Affective Computing Research Progress and Its Implications for Education Technology: A Bibliometric Analysis Based on Web of Science via VOSviewer

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Abstract. Affective Computing (AC) is a dynamic and evolving research field. This paper presents a bibliometric analysis of 1428 publications related to affective computing, extracted from the Web of Science database, using the VOSviewer software. Through an examination of the existing literature, the study investigates the quantity of AC publications, research countries, important institutions, and leading authors. Co-citation analysis reveals that *IEEE Transactions on Affective Computing* is the most influential source of literature. Keyword co-occurrence and clustering analysis identify five main research directions in AC: emotion recognition, physiological signal, human-computer interaction, deep learning, and electroencephalography. Lastly, the paper provides relevant recommendations for AC research in educational technology, focusing on personalized learning experiences, affective feedback, emotion recognition, and affective robots.

Keywords: Emotion Recognition · Physiological Signal · Deep Learning · Electroencephalography

1 Introduction

Affective Computing (AC) is an interdisciplinary field that focuses on the recognition of emotions (Bota et al., 2019), generation of emotions (Garcia-Garcia et al., 2018), and emotional processing (Caruelle et al., 2022) in human-computer interaction. AC emerged in the early 1990s, with a primary emphasis on understanding the fundamental principles and methods of emotion recognition and generation (Picard, 2000). As technology advanced and the demand for emotional intelligence grew, AC experienced rapid development. In 2010, the establishment of *IEEE Transactions on Affective Computing* (Picard, 2010) marked AC as a distinct research field. In recent years, with the rapid progress of machine learning and sensor technologies, researchers have actively explored the integration and analysis of multimodal data such as speech, facial expressions, and physiological signals, making AC pervasive across various domains (Assabumrungrat et al., 2022).

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In the current era of explosive growth in artificial intelligence, conducting research in AC holds significant theoretical and practical value. Theoretically, AC contributes to a better understanding and simulation of human emotions, providing methods and frameworks for studying emotions. Practically, AC enables computers to perceive, understand, express, and respond to human emotional states, finding wide applications in fields such as educational technology, healthcare, human-computer interaction, entertainment, and social media.

AC is an active research field that is continuously evolving, and it is crucial for researchers to have a comprehensive and objective understanding of the advancements and directions in AC. However, there is still a lack of objective evaluation and visual representation of the overall scientific knowledge in AC through bibliometric analysis, making it challenging to identify specific research directions that deserve special attention. Therefore, this paper employs VOSviewer software to conduct bibliometric analysis of AC-related research literature based on the Web of Science database and provides insights and analysis on how AC can enhance the quality of education technology and teaching.

2 Methodology

To ensure the authority of research data, this study utilized the Web of Science Core Collection as the data source, extracting data from three databases: Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), and Arts & Humanities Citation Index (AHCI). The indexing date range was set from January 1, 2000, to May 31, 2023, and the document types were limited to Article, Review Article, and Early Access. Furthermore, to ensure that the retrieved literature was closely related to this study, the search query was set as "TS = ("affective computing")". Ultimately, a total of 1428 relevant articles were retrieved as the data source for this study.

Bibliometric analysis is a quantitative research method based on a large-scale collection of literature data, aiming to reveal information about the quantity, quality, citation relationships, and research trends of the literature. Bibliometric analysis is often conducted using metrics and visualization tools. In this study, VOSviewer_1.6.19 was chosen as the bibliometric analysis tool to perform statistical analysis, co-citation analysis, co-occurrence analysis, and cluster analysis on the full records and references of the 1428 AC-related articles. Through these analyses, researchers can gain a more comprehensive understanding and evaluation of the current research status in specific areas of AC, providing references and guidance for future AC research.

3 Results

3.1 Publications Analysis

3.1.1 Publication Distribution Analysis

Table 1 presents the publication year data of the 1428 AC-related articles retrieved in this study. Based on the annual publication volume, the field of AC demonstrates a stable growth trend overall. Prior to 2009, the annual publication volume in AC ranged from

Table 1. Statistic of publication year

Year	Count	Percentage	Year	Count	Percentage	Year	Count	Percentage
2001	2	0.14	2009	16	1.12	2017	68	4.762
2002	5	0.35	2010	39	2.731	2018	89	6.232
2003	8	0.56	2011	20	1.401	2019	133	9.314
2004	14	0.98	2012	47	3.291	2020	161	11.275
2005	17	1.19	2013	48	3.361	2021	224	15.686
2006	18	1.261	2014	48	3.361	2022	230	16.106
2007	10	0.7	2015	70	4.902	2023	75	5.252
2008	18	1.261	2016	68	4.762	--	--	--

2 to 18 articles. From 2010 to 2018, the annual publication volume in AC ranged from 20 to 89 articles. Starting from 2019, the annual publication volume in AC ranged from 133 to 230 articles, with 75 articles already published in 2023, indicating an expected continuation of this trend.

3.1.2 National Analysis

Since 2000, a total of 78 countries/regions have been involved in AC research globally. Figure 1 presents a network of collaboration among the top 30 countries/regions based on the number of publications, created using VOSviewer. In terms of publication volume, countries such as China, the United States, the United Kingdom, Spain, and Germany have contributed significantly. In terms of collaboration relationships, China, the United Kingdom, and the United States emerge as countries with strong centrality. Extensive collaborative research has been conducted between China and the United Kingdom, the United Kingdom and Germany, as well as the United States and India.

3.1.3 Most Productive Institutions Analysis

Since 2000, a total of 1,550 institutions worldwide have been engaged in AC research. Table 2 presents the research output of the top 5 institutions in terms of publication volume. Among these high-producing institutions, "MIT" ranks first with the highest number of publications (TP = 29). On the other hand, "Univ Geneva" takes the lead in citation count (TC = 4,699). When using the TC/TP ratio as an indicator of research quality, "Univ Geneva" and "MIT" demonstrate remarkably high values of 223.76 and 138.86, respectively, in the field of AC. These values highlight the significant impact and citation visibility of publications from these two institutions, reflecting their high-quality research work and global influence.

3.1.4 Leading Authors Analysis

Since 2000, a total of 4,456 authors worldwide have conducted research in the field of AC. Table 3 presents the research output of the top 10 authors ranked by the "avg. norm.

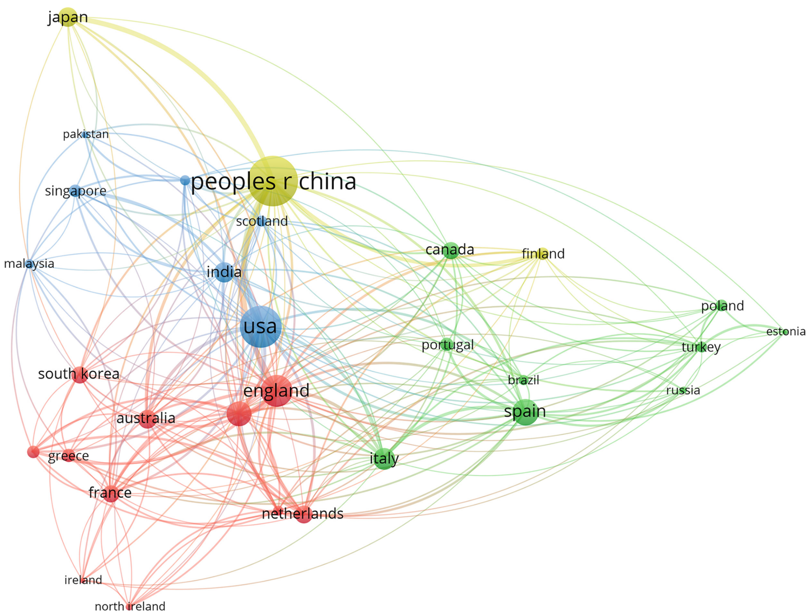

Fig. 1. Cooperation network relationship among countries/regions (Top 30)

Table 2. Most productive institutions (Top 5)

According to TP				**According to TC**			
Name	TP	TC	TC/TP	Name	TP	TC	TC/TP
mit	29	4027	138.86	univ geneva	21	4699	223.76
hefei univ technol	28	396	14.14	mit	29	4027	138.86
chinese acad sci	22	546	24.81	univ augsburg	20	1744	87.2
univ geneva	21	4699	223.76	chinese acad sci	22	546	24.81
univ augsburg	20	1744	87.2	hefei univ technol	28	396	14.14

Note: TP = Total Publications; TC = Total Citations

citations" indicator. In terms of publication quantity, "Schuller, Björn" holds the highest record with 14 articles as a single author. Regarding the average publication year, "Zhang, Jianhua," "Yin, Zhong," "Zhang, Wei," and "Bianchi-Berthouze, Nadia" have average publication years surpassing 2018, indicating recent activity in terms of publishing papers for these scholars. As for the average normalized citation count, "Soleymani, Mohammad" stands out as the most prominent scholar in terms of citation impact.

Table 3. Leading authors with avg. norm. citations (Top 10)

Author	No.of documents	Total citations	Norm. citations	Avg. Pub. Year	Avg. Citations	Avg. Norm. Citations
soleymani, mohammad	6	3411	32.3	2013.5	568.5	5.3873
pantic, maja	8	3422	31.4	2014.5	427.7	3.9277
pun, thierry	8	3264	30.6	2014.3	408	3.8313
zhang, jianhua	5	456	13.8	2018.4	91.2	2.7714
yin, zhong	6	493	15.6	2018.6	82.1	2.6053
scilingo, enzo pasquale	9	646	17.9	2016.8	71.7	1.9963
zhang, wei	3	108	5.8	2020.3	36	1.964
valenza, gaetano	9	649	17.6	2016.6	72.1	1.9557
bianchi-berthouze, nadia	9	217	11.1	2018.7	24.1	1.2413
schuller, bjoern	14	958	16.8	2016.1	68.4	1.2057

3.2 Co-Citation Analysis

3.2.1 Cited Sources Co-Citation Analysis

Figure 2 presents the co-citation analysis mapping of cited sources, created using VOSviewer. In this study, we focused on the cited sources with a citation frequency exceeding 288. Out of the total 20,950 cited sources in the dataset, 30 sources met this criterion. The visualization in Fig. 2 reveals that the most influential literature sources in the field of AC are primarily clustered into three main clusters.

In Fig. 2, the blue region represents the first cluster, with *IEEE Transactions on Affective Computing* being the most frequently cited and highly connected source. These literature sources provide comprehensive research, methodologies, and applications related to AC in the fields of artificial intelligence, computer science, and neuroscience. The red region in Fig. 2 represents the second cluster, with *Journal of Personality and Social Psychology* and *Cognition and Emotion* being typical sources. These sources offer foundational knowledge and theories in the fields of psychology and cognitive emotion. The green region in Fig. 2 represents the third cluster, with *Lecture Notes in Computer Science* and *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* being typical sources. These sources provide technical advancements and methodologies in computer vision and pattern recognition.

In summary, the most influential literature sources in the field of AC primarily originate from top conferences and journals in fields such as artificial intelligence, computer science, neuroscience, and psychology. These sources are widely cited and referenced in AC research.

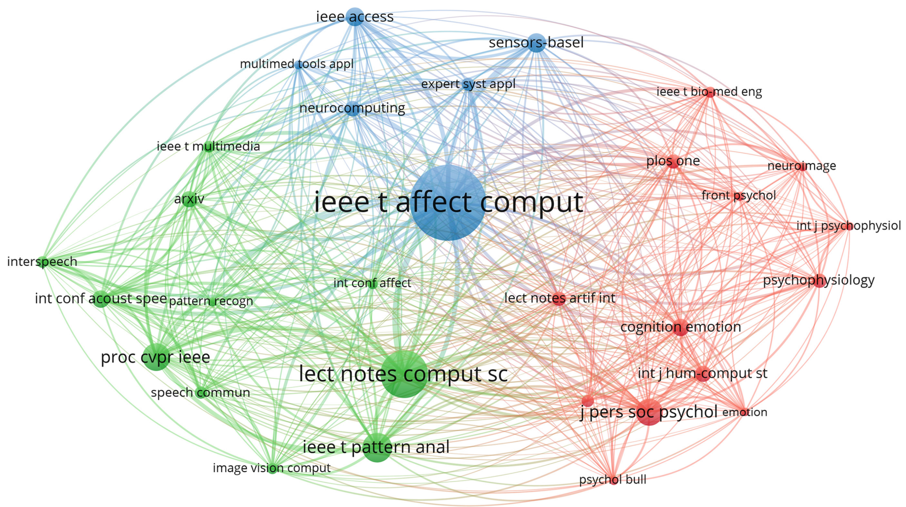

Fig. 2. The mapping of cited sources co-citation analysis (Top 30)

3.2.2 Cited References Co-Citation Analysis

Figure 3 depicts the co-citation analysis of cited references using VOSviewer software. In this analysis, the selected criteria for cited references are those with a citation frequency exceeding 60. Among the 55,677 references in the dataset, 20 references meet this criterion. The results shown in Fig. 3 reveal that the most influential literature in the field of AC is primarily concentrated within two clusters.

The red cluster in Fig. 3 represents the first cluster. Within Cluster 1, "Picard R.W., 1997, Affective Computing" and "Ekman P., 1992, Cognition Emotion" are the most frequently cited references with the highest total link strength. These references encompass the fundamental concepts, theories, and methodologies of affective computing. The green cluster in Fig. 3 represents the second cluster. Within Cluster 2, "Russell J.A., 1980, J Pers Soc Psychol" and "Koelstra S., 2012, IEEE T Affect Comput" are the most frequently cited references with the highest total link strength. These references pertain to emotion recognition and technologies related to affective computing.

In summary, the most influential literature in the field of affective computing covers a wide range, from early to recent classic studies. It encompasses foundational theories as well as specific techniques. These seminal references hold significant value for researchers in the field of affective computing, providing them with important references to understand the development history, core concepts, and key methodologies in this domain. Moreover, these classic references reflect the research trends and notable achievements in affective computing, offering researchers insights into the forefront advancements and future directions in the field.

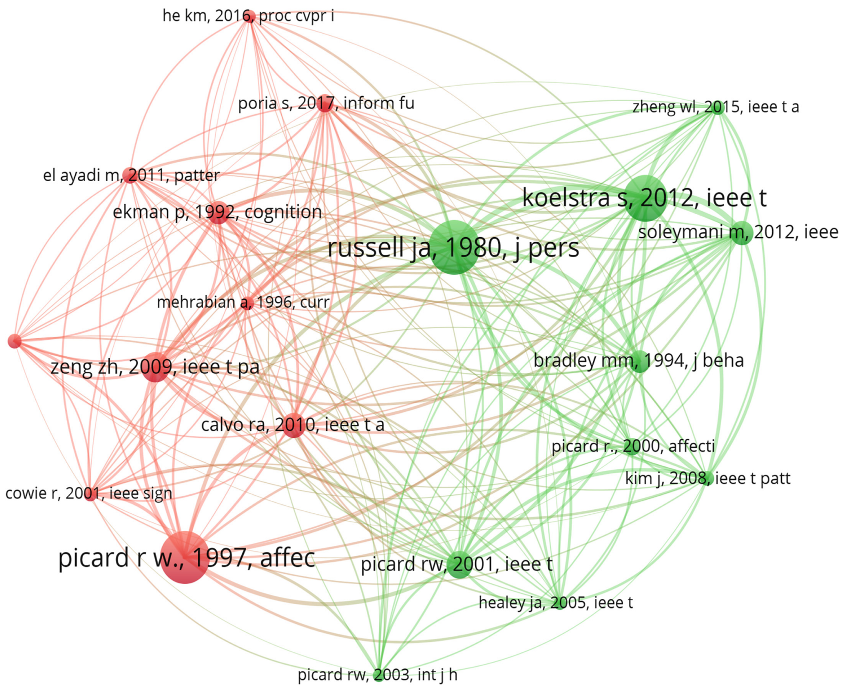

Fig. 3. The mapping of cited references co-citation analysis (Top 20)

3.3 Co-Occurrence Analysis

In this study, a co-occurrence analysis of author keywords was conducted using VOSviewer on a dataset of 1428 literature in the field of affective computing. Prior to the analysis, term merging was performed in VOSviewer. For instance, expressions such as "affective computation," "affective -computing," "affective-computing," and "emotional computing" were unified as "affective computing." Subsequently, author keywords with a co-occurrence frequency exceeding 19 were selected, resulting in 40 keywords that met the criteria. The co-occurrence analysis diagram of the keywords is presented in Fig. 4.

Figure 4 illustrates a visualization analysis where author keywords are represented as nodes and closely related keyword groups are depicted using different colors. In this generated visualization, the 40 high-frequency author keywords in the field of affective computing are clustered into five distinct groups based on their co-occurrence patterns. As a result, the field of affective computing can be categorized into five research directions.

3.3.1 Research Related to Emotion Recognition

Cluster 1 (Red): Within this largest cluster, ranked by the Total Link Strength (TLS) metric in VOSviewer, there are 12 keywords including "emotion recognition," "feature

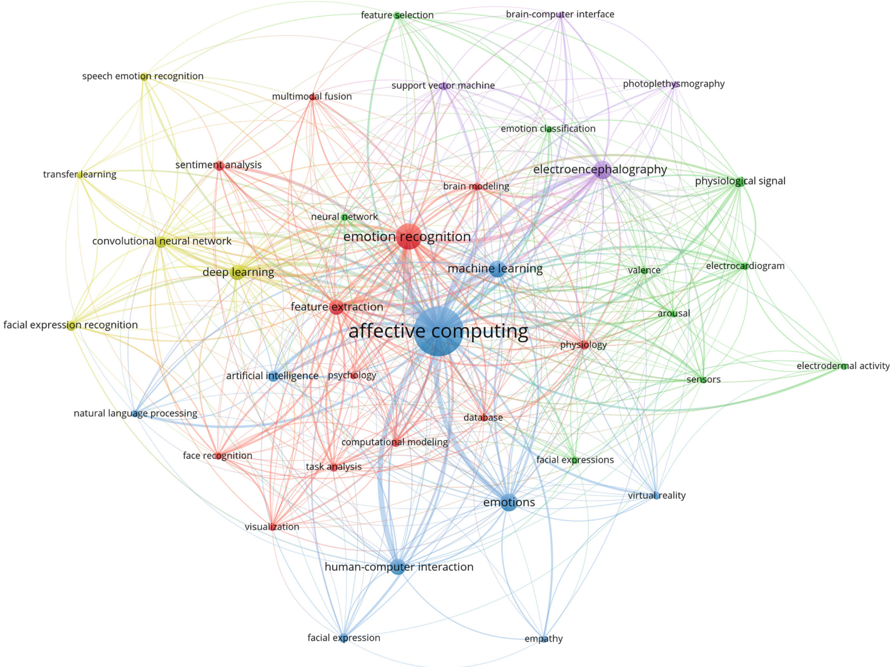

Fig. 4. The mapping of author keywords co-occurrence analysis (Top 40)

extraction," "physiology," "brain modeling," "task analysis," "face recognition," "computational modeling," "sentiment analysis," "database," "visualization," "psychology," and "multimodal fusion." Among them, "emotion recognition" has the highest TLS value (occurrences = 275, TLS = 699). Therefore, this cluster is named "emotion recognition," representing the first major research direction in the field of affective computing.

Affective computing is a field dedicated to the study of human emotion and emotion recognition is a vital aspect of this field. Emotion recognition aims to infer the emotional states expressed by individuals by analyzing their physiological signals, facial expressions, speech, and other multimodal data. Existing literature provides abundant research methods and datasets for emotion recognition, covering various applications and technological approaches in affective computing (Chen et al., 2021; X. Y. Chen et al., 2022). Researchers can draw inspiration from these methods and datasets to further advance the research and application of emotion recognition.

3.3.2 Research Related to Physiological Signal

Cluster 2 (Green): Within the second cluster, ranked by the Total Link Strength (TLS) metric in VOSviewer, there are 10 keywords including "physiological signal," "electrocardiogram," "valence," "arousal," "sensors," "neural network," "feature selection," "emotion classification," "electrodermal activity," and "facial expressions." Among them, "physiological signal" has the highest TLS value (occurrences = 42, TLS =

132). Therefore, this cluster is named "physiological signal," representing the second major research direction in the field of affective computing.

In affective computing, physiological signals refer to the signals obtained by measuring physiological changes in the human body. The literature now covers various studies on different physiological signals, including electrodermal activity, blood volume pulse, electroencephalogram, and others, used for emotion recognition, stress assessment, and affective quality analysis (Yin et al., 2022; Yu et al., 2021). Physiological signals play a crucial role in affective computing, as they provide information about individuals' emotional states and psychological activities through the measurement and analysis of physiological changes. This information is significant for emotion recognition, emotion monitoring, and various application domains.

3.3.3 Research Related to Human-Computer Interaction

Cluster 3 (Blue): Within the third cluster, ranked by the Total Link Strength (TLS) metric in VOSviewer, there are 9 keywords including "affective computing," "machine learning," "emotions," "human-computer interaction," "artificial intelligence," "natural language processing," "virtual reality," "facial expression," and "empathy." Among them, "affective computing" has the highest TLS value (occurrences = 968, TLS = 1324). Although "affective computing" has the highest TLS value, choosing it as a separate research area for analysis would disrupt the logical flow of this paper since the focus of this study is on affective computing itself. Therefore, this cluster is named "human-computer interaction," representing the third major research direction in the field of affective computing.

In affective computing, human-computer interaction refers to the methods of enabling computer systems to recognize, understand, and respond to users' emotional states in order to provide more intelligent and personalized interactive experiences. Existing literature covers research on using techniques such as facial expressions, visual data, and virtual reality for affective interaction. These methods and technologies aim to identify and analyze human emotions and achieve emotion perception and communication in human-computer interaction (Gall et al., 2021; Leong et al., 2023). Human-computer interaction in affective computing is a multidisciplinary field that involves knowledge from various domains such as computer vision, machine learning, psychology, and cognitive science. Researchers need to conduct more extensive interdisciplinary studies in the future.

3.3.4 Research Related to Deep Learning

Cluster 4 (yellow): Within the fourth cluster, ranked by the Total Link Strength (TLS) metric in VOSviewer, there are 5 keywords including "deep learning," "convolutional neural network," "facial expression recognition," "speech emotion recognition," and "transfer learning." Among them, "deep learning" has the highest TLS value (occurrences = 94, TLS = 250). Therefore, this cluster is named "deep learning," representing the fourth major research direction in the field of affective computing.

In affective computing, deep learning methods are widely employed, including deep convolutional neural networks, deep recurrent neural networks, and other deep learning architectures. Existing literature involves the utilization of deep learning methods to extract acoustic, linguistic, facial, or electroencephalogram features as inputs and then utilize deep learning models for emotion classification or regression tasks (Bhangale & Kothandaraman, 2023; Fouladgar et al., 2022). Deep learning models have the ability to learn high-level features from a large amount of data, which is crucial for enhancing the performance and accuracy of affective computing tasks.

3.3.5 Research Related to Electroencephalography

Cluster 5 (Purple): Within the fifth cluster, ranked by the Total Link Strength (TLS) metric in VOSviewer, there are 4 keywords including "electroencephalography," "support vector machine," "brain-computer interface," and "photoplethysmography." Among them, "electroencephalography" has the highest TLS value (occurrences = 133, TLS = 377). Therefore, this cluster is named "electroencephalography," representing the fifth major research direction in the field of affective computing.

In affective computing, electroencephalography (EEG) is widely utilized for the recognition, classification, and analysis of emotions and affect. EEG is a non-invasive method for measuring brain activity by recording electrical signals from the scalp, capturing the neural activity of the brain. Existing literature covers the utilization of EEG signals to explore various aspects of affective computing, including methods for emotion recognition, complex emotion classification, and affect recognition (ArulDass & Jayagopal, 2022; C. Q. Chen et al., 2022a, b). EEG in affective computing serves as a valuable tool, enabling researchers to extract information about an individual's emotional state from EEG signals, providing foundational research support for fields such as emotion recognition, emotion classification, and affect analysis.

4 Implications for Education Technology

Based on the literature analysis, we propose relevant recommendations for the research of affective computing (AC) in educational technology, focusing on personalized learning experiences, emotion feedback, emotion recognition, and affective robots.

Firstly, in educational technology, AC can be utilized to monitor learners' emotional states (Alsaid et al., 2023). It can also provide personalized emotion feedback and support to learners (Blazejowska et al., 2023), thereby helping learners adjust their learning experiences in a personalized manner to enhance learning outcomes.

Secondly, in educational technology, deep learning-based methods for analyzing physiological signals (Garg et al., 2023) and EEG-based emotion recognition approaches (Li et al., 2023) can be employed. By utilizing physiological signals and EEG data, it becomes possible to recognize learners' emotional states and adjust teaching strategies accordingly.

Lastly, in educational technology, AC can be applied to design and develop robots or virtual assistants that establish emotional connections with learners (Filippini & Merla, 2023), fostering both learning and emotional development among learners.

5 Conclusion

Based on the bibliometric analysis conducted in this study, we can conclude that affective computing is a rapidly developing research field, which has gone through an initial research stage before 2009, a stable development stage from 2010 to 2018, and a rapid development stage from 2019 onwards. Our co-occurrence analysis and clustering analysis have revealed five research directions in AC: emotion recognition, physiological signal, human-computer interaction, deep learning, and electroencephalography. Building on these findings, we provide relevant recommendations for AC research in educational technology, focusing on personalized learning experiences, emotion feedback, emotion recognition, and affective robots.

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