emotional artificial intelligence?

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