

RESEARCH ON EMOTION-COMPUTING-DRIVEN DESIGN: HOTSPOT EVOLUTION AND TREND ANALYSIS

Yulong SUN, Yixin ZOU
Guangdong University of Technology, China

ABSTRACT

Affective computing, as an important intersection of artificial intelligence and human-computer interaction, has rapidly developed in recent years in the areas of multimodal recognition, deep learning, and intelligent system applications, gradually becoming an important technological support for driving "human-centered" design innovation. Based on bibliometrics and knowledge mapping methods, this paper uses CiteSpace to conduct a visual analysis of 1,172 articles on affective computing and its design applications from the CNKI and Web of Science databases over the past 20 years. It systematically combs through the research trajectory, disciplinary distribution, hotspots evolution, and trend changes. By extracting keywords, the paper analyzes the development trends of international and domestic research in the field of affective computing and design, summarizes the development of affective computing over the past 20 years both domestically and internationally, and predicts future trends in the field as well as how affective computing and design research can be integrated.

Keywords: Emotion recognition, Affective computing, User study, Design

1 INTRODUCTION

Affective Computing was first proposed by Rosalind W. Picard of the Massachusetts Institute of Technology in the book *Affective Computing* (Picard, 1997). Its core concept is to build computing systems that can recognize, understand, express, and regulate human emotions. The goal of Affective Computing is not only to endow computers with the ability to "understand emotions" but also to enable technology to use emotions as a medium to promote more natural and human-centered interactions between humans and intelligent systems.

The core mission of design is to create experiences in a human-centered manner, shaping products and services with warmth through the harmonious integration of form, function, and emotion. It can be said that Affective Computing and design are highly aligned in their focus—both center on human emotional experiences. Therefore, introducing Affective Computing into the field of design can not only expand the perceptual dimensions of design but also promote a shift from "function-driven" to "emotion-driven" design. This endows products with the ability to perceive, empathize with, and respond to human emotions, achieving a deeper level of "emotional interaction design."

In recent years, with breakthroughs in deep learning, natural language processing, and multimodal perception technologies, the research and application of Affective Computing have ushered in new opportunities for development. For example, in the field of speech emotion recognition, the combination of deep learning and attention mechanisms has significantly enhanced the model's ability to capture emotional features [1]. In the area of text sentiment detection, deep learning models have demonstrated high accuracy and robustness in social media sentiment analysis and online customer service systems [2]. Meanwhile, multimodal emotion recognition has become a research hotspot, with researchers attempting to integrate multi-source information such as speech, facial expressions, and physiological signals to improve the accuracy and universality of emotion recognition [3]. Over the past two decades, Affective Computing research has evolved from single-modality (such as text sentiment recognition) to multimodality (combining speech, facial expressions, and physiological signals). This trend of "multimodality + intelligent perception" has provided design with new tools and contexts, transforming product design from a static presentation of form to a dynamic, intelligent medium that can "sense" and "respond" to users.

However, despite significant progress in the fields of artificial intelligence and cognitive science, the systematic application of Affective Computing in the field of design remains relatively underexplored. There is currently a lack of theoretical carding and visualization analysis of Affective Computing in design innovation, user experience optimization, and emotional interaction mechanisms. Therefore, in this context, conducting a visualization knowledge map study in the field of Affective Computing can not only reveal the academic development trajectory, research hotspots, and trends in this field but also provide a theoretical basis and methodological reference for integrating human-computer emotional interaction and innovative design in the discipline of design.

Therefore, based on bibliometrics, this study systematically analyzes research related to Affective Computing using the CiteSpace visualization tool. By visualizing the publication characteristics, research hotspots, and evolutionary trends, this study aims to reveal the knowledge structure and development direction of the Affective Computing field and explore its potential value and future directions in the context of design. This provides new ideas and insights for the research and practice of "emotional intelligent design."

2 MATERIALS AND METHODS

2.1 Data sources

The data for this study were primarily obtained from the China National Knowledge Infrastructure (CNKI) and the Web of Science Core Collection (WoSCC) provided by Clarivate Analytics. In CNKI's advanced search, the terms "Affective Computing" and "Sentiment Analysis" were used as the main subject headings, with an additional restriction requiring that the title, abstract, or keywords contain the term "Design". The Boolean search expression was defined as $SU = ("Affective\ Computing" OR "Sentiment\ Analysis" AND (TI OR AB OR KY) = ("design"))$. The time span was set from 2005 to 2025, and the source categories were limited to journals indexed in the PKU Core Journals and CSSCI databases. A total of 417 records were initially retrieved. After manual screening to exclude papers unrelated to the research topic (e.g., purely algorithmic or engineering-focused studies), 292 valid records were retained. The dataset was exported in Refworks format, including titles, abstracts, keywords, and bibliographic information, and named "download_1 - 292" according to the input requirements of CiteSpace.

For the WoSCC dataset, the search was conducted within the Topic (TS) field using the Boolean query $TS = ("Affective\ Computing" OR "Emotional\ Computing" OR "Emotion\ Recognition") AND TS = ("Design" OR "User\ Experience" OR "Interaction\ Design")$. The document types were restricted to "Article" and "Review", the language to English, and the time range to 2005 - 2025. The databases SCI, SSCI, and A&HCI within the core collection were included. The initial search yielded 3,085 publications, from which 880 relevant records were retained after manually removing studies unrelated to the research focus (such as those centered solely on medical emotion recognition or computer vision algorithms). The records were exported in Plain Text (Full Record and Cited References) format and saved as "download_1 - 500" and "download_501 - 880" for CiteSpace analysis.

Prior to data import, duplicate records were removed and synonym merging was performed (e.g., "emotion recognition" and "affective recognition" were treated as equivalent). A bilingual mapping process was applied to unify English and Chinese keywords. The main CiteSpace parameters were set as follows: Time Slicing = 2005 - 2025 (1-year per slice); Node Types = Keyword, Country, Institution, and Category; Threshold = Top 50 per slice; Clustering Method = Log-Likelihood Ratio (LLR); Burst Detection $\gamma = 1.0$ with a minimum duration of 2; and Pruning = Pathfinder + Pruning sliced networks. The resulting co-occurrence networks, clustering structures, and burst terms were further analyzed and visualized with the aid of Excel to ensure the reproducibility and transparency of the bibliometric analysis.

Table 1. Data sources

	CNKI	WoS
Retrieval mode	Subject + Key Phrase Search	Subject term
Keywords	Emotional computing, Design	Emotional computing, Affective computing
Literature category	PKU、CSSCI	SCI、SSCI
Time	2005-2025	2005-2025
Search for literature	417	3085
Effective literature	292	880

2.1 Analysis tools and research methods

In terms of research methodology, this paper focuses on bibliometrics and knowledge map visualization, employing both CiteSpace software and Excel tools for analysis. On one hand, CiteSpace is utilized to conduct in-depth processing of the literature, generating multi-dimensional visualizations such as co-occurrence maps, clustering networks, and timeline maps, thereby revealing the knowledge structure and developmental trajectory of affective computing research. On the other hand, Excel is used to perform preliminary statistical analysis of the retrieved data to ensure the comprehensiveness and rigor of the results. This combination of quantitative and visual strategies not only aids in understanding the overall trends of affective computing at the macro level but also captures the refinement and evolution of research topics at the micro level, thus enabling scholars to more intuitively and quickly grasp the developmental trends in this discipline.

The research samples are based on the two sets of data screened in the previous section: 880 relevant international articles and 292 relevant domestic articles. The analysis of these two datasets maintains the basic framework of quantitative statistics while emphasizing network relationships at different levels. Specifically, the quantitative analysis focuses on four aspects: annual changes in publication output, disciplinary distribution, research institution distribution, and contributions from countries/regions, to reflect the overall scale and developmental trends of the research. The co-occurrence network analysis is further elaborated by systematically sorting out keyword co-occurrence and its timeline, thereby revealing the evolution of research hotspots and frontier directions [5].

3 GENERAL SITUATION OF DOMESTIC AND FOREIGN RESEARCH

3.1 Statistics and Analysis of Publication Volumes of CNKI and WoS

In the course of this study, CiteSpace was first employed to convert and de-duplicate the screened Chinese- and English-language records, after which yearly publication counts were generated to capture the pace and evolution of affective-computing research. Excel was then used to examine the temporal and quantitative dimensions of the dataset, yielding the distribution shown in Figure 1. The results reveal a consistent upward trajectory for both Chinese and international publications, indicating that interest in affective computing is rising steadily worldwide. Nevertheless, the absolute scale of domestic output still lags far behind that of the international community—a gap that reflects differences not only in productivity but also in research resources, disciplinary foundations and developmental paths.

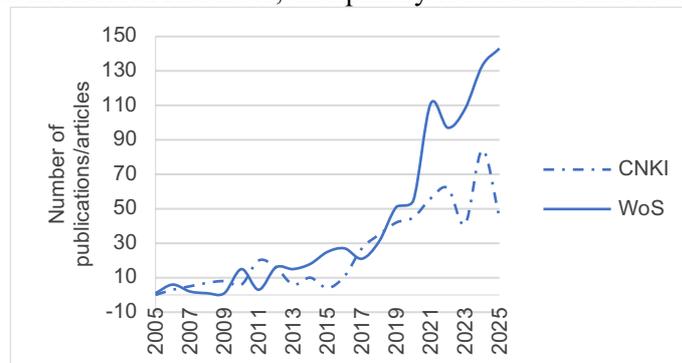


Figure 1. Statistical Analysis of Publication in the field of affective computing from CNKI and WoS
According to the CNKI and WoS data plotted in Figure 1, although global affective-computing research has grown without interruption, its tempo and magnitude differ markedly across regions. In general,

international output has expanded more rapidly; China started later and the gap widened after 2019, although recent years show clear signs of catch-up. This trend mirrors both technical breakthroughs in AI and the swift attention that design disciplines are paying to “emotional intelligence”. On the basis of these publication curves, the past two decades can be divided into three stages:

Stage 1 (before 2013): Annual output in both CNKI and WoS remained low—only single-digit or low-double-digit papers. Work focused on emotion recognition, affective modelling and sentiment analysis in human – computer interaction. From a design perspective, this stage supplied the technological underpinning for “emotional design”: researchers began using computational models to detect user emotions, laying the groundwork for products that could “respond affectively”. Affective computing was still in proof-of-concept, yet its intersection with psychology, cognitive science and design aesthetics provided an early theoretical blueprint for “emotion-mediated HCI design”.

Stage 2 (2014 – 2019): Publications in both databases climbed steadily to several dozen per year. Fuelled by deep learning and big data, sentiment analysis spread to text, speech and visual emotion recognition. Design disciplines absorbed these advances, leveraging sentiment analytics to read user emotions and applying “data-driven emotional design” to product interaction, service experience and visual communication. Examples include smart-home systems, educational interfaces and medical UIs that embed emotion-recognition algorithms to enhance comfort and affinity, signalling the shift from academic validation to design integration.

Stage 3 (2020 – present): Beginning in 2021, WoS output surged, peaking in 2023, while CNKI figures also rose. Research now centres on multimodal emotion recognition (text, voice, facial, physiological, EEG) and is increasingly intertwined with AI ethics, brain-inspired computing, affective robotics and empathic design. In design practice, this has opened the new frontier of “Affective Intelligent Design”. Designers no longer pursue accuracy of detection alone; they demand affective feedback and empathic exchange, enabling smart products to respond dynamically to user emotions and forging “perceive – empathize – respond” human – machine relationships. The field is thus moving from “emotion display” to “emotion interaction”, offering a fresh paradigm for future interactive and service design.

3.2 Subject distribution

Affective computing, as a highly complex interdisciplinary research topic, spans multiple academic fields including computer science, psychology, cognitive science, linguistics, education, and medicine. By analyzing the disciplinary distribution of research in affective computing, it is possible not only to reveal the core research hotspots and cutting-edge trends in this field, but also to identify the research characteristics of different disciplines in emotion modeling, emotion recognition, and affective interaction. More importantly, this interdisciplinary structure provides new research support and innovative directions for the field of design.

3.2.1 International subject distribution

By analyzing the disciplinary distribution of Web of Science data using CiteSpace and visualizing it with a Sankey diagram (Figure 2), it can be found that research on affective computing is mainly concentrated in the fields of computer science and engineering technology. Among them, artificial intelligence, information systems, and cybernetics are the disciplines with the highest publication output, indicating the core position of technology-driven research in this field.

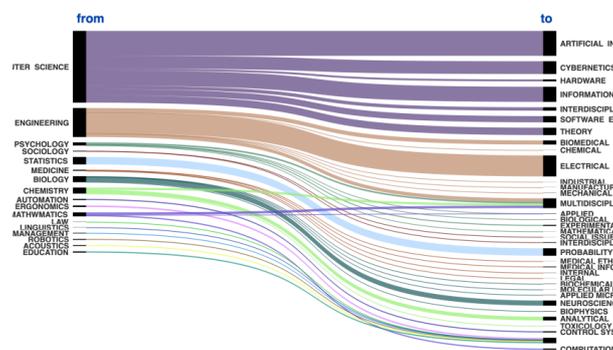


Figure 2. Sankey diagram chart in the WoS Database

However, from the perspective of centrality, interdisciplinary applications in computer science, neuroscience, and biomedical engineering have a higher degree of influence. This indicates that affective computing not only relies on the development of computer technology, but is also closely related to disciplines such as psychology, neuroscience, and cognitive science.

Table 2. Statistical Analysis of Subject Clustering in the WoS Database (Top 15 Categories)

Number	Frequency	Centrality	Starting year	Subject Distribution
1	292	0.20	2006	Computer Science, Artificial Intelligence
2	246	0.11	2006	Engineering, Electrical&Electronic
3	177	0.14	2006	Computer Science, Information Systems
4	150	0.05	2017	Computer Science, Cybernetics
5	87	0.02	2010	Telecommunications
6	86	0.00	2010	Computer Science, Theory&Methods
7	73	0.01	2013	Computer Science, Software Engineering
8	65	0.01	2006	Instruments & Instrumentation
9	59	0.23	2006	Neuroscience
10	48	0.18	2010	Engineering, Biomedical
11	47	0.01	2015	Physics. Applied
12	43	0.00	2014	Chemistry, Analytical
13	41	0.08	2012	Engineering, Multidisciplinary
14	40	0.03	2005	Multidisciplinary Sciences
15	40	0.42	2010	Ence. Interdisciplinary applications

Further observation of the temporal distribution reveals that early research was primarily concentrated in artificial intelligence and information science, gradually expanding to the fields of electrical and electronic engineering, education, and psychology around 2010, and more recently extending to materials science, acoustics, and multidisciplinary intersections. This trend indicates that affective computing is shifting from a singular focus on computer science to a multidisciplinary integration.

From the perspective of design, this multidisciplinary integration trend provides a solid technological and theoretical foundation for "emotion-driven design innovation." For instance, advancements in computer science and engineering enable designers to utilize algorithms, sensors, and artificial intelligence for real-time emotion recognition and feedback. Meanwhile, the involvement of neuroscience and psychology helps designers understand the deeper mechanisms of human emotional responses, thereby facilitating the creation of more empathetic and human-centered experiences in products, services, and interaction interfaces.

Overall, the disciplinary distribution of affective computing reveals a research evolution process from "technology-driven" to "experience-driven." It offers a new path for interdisciplinary integration in design, transforming design from merely constructing appearance and functionality to a comprehensive creative activity that integrates algorithmic intelligence, emotional perception, and humanistic care.

3.2.2 Domestic disciplinary distribution

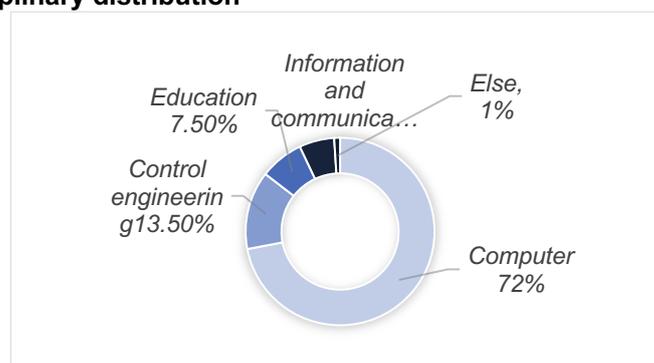


Figure 3. Statistical Distribution of Disciplines in CNKI Literature

From the disciplinary distribution statistics of CNKI (Figure 3), domestic research on affective computing is primarily concentrated in the field of computer science, followed by control engineering, educational technology, and information communication, showing a distinct "engineering and technology-oriented" characteristic. This distribution indicates that domestic scholars focus more on the practical applications of affective computing in algorithm implementation, system control, and intelligent interaction, with the research emphasis mainly on the technical pathways and system optimization. In contrast, the disciplinary distribution results from Web of Science show that, although international research on affective computing is also centered on computer science and engineering technology, it is more diversified. In addition to traditional technical fields such as artificial intelligence, information systems, and cybernetics, it also covers interdisciplinary directions such as neuroscience, biomedical engineering, psychology, education, and social sciences. This difference reflects that international research, while emphasizing technological innovation, places greater importance on the deep integration of affective computing with human cognition, psychological experience, and social behavior, presenting a research pattern that values both "scientific understanding" and "humanistic application."

From the perspective of design, this difference reveals that domestic research on affective computing still has room for improvement in "human-centered" experience innovation. The multidisciplinary integration model abroad indicates that affective computing has gradually evolved from a mere technical tool to a key support for understanding and shaping human-computer emotional interaction experiences. While domestic research has made rapid progress in algorithms and engineering implementation, it still needs to further introduce theoretical frameworks from psychology, behavioral science, and design to promote the development of "affective computing-driven design innovation." For example, introducing emotion recognition and modeling techniques into product interaction design, service design, and emotional experience systems can achieve more empathetic and emotionally responsive human-computer interactions, thereby enhancing the emotional expression and humanistic care of intelligent systems.

3.3 Distribution by country/region



Figure 4. International/Regional Co-occurrence Map of Literature in the WoS Database

Table 3. Statistical Analysis of Publication Outcomes by Countries in the WoS Database (Top 10)

Number	Frequency	Centrality	Starting year	Country
1	359	0.34	2006	CHINA
2	119	0.30	2006	USA
3	64	0.21	2006	ENGLAND
4	60	0.13	2017	INDIA
5	51	0.03	2010	GERMANY
6	46	0.20	2010	SPAIN
7	37	0.22	2013	KOREA
8	35	0.08	2006	ITALY
9	35	0.13	2006	JAPAN
10	31	0.16	2010	AUSTRALIA

After analyzing the country/region distribution in the Web of Science database (Figure 4), it was found that China has the highest number of publications in the field of affective computing, indicating the enthusiasm and proactivity of Chinese scholars in this area. This also suggests that when choosing

platforms for publishing research findings, domestic scholars tend to prefer international journals and academic conferences, which is closely related to the broader dissemination space that affective computing, as an interdisciplinary cutting-edge field, enjoys internationally. However, from the perspective of network centrality indicators, despite China's numerical advantage, its overall academic influence remains relatively limited. In contrast, European and American countries play a more prominent intermediary role in international cooperation networks, and their research findings are more representative in terms of quality and academic influence on a global scale. Therefore, while expanding the quantity of research findings, China should place greater emphasis on the production of high-quality research and the deepening of international cooperation networks.

Moreover, in terms of the temporal evolution of publications, both European and American countries and China initiated relevant research at an early stage, demonstrating a first-mover advantage in this field. In recent years, emerging developing countries such as India have gradually made their mark in the field of affective computing, with a noticeable increase in publications in recent years. This trend indicates that affective computing is not only a cutting-edge issue of concern to developed countries but is also becoming an important direction in the scientific research layout of developing countries, highlighting the field's extensive global influence and development potential.

3.4 Organization distribution



Figure 5. Co-occurrence Map of Institutions in WoS Database Literature

According to the statistical results of research institutions in the field of affective computing by CiteSpace (Table 3), it can be seen that the research power in this field is mainly concentrated in China and some internationally renowned universities and research institutes. Among them, University of Chinese Academy of Sciences (UCAS) ranks first with 26 publications and achieves a centrality index of 0.22, indicating that it not only has an advantage in quantity but also has a high influence in international academic cooperation and disciplinary networks. Second is Imperial College London in the UK, ranking second with 20 papers, but its centrality (0.07) is relatively low, indicating that its radiation capability in the international cooperation network is limited.

Table 4. List of High-frequency Research Institutions in the WOS Database (Top 10)

Number	Frequency	Centrality	Starting year	Organization
1	26	0.22	2014	Chinese Academy of Sciences
2	20	0.07	2012	Imperial College London
3	16	0.01	2018	University of Augsburg
4	14	0.09	2010	Tsinghua University
5	13	0.04	2021	Beijing institute of Technology
6	12	0.01	2016	Southeast University
7	11	0.02	2010	Centre National de la Recherche Scientifique
8	10	0.03	2022	Harbin institute of Technology
9	10	0.01	2012	Hefei University of Technology
10	10	0.07	2007	University of California

Among domestic universities, Tsinghua University (14 publications, centrality 0.09), Beijing Institute of Technology (13 publications, centrality 0.04), Southeast University (12 publications, centrality 0.01), Harbin Institute of Technology (11 publications, centrality 0.03), and Hefei University of Technology

(10 publications, centrality 0.01) all rank high on the list. These universities have strong research accumulations in artificial intelligence, control engineering, and human-computer interaction, reflecting the continuous investment and disciplinary advantages of China's high-level engineering-oriented institutions in the field of affective computing.

From an international perspective, the University of Augsburg in Germany (16 publications, centrality 0.01), the French National Center for Scientific Research (CNRS, 11 publications, centrality 0.02), and the University of California in the United States (10 publications, centrality 0.07) are also representative in this field. These institutions often combine their national strengths in neuroscience, psychology, and computer science to promote interdisciplinary research in affective computing.

Through bibliometric analysis of research institutions in the field of affective computing, it can be found that the top-ranked universities and research institutions not only represent the core research forces in this field but also reflect the main directions of disciplinary development. Therefore, when we undertake research tasks in the field of affective computing, the research content and directions of the highly ranked institutions and universities provide us with valuable references.

4 ANALYSIS OF RESEARCH HOTSPOTS AND TRENDS

4.1 Analysis of International Research Hotspots and Trends

4.1.1 Key Words with High Frequency

Keywords are a distillation and summary of the core content of a paper. By analyzing the frequency, correlation, and emergence of keywords in the literature of a particular field, one can quickly grasp the research topics and hotspots that scholars in that field are focusing on. This also helps to understand the overall situation and characteristics of current research findings, reveal the connections between research contents, and identify future development trends. In CiteSpace, by setting the node type to “Keywords” and keeping other parameters unchanged, while selecting items from the WOS database, a co-occurrence map of keywords can be generated (Figure 6).

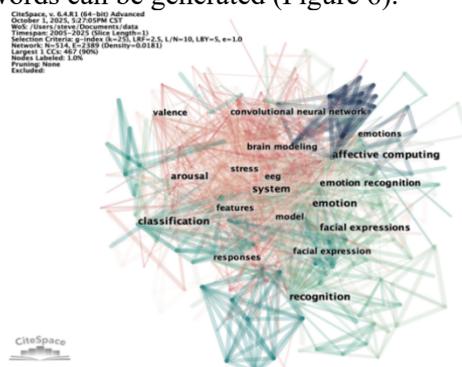


Figure 6. Co-occurrence Map of Keywords in WoS Database Literature

In the co-occurrence map, nodes correspond to keywords, and the size of each node is proportional to the frequency of the keyword. The betweenness centrality of each keyword is further calculated based on its frequency of occurrence. The top 15 keywords with the highest frequency are selected and listed in Table 4. By examining the map, it can be seen that in the international literature keyword network of this field, there are 514 nodes and 2,389 links, with a network density of 0.0181. The visualization analysis of keywords in the field of affective computing indicates that the research hotspots in this area exhibit a distinct concentration feature.

Table 5. Statistical Analysis of High-frequency Keywords in WoS (Top 15)

Number	Frequency	Centrality	Starting year	Keyword
1	297	0.17	2006	Affective computing
2	262	0.10	2008	Emotion recognition
3	117	0.16	2006	recognition
4	86	0.03	2018	Deep learning
5	83	0.14	2011	Classification
6	82	0.02	2021	Artificial intelligence

7	61	0.06	2015	Model
8	59	0.05	2013	Features
9	58	0.12	2011	Emotion
10	50	0.03	2019	Machine learning
11	47	0.04	2017	Facial expression recognition
12	43	0.02	2020	Fusion
13	39	0.06	2014	EEG
14	38	0.02	2020	Computational modeling
15	34	0.12	2011	System

The visualization analysis of keywords in the field of affective computing indicates that the research hotspots in this area exhibit a distinct concentration feature. Overall, "affective computing" (297 occurrences) is the core concept of the entire field and the most frequently appearing keyword. It constructs the research goal of "computing systems with emotional intelligence" and connects artificial intelligence (AI), psychology, cognitive science, and design. It serves as the foundational framework for studying human-computer emotional interaction.

"Emotion recognition" (262 occurrences) refers to the automatic identification of an individual's emotional state through signals such as speech, facial expressions, text, and electroencephalogram (EEG). It is a core task and technological entry point in affective computing, determining whether a computing system can understand human emotions. Keywords such as "classification," "features," and "emotion" are the most central and fundamental research topics within emotion recognition. For example, in Kim's study [7], it is pointed out that EEG-based emotion recognition mainly relies on the extraction of emotion-related features and the construction of classification models. The keyword "system" signifies the shift in affective computing from single-modality collection to multimodal modeling, integrating feature extraction, modeling methods, and system implementation to form a more comprehensive modeling framework.

"Deep learning" refers to learning methods based on multi-layer neural networks, which can automatically extract complex emotional features from raw data. The emergence of deep learning has also driven affective computing from traditional feature engineering to data-driven modeling, becoming the main driving force behind the explosive growth in research in recent years. It has significantly improved the accuracy of emotion recognition and prediction. "Machine learning" is an algorithmic framework that enables computers to "learn" emotional patterns from sample data, thereby making predictions or classifications on new inputs. It is a core technological approach for emotion recognition, emotion modeling, and emotion prediction.

"Artificial intelligence" in the field of affective computing represents a comprehensive disciplinary system that endows machines with the abilities to perceive, reason, learn, and interact. It provides algorithms, models, and interaction mechanisms for affective computing, enabling machines to be not only "intelligent" but also "emotional," thus advancing "intelligent computing" towards "emotional intelligence." "Fusion" in affective computing not only represents the integration and collaborative analysis of data from different modalities such as speech, facial expressions, text, and EEG but also signifies the practical application and deep integration of affective computing in vertical scenarios such as education, healthcare, and human-computer interaction through artificial intelligence.

Against this backdrop, design introduces new dimensions to affective computing research and practice. It extends beyond functionality to emphasize emotional experience and human-centered empathy. From human-computer interfaces to service systems and immersive environments, design serves as a key bridge between affective computing and human experience. While affective computing enables precise emotion recognition and adaptive feedback, design thinking provides a human-centered framework that balances algorithmic logic with emotional resonance. As Samsonovich [8] noted, the next generation of AI must engage in credible social-emotional interaction, requiring an emotional quotient that reflects genuine understanding. Thus, affective computing is shifting from a purely technological focus toward an integrated "technology-design-emotion" paradigm, fostering more empathetic and human-centered intelligent systems.

4.1.2 Timeline analysis

Further analysis incorporating the temporal dimension reveals (Figure 7) that early research primarily focused on foundational issues such as "features" and "emotion," which established the technological

pathways for emotion recognition. With the emergence of "classification" and "system," the research gradually expanded towards algorithm optimization and system application. In recent years, the addition of keywords such as "deep learning," "fusion," and "artificial intelligence" indicates that affective computing is progressively integrating with deep learning, multimodal recognition, and the broader artificial intelligence ecosystem. These high-centrality keywords not only reflect the evolutionary trends at the methodological level but also reveal that affective computing is shifting from a singular focus on recognition tasks to cross-domain integration and multi-scenario applications.

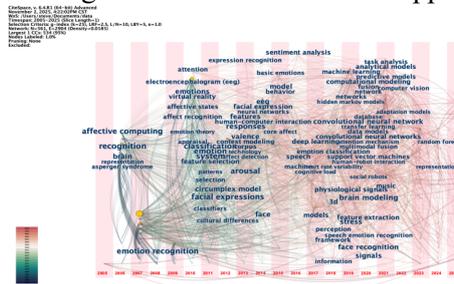


Figure 7. Time-axis map of keyword co-occurrence in the WOS database

By analyzing the timeline of the development of affective computing, it can be defined as the following four stages:

Initial Exploration Stage (2005 - 2010): Early research focused on foundational keywords such as "affective computing," "emotion recognition," "facial expressions," and "classification." The characteristic of research during this period was centered on emotion recognition, primarily relying on psychological models (such as the circumplex model), facial expression analysis, and single-modalities like speech and electroencephalogram (EEG) signals. Methodologically, it emphasized feature extraction and classification, focusing on the basic recognition and modeling of emotions. For example, van den Broek (2006) proposed a research method for computing emotion perception through facial electromyography [9], which identified four categories of emotions—positive, negative, mixed, and neutral—by measuring the physiological parameters of different facial muscle activities. Research during this period mainly laid the theoretical and methodological foundations for affective perception systems.

From the perspective of design, research at this stage was still at the level of "functional implementation of emotion recognition," with limited involvement of design. However, it provided the technical conditions for subsequent "emotion-driven design," prompting designers to begin considering how to use physiological signals and emotion modeling to understand user experience, thereby fostering the germination of user emotion research based on perceptual data in the field of design.

Technological Expansion and Methodological Diversification Stage (2011 - 2016): With the growth of datasets and computational power, research gradually expanded into directions such as "system," "sentiment analysis," "feature selection," "arousal," and "valence." Affective computing began to shift from single-modality recognition to multimodal information fusion. Researchers identified more complex emotional states through speech, facial expressions, and behavioral signals. For example, Xu (2013) proposed a multimodel interaction method for facial expression analysis [10], which improved the accuracy and convergence of real-time emotion recognition by optimizing clustering structures through multimodel distribution and interaction.

During this stage, affective computing gradually became application-driven, with design-related fields such as human-computer interaction (HCI) and virtual reality (VR) beginning to attract attention. Designers and computer scientists started exploring how to introduce emotion response mechanisms into interaction design, enabling systems to adjust interface performance and interaction experience based on user emotional feedback. The role of design during this stage shifted from "information presenter" to "shaper of emotional experience," propelling affective computing from rational computation to emotionally oriented intelligent design.

Deep Learning-Driven Stage (2017 - 2021): During this period, keywords such as "deep learning," "convolutional neural networks," "machine learning," "support vector machines," and "multimodal fusion" emerged collectively, indicating that affective computing had officially entered a stage combining data-driven and model-driven approaches. Due to the complexity and ambiguity of language, accurately recognizing emotions in narrative documents is a challenging task. Therefore, performance improvements can be achieved through deep learning [11]. The introduction of deep learning

significantly enhanced the accuracy and complexity of emotion recognition and sentiment prediction, with multimodal fusion (speech, facial expressions, physiological signals) becoming the mainstream direction. Mehta's research [12] elaborated on the many different industrial applications of automated personality detection based on machine learning and predicted that this trend would continue to develop. With the emergence of deep models and new architectures capable of complex functional mappings, more character detection architectures based on efficient multimodal fusion technologies are expected in the future.

At the design level, breakthroughs in deep learning provided stronger technical support for emotional design and user experience research. Designers no longer relied solely on subjective interviews or emotion questionnaires but could monitor user emotional responses in real-time through AI models, providing data support for optimizing interaction interfaces, generating virtual characters, and designing product experiences. The integration of design and algorithms propelled "emotion data-driven experience design" as a new trend, achieving a transformation from technical feasibility to emotional resonance.

Intelligent and Interdisciplinary Integration Stage (2022 - Present): In recent years, keywords such as "artificial intelligence," "brain modeling," "physiological signals," "predictive models," "transfer learning," "3D," and "database" have frequently appeared, indicating that the field is gradually entering a stage of deep integration with artificial intelligence, big data, and neuroscience. Research is no longer limited to recognizing emotions but explores how to simulate, predict, and even generate emotions to achieve more human-like intelligent systems. For example, Garbey (2023) [13] combined affective computing with artificial intelligence in medical scenarios, predicting patient emotions and disease progression through the analysis of speech, pulse, and linguistic data, providing new directions for personalized healthcare.

During this stage, the integration of affective computing and design has evolved into a human-centered emotional design paradigm. Design now serves not only as a visual outcome but also as a medium through which technological systems perceive and express emotions. With affective computing, designers can create products and environments capable of emotion perception, feedback, and empathy—shifting the focus from physical function and aesthetics to emotional experience. The convergence of affective computing, artificial intelligence, and neuroscience allows designers to analyze users' latent emotional states through data and predictive models, facilitating the transition from function-oriented to experience-oriented design. This interdisciplinary approach also enriches design research by introducing tools such as physiological signal - based user monitoring, interface optimization, and knowledge graph - driven emotional design. Overall, this evolution reflects a dual drive of technological advancement and design demand, underscoring the growing value of affective computing in design research.

4.2 Analysis of Domestic Research Hotspots and Trends

4.2.1 Key Words with High Frequency

After analyzing the keywords that appeared in WoS, the keywords from CNKI were also analyzed. The same procedure was followed as in the previous step. In CiteSpace, the node type was set to "Keywords", with all other parameters remaining unchanged. By selecting the literature items from the CNKI database, a keyword co-occurrence graph could be generated (Figure 8).

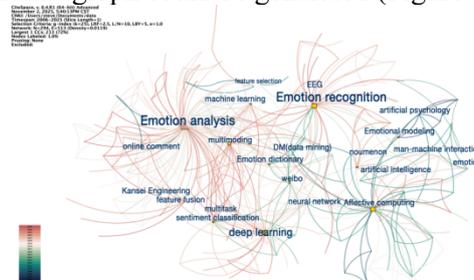


Figure 8. Co-occurrence Map of Keywords in CNKI Database Literature

As with the previous table, the top 15 keywords with the highest frequency of occurrence were selected, and their frequency, centrality, and starting year were organized into a table (Table 5). By examining

the map, it can be seen that in the international literature keyword network of this field, there are 294 nodes and 513 links, with a network density of 0.0119.

Table 6. Statistical Analysis of High-frequency Keywords in CNKI (Top 15)

Number	Frequency	Centrality	Starting year	Keyword
1	70	0.58	2010	Emotion analysis
2	35	0.22	2013	Emotion recognition
3	29	0.33	2007	Affective computing
4	27	0.21	2014	Deep learning
5	16	0.11	2019	Multimodal
6	11	0.03	2019	Feature fusion
7	9	0.00	2018	Electroencephalogram signal
8	8	0.05	2017	Machine learning
9	6	0.05	2013	Emotional Dictionary
10	6	0.05	2014	Emotion classification
11	6	0.03	2012	Neural network
12	6	0.05	2017	Artificial intelligence
13	6	0.02	2024	Contrastive learning
14	5	0.03	2011	Data mining
15	5	0.02	2006	Emotional model

Compared with the keyword distribution in the WoS database, we can observe some research tendencies with Chinese characteristics and practice orientation in the CNKI data. For example, the emergence of keywords such as "sentiment dictionary," "contrastive learning," and "data mining" reflects the unique development path of domestic affective computing research in the construction of semantic resources, model optimization, and data-driven applications. Compared with international research, domestic research places more emphasis on applying affective computing technology to actual systems and product design, a trend that provides new ideas and technical support for the integration of affective computing and design.

A "sentiment dictionary" is a semantic resource used to describe and quantify human emotions, mainly applied in sentiment analysis, public opinion monitoring, and affective interaction design. Its core task is to calculate the emotional polarity of words, categorizing vocabulary into positive, neutral, or negative [14]. This research also holds significant value in design—designers can use sentiment dictionaries to extract emotional features from user feedback, comments, or interaction texts, thereby guiding the emotional design of products. For example, in service and interface design, analyzing user language through sentiment vocabulary can identify emotional pain points, helping to build a mapping relationship between design semantics and emotional experience, and promoting the implementation of a "user-emotion-centered" design philosophy.

"Data mining" in affective computing mainly involves extracting emotional patterns from large-scale text or multimodal data to provide a data foundation for emotion recognition and modeling. With the surge in social media and user interaction data, data mining has become an important bridge connecting affective computing and design decision-making. For instance, design researchers can use sentiment data mining techniques to analyze user feedback on e-commerce platforms, film reviews, or social media, thereby gaining insights into the emotional responses and behavioral characteristics of different user groups. This not only helps build emotion-driven user profile models but also provides quantitative basis for optimizing design elements such as product form, interface interaction, and color style.

"Contrastive learning," an emerging machine learning method in recent years, enhances the representation ability of emotional features by learning the similarities and differences between samples. Compared with traditional feature engineering methods, contrastive learning is more suitable for capturing subtle emotional differences and dynamic changes. In design research, this method can be used to analyze users' emotional responses in different contexts, thereby achieving more adaptive emotionally responsive design. For example, in human-computer interaction and intelligent product design, a contrastive learning model can identify changes in users' emotional states, allowing the system to dynamically adjust the interaction tone, interface atmosphere, or visual elements to achieve an empathetic interactive experience.

Facilitating vertical deployment of large AI models: By equipping AI with the capacity to understand and respond to human emotional contexts, affective computing supplies the missing layer for large-model applications in design, mental-health, education and service experiences. Through affective semantic understanding and multimodal perception, it is evolving into the critical pathway for “affective intelligence” and “human – machine sympathy”.

Overall, affective computing is emerging as the bridge between human-centred design philosophy and intelligent technological innovation. It not only scientises and refines design-research methods but also furnishes practice with an emotional-cognition foundation and a catalyst for creativity. As technological integration deepens, design research will become simultaneously smarter and warmer, advancing toward a truly affective-intelligent design ecosystem.

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