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THE KNOWLEDGE DOMAIN OF AFFECTIVE COMPUTING: A SCIENTOMETRIC REVIEW

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ABSTRACT

Purpose – The aim of this study is to investigate the bibliographical information about Affective Computing identifying advances, trends, major papers, connections, and areas of research.

Design/methodology/approach – A scientometric analysis was applied using CiteSpace, of 5,078 references about Affective Computing imported from the Web-of-Science Core Collection, covering the period of 1991-2016.

Findings – The most cited, creative, bursts and central references are displayed by areas of research, using metrics and throughout-time visualization.

Research limitations/implications – Interpretation is limited to references retrieved from the Web-of-Science Core Collection in the fields of management, psychology and marketing. Nevertheless, the richness of bibliographical data obtained, largely compensates this limitation.

Practical implications – The study provides managers with a sound body of knowledge on Affective Computing, with which they can capture general public emotion in respect of their products and services, and on which they can base their marketing intelligence gathering, and strategic planning.

Originality/value – The paper provides new opportunities for companies to enhance their capabilities in terms of customer relationships.

Keywords: Affective computing; Knowledge domain; Scientometric; CiteSpace
1. Introduction

Emotions play an important role not only in successful and effective human-human communication, but also in human rational learning (Cambria, 2016). Affective Computing recognizes this inextricable link between emotions and cognition, and works to narrow the communication gap between the highly emotional human, and the emotionally-challenged computer, by developing computational systems that respond to the affective states of the user (Calvo & D’Mello, 2010). According to Rukavina, Sascha, Holger, et al. (2016), Affective Computing aims to detect users’ mental states, revealing which feature customers enjoy and excluding those that receive negative feedback. It, therefore, shows great potential to enhance companies’ capabilities to manage their customer relationships, by improving their marketing strategies, and constantly gathering and predicting the attitudes of the general public toward their products and brands. The basic principle behind most Affective Computing systems is that they automatically recognize and respond to users’ affective states during their interactions with a computer, and thus provide data which can be used to enhance the quality of the interaction. Essentially, this is achieved by measuring multimodal signals, namely, speech, facial expressions and/or psychobiology, and from these measurements, designing a computer interface which is more usable and effective. Affective Computing focuses on extracting a set of emotion labels (Picard, 1997; Zeng et al, 2009; Calvo & D’Mello, 2010; Schuller, Batliner, Steidl, & Seppil, 2011; Gunes & Shuller, 2012), and polarity detection, usually a binary classification task with output such as positive versus negative, or like versus dislike (Pang & Lee, 2008; Liu, 2012; Cambria et al, 2013).

According to Fridja (2007), emotions have a short life in the field of consciousness, motivating behavior that requires immediate attention. Lang (2010) confirms the measurement of emotions as being critical in the advertising process, pointing to the fact that emotions are often conveyed by an advertising slogan, which arouses an appeal within consumers that positively predisposes them towards the message being communicated, and thereby helping to deliver the desired image of brand position, which could generate enormous profit (Teixeira, Webel, & Piters, 2012). Several marketing researchers (e.g. Bagozzi, Gopinath & Nyer, 1999; Lee, Broderick & Chamberlain, 2007; Wang, Chien & Moutinho, 2015), state that Affective Computing supersedes self-report measures as a vehicle for evaluating emotions; and Cambria (2016) refers
to the design of automatic Web mining tools for use in real time, as one of the most active research and development areas in Affective Computing.

Notable fallouts in marketing and financial market prediction have raised the interest of the scientific community and the business world in Affective Computing, which allows for the leverage of human-computer interaction, information retrieval, and multimodal signal processing.

This study provides information about Affective Computing, by measuring and visualizing the retrieved bibliographic references from the Web-of-Science Core Collection, between 1991 and 2016. It organizes these references into homogeneous clusters, identifying the most relevant sub-areas of research, and those references which are the most innovative, with more citations, with more connections between sub-areas, and which are responsible for recent advances in Affective Computing.

Marketing intelligence gathering, and strategic planning based on this body of knowledge on Affective Computing, provides opportunities for companies to enhance their customer relationship capabilities, to capture general public emotions in respect of their products and services, and to react accordingly.

The remainder of this article consists of four sections. The next section deals with the methodology, explaining the data collection approach and the quality of CiteSpace results. The third section presents the results, identifying in clusters, the most efficient information on Affective Computing in metrical and graphical terms. Finally, concluding thoughts are offered in section four.

2. Methodology

Bibliographical records concerning Affective Computing, and published since 1991, were collected from the Web-of-Science of Thomson Reuters in the field of marketing, including the related areas of management and psychology. The resultant dataset contained 5,078 records relating to 782 core articles and 4,296 references that cite those articles at least once. This data set was exported to CiteSpace for the scientometric review. CiteSpace, is a free Java application for visualizing and analyzing emerging trends and changes in scientific literature/ It allows for a multiple-perspective structural, and temporal approach, and semantic patterns of references which help in interpreting the nature of clusters (Chen, 1999, 2013). Structural metrics include
centrality, modularity, and silhouette. High centrality identifies references that connect different clusters, and are responsible for the expansion of knowledge; high modularity shows that the references are distributed in non-overlapping clusters with clear boundaries; and high silhouette means great homogeneity of clusters, facilitating the uniformity of their labels.

Temporal metrics include citation burstness and novelty, burstness being used as a term to identify emergent references whose citation counts increase abruptly in a short period of time, and high novelty indicating references that represent creative ideas.

All the records were grouped into 40 non-overlapping and homogeneous clusters (#) based on their interconnectivity, applying the pathfinder pruning algorithm and a g-index with a scaling factor k =5. Seven major clusters were found in the references, and labeled #0 to #6. These account for 71.3% of the references (Figure 1).

Semantic metrics allows for clusters to be labeled according to three algorithms (weight term frequency TF*IDF; log-likelihood ratio LLR; mutual information MI), identifying sub-areas of research. The clusters sorted by size, labeled by TF*IDF are: “multichannel physiology” (#0), “physiological signal” (#1), “emergence” (#2), “naturalistic interaction” (#3), “speech” (#4), “delivery” (#5), and “agent” (#6). The first two clusters (#0 and #1) have been the more active sub-areas of research up to this point in time (2016).

![Figure 1: Seven major clusters in AC, labeled by TF*IDF](image-url)
3. Results from CiteSpace

The advantage of CiteSpace is its ability to provide the most useful information about Affective Computing in metrical and graphical terms, distributing the 5,078 references by clusters, identifying those with more links (centrality), that are cited, more creative (sigma), and more explosive (burstness). CiteSpace represents a fountain of opportunities for managers to capture general public emotion in respect of products and services, thereby enhancing the capabilities of companies to improve their customer relationships.

3.1 Characterization of the Major Clusters

The seven major clusters or areas of research, are labeled by these algorithms (TF*IDF; LLR; MI), according to the index terms coming from those references that cite members of each cluster, presented in Table 1. The oldest cluster in Affective Computing is “emergence” (#2), with an average year of publications 1997, and the youngest cluster is “physiological signal” (#1), with an average year of publications 2009. On average, the mean year difference between publication and citation varies between a minimum of 3 years, corresponding to the major clusters #0 (multichannel physiology) and #1, and a maximum of 7 years, corresponding to the “speech”, cluster #4.

| Cluster | Cited Mean | Cited Mean | Cited Mean |
|---------|------------|------------|------------|
| # Size | Size | Silhouette | TF*IDF | LLR | MI |
| 0 35 | 491 | 0.731 | multichannel physiology | multichannel physiology | modality |
| 1 27 | 263 | 0.802 | physiological signal | response | music |
| 2 23 | 92 | 0.965 | emergence | computer | human-computer interaction |
| 3 21 | 180 | 0.857 | naturalistic interaction | naturalistic interaction | order crossing |
| 4 21 | 229 | 0.724 | speech | strategies | audio-visual emotion |
| 5 18 | 157 | 0.731 | delivery | content delivery | modality |
| 6 12 | 78 | 0.95 | agent | agent | multi-score learning |

The largest cluster (#0) has 35 members and a silhouette value of 0.731, being labeled as “multichannel physiology” by both LLR and TFIDF, and as “modality” by MI. This cluster has 491 citations, being most quoted (0.17) in “Affect detection: an interdisciplinary review of models, methods, and their applications” (Calvo & D’Mello, 2010).
The second largest cluster (#1) has 27 members and a silhouette value of 0.802, being labeled as “response” by LLR, “physiological signal” by TFIDF, and “music” by MI. This cluster has 263 citations, being most quoted (0.11) in “Consistent but modest: a meta-analysis on unimodal and multimodal affect detection accuracies from 30 studies” (DMello & Kory, 2012).

The third largest cluster (#2) has 23 members and a silhouette value of 0.965, being labeled as “computer” by LLR, “emergence” by TFIDF, and “human-computer interaction” by MI. This cluster has 92 citations, being most quoted (0.3) in “On the role of embodiment in the emergence of cognition and emotion” (Pfeifer, 2011).

The fourth largest cluster (#3) has 21 members and a silhouette value of 0.857, being labeled as “naturalistic interaction” by both LLR and TFIDF, and as “order crossing” by MI. This cluster has 180 citations, being most quoted (0.38) in “Affect detection: an interdisciplinary review of models, methods, and their applications” (Calvo & D’Mello, 2010).

The fifth largest cluster (#4) has 21 members and a silhouette value of 0.724, being labeled as “strategies” by LLR, ”speech” by TFIDF, and “audio-visual spontaneous emotion recognition” by MI. This cluster has 229 citations, being most quoted (0.24) in “Cross-corpus acoustic emotion recognition: variances and strategies” (Schuller & all, 2010).

The sixth largest cluster (#5) has 18 members and a silhouette value of 0.731, being labeled as “delivery” by TFIDF, “content delivery” by LLR and “modality” by MI. This cluster has 157 citations, being most quoted (0.17) in “Affect detection: an interdisciplinary review of models, methods, and their applications” (Calvo & D’Mello, 2010).

The seventh largest cluster (#6) has 12 members and a silhouette value of 0.95, being labeled as “agent” by TFIDF and LLR and “multi-score learning” by MI. This cluster has 78 citations, being most quoted (0.42) in “Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features” (D’Mello & Graesser, 2010).

3.2 More innovative, central and cited references by cluster
Intellectual collaboration between references is fundamental to the overall understanding of a knowledge domain (Hu & Racherla, 2008). References in the literature with more connections between different clusters or sub-areas of research (centrality), more citations, and more innovative (sigma) are revolutionary scientific publications.

“Affective computing” (Picard, 1997) and “Toward machine emotional intelligence: Analysis of affective physiological state” (Picard, Vyzas & Healey, 2001) are the two most creative references ever in this area, according to their high sigma values; and, together with “Toward an affect-sensitive multimodal human-computer interaction” (Pantic & Rothkrantz, 2003), are central references for the expansion of knowledge due to their connection between different clusters, summarized below.

The book “Affective computing” (Picard, 1997), from cluster “emergence” (#2), states that the future “ubiquitous computing” environments will need to have human-centered designs instead of computer-centered designs, a fundamental component of human-human communication. Computing will move to the background, weaving itself into the fabric of our everyday living spaces and projecting the human user into the foreground. This reference prompted a wave of interest among computer scientists and engineers looking for ways to improve human-computer interfaces by co-ordinating emotion and cognition with task constraints and demands. Picard described three types of affective computing applications: first, systems that detect the emotions of the user, second, systems that express what a human would perceive as an emotion (e.g., an avatar, robot, and animated conversational agent), and third, systems that actually “feel” an emotion.

The paper “Toward machine emotional intelligence: Analysis of affective physiological state” (Picard, Vyzas & Healy (2001), from cluster “delivery” (#5), proposed that machine intelligence needed to include emotional intelligence and demonstrated results suggesting the potential for developing a machine’s ability to recognize human affective states given physiological signals.

The paper “Toward an affect-sensitive multimodal human-computer interaction” (Pantic & Rothkrantz, 2003), from cluster “naturalistic interaction” (#3), reviewed the efforts toward the single modal analysis of artificial affective expressions and discussed how to integrate into computers a number of components of human behavior in the context-constrained analysis of multimodal behavioral signals.
The more innovative, central and cited references are shown in Table 2, by title, authors, year, source and cluster.

Table 2: The more innovative, central and cited references by clusters in Affective Computing

| Title                                                                 | Authors                                    | Year | Citations | Sigma | Centrality | Source                        | #  |
|---------------------------------------------------------|-------------------------------------------|------|-----------|-------|------------|-------------------------------|----|
| A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions | Zeng, Z.H., Roisman, G.I; & Huang, T.S. | 2009 | 79        | 5.09  | 0.24       | IEEE T PATTERN ANAL           | 0  |
| Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications | Calvo, R.A.; & D’Mello, S. | 2010 | 61        | 4.66  | 0.15       | IEEE T AFFECT COMPUT          | 0  |
| Toward machine emotional intelligence: Analysis of affective physiological state | Picard, RW; Vyzas, E; & Healey, J. | 2001 | 38        | 334.24| 0.50       | IEEE T PATTERN ANAL           | 5  |
| Emotion recognition in human-computer interaction       | Cowie, R. , Douglas-Cowie, E; Tsapatsoulis, N.; & et al. | 2001 | 38        | 7.42  | 0.14       | IEEE SIGNAL PROC MAG          | 4  |
| Affective computing                                     | Picard, R.W.                              | 1997 | 35        | 688.39| 0.35       | Trends in Cognitive Sciences  | 2  |
| Toward an affect-sensitive multimodal human-computer interaction | Pantic, M; & Rothkrantz,L.J.M. | 2003 | 34        | 15.22 | 0.40       | P IEEE                        | 3  |
| Emotion recognition based on physiological changes in music listening | Kim, J., & Elisabeth, A. | 2008 | 31        | 1.22  | 0.04       | P IEEE                        | 0  |
| Automatic prediction of frustration                     | Kapoor, A.; Burleson,W.; & Picard, R.     | 2007 | 30        | 1.56  | 0.12       | Int.J.Human-Computer Studies  | 0  |
| Affective computing: challenges                         | Picard, R.W.                              | 2003 | 28        | 1.24  | 0.03       | Int.J.Human-Computer Studies  | 3  |
| DEAP: A Database for Emotion Analysis Using Physiological Signals | Koelstra, S.                              | 2012 | 26        | 1.18  | 0.02       | IEEE T AFFECT COMPUT          | 1  |

“A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions” (Zeng, Riisman, & Huang, 2009), and “Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications” (Calvo & D’Mello, 2010), are the references with more citations, both from the major cluster ”multichannel physiology” (#0), summarized below.

The paper “A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions” (Zeng, Riisman, & Huang, 2009), developed algorithms to detect subtleties and changes in the user’s affective behavior, in order to initiate interactions based on this implicit information rather than on explicit messages usually involved in the tradition interface devices, such as the keyboard and mouse. These algorithms are intended to process naturally-occurring human affective behavior, with a view to multimodal fusion for human affect analysis, including audiovisual, linguistic, paralinguistic and multi-cue visual fusion based on facial expressions, head movements, and body gestures.

The paper “Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications” (Calvo & D’Mello, 2010), stresses the need to include within Affective Computing practice, emotion theories
that have emerged, and that rely on cross-disciplinary collaboration and active sharing of knowledge. It reviews models that emphasize emotions as expressions, embodiments, outcomes of cognitive appraisals, social constructs, and products of neural circuitry, aiming to be a useful tool for new researchers by providing taxonomy of resources for further exploration and discussing different theoretical viewpoints and applications.

3.3 Trends in Affective Computing

A timeline view shows references through time and clusters (Figure 1). CiteSpace identifies all references by the first name of the author(s). The size of the nodes corresponds to the number of citations of the reference, i.e., a large node indicates many citations. Citations with an unexpected increase over a short period of time (burst strength) are marked as red rings around a node.

The position of “Automatic prediction of frustration” (Kappor, Burleson & Picard, 2007) in cluster #0, and “DEAP: A Database for Emotion Analysis Using Physiological Signals” (Koelstra, 2012) in cluster #1, are both marked with a star. “Toward an affect-sensitive multimodal human-computer interaction” (Pantic & Rothkrantz, 2003) is superimposed on “Affective computing: challenges” (Picard, 2003) in cluster #3.

The majority of references were published after 2000, and the more active clusters are #0 and #1, being essential to the literature of affective computing, the main papers about which have already been discussed.
Burstness provides a temporal perspective, indicating where the frequency of a reference increases abruptly in relation to its peers during a short period of time (Lee, Chen, & Tsai, 2016). A citation burst has two attributes: the intensity (strength), and the length of time the status lasts. Table 3 lists the references with the strongest citation bursts across the entire dataset, according to the clusters to which they belong. It can be seen that most of the references started to burst in year 2000 and have continued until 2016.

“Affective Computing” (Picard, 1997), from cluster #2, is the reference with the highest burst citation, having a significant statistical fluctuation over 2000-2005. “Emotion recognition in human-computer interaction” (Cowie, Douglas-Cowie, Tsapatsoulis, & et al., 2001), from cluster #4, over 2005-2009, and “Toward machine emotional intelligence: Analysis of affective physiological state” (Picard, Vyzas, & Healey, 2001), are respectively the second and third references with strong intensity, the last also showing the highest duration of six years, over 2003-2009, as well as “Toward an affect-sensitive multimodal human-computer interaction” (Pantic, & Rothkrantz, 2003), over the period 2005-2011.

“Emotion recognition in human-computer interaction” (Cowie, Douglas-Cowie, Tsapatsoulis, & et al., 2001), has also been one of the most comprehensive and widely cited reference in reviewing the efforts to reach a single modal analysis of artificial affective expressions, and in providing a comprehensive summary of qualitative acoustic correlations for prototypical emotions. The writers of that paper discuss the recognition of seven different human negative and neutral emotions, (bored, disengaged, frustrated, helpless, over-striened, angry, impatient) by technical systems, focusing on problems of data gathering and modelling, in an attempt to create a “Companion Technology” for Human Computer Interaction that allows the computer to react to human emotional signals.

“Affective computing: challenges”, (Picard, 2003), from cluster #3, shows a statistically significant fluctuation over the period 2006-2008. It raises and responds to several criticisms of affective computing, emphasizing the need for a balance, and articulated state-of-the art research challenges, especially with
respect to affect in human-computer interaction. This paper suggested that designers of future computing can continue with the development of computers that ignore emotions, or they can take the risk of making machines that recognize emotions, communicate them, and perhaps even “have” them, at least in the ways in which emotions aid in intelligent interaction and decision making.

References with greater burst impact by 2016 are “Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications” (Calvo & D’Mello, 2010), from cluster #0, over 2013-2016; “LIBSVM: A Library for Support Vector Machines” (Chang & Lin, 2011), over 2013-2016; “DEAP: A Database for Emotion Analysis Using Physiological Signals” (Koelstra, 2012), from cluster #1, over 2013-2016; “A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions“ (Zeng, Roisman & Huang, 2009), from cluster #0, over 2013-2016; and “Emotion recognition based on physiological changes in music listening” (Kim, & Elisabeth, 2008), from cluster #0, over 2012-2016.

With the exception of Zeng, Roisman and Huang, (2009) and Calvo and D’Mello, (2010), previously noted, below is a summary of the references that have an abrupt increase of citations by 2016.

“LIBSVM: A Library for Support Vector Machines” (Chang & Lin, 2011) presents details of how to implement a library for support vector machines (SVMs), and the package LIBSVM. It discusses in detail, issues concerning how to solve SVMs’ optimization problems, theoretical convergence, multi-class classification, probability estimates, and parameter selection.

“DEAP: A Database for Emotion Analysis Using Physiological Signals” (Koelstra, 2012), considered vital for multimedia information retrieval, characterizes multimedia content with relevant, reliable, and discriminating tags. This reference presents a multimodal dataset for the analysis of spontaneous emotions, where implicit tagging of videos using affective information helps recommendation and retrieval systems to improve their performance. The dataset was made publicly available and other researchers were encouraged to use this data for testing their own affective state estimation methods.

“Emotion recognition based on physiological changes in music listening” (Kim & Elizabeth, 2008), investigates the potential of physiological signals for emotion recognition as opposed to audiovisual emotion
channels such as facial expression or speech. This paper develops a novel scheme of emotion-specific multilevel dichotomous classification and shows an improvement in its performance compared with direct multiclass classification.

**Table 3: Trends on Affective Computing by periods of time**

| Authors                        | Source                  | Year | Strength | Begin | End  | 1999 - 2016 | #   |
|--------------------------------|-------------------------|------|----------|-------|------|-------------|-----|
| Picard                         | AFFECTIVE COMPUTING     | 1997 | 21.680   | 2000  | 2005 | ▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂▂�▂▂▂▂▂▂�▂▂▂▂▂�▂▂�▂▂��▂▂▂�▂��▂▂�▂��▂��▂���▂��▂���▂��▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂���▂��合
without imposing any burdens on the user (Fu, Leong, Hong, Grace, & et al., 2014). The importance of touch in communicating emotions and intensifying interpersonal communication has been analyzed in Affective Computing to detect and display emotions (Eid & Osman, 2016).

The development of systems capable of mining emotions and sentiments over the Web in real time to track public viewpoints on a large scale, represents one of the most active research and development areas, being important not only for commercial purposes but also for monitoring hostile communications or model cyber-issue diffusion (Cambria, 2016). The Web is evolving to become an area in which consumers are defining future products and services, as it has made users more enthusiastic about sharing their emotions and opinions through several online collaboration media, like social networks, online communities, blogs, and wikis, in all fields related to everyday life, such as commerce and tourism. With the increasing number of webcams installed in end-user devices such as smart phones, touchpads, and netbooks, an greater volume of affective information is being posted to social online services in an audio or audiovisual format rather than on a purely textual basis. Public opinion is destined to gain increased prominence, and so is affective computing with its capacity for recognizing and classifying emotions.

Table 4 provides examples of some recent research studies that have investigated references included in the two major clusters (#0 and #1) just discussed.

**Table 4: More relevant citers of the most active clusters**

| Title | Authors | Year | Source |
|-------|---------|------|--------|
| Fuzzy model of dominance emotions in affective computing | Bakhtiyari, K.; & Husain, H. | 2014 | EURAL COMPUTING & APPLICATIONS |
| Physiological mouse: towards an emotion-aware mouse | Fu, Y.; Leong, H.V.; Ngai, G.; Huang, M.X.; & Chan, S.C.F. | 2014 | IEEE 38th Annual International COMPSAC |
| Affective Computing and Sentiment Analysis | Cambria, E. | 2016 | IEEE Intelligent Systems |
| Affective Haptics: Current Research and Future Directions | Eid, M A., & Osman, H.A. | 2016 | IEEE Access |
| Time-delay neural network for continuous emotional dimension prediction from facial expression sequences | Meng, H.; Deng, J.; Chen, J., & Cosmas, J. | 2016 | IEEE TRANSACTIONS ON CYBERNETICS |
Affective computing is mainly interpreted in terms of emotions and sentiments, with an emphasis on the classification and recognition of emotions via human computer interaction, and the provision of implicit information about the changes in the affective states. This is depicted in Figure 2, which displays the keywords assigned to each reference in the dataset.

![Figure 2: Network with the relevant keywords](image)

**5. Concluding Thoughts**

This article has traced the advancement of affective computing through the analysis of expert references in the literature. It has done this by using computational techniques to discern patterns and trends at various levels of abstraction: cited, central, innovative, and burstness references; sources of publications; and keywords. The major clusters are #0, “multichannel physiology”, and the newest cluster #1 “physiological signal”, which continue to be the most cited, and to demonstrate the largest burst citations. The most creative and central references are those of Picard (1997), and Picard, Vyzaz and Heley (2001); and those with recent burstness are seen to come from Kim and Elizabeth (2008), Calvo and D’Mello (2010), Chang and Lin (2011), Koelstra (2012); and Zeng, Riisman and Huang (2009), the latter also being the most cited reference ever in this area.
Through its descriptive findings about Affective Computing, obtained efficiently via the use of CiteSpace, this paper provides opportunities for companies to enhance their capabilities in respect of customer relationships. It is up to managers to choose the most useful tools to capture and respond to the emotions of their customers about the products or services offered by their companies.

References

Bagozzi, R.P, Gopinoth, M., & Nyer, P.U. (1999). The Role of Emotions in Marketing. *Journal of the Academy of Marketing Science*, 27 (2), 184-206.

Bakhtiyari, K.; & Husain, H. (2014). Fuzzy model of dominance emotions in affective computing. Neural Computing & Applications , Vol: 25, Edition 6 , p: 1467-1477.

Calvo, R.A., & D’Mello (2010). Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications, IEEE Transactions on Affective Computing, 1(1), 18-37.

Cambria, E. et al., (2013). New Avenues in Opinion Mining and Sentiment Analysis, IEEE Intelligent Systems, 28(2), 15–21.

Cambria, E. (2016). Affective Computing and Sentiment Analysis. *IEEE Intelligent Systems*, 1541-1672.

Chang, C.C., & Lin, C.J. (2011). LIBSVM: A Library for Support Vector Machines. ACM Transactions on Intelligent Systems and Technology, Vol. 2, No. 3, Article 27

Chen, C. (1999). Visualizing semantic spaces and author cocitation net-works in digital libraries. Information Processing & Management, 35(3),401–420.

Chen, C. (2013). The Structure and Dynamics of Scientific Knowledge. In Mapping Scientific Frontiers; Springer: London, UK, pp. 163-199.

R. Cowie, E. Douglas-Cowie, N. Tsapatsoulis, G. Votsis, S. Kollias, W. Fellenz, and J.G. Taylor (2001) “Emotion Recognition in Human-Computer Interaction”, IEEE Signal Processing Magazine, (18):. 32-80, Jan. 2001.

D’Mello, S, & Graesser, A. (2010) Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features. User Modelling and User-Adapted Interaction 20 (2), 147–187.
D’Mello, S, & Kory, J. (2012). Consistent but Modest: A Meta-Analysis on Unimodal and Multimodal Affect Detection Accuracies from 30 Studies. ICMI ’12, October 22–26, 2012, Santa Monica, California, USA.

Frijda, N. (2007). The Laws of Emotion. London: Routledge.

Fu, Y.; Leong, H.V.; Ngai, G.; Huang, M.X.; & Chan, S.C.F. (2014). Physiological mouse: towards an emotion-aware mouse Edited by Chang, CK; Gao, Y; Hurson, A; et al. 38th Annual IEEE International Computer Software and Applications Conference (COMPSAC) Local:Vasteras, SWEDEN, Data: JUL 21-25, 258-263.

Gunes, H, & Schuller, B. (2012). Categorical and dimensional affect analysis in continuous input: Current trends and future directions. Image and Vision Computing 31 (2), 120-136

Hu, C.; & Racherla, P., (2008)). Visual representation of knowledge networks: A social network analysis of hospitality research domain. Int. J.. Hosp. Manag, 27, 302-312.

Kapoor, A., Burlesonc,W., & Picard, R.W (2007). Automatic prediction of frustration. Int. J. Human-Computer Studies 65: 724–736.

Koelstra, S.; Soleymani, M.; Yardani, A, & Nijholt, A (2912). DEAP: A Database for Emotion Analysis Using Physiological Signals. IEEE Transactions on Affective Computing, 3 (1):18-31.

Lang, P. J. (2010). Emotion and motivation: toward consensus definitions and a common research purpose. Emotion Review, 2(3), 229–233.

Lee, N., Broderick, A. J., & Chamberlain, L. (2007). What is ‘neuromarketing’? A discussion and agenda for future research. International Journal of Psychophysiology, 63, 199–204.

Lee, Y.C., Chen, C., & Tsai, X.T., 2016. Visualizing the Knowledge Domain of Nanoparticle Drug Delivery Technologies: A Scientometric Review. Applied Sciences 6(1):11 · January. DOI: 10.3390/app6010011.

Liu, B., (2012). Sentiment Analysis and Opinion Mining, Morgan and Claypool.

Pang, B., & Lee, L., (2008).Opinion Mining and Sentiment Analysis, Foundations and Trends in Information Retrieval, vol. 2, nos. 1–2, 1–135.

Pantic, M., & Rothkrantz , L.J.M.,(2003). Towards Emotion Recognition in Human Computer Interaction.P IEEE, Proceedings of the IEEE, 91(9): 1370-1390.

Phister, H.R.; Peter,C.; & Wollstädter, S. (2011) Human-computer-interaction: Effects of modality and message type. Interacting with Computers 23(4):372-383.
Picard, R. (1997). *Affective Computing*. Cambridge: The MIT Press.

Picard, RW; Vyzas, E; & Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and machine Intelligence*, 23(10):1175-1191.

Picard, RW (2003). Affective computing: challenges. *Int. J. Human-Computer Studies* 59 (2003) 55–64.

Kapoor, A; Burleson,W., and Picard, R., (2007). Automatic prediction if frustration. *Int. J. Human-Computer Studies*, 65:724-736.

Kim, J.; & Elizabeth, A. (2008). Emotion Recognition Based on Physiological Changes in Music Listening. *IEEE Transactions on pattern Analysis and machine Intelligence*, 30 (2):2067-2083.

Rukavina, S.; Sascha, G., Holder, H., Jun-Weng, T., Walter,S., & Traue, H. (2016). Affective Computing and the Impact of Gender and Age. Plos one. DOI: 10.1371

Schuller, B.; Vlasenko, R.; Eyben,F.; & all (2010). Cross-Corpus Acoustic Emotion Recognition: Variances and Strategies. *IEEE Transactions on Affective Computing*, 1 (2):119-131.: doi>10.1109/T-AFFC.2010.8

Schuller, B.; Batliner, A., Steidl, S., & Seppi,D. (2011). Recognising realistic emotions and affect in speech: State of the art and lessons learnt from the first challenge. *Speech Communication* 53 (9), 1062-1087.

Teixeira, T., Wedel, M., & Pieters, R. (2012) Emotion-induced engagement in internet video advertisements. *Journal of Marketing Research*, 49 (2), 144-159.

Wang, W.C., Chien C.S., & Moutinho, L. (2015). Do you really feel happy? Some implications of Voice Emotion Response in Mandarin Chinese. *Marketing Letters*, 26 (3), 391-409.

Zeng, Z.H., Riisman, G.I; & Huang, T.S., (2009). A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions. *IEEE T PATTERN ANAL*.31 (1):39-58.