Affective Computing White Paper

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ZHEJIANG LAB

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Foreword I

Emotions are known as the Grammar of Social Living. Affective computing aims to create a computing system that can perceive, recognize, and understand human emotions, and can respond intelligently, sensitively, and naturally to human emotions. Affective computing is the basic technology and significant premise for naturalized, anthropomorphic, and personified human-computer interaction, and also provides an optimal path for artificial intelligence decision-making, which is of great value for the unfolding of the intelligent and digital era. In recent years, China has become one of the most important rising powers in the field of affective computing, and more and more scholars have devoted themselves to research in this field. Meanwhile, China has also become one of the main positions for the enabling application of affective computing. Affective computing plays an important role in supporting high-quality economic development and digital reform.

The release of the White Paper is intended to respond to the needs of understanding and mastering the latest development trends of affective computing in academia and industry in China and even around the world, and to provide scientific researchers and industry practitioners with more complete blueprints of technology development and application trend insights to promote the development and transformation of affective computing. This White Paper has several distinctive features as follows:

Firstly, based on mainstream academic databases, Zhejiang Lab, National Science Library, Chinese Academy of Sciences, and other units analyzed more than 20,000 papers from 1997 to 2022 to get the data which have the advantages of covering the whole cycle of the field, the full scale of papers, and the whole process of scientific research, and the important research papers, patents and standards sorted out are helpful to clarify the key generic technologies and cutting-edge leading technologies, which have guiding significance for keeping track of the academic developments in the field of affective computing, and have great reference value for implementing different innovation approaches such as “building peaks on plateau” and from “Zero” to “One”.

Secondly, the White Paper depicts the discipline panorama of affective computing, including important research institutions, academic journals, international conferences, representative scientists, high-level societies, etc. It canvasses the cooperative ecosystem, which plays a directive role in the construction of discipline and the establishment of major research funds. Chinese scholars have made remarkable progress in the field of disciplines, initially forming the high-level talent echelons, and accounting for a relatively high proportion of classic scholars and important research positions. However, China has weak leadership ability in academic journals and international conferences, which hinders the improvement of disciplinary doscourse power and does not match the fact that China ranks first in the world in the number of published papers in this field. To a certain extent, this situation hinders the development of Chinese scientists as an academic community and is not conducive to the change of status from followers to leaders.

Thirdly, the white paper attaches great importance to the research on the Commercialization of research fingings and application of affective computing. The report to the 20th CPC National Congress highlighted, “Accelerating the implementation of the innovation-driven development strategy. Setting our sights on the global frontiers of science and technology, national economic development, the major needs of the country, and the health and safety of the people, we should speed up efforts to achieve greater self-reliance and strength in science and technology.” The quantitative analysis and case studies of the applications are helpful to guide the general scientists to carry out scientific research for the main economic battlefield and major practical needs. At the same time, they will promote the relevant practitioners to deepen understanding and awareness of the technical panorama, promote the exploration of economic entities to increase the enabling application of affective computing, accelerate the transformation and upgrading of the digital economy and the iterative application of artificial intelligence technology, and promote the value reshaping of more enterprises from downstream to midstream or upstream of the industrial chain.

The White Paper takes solid steps in the above three aspects that lays a foundation for predicting future trends in the field of affective computing. The White Paper also has a special chapter to look forward to technology trends and industry applications. The future trends predict what the future will be, which cannot be accurately predicted, but an accurate grasp of the past and the present provides a trace for the development of affective computing. The world is undergoing major changes unseen in a century, and this change is not limited to a specific moment or event, one country or region, but is a profound and sweeping change of the times. I firmly believe that China’s influence in the field of affective computing will continue to grow rapidly, and we are pleased to see this unstoppable power providing a constant impetus for academic development and enabling application of affective computing.

Chair Professor of the UESTC
Emeritus Professor of the University of Tokushima
Academician of the EAJ
Academician of the EUAS
November 2022

Foreword II

In recent years, China's development in the field of artificial intelligence (AI) technology has progressed rapidly. The last generation of AI technology is "blossoming" in terms of research and development, industrial applications and connotation popularization. Through the efforts of a large number of scientists and practitioners, China has caught up with the countries who reach the world advanced level in the first stage of AI development in just a few years. China is developing cutting-edge information technology such as AI not only for realizing the rejuvenation of the Chinese nation, but also for the sustainable development throughout the world and human progress.

As a deeply local-rooted international professional services firm, Deloitte percepts the mission and is pleased to get on board with the development planning and resource and transformation practice of the new generation AI technology, i.e. affective computing. Like many scientists and practitioners, we clearly foresee the importance of the emotional mind in the overall cluster of intelligent technologies. Affective computing is a multidisciplinary cutting-edge technology covering psychology, cognitive science, computer science, mathematics, etc., so we need to form a win-win situation through an ecological network composed of multiple roles and realize their respective demands, so as to promote the development of affective computing technology from research and development to transformation and popularization. For this purpose, under the initiative and guidance of Zhejiang Lab, Deloitte received strong support from experts and scholars from Shanghai Scientific & Technical Publishers, National Science Library, Chinese Academy of Sciences, the Institution of Engineering and Technology, Amazon Web Services and SHNU through the ecological network group accumulated over the years of innovation, to jointly complete the writing and release of the "Affective Computing White Paper".

Since affective computing is a cutting-edge technology that few people have get into this field in the past, it is naturally difficult to summarize, interpret and analyze the relevant information of the current global affective computing technology, especially in the face of technology change with each passing day, we meet the biggest challenge that ensure the timeliness of content and release a white paper with the fastest speed, highest quality and most complete information. The implementation of such a task is like initiating and managing a big scientific project, and it also fully tests the collaboration and tacit understanding among the participants. In the more than half a year of writing the White Paper, nearly 50 academic leaders, scholars, experts and industry leaders who participated in the guidance and writing of the White Paper resolutely broke geographical restrictions and completed the White Paper on time and with high quality under the uncertain environment of the frequent COVID-19 pandemic, and that is exciting.

This White Paper can be regarded as a concise encyclopedia of the development and application of affective computing technology, and it introduce the affective computing technology from three aspect: the history of human research on their own emotions, how to bionically implement affective computing through the means of information technology, and the scenario applications that have been implemented. This content arrangement fully places the engagement team's expectations on the scientific research and commercial application of affective computing technology. We always firmly believe that a good technology is inseparable from the enlightenment of cutting-edge science, nor from the substantive connection with social and economic development. The release of the White Paper does not mean the end of the engagement team's work, but the prelude to China's technical research and application transformation in affective computing technology. We sincerely hope that more individuals and teams with enthusiasm for affective computing technology will join us and make more contributions to the new generation AI technology to enable social stability, national prosperity, and human development.

Member of the National Committee of the CPPCC
Chair of Deloitte China
November 2022

Table of Contents

Preface

Affective computing is an interdisciplinary field involving computer science (including intelligent science), brain and psychological sciences (including psychology and neuroscience), social science (including sociology, economics, and management science), medicine etc., and gradually becomes a global academic and engineering hotspot. The “Research Fronts 2021: Active Fields, Leading Countries” released by the Institutes of Science and Development under the Chinese Academy of Sciences shows that the Research Hotspot Index of the related research with “multimodal affective computing” as the core ranks in Top 10. According to the bibliometrics analysis of the literature provided by the Institute of Engineering and Technology (IET), the amount of published papers in the field of affective computing grows rapidly, and the scholars in China and the United States have become the most representative researchers in this field. Review papers published in the *Nature* Portfolio journals show that the researchers from China have risen rapidly from 2016 to 2020. The total amount of papers has surpassed that of the United States, and more and more research institutions and high-tech companies are devoting themselves to the research and practice of affective computing.

In order to respond to the needs of academia and industries in China and around the world to understand and grasp the latest development trends of affective computing, and to provide scientific researchers and industry practitioners with more complete blueprints of technology development and application trends to promote the development and transformation of affective computing, a joint engagement team is initiated by the Research Center for Multi-Modal Intelligence of the Research Institute of Artificial Intelligence under the Zhejiang Lab, and jointly set up by De.InnoScience, Shanghai Scientific & Technical Publishers (SSTP), National Science Library, Chinese Academy of Sciences (CAS), the Institution of Engineering and Technology (IET) and to promote the release of the “Affective Computing White Paper” (hereinafter referred to as the “White Paper”).

Under the background of Human-Computer Symbiosis, the deepening understanding of human emotions, the further popularization of “IQ + EQ” of intelligent machines, the iterative upgrading of emotional intelligence, and the Industrial transformation driven by the digital economy will become important driving forces in innovation for the discipline development, technology evolution and industry progress of affective computing. During the preparation of the White Paper, the engagement team fully researches the technical development and emotion process of affective computing and its related disciplines, and with the joint efforts of experts from academia and industries, the Report finally forms a “comprehensive” and “holistic” framework, in order to enable researchers and practitioners to have a comprehensive understanding of the latest development of affective computing, and to think about the future trend of affective computing from a broader and longer-term perspective.

Chapter I
Theoretical Overview

Affective computing is an interdisciplinary field involving computer science, brain and psychological sciences, social science, etc. Computer science and electromechanical science focus on providing various IT means and engineering capabilities, which can implement digital reconstruction and computing implementation of emotional perception, recognition, understanding, feedback, etc., so that machines can have an emotional mind similar to that of humans. The field of psychology and consciousness in brain and psychological sciences focuses on providing theories of the basic definition of human emotions and the meaning of the structure of relevant elements, which lay the foundations for the modeling of the theory of the emotions. Cognitive neuroscience, another branch of brain and psychological science, focuses on the mechanism of human brain's emotion processing and the establishment of functional network of psychological elements related to emotion, which provides key inspiration and strategic guidance for the development of affective computing models. The social science and medical science are very useful for the application of affective computing and function as the source of scenario design for such technologies.

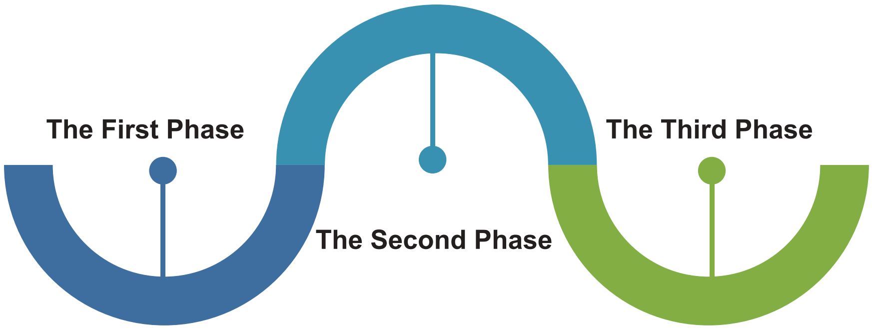
It can be seen that affective computing is a field that needs to be jointly promoted by multiple disciplines, and it is also a field where the actual needs of the industry force technological progress and iteration.

1.1 Emotions in Human Society

1.1.1 The Significance of Emotions for Human Beings

Known as the Grammar of Social Living, emotion is an important carrier of information exchange, relationship maintenance and ideological communication between people, and an important force to promote the growth and prosperity of human civilization. According to the evolution of species, emotion is considered to be the psychological element that guarantees human's basic survival ability, forms social habits, and supports high-level thinking. If human beings were not emotional, then we would be kept alive only by primitive impulses and the desire to survive, and it would be almost impossible for such species to develop a highly developed social civilization. Although emotions play an important role in the whole process of human evolution, people's cognition and emphasis on the function of emotion has gone through a long process.

Nowadays, various theories of human emotions have taken shape. The research on these theories dates back about 3,000 years to early human civilization. The journey can be roughly divided into three phases (See Figure 1-1).



The exploratory and discursive phase that occurred during the European Renaissance and before (around the 17th-18th centuries AD and before)

The scientific enlightenment phase that occurred between the French Enlightenment and the birth of scientific psychology (around the 17th-18th centuries AD to the end of the 19th century AD)

The development and application phase that occurred after the birth of scientific psychology (late 19th century AD and beyond)

Figure 1-1 Three Phases in the Development of Theories of Emotion

The main activity of the first phase is to try to identify and clarify "emotion" and its related concepts. In the early Eastern civilization, the philosophies of the *I Ching* and various schools of thought in ancient China, and ancient Indian philosophy all understood and elaborated on emotions. For example, *Li Ji: Li Yun* put forward the concept of "seven emotions" and "What is human emotions? The seven emotions refer to joy, anger, sorrow, fear, love, disgust, and desire, which are innate abilities." In the early Western civilization, the ancient Greek physician Hippocrates (460-377 BC) proposed the "humoral theory" of human beings under the ancient system of physiological medicine. He believed that the humors were the material basis of the nature of the human body, and that people who were dominated by different humors were more likely to show a certain or several specific emotions. This also seems to have potential mapping and connection with the contemporaneous theory of four temperaments (Choleric, Sanguine, Phlegmatic, and Melancholic).

The main activity of the second phase is to verify these concepts in a scientific perspective and to clarify the functional relationships between them. The two major camps of "emotion" research in this phase are modern physiological medicine and scientific psychology. In the modern system of physiological medicine, the famous biologist Charles Darwin's *The Expression of Emotion in Man and Animals* is recognized as a masterpiece of "emotion" research on par with his *On the Origin of Species*. In this book, Darwin presented the general expressions that humans have, such as pain, cry, joy, hate, anger, and so on. On this basis, he further discussed the emotions, thought processes and the corresponding physiological manifestations based on these expressions. This is considered to be the beginning of modern scientific research on emotions and their behaviors. In the scientific psychology, American psychologists Stanley Schachter and Jerome Singer jointly proposed the Attribution Theory of Emotion, which is considered to be the theoretical basis for the implementation of the emotional functions of artificial intelligence. The theory holds that emotions come both from the cognitive evaluation of physiological responses and from the cognitive evaluation of the situations that lead to those responses. This interpretation provides strategies and ideas for the realization of emotional intelligence.

The third phase is the integration of psychology, physiology and information technology. In the more than half a century since German psychologist Wilhelm Wundt founded scientific psychology, schools of psychology have sprung up all over the world. These schools all have different perspectives of cognition and theory about emotions. At the same time, with the development of modern physiological medicine, the study on brain mechanism of emotional function from a neuroscientific perspective has been developed in the long term. American psychologist Paul Ekman developed a theory of the seven basic human expressions that is now regarded as a universal standard, and these expressions refer to happiness, sadness, anger, disgust, surprise, contempt, and fear. Moreover, the Facial Action Coding System (FACS) developed by Ekman is considered to be a key technology for machine vision to read human expressions. In 1997, Rosalind Picard from MIT Media Lab proposed a clear definition of affective computing, officially opening a new era of artificial intelligence to achieve emotional intelligence.

Combining the understanding of the nature and role of emotions in different periods, the significance of emotions to human beings can be summarized into the following five aspects:

Firstly, survival function is physiological response that humans perform to adapt to their environment and to facilitate survival and development, such as tension and stress in dangerous environments, anger and excitement when intruded and threatened, and joy and excitement when food and survival necessities are obtained. Emotions continuously reinforce the human ability to adapt and utilize the environment and form learned physiological responses that regulate the individual's attention, memory, perception, etc., so as to obtain continuous rights to survival and development in the process of evolution.

Secondly, the communication function is essential. According to Nobel laureate in economics and American psychologist Herbert Simon, the recognition and expression of emotion is necessary for the communication and understanding of information. Emotions are crucial to the accurate expression and understanding of human intentions, and the same verbal language expressed with different emotions has completely different connotations. Thus, emotions are inseparable from language and play a key role of semantic disambiguation, which is crucial for both the sender and receiver of the information. This is also an important reason why face-to-face communication is required for important matters. Compared with speech or text communication, the expression of emotional connotations such as facial expressions and body movements in face-to-face scenarios can help reduce misunderstandings and enhance mutual trust.

Thirdly, for the decision-making function, Nobel laureate in economics and American psychologist Daniel Kahneman believes that the brain makes decisions in two ways: fast ("System I") and slow ("System II"). The common unconscious "System I" mainly relies on emotions and experience to make quick judgments, while the conscious "System II" mainly relies on rational thought. Thus, emotions are widely involved in human higher-order thinking and decision-making processes, and profoundly influence the decision outcome and decision efficiency.

Fourthly, for the motivational function, emotions can motivate and sustain an individual's behavior, and have a significant impact on the individual's the degree of resource investment, the persistence of behaviors, and the assessment of behavioral outcomes.

Finally, for the maintenance function, emotions are the maintenance ties of classes, ethnic groups, families, etc. in the process of human socialization, the core of low-cost maintenance of human social relations, and the potential social interaction contract, which is closely related to the individual's code of conduct and moral constraints.

Therefore, the nature and function of emotions determine that emotions are inseparable from human survival and development and are of great significance to the progress of human society.

1.1.2 Affective Theory Modeling

Theories about emotions are very rich and have been expanded and enriched over time. Early theories of emotion were mostly based on physiology. As we can see from Figure 1-2, emotion is a very complex and wide-ranging concept.

The connotation of human emotions is very rich. In ancient China, there were discussions on "seven emotions" and "affect, reason and law", and concepts related to affects and mind were collectively called "sentiment". With the popularization of vernacular and the introduction of modern western scientific systems, the concepts of "affect", "emotion", and "feeling" have been gradually separated from the concept of "sentiment". In this White Paper, "emotion", "affect", or "feeling" carries with it a meaning all its own, with reference to the notes on Chinese-English translation by Fu Xiaolan from the Institute of Psychology, CAS.

The word "emotion" comes from the Latin word's "e" (meaning "outward") and "movere" (meaning "to move"), and is constructed to mean move-

James-Lange Theory

Emotion is an inevitable product of the activity of the autonomic nervous system.

Cannon-Bard Theory

On the basis of James-Lange Theory, the Cannon-Bard Theory further proposed that in addition to the peripheral nervous system, the more critical is the thalamus of the central nervous system, which is the central system that influences the generation and change of emotion.

Appraisal Theory of Emotions

The degree of excitation of the cerebral cortex is also an important access to affective arousal, and the cerebral cortex and subcutaneous tissue work together to produce emotion. The theory divided the process of emotion generation into situational stimulation, emotion evaluation, and emotion generation, and introduced cognitive theory into the field of research on emotions for the first time, which paved the way for the formulation of the Schachter-Singer Theory.

Schachter-Singer Theory

In addition to physiological arousal, the more critical aspect of individual emotion is cognitive arousal. Emotion is the result of the combination of peripheral environmental stimuli and the individual's physiological condition, which is expressed through the cerebral cortex. The sensory collection and judgmental processing of emotional information is a cognitive process, and the related model is known as the affective arousal model.

Cognitive Assessment Theory

Emotion is the result of interaction between human and environment, and people constantly make primary, secondary and third evaluations of their surroundings, and these three evaluations reflect the cognitive process of emotion.

Figure 1-2 Early Theories of Emotion

ment, motion, emphasizing a very brief but intense experience. In contrast to feeling and affect, British psychologists Michael Eysenck and Mark Keane believe that affect has a wide range of meanings, representing different inner experiences such as emotions, moods, and preferences. According to Chinese psychologists Meng Shaolin and Huang Xiting, affect is the subjective experience of emotional processes, while feeling is a general term for the category of mental phenomena such as emotion and affect. Based on the above views, this White Paper argues that emotion is the process of affective response, feeling is the content of affective response, and affect covers the meaning of the above words and is a general term for emotion and feeling, etc. Referring to the practice in the field of affective computing and the definition from Meng Zhaolan, which is "a process of psychological activity and psychological motivation force that is composed of multiple components, multi-dimensional structure, and multi-level integration, interacting with cognition for organism survival and adaptation and interpersonal interaction." This White Paper defines these academic terms collectively as "affect" (concepts that are no longer distinguished in subsequent chapters). Affect is a psychological state that includes cognitive, physiological, experiential, and behavioral elements, and is an evolutionary product of the organism's response to and control of its survival environment.

In the field of affective computing, the most widely used theoretical model is the emotion classification theoretical model, which mainly includes discrete emotion model and dimensional emotion model. The discrete emotion model divides emotions into independent labels, each of which is not related to each other. Using factor analysis, American psychologist Carroll Izard developed 11 basic emotion classification models, including interest, surprise, pain, disgust, pleasure, anger, fear, sadness, shyness, contempt, and repentance. Paul Ekman's facial expression analysis led to a more generally accepted model of seven basic emotion classifications, including happiness, sadness, anger, disgust, surprise, fear, and contempt.

The discrete emotion model is more in line with the expression form of human cognition and daily life, mainly reflecting the basic types of human emotions, with clear distinction and natural interpretability. The dimensional emotion model uses the emotional space to represent different emotions through multi-dimensional vectors. The representative two-dimensional classification model of emotion is American psychologist James Russel's circumplex model (See Figure 1-3), which is also called the VA (Valence–Arousal) emotion model because of its horizontal and vertical axis structure (horizontal axis indicates valence, with left and right indicating negative emotion and positive emotion respectively; vertical axis indicates arousal, with top and bottom indicating high and low arousal respectively).There are many kinds of three-dimensional classification models of emotion, mainly defining the type of emotion through the axes and poles. All emotions are distributed in different positions between the two poles of each axis, and the two commonly used are the three-dimensional emotion model consisting of pleasure, arousal, and dominance, and the three-dimensional emotion model consisting of pleasure, activation, and attention. Another three-dimensional model of emotion is the "Emotion Wheel" model based on the evolutionary theory of emotion proposed by American psychologist Robert Plutchik (See Figure 1-4), also known as the inverted cone three-dimensional model of emotion, which contains three dimensions: polarity, similarity, and intensity. Unlike the traditional dimensional model of emotion, this model is part of the evolutionary theory of emotion, which systematically explains the eight basic emotions and puts forward the important statement that "other emotions (compound emotions) are a combination of basic emotions". The four-dimensional model of emotion classification is not widely accepted because it is too abstract and complex. At present, the two-dimensional classification model and the three-dimensional classification model

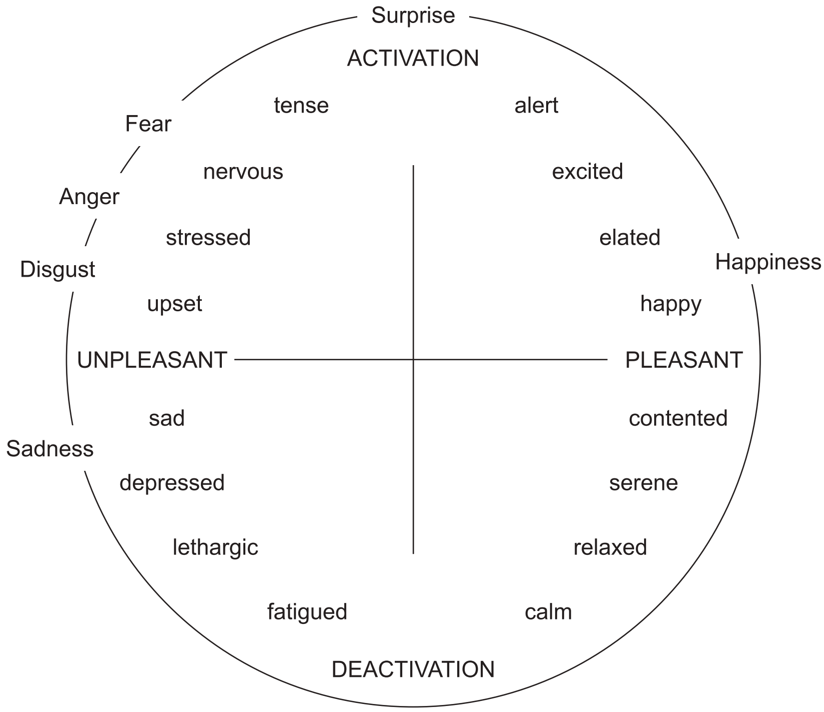


Figure 1-3 American Psychologist James Russel's Circumplex Model, the VA (Valence–Arousal) Emotion Model

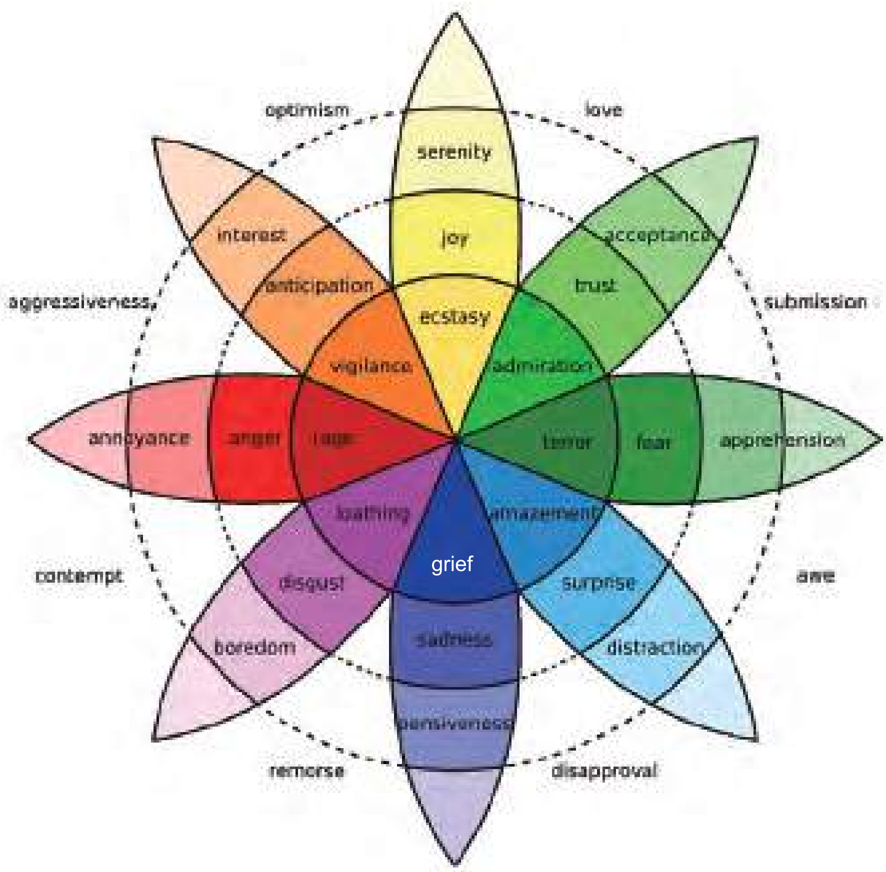


Figure 1-4 "Emotion Wheel" Model Proposed by American Psychologist Robert Plutchik of emotion are more frequently used. Based on these theoretical models, the researchers have tried to quantify emotions and convert them into objective and representable data in order to promote the development of human-computer interaction and research on emotional experience.

1.2 Evolution, Definition and Content of Affective Computing

1.2.1 Evolution of Affective Computing

Since the concept of artificial intelligence was proposed in 1956, research on affective computing has become increasingly active (See Figure 1-5).

The research on affective computing in China started in the 1990s. In the past 20 years, the research of affective computing in China has flourished, and it has developed from the original independent research to internationalization, alliance and systematization (See Figure 1-6).

1.2.2 Definition of Affective Computing

Marvin Minsky, the "father of artificial intelligence," was asked about machine emotions, and he argued that the heart of the problem is not whether intelligent machines can have emotions, but whether machines without emotions can be intelligent. Although he was the first to propose the idea of making computers capable of emotions, the first person recognized in the academic community to formally propose a complete definition of affective computing was Rosalind Picard. In her book *Affective Computing*, she defines affective computing as computing that addresses the external manifestations of people, can be measured and analyzed, and can exert influence on emotions. In addition, there are some scholars who offer different insights. Unlike Rosalind Picard's cognitivist framework, the Swedish computer scientist Kristina Höök and the American computer scientists Phoebe Sengers and Paul Dourish started from phenomenology and argued that emotions in affective computing are constructed in the process of interaction between people and between people and machines.Fuji Ren, an academician of the Japanese Academy of Engineering, believes that affective computing aims to narrow the communication gap between computers and humans by developing systems and devices that can recognize, express and process human emotions. Hu Baogang and his team at the Institute of Automation of the CAS believe that the purpose of affective computing is to establish a harmonious human–computer environment by enabling computers to recognize, understand, express, and adapt to human emotions, and to make computers have higher-level and more comprehensive intelligence. Li Taihao, the member of the Research Center for Multi-Modal Intelligence of the Research Institute of Artificial Intelligence of Zhejiang Lab, believes that affective computing is to enable computers to perceive, recognize, understand emotions and make anthropomorphic emotional expressions.

1.2.3 Research Content of Affective Computing

The research content of affective computing mainly includes five aspects (See Figure 1-7). The models of the basic theory of emotion mainly include two types: discrete emotion model and dimensional emotion model (See Figure 1-8). Discrete model and dimensional model have their own advantages and disadvantages, and the specific model to be used depends on the actual application tasks and scenario requirements.

In terms of signal data collection, as the most important communication tool for human beings, language has formed massive data resources on various communication carriers, providing big data resources for text mining. Therefore, the cost of language signal acquisition is the lowest,

1956

A meeting at Dartmouth College discussed how to use machines to simulate human intelligence. At the meeting, the concept of Artificial Intelligence (AI) was proposed for the first time, and AI technology was born. Since then, people have begun to develop human-like intelligent systems by studying the laws of human intelligent activities, so that computers can simulate human intelligent behavior. The previous research basically focused on the realization of human rationality and logical activity laws in machines. At the same time, psychologists are gradually advancing the study of sensibility or emotion.

1960

Daniel Katz, an American social psychologist, published a theory on attitude function, revealing that attitude has four basic functions, i.e. adaptive function, self-defense function, cognitive function, and value expression function.

1990

The American psychologists Peter Salovey and John Mayer published an article called *Emotional Intelligence*, describing the framework they had created for emotional intelligence. The article argues that emotion is also a kind of intelligence with processing power and emphasizes the cognitive component and processing capacity of emotion.

1997

Rosalind Picard published *Affective Computing*, a systematic discussion of affective computing. At this point, this interdisciplinary subject began to receive widespread attention.

1998/1999/2004

The Association for the Advancement of Artificial Intelligence (AAAI) held professional academic conferences on artificial emotion and cognition in 1998, 1999, and 2004, respectively. During the same period, “Kansei Engineering” was gradually developed in Japan, i.e., to realize the satisfaction of human sentimental demand from the perspective of engineering, and to transition the research on emotional information from the perspective of psychology to the integration of psychology, electromechanical science, information science and other related disciplines. In Europe, many universities have established research groups on the relationship between emotion and intelligence.

2004-2007

The European Union established a human-computer interaction emotion engagement called HUMAINE, which aims to lay the foundation for the development of affective guidance systems that can record, model and influence human emotions. Twenty-seven EU universities are jointly involved in the engagement.

2010

IEEE Transactions on *Affective Computing* was founded and is the first journal in the field of affective computing. It was founded by the world’s largest non-profit professional and technical association, the Institute of Electrical and Electronics Engineers (IEEE).

Figure 1-5 Development of Affective Computing in Foreign Countries

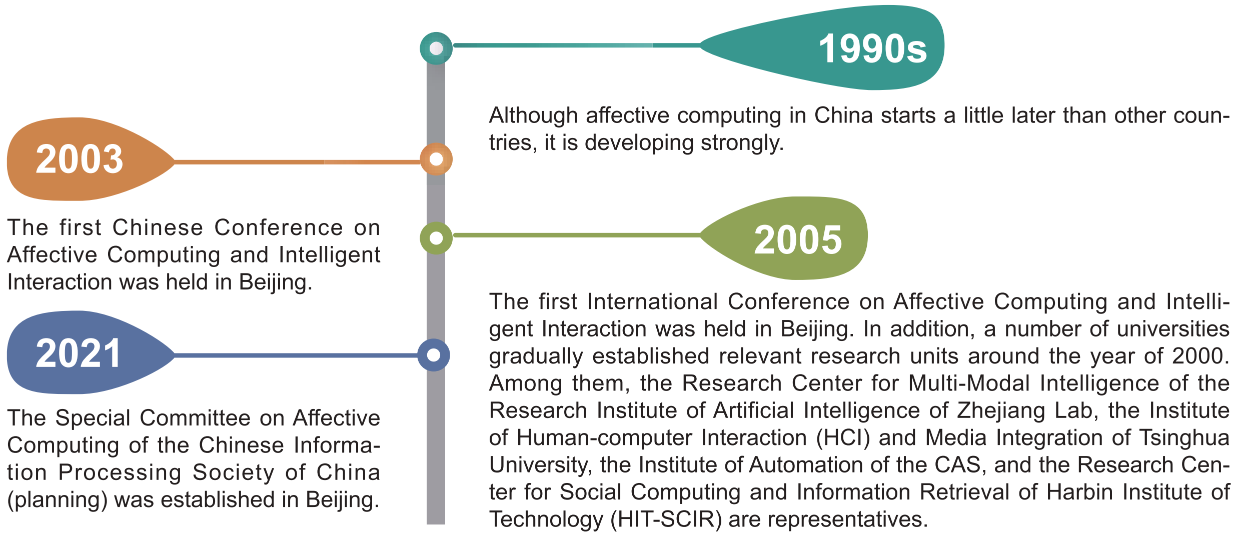


Figure 1-6 Development of Affective Computing in China

Figure 1-7 Research Content of Affective Computing

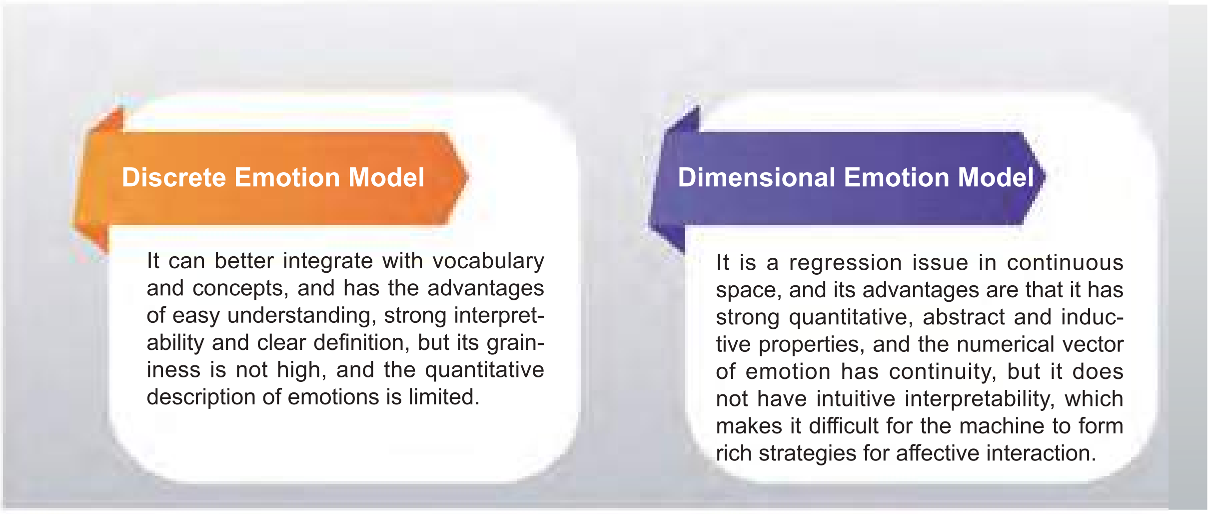


Figure 1-8 Models of the Basic Theory of Emotion

but the data quality is uneven, which is prone to grammatical errors, garbled characters and other problems, which would adversely affect emotion recognition.

Because of the lower cost of cameras, microphones, and other sensors, and being without direct contact with the user, it is more convenient to collect emotional signals such as speech and facial expressions. The amount of data in these areas is very large, and the number of related research papers is also large, and many data come directly from the actual scene. Compared with text, speech, expression, and other signal data, physiological data has the advantage of reflecting individual's affective state more directly, objectively, and realistically, and is less influenced by individual's subjective consciousness. Therefore, physiological data has become one of the research hotspots in the field of affective computing. At present, in the field of affective computing, the common physiological data include electroencephalogram (EEG), galvanic skin response (GSR), respiratory (RSP), skin temperature (SKT), electrocardiogram (ECG), electromyogram (EMG), blood volume pulse (BVP), electrooculogram (EOG), etc. Since the acquisition of physiological data requires the wearing of more complex and costly physiological data sensors, which is more difficult to be promoted in practical applications. Currently, the scale of physiological data used in the laboratories or research institutes is generally small.

For text data, speech data, visual data, physiological data, etc., researchers have developed corresponding data analysis algorithms and tools (See Figure 1-9).

① ***Text data analysis***. Traditional text sentiment analysis performs sentiment analysis by constructing a domain-specific sentiment dictionary and then referring to the mapping relationship between sentiment words and text, but the specific properties of the dictionary limit its text sentiment analysis's ability to be applied in multiple fields. In recent years, with the development of deep learning, the pre-trained models for language represented by Bidirectional Encoder Representation from Transformers (BERT) and Generative Pre-Training (GPT) based on Transformer model have been successful in a variety of sentiment analysis tasks, which has attracted great attention from academia and industries.

② ***Speech data analysis.*** Speech emotion rec-

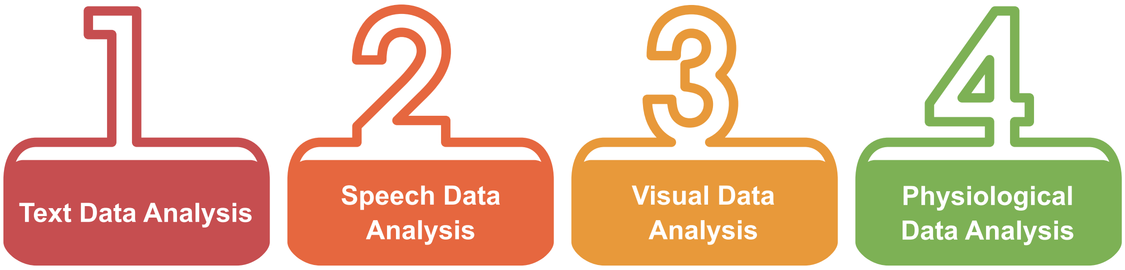


Figure 1-9 Data Analysis Algorithms and Tools

ognition draws on the technologies of linguistics and acoustics, and in addition to analyzing grammar and semantics, it also recognizes acoustic feature information related to affective states, such as pacing, voice and intonation. Currently, the VGGish model and wav2vec model are more widely used to extract speech features of emotion.

③ ***Visual data analysis.*** In the video and image emotion recognition such as facial expressions, body movements and scene environments, the research on facial expression recognition occupies the main part.The Facial Action Coding System (FACS) proposed by Paul Ekman et al. is a classical and basic expression recognition model that is simple but widely used. Based on deep emotional features of deep neural networks, neural network models trained using face emotion recognition datasets, such as VGGNet, have achieved good results.

④ ***Physiological data analysis.*** Compared with the text, speech, and expression signals mentioned above, the recognition of physiological signals is more difficult, and physiological signals have unique properties. For example, when computing EEG data, a more complicated pre-processing process needs to be carried out, including electrode position localization, band-pass filtering, conversion reference, analysis segment interception, artifact removal, bad electrode interpolation, etc. Subsequently, feature extraction, feature dimension reduction and other steps have to be taken, and finally, machine learning classifier is applied to recognize emotions. Since 2018, the number of papers using deep learning methods to carry out EEG data affective computing has shown a large growth trend. Convolutional Neural Network (CNN), Deep Belief Networks (DBN), Recurrent Neural Network (RNN), and Stacked Auto Encoders (SAE) have been commonly used.

Early affective computing is generally Unimodal. That is, data analysis and emotion recognition are performed on one of the modalities such as text, speech, expression, body movement, and physiological signal. However, when people express emotions, they often express them jointly through multiple channels, and the emotion information obtained by using emotion recognition is relatively limited. Human emotions are rich, delicate, and expressed in various forms, which requires fusion of multiple information sources, integrated processing, and coordinated optimization in order to recognize human emotions as accurately as possible. Multimodal fusion algorithms use information from different modalities to integrate into a stable multimodal representation, thus effectively solving this problem. According to the different fusion stages, common multimodal fusion methods can be classified as early fusion based on feature level, hybrid fusion based on model level, and final fusion based on decision level.

Based on the analysis and recognition results of emotions, the machines pass expressions and responses with emotional temperature to users through facial expressions, emotional response generation, body movements, etc. For example, synthesize speech by using the specific voice style and integrating the text content to allow the machines to express specific emotions. This process requires the input of synthesized text content and a specific style of voice into the neural network, and then allows the neural network to synthesize a specific style of speech. If you want to express emotions through body movements, it is necessary to first analyze the basic units of action, and then synthesize corresponding interactive actions based on the mapping relationship between emotions and unit combinations for the machines to execute.

1.3 Significance of Affective Computing

(1) Affective computing is a fundamental technology and an important prerequisite for naturalized, anthropomorphic and personalized human-computer interaction.

Firstly, affective computing gives “depth” to human–computer interaction. Although computers already have powerful computing power, they are unable to interact with people in a deep and natural way without the ability to feel emotions similar to people. Rosalind Picard has stated that she was limited in her research on artificial intelligence because she seemed to ignore emotions or was unable to fully understand the mechanisms of emotion in all aspects of her research, which led her to propose the concept of affective computing and conduct research on it.The recognition and expression of emotion is necessary for the communication and understanding of information, and making machines equipped with emotional intelligence can contribute to the deep perception and understanding of interactive information. Secondly, affective computing allows human–computer interaction to have “warmth”. The interaction between human and machine is no longer cold and programmed, but more intimate and empathetic, highlighting the humanism, human understanding and humanistic care. Finally, affective computing gives human-computer interaction an “attitude.” The machines have personalized characteristics, personality and even self-awareness, thus bringing a new human-computer symbiosis ecology.

(2) Affective computing provides an optimized path for AI decision-making.

In the 17th and 18th centuries, the mind-body dualism proposed by the French philosopher René Descartes dominated thought in the western world. Descartes refused to acknowledge the role of emotions in rational decision-making, arguing that that people lose their autonomy when they are dominated by emotions. However, numerous studies have now shown that emotions play an important and positive role in rational thinking processes such as decision making, understanding, and learning, and influence the final outcome. Cognitive neuroscientists have provided solid scientific evidence for the theory that emotion has an effect on cognition through studies of pathology of affective disorders, neurophysiology, and neuroimaging. Numerous studies have shown that the purely rational decision-making process is often not the optimal solution when solving certain problems. The addition of emotion in the decision-making process may help people find better solutions. Therefore, the input of affective variables in the AI decision-making process may help the machine to make more humane decisions.

(3) Affective computing can be widely used in many fields, which is of great value to open the intelligent and digital era.

Currently, affective computing is being used in many fields such as education and training, healthcare, and commercial service to greatly improve the quality of life and happiness of people.

In the field of education and training, the entry point of affective computing is mainly to identify the affective state of learners and then give corresponding feedback and adjustment. For example, teachers can further understand students’ participation through the emotional teaching intelligence system, so that they can adjust the teaching rhythm and content in time and improve the teaching plan. The intelligence system can use sentiment analysis to explore topics of interest to students, and then make customized learning content recommendations. Students can also use the intelligence system to provide real teaching feedback and improve the comprehensiveness and accuracy of teaching evaluation.The advantage of the intelligence system is that it can be used in traditional classrooms as well as embedded in web-based software for online classroom applications. Especially under the influence of the COVID-19 pandemic, online education and training are used in a wider and more frequent scenario, but distance education lacks an emotional classroom atmosphere with face-to-face interaction, so online classrooms using affective computing are worth applying and promoting. In addition to classroom education, affective computing is also beneficial to the research and development of educational games and educational robots. Games and robots that incorporate affective elements can bring better human–computer interaction experiences, thus achieving the purpose of education and training more effectively.

In the field of healthcare, especially in the treatment of mental diseases, affective computing can scientifically and objectively identify and judge patients' emotions, which is a useful supplement to traditional diagnostic methods that are more subjective, such as behavior observation and scale filling. Objective data is conducive to the improvement of personalized and precision the standards, and based on the collected data, the most appropriate treatment plan can be tailored for the patient.

In the field of commercial service, the application of affective computing is even more extensive. Consumer experience is highly related to emotions, and affective computing can help companies understand the inner world of consumers and the triggers that drive consumer behavior. The resulting information can help companies develop forward-looking business strategies. In addition, products that incorporate affective computing can provide consumers with more intimate services.

Furthermore, affective computing can be used for security guard and public sentiment monitoring to improve monitoring quality while reducing labor costs and ensuring social harmony, stability, and security.

In general, although the research and application of affective computing doesn't last long, its potential is huge. Most of modern science has developed in the process to understand and transform the external world, but currently, people's understanding of their inner world is still in a relatively superficial stage. Therefore, affective computing is a qualitative leap under the framework of artificial intelligence, reflecting a higher level of intelligence, and help lead human beings to a harmonious human–machine symbiotic society.

Chapter Ⅱ Technological Overview

With the continuous development of computer science and the increasing demand of society for personalized human–computer interaction, the importance of affective computing in human-computer interaction is becoming more and more prominent, and research on human–computer interaction based on the understanding and expression of emotions has received extensive attention in various fields.

Affective computing plays an indispensable role in many activities such as human perception, reasoning, decision-making, planning, creation, and social interaction. The research on affective computing is of great importance in the behavioral analysis science. Affective computing can be broadly classified into unimodal affective computing and multimodal affective computing, and this chapter develops further introduction to affective computing in order as shown in Figure 2-1.

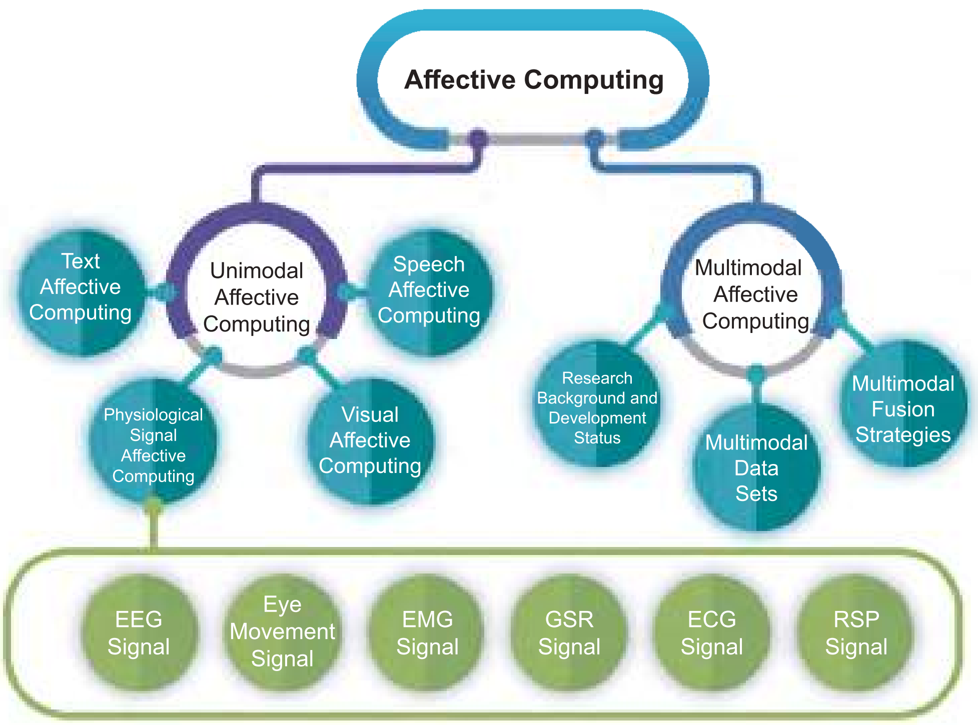


Figure 2-1 Affective Computing Research Framework

2.1 Unimodal Affective Computing

Unimodal affective computing contains four main modalities: text, speech, vision, and physiological signal. The introduction of their technologies is given below, respectively.

2.1.1 Text Affective Computing

Text is the medium through which people communicate with one another due to the limitations of time and space, and it is also a carrier for recording information. Texts record the activities of human thinking and consciousness, and some of them are bound to have emotional tendencies, so the mining, research, and application of this part of information are the main content of text affective computing.

(1) Research Background and Development Status

For unstructured data such as language, machines cannot directly understand, so NLP came into being. NLP has two core tasks, namely NLU: Natural Language Understanding, which is to understand long texts such as sentences, paragraphs, and discourses through grammatical analysis, syntactic analysis, and semantic analysis; and NLG: Natural Language Generating, which is the conversion of non-verbal data into a language format that humans can understand. NLP builds a bridge between humans and computers.

Due to the huge and complex big data, manual analysis is costly and time-consuming. The application of data technology and AI technology to analyze the emotion of text can greatly improve the efficiency and accuracy. Therefore, text affective computing has emerged and become a major research hotspot in NLP. Currently, Text affective computing belongs to the field of computational linguistics, which mainly studies the correspondence between affective states and text information. Text emotion recognition mainly consists of text emotional feature annotation, text emotional feature extraction algorithm and text emotion classification technology.

Since computers cannot recognize text, it needs to be converted into a vector before analysis. At present, the common methods for generating vectors from text include CNN, RNN, Long Short-Term Memory (LSTM). Text sentiment analysis methods are roughly divided into analysis methods based on sentiment dictionary, analysis methods based on traditional machine learning, and analysis methods based on deep learning.

(2) Data Sets

NLP data sets are mainly produced by language type, among which the data sets related to the field of Chinese text classification are: THUCNews dataset generated by filtering the historical data of Sina News RSS subscription channel between 2005 and 2011, weibo_senti_100k and simplifyweibo_4_ moods generated according to Sina Weibo, Toutiao news text classification dataset, SogouC and SogouCS developed by Sogou Lab, and DataHub, a service module accessed by the data center with Tencent Cloud message queue CKafka going live. The relevant data sets in the field of English text classification are: Amazon Reviews Dataset, Enron Email Dataset, IMDB Dataset containing more than 50,000 movie reviews, and WordNet, a large English vocabulary database.

(3) Principal Methods

The primary research problem of text sentiment analysis is emotion classification, and there are roughly five mainstream emotion classification methods: the method of comparative analysis by building a sentiment dictionary with emotional tendencies, the method based on machine learning, the method based on sentiment dictionary + machine learning, the method based on weak annotation, and the method based on deep learning.

There are three main types of sentiment analysis methods based on traditional machine learning: supervised learning, semi-supervised learning, and unsupervised learning. Supervised learning, which is essentially classification, is a method of training existing training samples to obtain an optimal model, then mapping all the inputs to the corresponding outputs, and simply judge the outputs to achieve the purpose of classification. The common supervised learning methods include K-Nearest Neighbor (KNN), Naive Bayes, Support Vector Machine (SVM). Unsupervised learning doesn't have any training samples and requires modeling the data directly. The commonly used methods are: K-means clustering algorithm (K-means), Principal Component Analysis (PCA). Semi-supervised learning method is a learning method that combines supervised learning and unsupervised learning.

Although the above methods are simple and easy to understand, and also have high stability, they have the defects of insufficient precision and reliance on manual operations. The analysis method based on deep learning provides a good complement in these two aspects. One is that the introduction of neural networks makes the prediction precision of the model improved; the other is that the complexity of work is reduced by not requiring additional construction of dictionaries, and the reliance on manual operations is reduced.For example, LSTM can coherently follow the texts, and BERT can use the full text as a training sample to extract features.

When people read a text, they infer the true meaning of the current word based on the understanding they already have of the previously seen word, i.e., the idea is persistent. Therefore, RNN is first applied to NLP to ensure the persistence of information and the coherence of information, among which the classical RNNs are LSTM and Gate Recurrent Unit (GRU). As the application of neural networks in NLP progresses, researchers have found that combined neural networks often have performance gains over single neural networks. For example, capturing local features (CNN) after the neural layer of LSTM can further improve precision. However, RNN is not perfect, especially the mechanism of RNN suffering from the problem of long-range gradient disappearance, and for longer sentences, the hope is impractical that the input sequence can be converted into a fixed-length vector to preserve all valid information. In order to solve the problem of information loss caused by the conversion from long sequences to fixed-length vectors, the Attention Mechanism is introduced. In 2018, Google's BERT model brought pre-training to the public's vision, i.e., the language model is trained through a large number of unlabeled language texts, so as to obtain a set of model parameters. By using this set of parameters to initialize the model, and then fine-tuning the existing language model on the basis of specific tasks, the precision of the model can be improved.

(4) Problems and Challenges

Due to the complexity of language, text extraction still faces many challenges, such as the extraction of textual implicit content, the emergence of non-standardized text, and the text sentiment analysis in different languages. In view of the complexity of the application scope of text sentiment analysis, the application scope of the model is often relatively small, and it is difficult to maintain good performance in multiple application scenarios. In addition, the limited data set also limits the application of text sentiment analysis in diverse scenarios.

Although text can independently express certain emotions, human communication is always carried out through the comprehensive expression of information. Therefore, multimodal sentiment analysis is more in line with people's perception of emotions and more in line with the patterns of human expression of emotions. The findings of the study also reveal the fact that multimodal sentiment analysis works better than single text sentiment analysis. Based on the common ways of modality combination, two types of multimodal analysis are derived from text sentiment analysis:

text–audio analysis and video–text analysis. This is also a common area of concern for researchers.

2.1.2 Speech Affective Computing

(1) Research Background and Development Status

Traditional speech processing systems only focus on the accuracy of speech vocabulary transmission. With the rapid development of speech recognition technology, how to recognize emotions in speech has become an emerging research direction in the field of speech recognition. Nowadays, the interaction between "things" and "people" has become more frequent and important, and speech interaction, the most natural interaction between people, has become a more ideal human–computer interaction solution in the Internet of Things.

Speech emotion refers to the emotion of the speakers contained in the speech signal, which are mainly manifested in two parts: one is the language emotional content contained in the speech, and the other is the emotional characteristics of the voice itself, such as the change of pitch. Computing related to speech sentiment are called speech affective computing. The research content of speech affective computing includes speech emotion recognition and speech emotion synthesis.

(2) Data Sets

Speech emotion data sets are an important part of speech affective computing. At present, there are two main ways to classify the data sets, according to the generation method of emotion speech and the descriptive model of emotion, respectively. According to the way of speech generation, speech emotion data sets can be classified into three categories, namely, performative, guided, and natural; according to the description model of emotion, the data sets can be classified into two categories, namely, discrete emotion data sets, and dimensional emotion data sets. The commonly used representative data sets are shown in Figure 2-2.

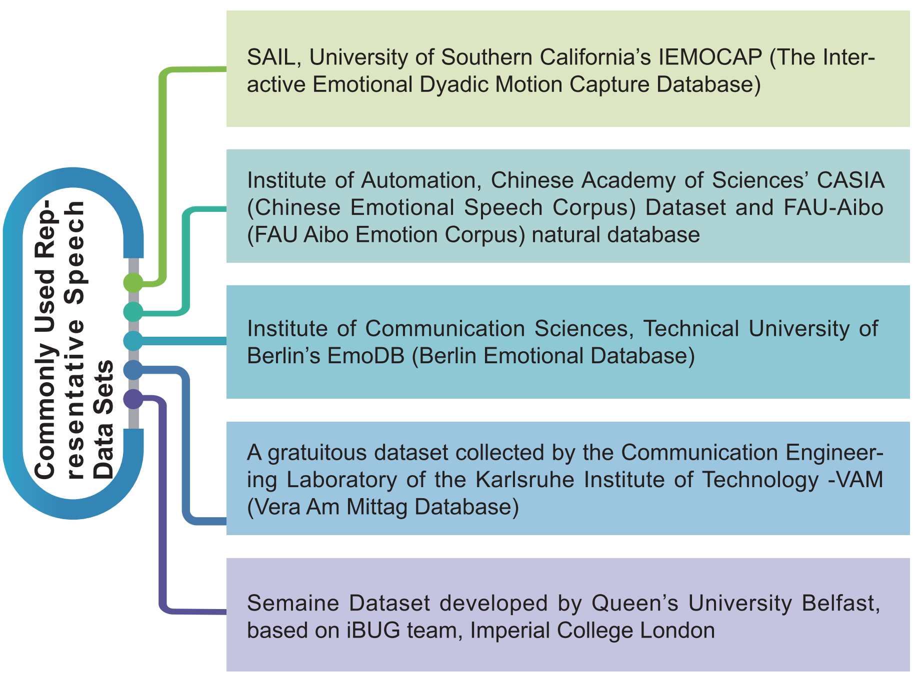


Figure 2-2 Commonly Used Representative Speech Data Sets

(3) Principal Methods

The methods used by speech emotion recognition systems to classify the potential emotion of a given speech include traditional methods and the methods based on deep learning. Firstly, two types of traditional classifiers are introduced: one is statistical-based classifier and the other is discriminative-based classifier. Statistical-based classifiers mainly include Hidden Markov Model (HMM), Gaussian Mixture Model (GMM), and KNN. Discriminative-based classifiers mainly include Artificial Neural Network (ANN), Decision Tree, and SVM. Deep learning algorithms, which are widely used in the field of speech emotion recognition due to their multi-level structure and efficient results, mainly include Deep Boltzmann Machine (DBM), RNN, CNN, LSTM, and LSTM with the introduction of Attention Mechanism.

(4) Problems and Challenges

Although speech affective computing has a broad application prospect, it has not yet reached a mature stage. At present, the problems to be solved in speech affective computing include the lack of widely recognized data sets, difficulty in labeling, and unclear relationship between acoustic features and sentiment mapping of speech.

2.1.3 Visual Affective Computing

(1) Research Background and Development Status

In the era of social media, with the popularity of mobile terminals with photo functions, all kinds of images and videos are flooding into the Internet, which provide researchers of affective computing with numerous research data resources, and people try to use suitable models to recognize the emotional information carried by pictures and videos.

The current research hotspots of visual affective computing include: facial expression-based emotion recognition research and body movement-based emotion recognition research. Specifically, facial expression-based emotion recognition mainly uses traditional computer visual and deep learning to understand facial features and emotions; body movement-based emotion recognition research mainly uses human body movements to obtain human emotion information. Compared with facial expression, body movement has greater freedom, which enables it to express more complex emotions and even intentions in richer ways, helping to enable machines to understand richer and more subtle emotions, and then tap deeper emotions and intentions in the individual's heart.

(2) Data Sets

Visual emotion data sets can be divided into image emotion data sets (See Figure 2-3) and video emotion data sets (See Figure 2-4).

(3) Principal Methods

Visual affective computing focuses on perceiving and understanding human emotions from visual information and can be studied by traditional machine learning methods and the methods based on deep learning.

Traditional machine learning methods mainly include: Histogram of Oriented Gradient (HOG), SVM, KNN, Random Forest. However, when faced with today's exploding amount of visual content data, traditional machine learning methods are difficult to deal with the scalability and generalization of multimedia content data quickly and accurately.

In recent years, deep learning has achieved good results in many fields, especially in computer vision fields such as image classification, image recognition, and image retrieval.

Compared with traditional methods, deep learning methods for visual affective computing have better robustness and accuracy, so it is widely used in the field of vision-based affective computing and sentiment analysis. Image affective computing methods are represented by CNN method, which mainly uses deep learning to automatically

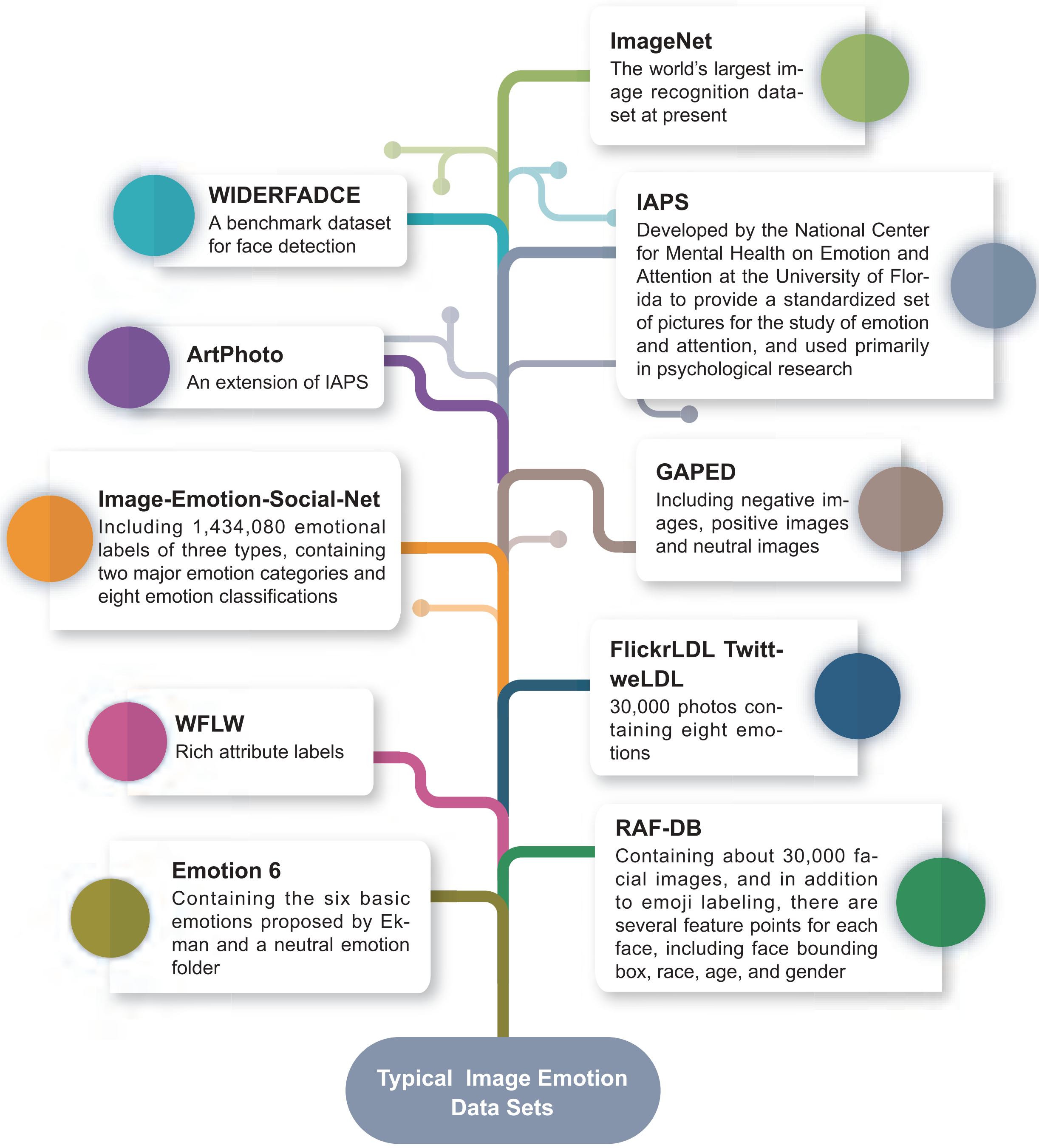


Figure 2-3 Image Emotion Data Sets

learn effective or strong features that are helpful for emotion classification from a large amount of image data, so as to further improve the image affective computing or classification ability. Video affective computing methods are mainly based on RNN, and this kind of deep learning methods is good at processing sequence inputs such as videos, which are widely used in computer vision tasks.

(4) Problems and Challenges

Visual affective computing faces many challeng-

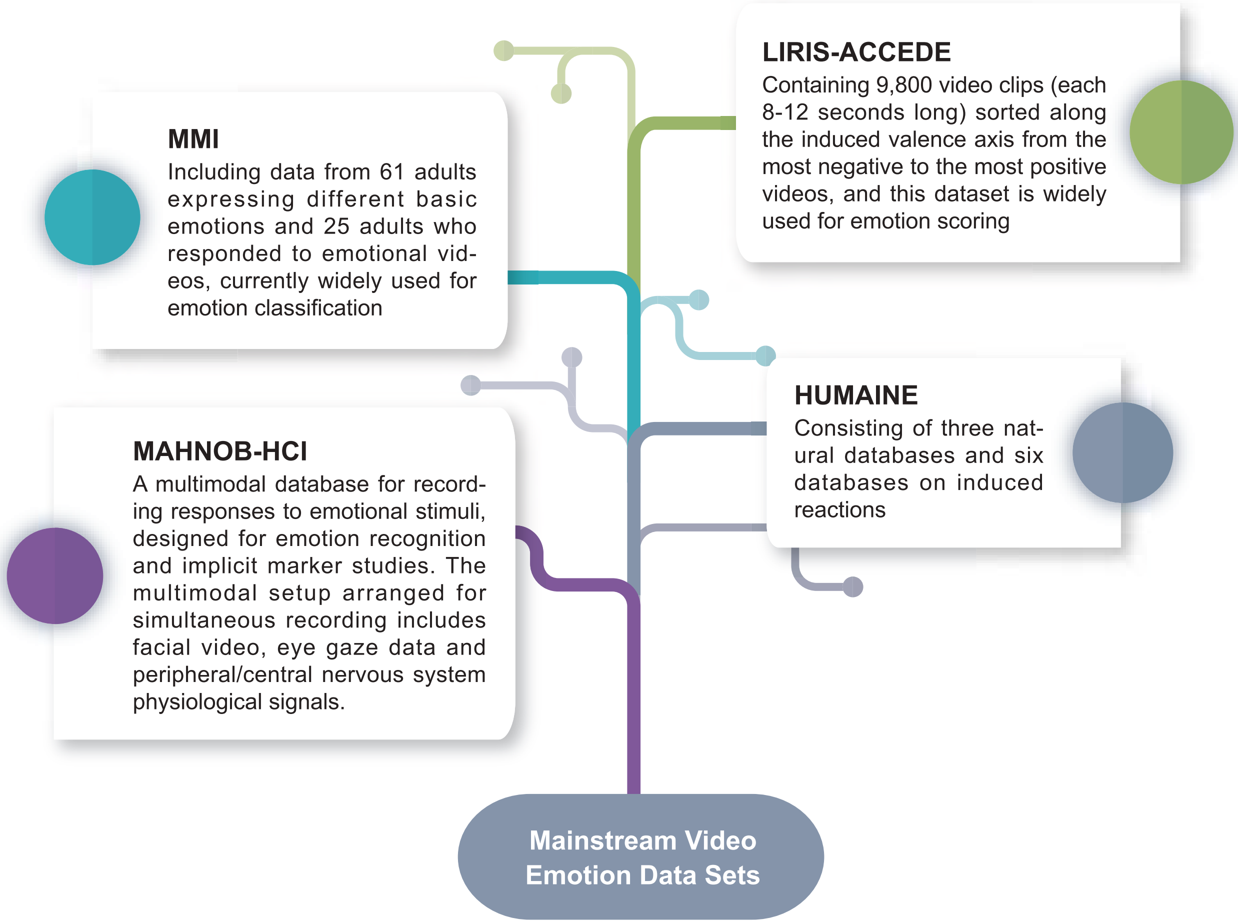


Figure 2-4 Video Emotion Data Sets

es in practical applications: One is the semantic gap. The semantic gap is the bias caused by the inconsistency between the visual information of the image acquired by the computer and the semantic information of the user's understanding of the image. Another is the problems related to the accuracy of emotion representation and the difficulty of annotation.

2.1.4 Physiological Signal Affective Computing

(1) Research Background and Development Status

Physiology-based affective computing has increased dramatically with the popularity of accurate small, portable and low-cost sensors. Broadly, all physical changes can be seen as the physiological signals. The most commonly used physiological characteristics in the research on affective computing are EEG, heart rate, and heart rate variability, as well as the GSR.

(2) Common Physiological Signals

① EEG Signal

Compared with other physiological signals, EEG signals have the features of direct objectivity, being difficult to disguise and easy to quantify, and diversified characteristics, and have direct correlation with emotions, which can show higher emotion recognition accuracy, so they have become one of the most widely used signals in emotion recognition based on physiological signals. The most important process in EEG signal preprocessing is to remove artifacts and noise and strip the electrical activity associated with emotions so as to extract various features such as time domain features (e.g. ERP, signal statistics, instability index, higher-order cross features, fractal dimension), frequency domain features (e.g. power spectral density, differential entropy), time-frequency domain features (e.g. ERS, ERD, time-frequency differential entropy), nonlinear dynamics features, and space domain features, and bring them into classifier for classification. The methods based on deep learning such as CNN, DBN, and Deep Residual Network (DRN) have also been used for the process of classifying emotions based on EEG signal.

② Eye Movement Signal

Eye movement signal is mainly acquired by eye-tracking technology, which records the data of human eye movements in time and space. These data mainly include fixation duration, fixation position, pupil size, and electrooculogram signal, among which the electrooculogram signal is the more widely used signal in the eye movement signal. It extracts features by various ways such as Hjorth parameters and discrete wavelet transform, so as to bring them into the classifier for classification. Deep learning algorithms are also gradually applied to several emotion recognition processes such as feature extraction, feature fusion, and emotion classification to enhance the effectiveness of affective computing tasks.

③ EMG Signal

EMG signal is mainly obtained by detecting the surface voltage generated during muscle contraction by electrodes, thus obtaining EMG data, and the main data sets include DEAP, DECAF, HR-EEG4EMO, BioVid Emo DB. The characteristics of EMG signal generally contain two aspects: time domain and time-frequency domain. The time domain mainly extracts statistical features such as mean, standard deviation, maximum value, minimum value of EMG signal. The time-frequency domain mainly decomposes the EMG signal by wavelet transform and extracts the mean and standard deviation of wavelet coefficients in each layer. The pre-processing of the EMG signal includes filtering, noise reduction, and feature extraction based on time domain, frequency domain and combination of time and frequency domain, etc. The wavelet transform and independent component analysis (ICA) algorithm are used for feature selection and dimensionality reduction, so that they can be brought into the classifier in the traditional method or deep learning algorithm for classification.

④ GSR Signal

GSR signal is a commonly used indicator for affective computing and is dependent on the body's sweat gland secretion, with conductance varying as sweat ions fill the sweat glands. Skin conductance can be measured anywhere on the body, with the most common electrode placement being at the end of the middle and index fingers of the hand. Skin conductance level (SCL) and skin conductance response (SCR) are two important features for affective computing. The main data sets include CASE, DEAP, HR-EEG4EMO, BioVid Emo DB, etc. The pre-processing of GSR signal includes noise reduction, normalization, etc., and feature extraction by extracting statistical features or algorithm optimization, and finally put them into the appropriate classifier for affective computing.

⑤ ECG Signal

ECG signal is a synthesis of the action potentials generated by the cardiomyocytes when the human heart beats. ECG signal can reflect the activity of the heart, and changes in emotion can also directly lead to changes in cardiac activity, so ECG signal can also be used in the field of emotion recognition. ECG features mainly include PQRST, heart rate, heart rate variability (SDNN, SDANN, rMSSD, Pnn50, etc.). There are few publicly available emotional ECG datasets, and the most commonly used datasets are the emotional physiology dataset from the University of Augsburg, Germany and HR-EEG4EMO dataset.

⑥ RSP Signal

Breathing is an important physiological process in the human body, and as emotional states change, the activity of the respiratory system changes in speed and depth. Therefore, we can identify people's internal affective and emotional changes by studying RSP signal. The common features include respiratory rate, average respiratory level, longest and shortest time between consecutive breaths, deep and shallow breaths, intervals between adjacent respiratory waves, first-order differential and second-order differential of respiratory amplitude, etc. The common data sets are DEAP database, HR-EEG4EMO dataset, and the MIT emotional physiology dataset.

(3) Problems and Challenges

Although emotion recognition technology based on physiological signals has achieved many successful cases, there are many unsolved scientific problems. The first is the inconvenience of signal acquisition.Measuring physiological signals is the first step in establishing a physiological affective computing system, but the sensors used to detect signals are greatly limited by the site, environment, operability, and other problems, and also face problems such as poor wearability, and weak computing ability; secondly, the versatility of physiological signals is low, such as changes with age or certain diseases, so people's direct physiological signal data would be different, even if the same person. Physiological signals are affected with changes in physical activity, conversation or posture, and this is not directly related to emotional changes. In addition, other problems include inaccurate emotion annotation, difficulty in windowing data, cumbersome sampling, data processing and computing issues, many-to-one mapping between non-emotional and emotional physiological effects, user privacy issues.

2.2 Multimodal Affective Computing

Although facial expressions, body movements, and speech can be independently understood and expressed emotionally, people's mutual communication is always carried out through the comprehensive performance of different modal information. Multimodal sentiment analysis can complement the information between different modalities and use it for disambiguation, making sentiment analysis more accurate, more robust, and more in line with human natural expression. This makes multimodal affective computing one of the hottest topics in the field of artificial intelligence today.

2.2.1 Research Background and Development Status

Since unimodal information is insufficient and easily influenced by various external factors, such as facial expressions are easily masked and speech is easily disturbed by noise. In addition, when the individual subjectively masks the emotional signal or the emotional signal of a single channel is affected by other signals, the performance of sentiment analysis will be significantly reduced. Human emotions are usually presented in a variety of modalities, and the brain has a multi-stage fusion phenomenon when integrating multi-sensory information. Multimodal sentiment analysis can effectively utilize the synergistic complementarity of information from different modalities to enhance emotional understanding and expression. The introduction of multimodal affective computing is the key to improve the robustness and performance superiority of the model.

At present, research on multimodal affective computing mainly focuses on methods for emotion recognition and understanding. The development trend of multimodal affective computing is concentrated in four aspects:integrating semantic information to accurately understand emotions at multiple scales, and conducting multimodal sentiment analysis from multiple dimensions;enhancing the robustness of affective computing in complex environments, realizing accurate recognition of the target object's affective state under non-collaborative open mode for high-dimensional fragmented open source data;combining with pre-training and multi-task joint training methods to realize multimodal affective computing in more scenarios;exploring a universal multimodal affective computing model, and realizing zero-cost migration of multimodal affective computing applications by adapting to multi-scenario applications.

2.2.2 Multimodal Data Sets

In response to the urgent need for multimodal affective computing, Carnegie–Mellon University in the United States proposes a large-scale multimodal affective computing dataset, CMU-MOSEI. CMU-MOSEI contains video text, acoustic features extracted by the COVAREP.

In terms of labels, CMU-MOSEI dataset have emotion labels, and measures the strength of emotion, which can support fine-grained sentiment analysis tasks. At present, the mainstream physiological signal-based multimodal affective computing resources mainly use audio and video stimulation methods to induce emotions, synchronously collect multimodal physiological signals, and then analyze the responses of the central nervous system and autonomic nervous system under different emotions to achieve emotion recognition based on multimodal physiological signals. The typical computing resources include data sets such as DEAP, DECAF and HR-EEG4EMO, as well as EEG, GSR, RSP, SKT, ECG, EMG, BVP, EOG,. Participants scored their feelings from dimensions such as arousal, potency, likes or dislikes, dominance, and familiarity. Since factors (such as gender and age) of the subject have an important impact on emotional arousal, the introduction and modeling of relevant demographic information should be considered.

2.2.3 Multimodal Fusion Strategies

Currently, most of the emerging research methods are based on multimodal emotional features and fusion algorithm innovations to improve the accuracy of emotion classification. The quantity and dimensionality of information on human emotions conveyed by each module in affective computing are different. In human–computer interaction, there are still missing and imperfect problems in different dimensions, so the affective computing should start from multiple dimensions as much as possible to fill in the single and imperfect emotional channel, and finally determine the emotional tendency by multi-result fitting.

In terms of modal fusion, multimodal affective computing can be divided into two routes: model-agnostic and model-reliance. Model-agnostic includes feature-level fusion (pre-fusion), decision-level fusion (post-fusion), and hybrid fusion. Feature-level fusion is mainly done first by constructing feature sets or hybrid feature spaces and then feeding them to classification models for classification decisions. The key to decision-level fusion is to find out the confidence level of different modalities in the decision stage, and then to make coordinated and joint decisions. Hybrid fusion includes both of these fusions. Model-reliance designs special structures for multimodal fusion. Kernel function-based fusion and graph-based fusion are often used for shallow models, while neural network-based fusion, tensor-based fusion, and attention mechanism-based fusion are mostly used for deep models. Model-level fusion can input different modal features to different model structures separately before further feature extraction.

Decision-level fusion is easier to perform compared to feature-level fusion, but it is crucial to explore the importance of each modality for emotion recognition. Model-level fusion does not need to focus on exploring the importance of each modality, but rather needs to build a suitable model based on the modality characteristics and jointly learn the association information. In general, compared with decision-level fusion and feature-level fusion, the biggest feature of model-level fusion is the flexibility to choose the location of fusion. In recent years, multi-stage and multimodal emotion fusion has been proposed, i.e., a unimodal model is trained first, and its implied state is spliced with another model feature to obtain a bi-modal model and retrained, and so on to obtain a multimodal model.

2.2.4 Problems and Challenges

Solving the problems of multimodal affective computing requires richer accumulation of modal information and fine-grained alignment between different modalities, which undoubtedly puts forward higher requirements for the refinement and integration of multimodal information. At the same time, due to the influence of emotional information capture technology and the difficulty of labeling, the establishment of high-quality multimodal data sets is one of the major challenges at present. The traditional multimodal learning paradigm does not pay enough attention to the information of association relationship between features and the higher-order information of features, while the deep multimodal learning paradigm lacks large-scale emotional data resources, and the research on the emotional understanding model of multimodal feature fusion needs to be deepened. For example, it integrates semantic information for accurate understanding of multi-scale emotions, enhances the robustness of affective computing in complex environments, and explores general multimodal affective computing models. The improvement of these technologies will further promote the research and development of multimodal affective computing.

Chapter Ⅲ Achievements

This chapter is based on the data of scientific and technical literature. If there is no other special description in the text, the statistical caliber is shown in Table 3-1, and the retrieval strategies is shown in Table 3-2.

In addition, the following databases are used in the White Paper.

Incite database: This database is based on the publication data of all literature types based on the data of the seven indexed databases of the Clarivate Analytics Web of Science Core Collection for publication counting and indicator calcu-

Table 3-1 Statistical Caliber

Source of papers	Web of Science Core Collection database①
Source of patents	Derwent Innovations Index database②
Date of data collection	Jul. 21, 2022
Type of papers	Proceedings Paper, Article, Review Article, Early Aceess
Citation statistical method	The deadline for citation frequency statistics is Jul. 21, 2022, and papers that are not within this time frame and their citation frequencies are not within the scope of citation statistics.
Data cleansing specifications	The names of institutions are cleansed and standardized by both machine and manual methods, but the irregularities in writing of institution names when scientists publish papers may cause omissions in the statistics of papers and deviations in the calculation results of indicators.
Definition of Chinese papers	Including Chinese mainland, Hong Kong, Macao and Taiwan.
Author statistical method	Author statistical method will be explained, including the statistics of first author and all authors.

① Web of Science Core Collection is the world's leading citation database, including Science Citation Index Expanded, Social Sciences Citation Index, Arts & Humanities Citation Index, Emerging Sources Citation Index, Conference Proceedings Citation Index - Science (CPCI-S), Conference Proceedings Citation Index - Social Sciences & Humanities (CPCI-SSH) and other ten indexed databases.

② Derwent Innovations Index (DII), published by Thomson Reuters IP & Technology Group, comprising the Derwent World Patent Index® (DWPI) and Derwent Patents Citation Index® (DPCI).

Table 3-2 Retrieval Strategies

Index Fields	Strategies
TS	“affective recognition”OR“mood recognition”OR“affective computing”OR“artificial emotional intelligence”OR“emotion AI”OR“expression recognition”OR“emotion recognition”OR“emotion learning”OR“sentiment analysis”OR“sentiment recognize”
WC	Computer Science Artificial Intelligence OR Engineering Electrical Electronic OR Computer Science Theory Methods OR Computer Science Information Systems OR Computer Science Interdisciplinary Applications OR Telecommunications OR Neurosciences OR Computer Science Software Engineering OR Psychiatry OR Computer Science Cybernetics OR Psychology Multidisciplinary OR Automation Control Systems OR Computer Science Hardware Architecture OR Engineering Multidisciplinary OR Robotics OR Engineering Biomedical OR Acoustics

lation, so as to provide performance analysis for researchers.

Science Indicator (ESI) database: ESI is an in-depth analytical research tool based on the Web of Science database. ESI can identify influential countries, institutions, papers, and publications, as well as research fronts, in a particular field of study.

Journal Citation Records (JCR) database: JCR is a multidisciplinary journal review tool. JCR provides a journal review resource based on statistical information on citation data. JCR can measure the impact of a study at the journal level, and show the interrelationship between citing and cited journals by indexing and statistics on references.

3.1 Research Trends in the Field of Affective Computing

It has been 26 years since Picard formally introduced the concept of affective computing in 1997, and a large number of scientific papers have been produced by researchers in the field. In this section, the Web of Science Core Collection database is used as the data base to search for papers in the field, and the retrieval results show that a total of 27,434 papers have been published worldwide so far. Among them, 13,836 are conference papers, with conference papers and journal papers accounting for about 50% each.

3.1.1 Overall Trend

As shown in Table 3-3 and Figure 3-1 From 1997 to 2009, the number of global published papers in the field increased steadily, and although there were occasional fluctuations, the overall trend of growth was observed; from 2010 to 2019, the rise of deep learning promoted the rapid development of the field of affective computing, and the number of published papers in related fields rose rapidly presenting an explosive growth phase of research, and the annual volume of published papers in 2019 reached 3,208; after 2019, as the innovation of deep learning methods entered the plateau, the research in the field of affective computing also entered the plateau, and the rising trend of research enthusiasm slowed down. In 2022, there was a sharp decline due to the incomplete data resulting from the statistical time window not covering the whole year.

3.1.2 Major Research Positions (Analysis by Country/Region)

This section uses the countries/regions of all authors and first author to conduct quantitative statistics to analyze the major research positions in the field of affective computing. As shown in Table 3-4, among the top 20 countries in the global af-

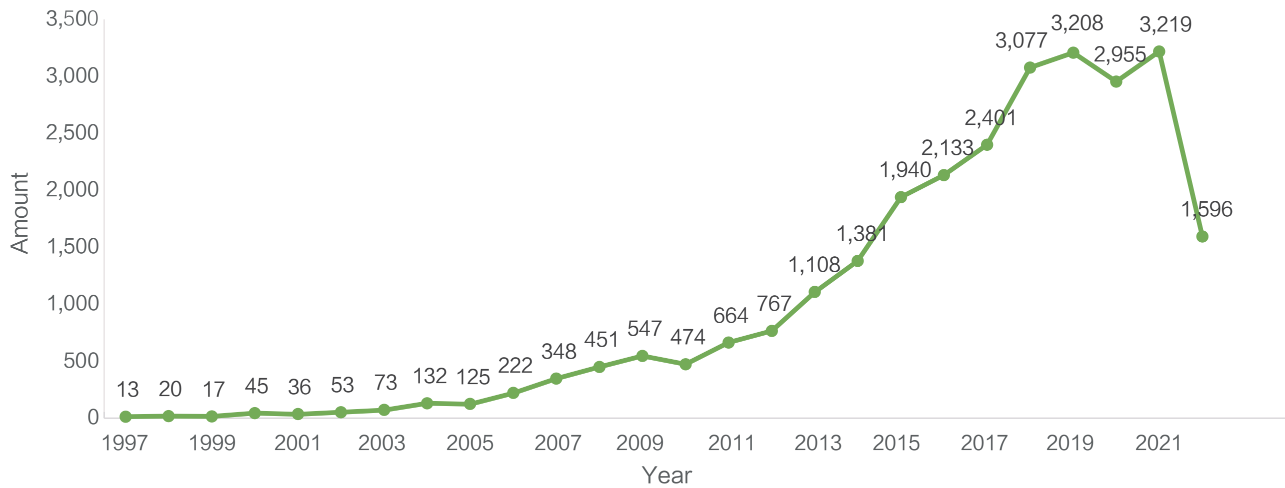


Figure 3-1 Trend of Published Papers in the Field of Affective Computing (Incomplete Statistics for 2022)

Table 3-3 Overall Trend of Published Papers in the Field of Affective Computing

Year	Amount	Percentage/%
1997	13	0.05
1998	20	0.07
1999	17	0.06
2000	45	0.16
2001	36	0.13
2002	53	0.19
2003	73	0.27
2004	132	0.48
2005	125	0.46
2006	222	0.81
2007	348	1.27
2008	451	1.64
2009	547	1.99
2010	474	1.73
2011	664	2.42
2012	767	2.80
2013	1,108	4.04
2014	1,381	5.03
2015	1,940	7.07
2016	2,133	7.78
2017	2,401	8.75
2018	3,077	11.22
2019	3,208	11.69
2020	2,955	10.77
2021	3,219	11.73
2022	1,596	5.82

(Continue)

fective computing field, China is the country with the largest number of all authors and first authors, accounting for 24% and 23% of the total number of published papers. China, the United States, India, the United Kingdom, and Germany are the top five in terms of all authors and first author of published papers, and are the most important research positions in the field of affective computing. The United States ranks second in terms of all authors of published papers, but its first author

Table 3-4 Top 20 Countries in Terms of Published Paper in the Field of Affective Computing

No.	Country of all authors	Amount	Country of first author	Amount
1	China	6,905	China	6,448
2	USA	4,085	India	2,938
3	India	3,075	USA	2,864
4	UK	2,136	UK	1,244
5	Germany	1,482	Germany	1,104
6	Japan	1,145	Italy	873
7	Italy	1,111	Japan	856
8	Australia	1,062	South Korea	799
9	Spain	996	Spain	742
10	Canada	933	Australia	708
11	South Korea	925	Canada	622
12	France	852	France	537
13	Netherlands	684	Turkey	532
14	Turkey	634	Netherlands	423
15	Saudi Arabia	565	Malaysia	391
16	Singapore	515	Brazil	389
17	Malaysia	481	Pakistan	368
18	Pakistan	460	Greece	365
19	Brazil	457	Singapore	323
20	Greece	425	Iran	319

ranks third, ranking behind India. The number of published papers by the top 20 countries in terms of all authors in the field of affective computing over the years is detailed in Appendix 1.

The top 10 countries were counted with 4-year period for published papers, except for 2021-2022 with 2-year period. The results are shown in the table below.

As shown in Figure 3-2, there is a large change in the volume of published papers from China and the United States throughout the period. From 1997 to 2004, the number of published papers in the United States far exceeded that in China, where the total number of published papers in China was 20% of that in the United States during the period of 1997-2000, and rose to 31% of that in the United States during the period of 2001-2004.

Since 2005, the number of published papers in China overtook that in the United States, and from 2021 to 2022, the number of published papers in China was about three times that in the United States. This shows that China has accumulated research in the field of affective computing faster in recent years, and the number of researches has a certain advantage compared with that of the United States. In addition, the number of published papers in India has surpassed that of the United States in the past two years, which shows that India is becoming a major research position in the field of affective computing.

Table 3-5 Top 10 Countries in the Field of Affective Computing with 4-Year Period of Publication Statistics

No.	Country	Amount						
		1997-2000	2001-2004	2005-2008	2009-2012	2013-2016	2017-2020	2021-2022
1	China	6	29	298	492	1 374	2 983	1 586
2	The United States	31	94	248	456	1 049	1 620	544
3	India	1	1	14	104	727	1 456	666
4	The United Kingdom	6	56	124	239	517	856	309
5	Germany	7	21	110	198	400	538	188
6	Japan	28	29	97	130	270	423	160
7	Italy	1	7	37	93	322	445	186
8	Australia	2	10	42	115	249	432	194
9	Spain	1	9	36	112	235	404	185
10	Canada	3	13	39	113	256	362	135

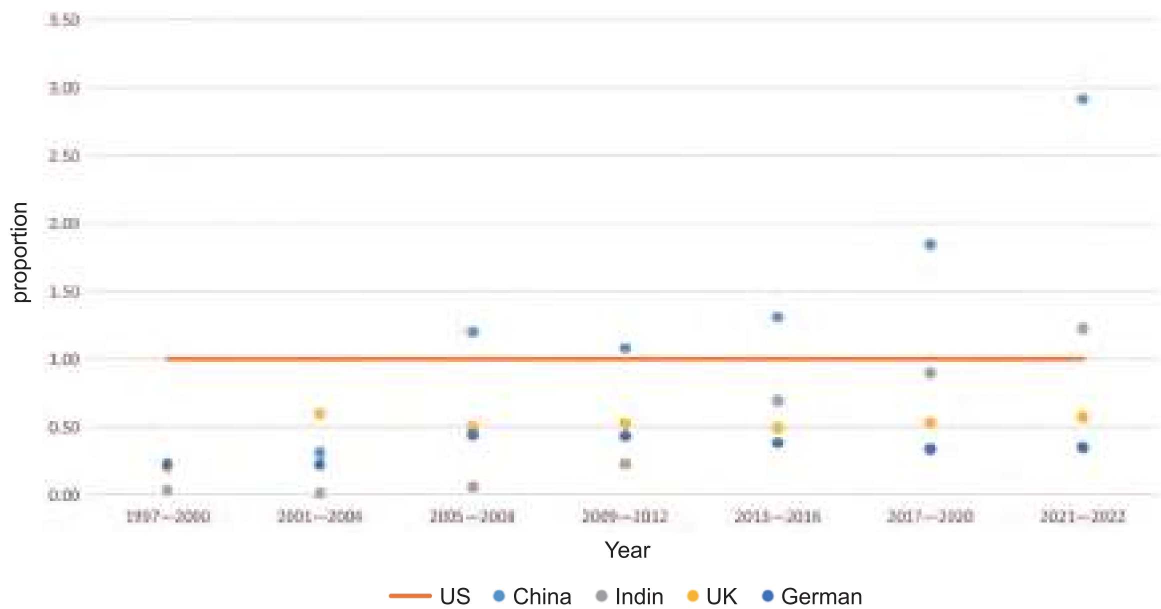


Figure 3-2 Top 5 Countries in the Field of Affective Computing Compared to the US

3.1.3 Mainstream Journals

This section analyzes the data based on journal papers. 13,598 journal papers are distributed in 1,204 journals. As shown in Table 3-6, the journal with the highest number of papers is IEEE ACCESS containing 650 papers. This journal is the classified Q2 in the fields of 2021 JCR TELECOMMUNICATIONS, ENGINEERING, ELECTRICAL & ELECTRONIC, and COMPUTER SCIENCE & INFORMATION SYSTEMS. The impact factor is 3.476.

Among the 1204 journals, 834 journals have impact factor in the 2021 JCR. As shown in Table 3-7, the distribution of impact factor of the 834 journals is shown in the following table. Among them, 26 journals have impact factor greater than 10, and the 5 journals with the highest impact factor are *American Journal of Psychiatry* (19.242). *IEEE Transactions on Cybernetics* (19.118), *Information Fusion* (17.564), *Brain* (15.255), and *ACM Computing Surveys* (14.324). . As shown in Figure 3-3, the impact factor of most science journals is distributed in the two ranges of $2 \leqslant \text{IF} < 4$ and $4 \leqslant \text{IF} < 7$.

3.1.4 Field Distribution

This section analyzes the field distribution based on the statistics of the Web of Science Categories of affective computing papers. Web of Science includes 254 categories[3] for journals and each journal in the Web of Science Core Collection is assigned one or more Web of Science Categories. A maximum of 6 categories can be assigned to one journal. All articles in the journal will be included in corresponding Web of Science Categories publishing the journal.

When selecting Web of Science Categories for a journal, the standards considered include themes and scope of the journal, relations between the

③ http://webofscience.help.clarivate.com/en-us/Content/wos-core-collection/wos-core-collection.htm?Highlight=category

Table 3-6 Top 20 Journals in Terms of Published Papers

No.	Publication Name	Amount
1	*IEEE Access*	650
2	*Multimedia Tools and Applications*	330
3	*Frontiers in Psychology*	285
4	*IEEE Transactions on Affective Computing*	285
5	*Sensors*	260
6	*Expert Systems with Applications*	231
7	*Neurocomputing*	223
8	*Applied Sciences-Basel*	199
9	*International Journal of Advanced Computer Science and Applications*	198
10	*Psychiatry Research*	185
11	*Knowledge-Based Systems*	174
12	*Schizophrenia Research*	133
13	*Neuropsychologia*	129
14	*Journal of Intelligent & Fuzzy Systems*	117
15	*Neural Computing & Applications*	107
16	*Information Processing & Management*	104
17	*Cognitive Computation*	92
18	*Electronics*	91
19	*IEEE Transactions on Multimedia*	85
20	*Information Sciences*	84

Table 3-7 Distribution of Journal Impact Factor

Journal Impact Factor	Amount
$\text{IF} \geqslant 10$	26
$7 \leqslant \text{IF} < 10$	70
$4 \leqslant \text{IF} < 7$	209
$2 \leqslant \text{IF} < 4$	322
$1 \leqslant \text{IF} < 2$	153
$\text{IF} \leqslant 1$	54

author and the editorial board, the funding agencies, references.

Affective computing papers cover 158 Web of Science categories in total, including computer, communication, engineering, psychology, and medicine.

The top 20 categories with the most publications are shown in Table 3-8. The most popular category is Computer Science, Artificial Intelligence with 10,470 publications, accounting for 36.31% of the total publications, followed by Engineering, Electrical & Electronic with 8,514 publications, accounting for 29.52% of the total publications.

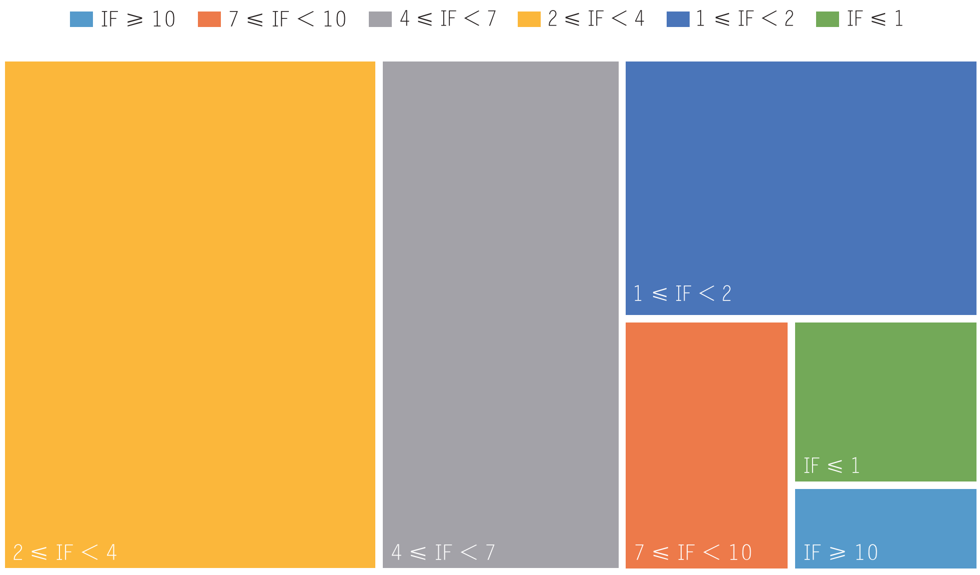


Figure 3-3 Chart of Journal Impact Factor

Table 3-8 Top 20 Categories with the Most Publications

No.	Web of Science Categories	Number of Publications	Percentage of the total publications/%
	Name		
1	Computer Science, Artificial Intelligence	10,470	36.31
2	Engineering, Electrical & Electronic	8,514	29.52
3	Computer Science, Theory & Methods	7,454	25.85
4	Computer Science, Information Systems	7,257	25.16
5	Computer Science, Interdisciplinary Applications	3,133	10.86
6	Telecommunications	2,671	9.26
7	Computer Science, Software Engineering	2,424	8.41
8	Neurosciences	2,288	7.93
9	Psychiatry	2,219	7.69
10	Computer Science, Cybernetics	1,587	5.5

(Continue)

No.	Web of Science Categories	Number of Publications	Percentage of the total publications/%
	Name		
11	Imaging Science & Photographic Technology	918	3.18
12	Automation & Control Systems	871	3.02
13	Computer Science Hardware & Architecture	871	3.02
14	Psychology, Multidisciplinary	827	2.87
15	Engineering, Multidisciplinary	772	2.68
16	Robotics	704	2.44
17	Clinical Neurology	661	2.29
18	Psychology	623	2.16
19	Engineering, Biomedical	594	2.06
20	Acoustics	554	1.92

3.2 Top International Conferences

This section combines the *List of International Academic Periodicals and Conferences Recommended by CCF* and *CORE Computer Science Conference Rankings* as well as expert opinions to form a list of top international conferences in affective computing.It is worth noting that this section is organized and summarized only according to the currently available catalogs and rankings, and shall not be used as a basis for academic evaluation. In addition, the impact of a conference is not directly and positively related to a single paper published at it. The affective computing conferences with many publications and high impacts are listed in Table 3-9.

Table 3-9 Top International Conferences in Affective Computing

No.	Conference Name		CCF RANK	CORE RANK
	Name	Abbreviation		
1	ACM International Conference on Multimedia	ACM MM	A	A+
2	AAAI Conference on Artificial Intelligence	AAAI	A	A+
3	Annual Meeting of the Association for Computational Linguistics	ACL	A	A+
4	IEEE Conference on Computer Vision and Pattern Recognition	CVPR	A	A
5	IEEE International Conference on Computer Vision	ICCV	A	A+
6	International Conference on Affective Computing and Intelligent Interaction	ACII	—	—

(Continue)

No.	Conference Name		CCF RANK	CORE RANK
	Name	Abbreviation		
7	IEEE International Conference and Workshops on Automatic Face and Gesture Recognition	FG	C	B
8	IEEE International Conference on Acoustics, Speech and SP	ICASSP	B	B

Note: "CCF RANK" and "CORE RANK" are included in the List of International Academic Periodicals and Conferences Recommended by CCF and the CORE Computer Science Conference Rankings, respectively.

3.2.1 ACM International Conference on Multimedia (ACM MM)

ACM MM is a conference ranked A on "Computer Graphics and Multimedia" in the List of *International Academic Periodicals and Conferences Recommended by CCF*. ACM MM is held once a year since its inception in 1993, shaping the research landscape with new ideas via oral, video and poster presentations, tutorials, panels, exhibits, workshops, doctoral symposium, and multimedia grand challenge. ACM MM focuses on advancing multimedia research and applications, including but not limited to images, text, audio, voice, music, sensors and social data. The research topics covered in the conference include 4 themes containing 12 areas (see Figure 3-4).

Emotional and social signals engage users with multimedia through user sentiment analysis.

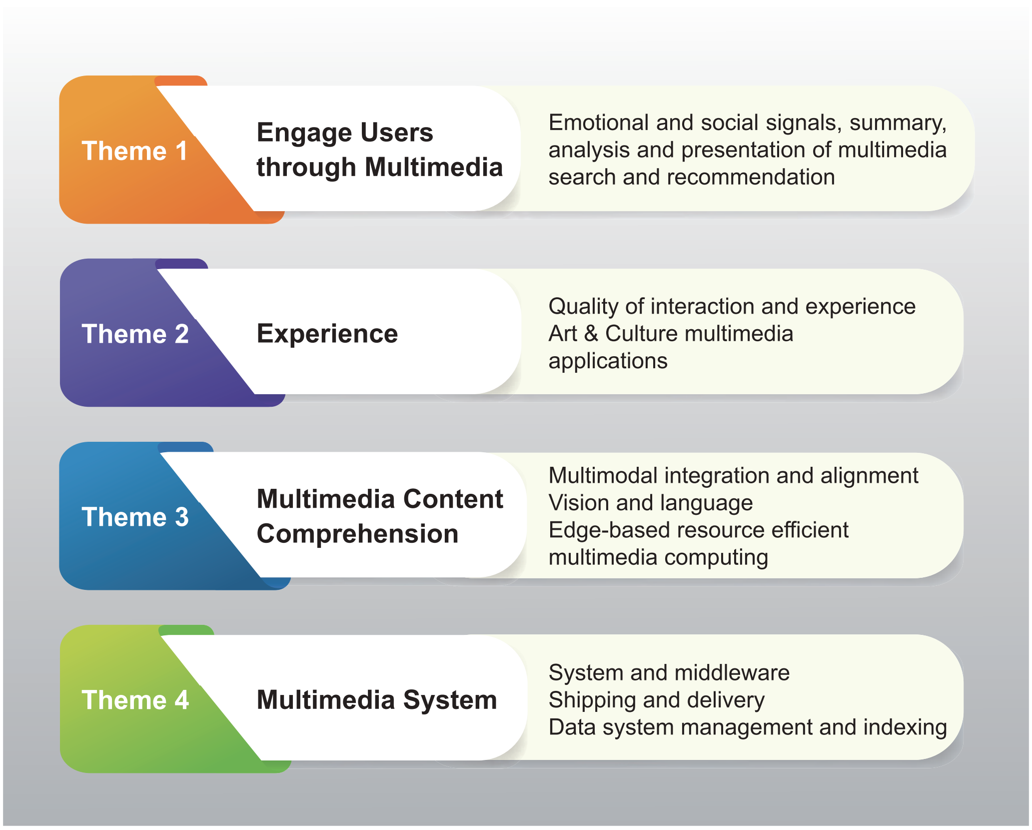


Figure 3-4 Themes Covered in ACM MM

3.2.2 AAAI Conference on Artificial Intelligence (AAAI)

AAAI Conference on Artificial Intelligence④ is one of the top artificial intelligence conferences organized by the Association for the Advancement of Artificial Intelligence (AAAI), an artificial intelligence conference ranked A in the *List of International Academic Periodicals and Conferences Recommended by CCF* and an A+ conference in the *CORE Computer Science Conference Rankings*. From 2018 to 2022, a total of 95 affective computing papers were published at AAAI conference.

AAAI Conference on Artificial Intelligence also set up affective computing workshops, such as Affective Content Analysis Workshop in 2018 which mainly conducted affective computing on context and voice and constructed standardized baselines, datasets, and evaluation metrics for affective computing process.

3.2.3 Annual Meeting of the Association for Computational Linguistics

The Annual Meeting of the Association for Computational Linguistics is the premier conference in the field of computational linguistics concerned with computational approaches to natural language held by the Association for Computational Linguistics (ACL), which is an important international scientific and professional association dedicated to the study of computational problems involving human languages. The association was founded in 1962 named the Association for Machine Translation and Computational Linguistics (AMTCL) and changed its name to ACL in 1968. ACL holds the Annual Meeting of the Association for Computational Linguistics each summer and sponsors the *Computational Linguistics* published by MIT press, which is the main publication in such field. Annual Meeting of the Association for Computational Linguistics ranks A in the artificial intelligence field of the *List of International Academic Periodicals and*

Conferences Recommended by CCF and A+ in *CORE Computer Science Conference Rankings*. The conference aims to study the computational models of various languages to provide computational explanations for specific linguistic or psycholinguistic phenomena.

3.2.4 IEEE Conference on Computer Vision and Pattern Recognition (IEEE CVPR)

IEEE CVPR is the top computer vision annual conference, co-sponsored by the IEEE Computer Society and the Computer Vision Foundation. Users have access to conference papers through the Computer Vision Foundation. IEEE CVPR ranks A in the artificial intelligence field of both the *List of International Academic Periodicals and Conferences Recommended by CCF* and the *CORE Computer Science Conference Rankings*.

3.3 Top Journals

Top journals have not yet been explicitly defined. This section marks top journals according to the journal ranking table and the JCR ranking table of the National Science Library, Chinese Academy of Sciences, both of which are calculated based on impact factors. It is important to note that the impact factor is a common index to reflect, to a certain extent, the influence rather than the quality of journals.

④ *The List of International Academic Periodicals and Conferences Recommended by CCF includes* A, B and C categories. In CCF's catalog, conference papers are referred to as "Full paper" or "Regular paper" (long articles officially published), while other format papers, such as Short paper, Demo paper, Technical Brief, Summary, and Workshop accompanying the conference, are not considered.

(1) Impact factor (IF)

IF is an important index for evaluating journals proposed by Eugene Garfield, director of the U.S. Institute for Scientific Information, in 1972. This index is a relative quantity index, aiming to adjust and amend the problem of excessive citation of journals.

IF is a ratio of the citations of a journal in a given year for papers published in previous two years to the citable items in previous two years, i.e.,

IF = the citations of a journal in a given year for papers published in previous two years / the citable items in previous two years

(2) Journal Citation Reports (JCR)

JCR includes the citation data among about 12,000 journals in SCI, and has performed statistics and calculations on it. It also defined indices such as IF for each journal. As of the report date, JCR 2021 is the latest journal citation reports. JCR divides journals into 21 Groups and 254 Categories, and a journal can fall into more than one Category.

(3) CAS JCR Journal Ranking

The CAS JCR journal ranking is the research result of the National Science Library, Chinese Academy of Sciences. The basic version of the CAS JCR journal ranking table ranks the SCI journals in JCR published by Clarivate Analytics each year within the discipline based on the 3-year average IF. In order to keep the consistency among the journal rankings over years and to reduce the impact of IF fluctuations, CAS's ranking table calculates the 3-year average IF by the following formula:

3-year average IF = (IF of current year + IF of last year + IF of the year before last)/3

The CAS JCR journal ranking includes both the Group and Category discipline system. The Category discipline system is based on the JCR disciplines published by Clarivate Analytics. The Group discipline system consists of 13 Groups disciplines: geology, geological astronomy, environmental science, agriculture and forestry science, engineering technology, physics, chemistry, biology, mathematics, medicine, social science, management science, and comprehensive journals.

Among the 1,204 affective computing journal articles, 247 are included in JCR Q1. Please refer to appendix 2. Based on the number of articles published and the computing related field, the top 10 high-level affective computing academic journals are selected as listed in Table 3-10.

3.3.1 IEEE Transactions on Affective Computing

The *IEEE Transactions on Affective Computing*[⑤] is a cross-disciplinary and international archive journal aimed at disseminating results of research on the design of systems that can recognize, interpret, and simulate human emotions and related affective phenomena.

The journal covers but is not limited to the following topics: Sensing & analysis, algorithms and features for the recognition of affective state from face and body gestures; Analysis of text and spoken language for emotion recognition; Analysis of prosody and voice quality of affective speech; Recognition of affective state from central (e.g. fMRI, EEG) and peripheral (e.g. GSR) physiological measures; Methods for multimodal recognition of affective state; Recognition of group emotion; Methods for data collection (e.g. mood induction and elicitation) or technical methodology (e.g. motion capturing) with respect to psychological issues; Tools and methods of annotation for provision of emotional corpora.

⑤ IEEE. https://ieeexplore.ieee.org/xpl/aboutJournal.jsp?punumber=5165369

Table 3-10 High-level Affective Computing Journals

No.	Journal Name	Web of Science	IF
1	*IEEE Transactions on Affective Computing*	Computer Science, Cybernetics/Computer Science, Artificial Intelligence	13.990
2	*Expert Systems with Applications*	Computer Science, Artificial Intelligence/Engineering, Electrical & Electronic/Operations Research & Management Science	8.665
3	*Knowledge-Based Systems*	Computer Science, Artificial Intelligence	8.139
4	*Information Processing & Management*	Computer Science, Information Systems/Information Science & Library Science	7.466
5	*IEEE Transactions on Multimedia*	Computer Science, Software Engineering/Computer Science, Information Systems/Telecommunications	8.182
6	*Information Sciences*	Computer Science, Information Systems	8.233
7	*Pattern Recognition*	Computer Science, Artificial Intelligence/Engineering, Electrical & Electronic	8.518
8	*Applied Soft Computing*	Computer Science, Interdisciplinary Applications/ Computer Science, Artificial Intelligence	8.263
9	*Decision Support Systems*	Operations Research & Management Science/Computer Science, Information Systems/Computer Science, Artificial Intelligence	6.969
10	*Future Generation Computer Systems-The International Journal of Escience*	Computer Science, Theory & Methods	7.307

This journal is included in the Group of engineering and technology in CAS's journal ranking table. It is divided into Q2 in CAS's Category-computer science(artificial intelligence) and computer-(science, cybernetics), and Q1 in JCR's Category-computer science(artificial intelligence) and computer science(cybernetics).This journal is a non-OA journal with 13.990 for IF and 13.634 for non-self-citation IF in 2021. This journal is published quarterly, and the annual publication volume is 84 articles in 2021.

3.3.2 Expert Systems with Applications

Expert Systems with Applications aims to publish papers dealing with the design, development, testing, implementation, and management of expert and intelligent systems. This journal is included in the Group of engineering and technology in CAS's journal ranking table. It is divided into Q2 in CAS's Category-computer science (artificial intelligence, electrical & electronic and operations research & management science), and Q1 in JCR's Category-computer science (artificial intelligence, electrical & electronic and operations research & management science). This journal is an OA journal with 8.665 for IF and 7.494 for non-self-citation IF in 2021. This journal is published weekly, and the annual publication volume is 1,863 articles in 2021.

3.3.3 Knowledge-Based Systems

Knowledge-based Systems is an international and interdisciplinary English journal in the field of artificial intelligence published in Netherlands. The journal is designed to focus on research based on knowledge and other artificial intelligence technique systems with the following objectives and capabilities: cognitive interaction and brain-computer interface, intelligent decision support systems, prediction systems and warning systems, and data science theory, methodologies and techniques. This journal is included in the Group of engineering and technology in CAS's journal ranking table. It is divided into Q2 in CAS's Category-computer science (artificial intelligence), and Q1 in JCR's Category-computer science (artificial intelligence). This journal is a non-OA journal with 8.139 for IF and 7.194 for non-self-citation IF in 2021. This journal is published eight times a year and the annual publication volume is 951 articles in 2021.

3.3.4 Information Processing & Management

Information Processing & Management is an English journal publishing cutting-edge original research at the intersection of computing and information science in Britain. This journal is included in the Group of engineering and technology in CAS's journal ranking table. It is divided into Q2 in CAS's Category-computer science (information systems), and Q1 in JCR's Category-information systems, information science & library science. This journal is a non-OA journal with 7.466 for IF and 5.910 for non-self-citation IF in 2021. This journal is bimonthly, and the annual publication volume is 340 articles in 2021.

3.4 Important Research Results

Important research results are divided into three parts in this section according to the data sources: ESI Highly Cited Papers and Hot Papers, award-winning papers of important conferences in a field, and award-winning papers of important journals in a field.

3.4.1 ESI Highly Cited Papers and Hot Papers

Essential Science Indicators (ESI) is an analytical tool that helps you identify top-performing research in Web of Science Core Collection. ESI surveys more than 11,000 journals from around the world to rank countries, institutions, journals, papers and authors in 22 broad fields[⑥] based on publication and citation performance. ESI is sourced from the Science Citation Index-Expanded (SCIE) and the Social Sciences Citation Index (SSCI) in Web of Science Core Collection. The number of citations includes those from indexed journals in the Science Citation Index Expanded, Social Science Citation Index, and Arts & Humanities Citation Index. Data include bimonthly updates to rankings and citation counts.

The data used in this section was published on July 14, 2022, for the second bimonthly of 2022. Data cover a rolling 10-year and 4-month period, i.e., Jan. 1, 2012 to Apr. 30, 2022. Inclusion in ESI requires meeting certain citation thresholds. Only the most highly cited countries, institutions, papers, journals, and authors are included in ESI. Table 3-11 shows the citation thresholds for Highly Cited Papers and Hot Papers. Highly Cited Papers are papers that have received enough citations to place them in the top 1% when compared to all other papers published in the same year in the same field. For Hot Papers, only papers published in the last 2 years are considered. Hot Papers are receiving citations quickly after publication. These papers have been cited enough times to place them in the top 0.1% when compared to peer papers.

⑥ ESI uses 22 broad disciplines to rank entities and identify top-performing papers. Each journal is assigned to only one field. In the case of multidisciplinary journals, reclassification is done at the paper level, based on an analysis of the cited references.

Table 3-11 Citation Thresholds for Highly Cited Papers and Hot Papers

Entity	Percentile/%	Data Years
Highly Cited Papers	1	10
Hot Papers	0.1	2

ESI Highly Cited Papers and Hot Papers in affective computing are listed in Table 3-12. There is a total of 153 Highly Cited Papers in this issue, of which 5 are Hot Papers.

Table 3-12 Highly Cited Papers and Hot Papers in Affective Computing (Top 50)

No.	Author	Title	Citations	Publication Year
1	Ganin, Y; Ustinova, E; Ajakan, H; Germain, P; Larochelle, H; Laviolette, F; Marchand, M; Lempitsky, V	Domain-Adversarial Training of Neural Networks	1,752	2016
2	Koelstra, S; Muhl, C; Soleymani, M; Lee,JS; Yazdani, A; Ebrahimi, T; Pun, T; Nijholt, A; Patras, I	DEAP: A Database for Emotion Analysis Using Physiological Signals	1,580	2012
3	Mohammad, SM; Turney, PD	Crowdsourcing A Word-Emotion Association Lexicon	737	2013
4	Frick, PJ; Ray, JV; Thornton, LC; Kahn, RE	Can Callous-Unemotional Traits Enhance the Understanding, Diagnosis, and Treatment of Serious Conduct Problems in Children and Adolescents? A Comprehensive Review	640	2014
5	Baltrusaitis, T; Ahuja, C; Morency, LP	Multimodal Machine Learning: A Survey and Taxonomy	605	2019
6	Soleymani, M; Lichtenauer, J; Pun, T; Pantic, M	A Multimodal Database for Affect Recognition and Implicit Tagging	596	2012
7	Zheng, WL; Lu, BL	Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks	573	2015
8	Feldman, R	Techniques and Applications for Sentiment Analysis	572	2013
9	Ravi, K; Ravi, V	A Survey on Opinion Mining and Sentiment Analysis:Tasks, Approaches and Applications	571	2015
10	Cambria, E; Schuller, B; Xia, YQ; Havasi, C	New Avenues in Opinion Mining and Sentiment Analysis	551	2013
11	Thelwall, M; Buckley, K; Paltoglou, G	Sentiment Strength Detection for the Social Web	540	2012
12	Gravina, R; Alinia, P; Ghasemzadeh, H; Fortino, G	Multi-Sensor Fusion in Body Sensor Networks:State-of-the-art and research challenges	467	2017

(Continue)

No.	Author	Title	Citations	Publication Year
13	Poria, S; Cambria, E; Bajpai, R; Hussain, A	A Review of Affective Computing: From Unimodal Analysis to Multimodal Fusion	458	2017
14	Eyben, F; Scherer, KR; Schuller, BW; Sundberg, J; Andre, E; Busso, C; Devillers, LY; Epps, J; Laukka, P; Narayanan, SS; Truong, KP	The Geneva Minimalistic Acoustic Parameter Set (GeMAPS) for Voice Research and Affective Computing	448	2016
15	Poria, S; Cambria, E; Gelbukh, A	Aspect Extraction for Opinion Mining with A Deep Convolutional Neural Network	444	2016
16	Zhang, L; Wang, S; Liu, B	Deep Learning for Sentiment Analysis: A Survey	439	2018
17	Jenke, R; Peer, A; Buss, M	Feature Extraction and Selection for Emotion Recognition from EEG	397	2014
18	Kiritchenko, S; Zhu, XD; Mohammad, SM	Sentiment Analysis of Short Informal Text	381	2014
19	Lopes, AT; deAguiar, E; DeSouza, AF; Oliveira-Santos, T	Facial Expression Recognition with Convolutional Neural Networks: Coping with Few Data and the Training Sample Order	362	2017
20	Barrett, LF; Adolphs, R; Marsella, S; Martinez, AM; Pollak, SD	Emotional Expressions Reconsidered: Challenges to Inferring Emotion from Human Facial Movements	360	2019
21	Sariyanidi, E; Gunes, H; Cavallaro, A	Automatic Analysis of Facial Affect: A Survey of Registration, Representation, and Recognition	356	2015
22	Rivera, AR; Castillo, JR; Chae, O	Local Directional Number Pattern for Face Analysis: Face and Expression Recognition	340	2013
23	Moraes, R; Valiati, JF; Neto, WPG	Document-Level Sentiment Classification: An Empirical Comparison Between SVM and ANN	328	2013
24	Chen, T; Xu, RF; He, YL; Wang, X	Improving Sentiment Analysis Via Sentence Type Classification Using Bilstm-CRF and CNN	314	2017
25	Mollahosseini, A; Hasani, B; Mahoor, MH	Affectnet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild	313	2019
26	Dawel, A; O'Kearney, R; McKone, E; Palermo, R	Not Just Fear and Sadness: Meta-Analytic Evidence of Pervasive Emotion Recognition Deficits for Facial and Vocal Expressions in Psychopathy	308	2012

(Continue)

No.	Author	Title	Citations	Publication Year
27	Craik, A; He, YT; Contreras-Vidal, JL	Deep Learning for Electroencephalogram(EEG) Classification Tasks: A Review	306	2019
28	Soleymani, M; Pantic, M; Pun, T	Multimodal Emotion Recognition in Response to Videos	302	2012
29	Bird, G; Cook, R	Mixed Emotions: The Contribution of Alexithymia to the Emotional Symptoms of Autism	299	2013
30	Mostafa, MM	More Than Words: Social Networks' Text Mining for Consumer Brand Sentiments	297	2013
31	Hiser, J; Koenigs, M	The Multifaceted Role of the Ventromedial Prefrontal Cortex in Emotion, Decision Making, Social Cognition, and Psychopathology	295	2018
32	Kleinsmith, A; Bianchi-Berthouze, N	Affective Body Expression Perception and Recognition: A Survey	287	2013
33	Baek, H; Ahn, J; Choi, Y	Helpfulness of Online Consumer Reviews:Readers' Objectives and Review Cues	287	2012
34	Zeng, NY; Zhang, H; Song, BY; Liu, WB; Li, YR; Dobaie, AM	Facial Expression Recognition Via Learning Deep Sparse Autoencoders	286	2018
35	Schouten, K; Frasincar, F	Survey on Aspect-Level Sentiment Analysis	277	2016
36	Bakermans-Kranenburg, MJ; van IJzendoorn, MH	Sniffing Around Oxytocin: Review and Meta- Analyses of Trials in Healthy and Clinical Groups with Implications for Pharmacotherapy	277	2013
37	Cummins, N; Scherer, S; Krajewski, J; Schnieder, S; Epps, J; Quatieri, TF	A Review of Depression and Suicide Risk Assessment Using Speech Analysis	271	2015
38	Happy, SL; Routray, A	Automatic Facial Expression Recognition Using Features of Salient Facial Patches	267	2015
39	Nassirtoussi, AK; Aghabozorgi, S; Teh, YW; Ngo, DCL	Text Mining for Market Prediction: A Systematic Review	264	2014
40	Lu, JW; Zhou, XZ; Tan, YP; Shang, YY; Zhou,J	Neighborhood Repulsed Metric Learning for Kinship Verification	261	2014
41	Corneanu, CA; Simon, MO; Cohn, JF; Guerrero, SE	Survey on RGB, 3D, Thermal, and Multimodal Approaches for Facial Expression Recognition: History, Trends, and Affect-Related Applications	260	2016
42	Nassif, AB; Shahin, I; Attili, I; Azzeh, M; Shaalan, K	Speech Recognition Using Deep Neural Networks: A Systematic Review	259	2019

(Continue)

No.	Author	Title	Citations	Publication Year
43	Pinkham, AE; Penn, DL; Green, MF;-Buck, B; Healey, K; Harvey, PD	The Social Cognition Psychometric Evaluation Study: Results of the Expert Survey and RAND Panel	259	2014
44	Kupferberg, A; Bicks, L; Hasler, G	Social Functioning in Major Depressive Disorder	258	2016
45	Zhao, JF; Mao, X; Chen, LJ	Speech Emotion Recognition Using Deep 1D & 2D CNN LSTM Networks	255	2019
46	Hassan, MM; Uddin, MZ; Mohamed, A; Almogren, A	A Robust Human Activity Recognition System Using Smartphone Sensors and Deep Learning	251	2018
47	Jelodar, H; Wang, YL; Yuan, C; Feng, X; Jiang, XH; Li, YC; Zhao, L	Latent Dirichlet Allocation (LDA) and Topic Modeling: Models, Applications, A Survey	248	2019
48	Guha, T; Ward, RK	Learning Sparse Representations for Human Action Recognition	247	2012
49	Vellante, M; Baron-Cohen, S; Melis, M; Marrone, M; Petretto, DR; Masala, C; Preti, A	The Reading the Mind in the Eyes Test:Systematic Review of Psychometric Properties and A Validation Study in Italy	244	2013
50	Yu, Y; Duan, WJ; Cao, Q	The Impact of Social and Conventional Media on Firm Equity Value: A Sentiment Analysis Approach	239	2013

Hot Paper 1 EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks

Author: Tengfei Song, Wenming Zheng, Peng Song, Zhen Cui

Abstract: In this paper, a multichannel EEG emotion recognition method based on a novel dynamical graph convolutional neural networks (DGCNN) is proposed. The basic idea of the proposed EEG emotion recognition method is to use a graph to model the multichannel EEG features and then perform EEG emotion classification based on this model. Being different from the traditional graph convolutional neural networks (GCNN) methods, the proposed DGCNN method can dynamically learn the intrinsic relationship between different EEG channels, via training a neural network so as to benefit for more discriminative EEG feature extraction. Then, the learned adjacency matrix is used to learn more discriminative features for improving the EEG emotion recognition.

Hot Paper 2 GCB-Net: Graph Convolutional Broad Network and Its Application in Emotion Recognition

Author: Tong Zhang, Xuehan Wang, Xiangmin Xu, C. L. Philip Chen

Abstract: In this work, a Graph Convolutional Broad Network (GCB-Net) was designed for exploring the deeper-level information of graph-structured data. It used the graph convolutional layer to extract features of graph-structured input and stacks multiple regular convolutional layers to extract relatively abstract features. The final concatenation utilized the broad concept, which preserves the outputs of all hierarchical layers, allowing the model to search features in broad spaces. To improve the performance of the proposed GCB-Net, the broad learning system (BLS) was applied to enhance its features.

Hot Paper 3 Review on Psychological Stress Detection Using Biosignals

Author: Giorgos Giannakakis, Dimitris Grigoriadis, Katerina Giannakaki, Olympia Simantiraki, Alexandros Roniotis, Manolis Tsiknakis

Abstract: This review investigates the effects of psychological stress on the human body measured through biosignals. It is also explored multimodal biosignal analysis and modelling methods for deriving accurate stress correlates. This paper aims to provide a comprehensive review on biosignal patterns caused during stress conditions and reliable practical guidelines towards more efficient detection of stress.

Hot Paper 4 ABCDM: An Attention-based Bidirectional CNN-RNN Deep Model for Sentiment Analysis

Author: Mohammad Ehsan Basiri, Shahla Nemati, Moloud Abdar, Erik Cambria, U. Rajendra Acharya

Abstract: In this paper, an Attention-based Bidirectional CNN-RNN Deep Model (ABCDM) was proposed. By utilizing two independent bidirectional LSTM and GRU layers, ABCDM will extract both past and future contexts by considering temporal information flow in both directions. Also, the attention mechanism is applied on the outputs of bidirectional layers of ABCDM to put more or less emphasis on different words. To reduce the dimensionality of features and extract position-invariant local features, ABCDM utilizes convolution and pooling mechanisms. The effectiveness of ABCDM is evaluated on sentiment polarity detection which is the most common and essential task of sentiment analysis. Experiments were conducted on five review and three Twitter datasets. The results of comparing ABCDM with six recently proposed DNNs for sentiment analysis show that ABCDM achieves state-of-the-art results on both long review and short tweet polarity classification.

Hot Paper 5 Deep Learning-Based Text Classification: A Comprehensive Review

Author: Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, Jianfeng Gao

Abstract: In this paper, we provide a comprehensive review of more than 150 deep learning-based models for text classification developed in recent years, and discuss their technical contributions, similarities, and strengths. We also provide a summary of more than 40 popular datasets widely used for text classification. Finally, we provide a quantitative analysis of the performance of different deep learning models on popular benchmarks, and discuss future research directions.In addition, the non-Hot Papers that have received over 1,000 citations include:

Paper 1 DEAP: A Database for Emotion Analysis Using Physiological Signals

Author: Sander Koelstra, Christian Muhl, Mohammad Soleymani, Jong-Seok Lee, Ashkan Yazdani, Touradj Ebrahimi, Thierry Pun; Anton Nijholt Ioannis Patras

Abstract: We present a multimodal dataset for the analysis of human affective states. The EEG and peripheral physiological signals of 32 participants were recorded as each watched 40 one-minute long excerpts of music videos. Participants rated each video in terms of the levels of arousal, valence, like/dislike, dominance, and familiarity. For 22 of the 32 participants, frontal face video was also recorded. Methods and results are presented for single-trial classification of arousal, valence, and like/dislike ratings using the modalities of EEG, peripheral physiological signals, and multimedia content analysis. Finally, decision fusion of the classification results from different modalities is performed.

Paper 2 A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions

Author: Zhihong Zeng, Maja Pantic, Glenn I. Roisman, Thomas S. Huang

Abstract: Automated analysis of human affective behavior has attracted increasing attention from researchers in psychology, computer science, linguistics, neuroscience, and related disciplines. However, the existing methods typically handle only deliberately displayed and exaggerated expressions of prototypical emotions despite the fact that deliberate behavior differs in visual appearance, audio profile, and timing from spontaneously occurring behavior.

To address this problem, efforts to develop algorithms that can process naturally occurring human affective behavior have recently emerged. Moreover, an increasing number of efforts are reported toward multimodal fusion for human affect analysis including audiovisual fusion, linguistic and paralinguistic fusion, and multi-cue visual fusion based on facial expressions, head movements, and body gestures. This paper introduces and surveys these recent advances. We first discuss human emotion perception from a psychological perspective. Next, we examine available approaches to solving the problem of machine understanding of human affective behavior, and discuss important issues like the collection and availability of training and test data. We finally outline some of the scientific and engineering challenges to advancing human affect sensing technology.

Paper 3 Lexicon-Based Methods for Sentiment Analysis

Author: Maite Taboada, Julian Brooke, Milan Tofiloski, Kimberly Voll, Manfred Stede

Abstract: We present a lexicon-based approach to extracting sentiment from text. The Semantic Orientation CALculator (SO-CAL) uses dictionaries of words annotated with their semantic orientation (polarity and strength), and incorporates intensification and negation. SO-CAL is applied to the polarity classification task, the process of assigning a positive or negative label to a text that captures the text's opinion towards its main subject matter. We show that SO-CAL's performance is consistent across domains and in completely unseen data. Additionally, we describe the process of dictionary creation, and our use of Mechanical Turk to check dictionaries for consistency and reliability.

Paper 4 Facial Expression Recognition Based on Local Binary Patterns: A Comprehensive Study

Author: Caifeng Shan, Shaogang Gong, Peter W. McOwan

Abstract: Automatic facial expression analysis is an interesting and challenging issue, and impacts important applications in many areas such as human-computer interaction and data-driven animation. Deriving an effective facial representation from original face images is a vital step for successful facial expression recognition.

In this paper, we empirically evaluate facial representation based on statistical local features (Local Binary Patterns, LBP) for person-independent facial expression recognition. Different machine learning methods are systematically examined on several databases. Extensive experiments illustrate that LBP features are effective and efficient for facial expression recognition. We further formulate Boosted-LBP to extract the most discriminant LBP features, and the best recognition performance is obtained by using Support Vector Machine classifiers with Boosted-LBP features. Moreover, we investigate LBP features for low-resolution facial expression recognition, which is a critical problem but seldom addressed in the existing work. We observe in our experiments that LBP features perform stably over a useful range of low resolutions of face images, and yield promising performance in compressed low-resolution video sequences captured in real-world environments.

Paper 5 Emotion Recognition in Human–Computer Interaction

Author: Roddy Cowie; Ellen Douglas-Cowie; Nicolas Tsapatsoulis; George Votsis; Stefanos Kollias; Winfried Fellenz; John G. Taylor

Abstract: Two channels have been distinguished in human interaction: one transmits explicit messages, and the other transmits implicit messages. Both linguistics and technology have invested enormous efforts in understanding the first, explicit channel, but the second is not as well understood. Understanding the other party's emotions is one of the key tasks associated with the second, implicit channel. To tackle that task, signal processing and analysis techniques have to be developed, while, at the same time, consolidating psychological and linguistic analyses of emotion. This article aims to develop a hybrid system capable of using information from faces and voices to recognize people's emotions.

Paper 6 On the Universality and Cultural Specificity of Emotion Recognition: A Meta-Analysis

Author: Hillary Anger Elfenbein, Nalini Ambady

Abstract: A meta-analysis examined emotion recognition within and across cultures. Emotions were universally recognized at better-than-chance levels. Accuracy was higher when emotions were both expressed and recognized by members of the same national, ethnic, or regional group, suggesting an in-group advantage.

This advantage was smaller for cultural groups with greater exposure to one another, measured in terms of living in the same nation, physical proximity, and telephone communication. Majority group members were poorer at judging minority group members than the reverse. Cross-cultural accuracy was lower in studies that used a balanced research design, and higher in studies that used imitation rather than posed or spontaneous emotional expressions. Attributes of study design appeared not to moderate the size of the in-group advantage.

3.4.2 Award-winning Papers of Important Conferences

This section analyzes the award-winning papers of important conferences in affective computing in order to understand the important research results published through conferences in recent years.

(1) Award-winning Papers of ACM International Conference on Multimedia (Best Demo paper).

Time: 2016

Title: SentiCart: Cartography and Geo-contextualization for Multilingual Visual Sentiment

Author: Brendan Jou, Margaret Yuying Qian, Shih-Fu Chang

Abstract: Where in the world are pictures of cute animals or ancient architecture most shared from? And are they equally sentimentally perceived across different languages? We demonstrate a series of visualization tools, that we collectively call SentiCart, for answering such questions and navigating the landscape of how sentiment-biased images are shared around the world in multiple languages. We present visualizations using a large-scale, self-gathered geodata corpus of

＞1.54M geo-references coming from over 235 countries mined from ＞15K visual concepts over 12 languages. We also highlight several compelling data-driven findings about multilingual visual sentiment in geo-social interactions.

(2) Award-winning Papers of Annual Meeting of the Association for Computational Linguistics (Best paper awards)[⑦]

Time: 2011

Title: Fine-Grained Sentiment Analysis with Structural Features

Author: Cäcilia Zirn, Mathias Niepert, Heiner Stuckenschmidt, Michael Strube

Abstract: Sentiment analysis is the problem of determining the polarity of a text with respect to a particular topic. For most applications, however, it is not only necessary to derive the polarity of a text as a whole but also to extract negative and positive utterances on a more finegrained level. Sentiment analysis systems working on the (sub-) sentence level, however, are difficult to develop since shorter textual segments rarely carry enough information to determine their polarity out of context. In this paper, therefore, we present a fully automatic framework for fine-grained sentiment analysis on the sub-sentence level combining multiple sentiment lexicons and neighborhood as well as discourse relations to overcome this problem. We use Markov model to integrate polarity scores from different sentiment lexicons with information about relations between neighboring segments, and evaluate the approach on product reviews. The experiments show that the use of structural features improves the accuracy of polarity predictions achieving accuracy scores of up to 69%.

3.4.3 Award-winning Papers of Important Journals

In 2021, the editorial board of IEEE Transactions on *Affective Computing* selected 7 best papers from 122 papers published in the transaction between May 2017 and December 2019, which are listed as below:

Paper 1 EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks

Author: Tengfei Song, Wenming Zheng, Peng Song, Zhen Cui

Abstract: The paper pioneers the introduction of a graph to the characterization of functional connectivity between EEG electrodes. It proposes a DGCNN model for EEG emotion recognition and the idea and method of adaptively acquiring the inter-electrode adjacent relationship (Graph: Adjacent Matrix) by network dynamical learning, breaking the technical bottleneck of constructing graph adjacent matrix in the case of uncertain brain functional connectivity.

Paper 2 Personalized Multitask Learning for Predicting Tomorrow's Mood, Stress, and Health

Author: Sara Taylor, Natasha Jaques, Ehimwenma Nosakhare, Akane Sano, Rosalind Picard

Abstract: We employ Multitask Learning (MTL) techniques to train personalized ML models which are customized to the needs of each individual. Three formulations of MTL are compared: ①MTL deep neural networks, which share several hidden layers but have final layers unique to each task; ②multi-task multi-Kernel learning, which feeds information across tasks through kernel weights on feature types; and ③a Hierarchical Bayesian model in which tasks share a common Dirichlet Process prior. Empirical results demonstrate that using MTL to account for individual differences provides large performance improvements over traditional machine learning methods and provides personalized, actionable insights.

⑦ https://www.aclweb.org/aclwiki/Best_paper_awards

Paper 3 Identifying Stable Patterns over Time for Emotion Recognition from EEG

Author: Wei-Long Zheng, Jia-Yi Zhu, Bao-Liang Lu

Abstract: In this paper, we investigate stable patterns of electroencephalogram (EEG) over time for emotion recognition using a machine learning approach. Up to now, various findings of activated patterns associated with different emotions have been reported. However, their stability over time has not been fully investigated yet. In this paper, we firstly design multiple emotion-evoking experiments across time. Then, we systematically evaluate the performance of various popular feature extraction, feature smoothing and pattern classification methods with the DEAP and SEED datasets. The experimental results indicate that stable patterns exhibit consistency across sessions; the lateral temporal areas activate more for positive emotions than negative emotions in beta and gamma bands; the neural patterns of neutral emotions have higher alpha responses at parietal and occipital sites; and for negative emotions, the neural patterns have significant higher delta responses at parietal and occipital sites and higher gamma responses at prefrontal sites. The performance of our emotion recognition models shows that the neural patterns are relatively stable within and between sessions. These results provide theoretical assurance of data validity for emotion recognition using EEG signals.

Paper 4 Emotions Recognition Using EEG Signals: A Survey

Author: Soraia M. Alarcão, Manuel J. Fonseca

Abstract: In this paper, we present a survey of the neurophysiological research performed from 2009 to 2016, providing a comprehensive overview of the works in emotion recognition using EEG signals. We focus our analysis in the main aspects involved in the recognition process (e.g., subjects, features extracted, classifiers), and compare the works per them. From this analysis, we propose a set of good practice recommendations that researchers must follow to achieve reproducible, replicable, well-validated and high-quality results.

Paper 5 Automatic Analysis of Facial Actions: A Survey

Author: Brais Martinez, Michel F. Valstar, Bihan Jiang, Maja Pantic

Abstract: As one of the most comprehensive and objective ways to describe facial expressions, the Facial Action Coding System (FACS) has recently received significant attention. Over the past 30 years, extensive research has been conducted by psychologists and neuroscientists on various aspects of facial expression analysis using FACS. Automating FACS coding would make this research faster and more widely applicable, opening up new avenues to understanding how we communicate through facial expressions. Such an automated process can also increase the reliability, precision and temporal resolution of coding. This paper provides a comprehensive survey of research into machine analysis of facial actions. We systematically review all components of such systems: pre-processing, feature extraction and machine coding of facial actions. In addition, the existing FACS-coded facial expression databases are summarized. Finally, challenges that have to be addressed to make automatic facial action analysis applicable in real-life situations are discussed. There are two intentions for us to write this survey paper: the first is to provide an up-to-date review of the existing literature, and the second is to offer some insights into the future of machine recognition of facial actions: what are the challenges and opportunities that researchers in the field face.

Paper 6 Building Naturalistic Emotionally Balanced Speech Corpus by Retrieving Emotional Speech from Existing Podcast Recordings

Author: Reza Lotfian, Carlos Busso

Abstract: The lack of a large, natural emotional database is one of the key barriers to translate results on speech emotion recognition in controlled conditions into real-life applications. Collecting emotional databases is expensive and time demanding, which limits the size of existing corpora. Current approaches used to collect spontaneous databases tend to provide unbalanced emotional content, which is dictated by the given recording protocol (e.g., positive for colloquial conversations, negative for discussion or debates). This paper proposes a novel approach to effectively build a large, naturalistic emotional database with balanced emotional content, reduced cost and reduced manual labor. It relies on existing spontaneous recordings obtained from audio-sharing websites. The proposed approach combines machine learning algorithms to retrieve recordings conveying balanced emotional content with a cost-effective annotation process using crowdsourcing, which makes it possible to build a large scale speech emotional database. This approach provides natural emotional renditions from multiple speakers, with different channel conditions and conveying balanced emotional content that are difficult to obtain with alternative data collection protocols.

Paper 7 AMIGOS: A Dataset for Affect, Personality and Mood Research on Individuals and Groups

Author: Juan Abdon Miranda-Correa, Mojtaba Khomami Abadi, Nicu Sebe, Ioannis Patras

Abstract: We present AMIGOS-A dataset for Multimodal research of affect, personality traits and mood on Individuals and Groups. Different to other databases, we elicited affect using both short and long videos in two social contexts, one with individual viewers and one with groups of viewers. The database allows the multimodal study of the affective responses, by means of neuro-physiological signals of individuals in relation to their personality and mood, and with respect to the social context and videos' duration. The data is collected in two experimental settings. In the first one, 40 participants watched 16 short emotional videos. In the second one, the participants watched 4 long videos, some of them alone and the rest in groups. The participants' signals, namely, Electroencephalogram (EEG), Electrocardiogram (ECG) and Galvanic Skin Response (GSR), were recorded using wearable sensors. Participants' frontal HD video and both RGB and depth full body videos were also recorded. Participants' emotions have been annotated with both self-assessment of affective levels (e.g., valence, arousal, control, familiarity, and liking) felt during the videos as well as external-assessment of levels of valence and arousal. We present a detailed correlation analysis of the different dimensions as well as baseline methods and results for single-trial classification of valence and arousal, personality traits, mood, and social context. The database is made publicly available.

3.5 Representative Patents and Standards

3.5.1 Representative Patents

Derwent Innovations Index is the most comprehensive value-added patent information database around the world. It covers over 14.3 million basic inventions from almost 60 worldwide patent-issuing authorities, accounting for 96% of the world's patents. The database dates from 1963 and provides researchers with comprehensive information of inventions in the fields of chemistry, electronic and electrical, and engincring technology worldwide. It is also one of the most authoritative databases for searching global patents and is used and trusted by patent office examiners in more than 40 countries.

This section conducts searches based on the subjects (patent name + abstract), and selects valid invention patents with transfer records or licensing records and high value to form representative patents in affective computing field.

Patent transfer refers to a contract concluded by which a patentee, as the transferor, transfers the ownership or holding right of the patent to a transferee, and according to which the transferee pays the agreed price. The transferee who obtains the patent right through the contract becomes the new legal patentee. Screen patents in affective computing for transferred patents with incopat patent value of 10 as listed in Table 3-13.

Table 3-13 Important Transferred Patents in Affective Computing

No.	Publication No.	Patent name	Patentee	Transferee	Legal matter
1	CN110675859B	Multi-emotion recognition methods, systems, medium and devices combing speech and text	South China University of Technology	Guangdong Lvan Industry and Commerce Co., Ltd.	Transfer
2	US10902058B2	Cognitive content display device	IBM	Kyndryl, Inc	Transfer
3	CN108806667B	Simultaneous recognition of speech and emotion based on neural network	Chongqing University	Sevnce Robotics Co., Ltd.	Transfer
4	CN105469065B	Discrete emotion recognition method based on recurrent neural network	Institute of Automation, Chinese Academy of Sciences	Beijing Zhongke Ouke Technology Co., Ltd.	Transfer
5	CN104200804B	A multi-class information coupled emotion recognition method for human-computer interaction	Hefei University of Technology	Shandong Xinfa Technology Co., Ltd.	Transfer
6	US9436674B2	Signal processing approach to sentiment analysis for entities in documents	Attivio Inc	Servicenow, Inc	Transfer
7	CN103377293B	Holographic touch interactive display system with multi-source input and intelligent information optimization processing	Changzhou Campus Of Hohai University	Jiangsu Mingwei Wansheng Technology Co., Ltd.	Transfer
8	CN104995650A	Method and system for generating composite indexes using social media-derived data and sentiment analysis	Thomson Reuters	Financial and Risk Organization Ltd.	Transfer
9	CN103049435B	Method and device for fine-grained sentiment analysis of text	Zhejiang Gongshang University	Hangzhou Naokeding Technology Co., Ltd.	Transfer
10	CN101872424B	Fuzzy and syncretic facial expression recognition method based on optimal channel through Gabor transform	Chongqing University	Beijing Picohood Technology Co., Ltd.	Transfer

Patent licensing refers to the act that the patentee licenses his patented technology to others, during which the patentee becomes the licensor and the party accepts the technology becomes the licensee. A patent enforcement license contract is signed between the licensor and the licensee.

Some important domestic licensed patents in affective computing are listed in Table 3-14.

In addition, a number of high-level affective computing patents have been authorized by new domestic R&D institutions, as listed in Table 3-15.

Table 3-14 Important Domestic Licensed Patent in Affective Computing

No.	Publication No.	Patent name	Licensor	Licensee	Legal matter
1	CN111506700B	Fine-grained sentiment analysis method based on context-aware embedding	Hangzhou Dianzi University	UTRY	Licensing
2	CN110110840B	An associative memory emotion recognition circuit based on memristance neural network	China University of Geosciences, Wuhan	Wuhan Haibo Wulian Technology Co., Ltd., Wuhan Qiyi Information Technology Service Co., Ltd.	Licensing
3	CN107045618B	Facial expression recognition method and device	Yi+	Apple R&D (Beijing) Co., Ltd.	Licensing
4	CN107609132B	A sentiment analysis method for Chinese text based on semantic ontology library	Hangzhou Dianzi University	UTRY	Licensing
5	CN106570474B	A micro-expression recognition method based on 3D convolutional neural network	Nanjing University of Posts and Telecommunications	Nanjing Causal Artificial Intelligence Research Institute Co., Ltd.	Licensing

Table 3-15 High-level Affective Computing Patents Authorized by New Domestic R&D Institutions

No.	Publication No.	Patent name	Authorizer	Patent status
1	CN113837153A	Real-time emotion recognition method and system incorporating pupil data and facial expressions	Zhejiang Lab	Authorized
2	CN114049678A	Facial motion capture method and system based on deep learning	Zhejiang Lab	Authorized
3	CN113611286A	Cross-language speech emotion recognition method and system based on common feature extraction	Zhejiang Lab	Authorized
4	CN113576482A	Attentional bias training evaluation system and method based on composite expression processing	Zhejiang Lab	Authorized

(Continue)

No.	Publication No.	Patent name	Authorizer	Patent status
5	CN113378806A	Audio driven face animation generation method and system based on composite emotion coding	Zhejiang Lab	Authorized
6	CN113257225A	Emotion and speech synthesis method and system incorporating lexical and phonetic pronunciation features	Zhejiang Lab	Authorized
7	CN112712824A	Speech and emotion recognition method and system incorporating group information	Zhejiang Lab	Authorized
8	CN112545519A	Real-time assessment method and assessment system for group sentiment homogeneity	Zhejiang Lab	Authorized
9	CN113191212A	Driver road rage risk warning method and system	Institute of Artificial Intelligence, Hefei Comprehensive National Science Center (Anhui Artificial Intelligence Lab)	Authorized

3.5.2 Representative Standards

(1)International Standards

International standards refer to the standards developed by the International Organization for Standardization (ISO)⑧, International Electrotechnical Commission (IEC) and International Telecommunication Union (ITU), and those developed by other international organizations⑨ confirmed and published by ISO. International standards are used uniformly around the world.

Information Technology-Affective Computing User Interface (AUI) (ISO/IEC 30150-1: 2022), of which the Part 1 (Model) was published in June 2022 and the Part 2 (Affective characteristics) is under construction.

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⑧ https://www.iso.org/standards-catalogue/browse-by-ics.html

⑨ Currently, other international organizations confirmed and published by ISO includes Bureau International des Poids et Mesures (BIPM), Bureau International pour la Standardisation des Fibres Artificielles (BISFA), Codex Alimentarius Commission (CAC), Consultative Committee for Space Data Systems (CCSDS), Conseil International du Batiment (CIB), Commission Internationale de l´Eclairage (CIE), Conseil Internation des Machines a Combustion (CIMAC), Fédération Dentaire Internationale (FDI), Fédération Internationale de Documentation (FID), International Atomic Energy Agency (IAEA), International Air Transport Association (IATA), International Civil Aviation Organization (ICAO), International Association for Cereal Science and Technology (ICC), International Commission on Irrigation and Drainage (ICID), (International Commission on Radiological Protection (ICRP), International Commission on Radiation Units and Measurements (ICRU), International Diary Federation (IDF), The Internet Engineering Task Force (IETF), International Federation of Library Associations and Institutions (IFLA), International Federal of Organic Agriculture Movement (IFOAM), International Gas Union (IGU), International Institute of Refrigeration (IIR), International Labour Organization (ILO), International Maritime Organization (IMO), International Seed Testing Association (ISTA), International Union of Pure and Applied Chemistry (IUPAC), International Wool Textile Organisation (IWTO), Office International des Epizooties (OIE), Organisation Internationale de Métrologie Légale (OIML), Organisation Internationale de la Vigne et du vin (OIV), International Union of Laboratories and Experts in Construction Materials, Systems and Structures (RILEM), China Council for the Promotion of International Trade (TarFIX), Union Internationale des Chemins de Fer (UIC), The United Nations Centre for Trade Facilitation and Electronic Business (UN/CEFACT), United Nations Educational, Scientific and Cultural Organization (UNESCO), World Customs Organization (WCO), World Health Organization (WHO), World Intellectual Property Organization (WIPO), World Meteorological Organization (WMO), etc.

(2) Domestic Standards

Artificial Intelligence-Affective Computing User Interface-Model (GB/T 40691-2021) was jointly drafted by the Institute of Software Chinese Academy of Sciences, the Institute of Automation, Chinese Academy of Sciences, the Institute of Psychology, Chinese Academy of science and iFLYTEK. It was published on Oct. 11, 2021, and became effective on May 1, 2022. These standards provide a common model and an interaction model based on affective computing user interface, describing the modules of emotion representation, emotional data collection, emotion recognition, emotion resolution, emotion expression, etc. They are applicable to the design, development and application of affective computing user interface.

(3) Group Standards

Specification of Intelligent Psychological Services (T/ZAITS 20401-2022) was jointly drafted by Zhejiang Lianxin Technology Co., Ltd., Zhejiang Lab, Zhejiang Fangda Standard Information Co., Ltd., Department of Psychology and Behavioral Sciences, Zhejiang University, Zhejiang University of Technology, Hangzhou Normal University School of Nursing, Suzhou Qifa Management Consulting Co., Ltd., Beijing Xunbao Technology Co., Ltd. and Shenmu Xinzheng Psychology Health Services Co., Ltd. under the organization of Zhejiang Intelligent Technology Standard Innovation Promoting Association. It was published and implemented on Jan 28, 2022. This standard specifies the terminology and definition, service system composition and service model, capability requirements for service system, service content, service process, establishment of psychological service files and information security requirements of intelligent psychological services. It mainly applies to provide intelligent psychological services for all people except infants and children by using the digital intelligence technology, and to be referred to in auxiliary psychological services provided by medical institutions and psychiatrists.

Chapter Ⅳ
Scientific Research

4.1 Scholar Distribution and Representative Scientists

4.1.1 Map of Global Scholars

(1)Distribution of Global Scholars

This section makes a statistical analysis on the countries of the first authors of affective computing papers, so as to form a macro understanding of the global distribution of scholars in the field.

Based on the distribution analysis of scholars, it is obvious that Asia is the region with the highest concentration of scholars in the field. As shown in Table 4-1 and Figure 4-1, China has the largest number of scholars in the field (3,474), followed by the United States (2,083), and India (2,001).

Table 4-1 Countries of the First Authors of Affective Computing Papers (Top 20)

No.	Country	Scholar Number	No.	Country	Scholar Number
1	China	3,474	11	Australia	455
2	USA	2,083	12	France	382
3	India	2,001	13	Turkey	369
4	UK	864	14	Netherlands	300
5	Germany	713	15	Malaysia	265
6	Italy	592	16	Brazil	321
7	Japan	551	17	Pakistan	268
8	Spain	467	18	Iran	216
9	Canada	463	19	Greece	213
10	South Korea	456	20	Singapore	180

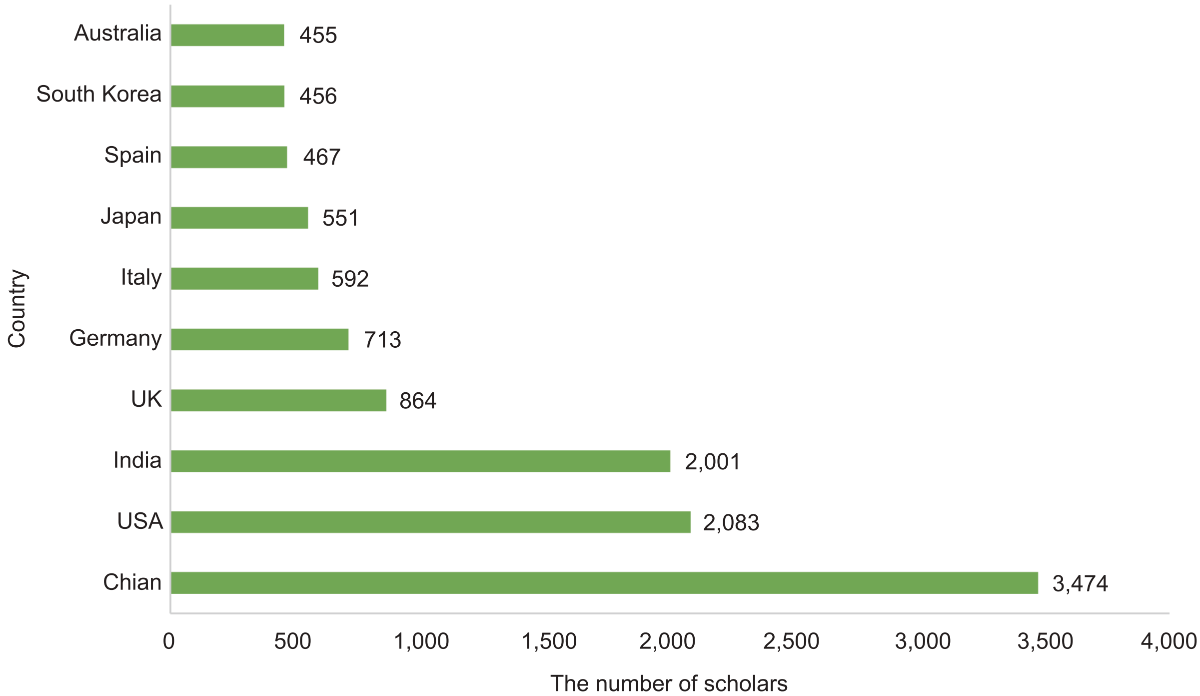

Figure 4-1 Scholars in Top 10 Countries

(2) Distribution of h-index

The h-index of a total of 47,998 authors with more than 0 citations was counted, and the results are shown in Table 4-2. The highest h-index is 53, and the number of authors with h-index greater than 50 is 1. The number of authors with h-index located in 1-10 reaches the most, i.e., 47,881.

Table 4-2 h-index of Authors

h-index	Number of authors
1 ~ 10	47,881
11 ~ 20	104
21 ~ 30	9
31 ~ 50	3
＞50	1

(3) Sino-Foreign Cooperation

Extensive international cooperation has been conducted in affective computing, and a figure of the cooperation among the countries with top 10 publications is shown in Table 4-2.

China and the USA leads with 540 publications, followed by China and the UK with 256 publications. The information about the cooperation among the top 20 countries is detailed in appendix 3.

China has extensive cooperation with other countries, and 1,707 of 6,905 Chinese publications are joint publications, accounting for 24.72% of the total. The main countries cooperating with China are shown in Table 4-3, among which, China and the USA accounts for 31.64% of the total with 540 publications, involving 2,168 scholars, followed by China and the UK. Publications by China and Singapore, and China and Finland are highly cited indicating the high-quality cooperation between the countries.

4.1.2 Distribution of Chinese Scholars

This section analyzes the first authors of papers in affective computing for their locations as shown

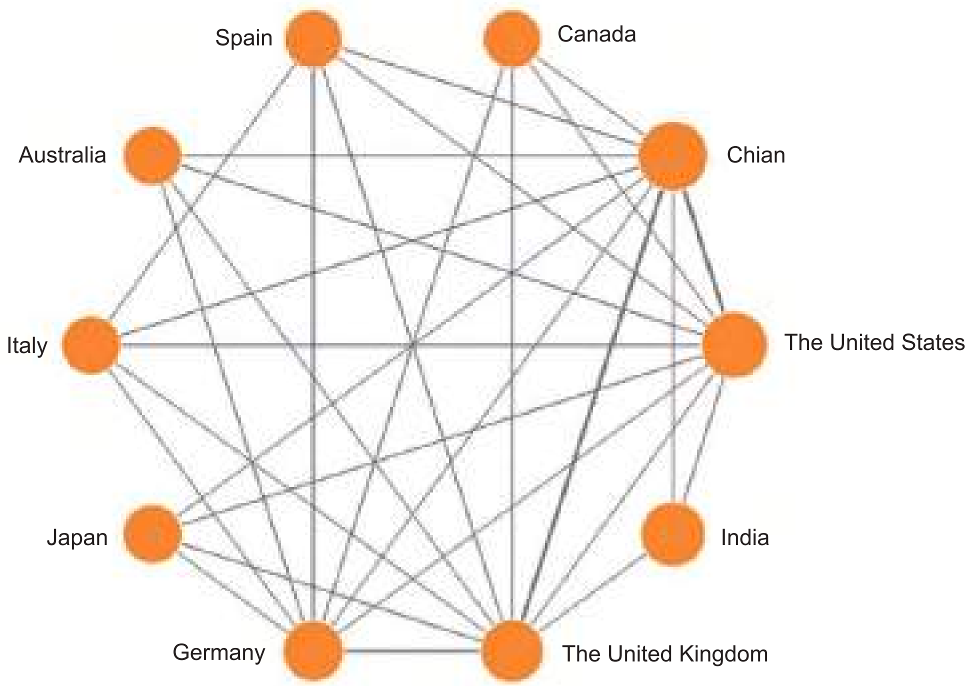

Figure 4-2 Cooperation among the Countries with a Top 10 Publication in Affective Computing

in Table 4-4 and Figure 4-3. Beijing leads with 1,053 scholars, followed by Guangdong with 513 scholars. Jiangsu, Taiwan and Shanghai rank third, fourth and fifth, respectively.

Table 4-3 Main Countries Cooperating with China on Affective Computing Publications

No.	Countries	Publication Number	Citation Number	Average Citation Number	Scholar Number
1	China-the USA	540	11,568	21	2,168
2	China-the UK	256	4,430	17	1,057
3	China-Japan	212	1,992	9	505
4	China-Australia	169	1,628	10	749
5	China-Singapore	123	3,774	31	488
6	China-Canada	106	1,931	18	411
7	China-Finland	66	1,982	30	152
8	China-Germany	58	1,273	22	314
9	China-India	54	644	12	203
10	China-France	44	595	14	205

Table 4-4 Regions with a Top 20 Affective Computing Scholars

No.	Regions	Scholar Number	No.	Regions	Scholar Number
1	Beijing	1,053	11	Sichuan	194
2	Guangdong	513	12	Shandong	183
3	Jiangsu	442	13	Tianjin	161
4	Taiwan	430	14	Liaoning	160
5	Shanghai	373	15	Chongqing	155
6	Zhejiang	298	16	Hunan	149
7	Hubei	272	17	Fujian	121
8	Hong Kong	247	18	Heilongjiang	117
9	Shaanxi	242	19	Henan	94
10	Anhui	201	20	Hebei	68

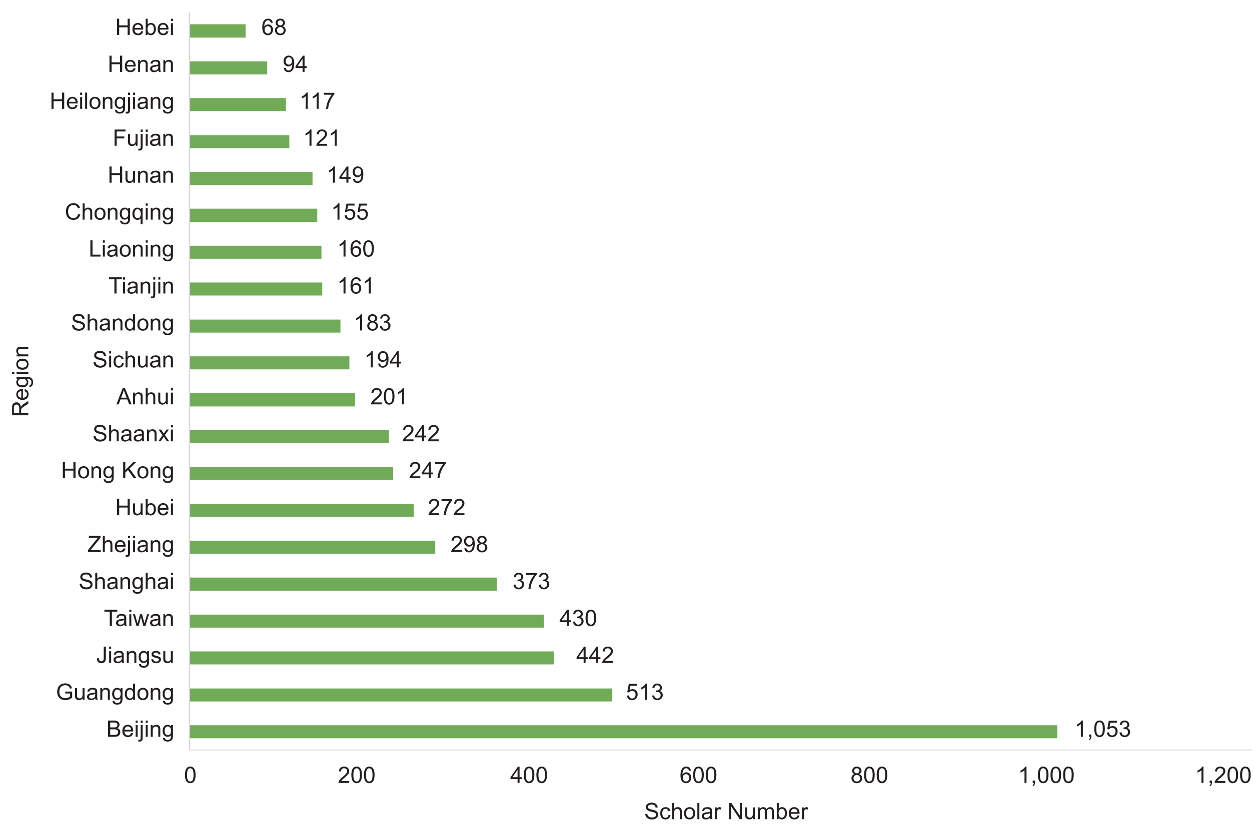

Figure 4-3 Regions with a Top 20 Affective Computing Scholars

4.1.3 Global Representative Scholars

This section identifies representative scholars in affective computing based on multiple indices such as number of papers, research contributions, and peer comments, as shown in Table 4-5. It shall be noted that this section is for reference only and is not intended as a basis for evaluation due to the variability of the indices for talent evaluation and the differences in the sources of statistical data.

4.1.4 Highly Cited Researchers

Based on the “Highly Cited Chinese Researchers” list published by Elsevier in 2021, the scholars in affective computing field found among 4,701 Chinese scholars are shown in Table 4-6.

4.2 Top Association

4.2.1 Association for the Advancement of Affective Computing (AAAC)

AAAC⑩ is a professional, world-wide association for researchers in affective computing, emotions and human-machine Interaction, responsible for the bidding and organization of the International Conference on Affective Computing and Intelligent Interaction (ACII).

4.2.2 Professional Committee of Emotional Intelligence of the Chinese Association for Artificial Intelligence

The Professional Committee of Artificial Psychology and Artificial Emotion of the Chinese Association for Artificial Intelligence⑪ (“Professional Committee”) was established in 2007, the first academic organization for affective computing in the field of electronic information science in China. The research areas of the Professional

⑩ https://aaac.world/

⑪ http://caai.cn/index.php?s=/home/article/detail/id/1046.html

Table 4-5 Representative Scholars in Affective Computing

No.	Scholars	Work Unit
1	Fuji Ren	The University of Tokushima
2	Rosalind Picard	Massachusetts Institute of Technology
3	Erik Cambria	Nanyang Technological University
4	Bjoern Schuller	Imperial College London
5	Wenming Zheng	Southeast University
6	Maja Pantic	Imperial College London
7	Guoying Zhao	University of Oulu
8	Bao-liang Lu	Shanghai Jiao Tong University
9	Carlos Busso	The University of Texas at Dallas
10	Shrikanth Narayanan	University of Southern California

Table 4-6 Highly Cited Chinese Researchers in Affective Computing

Name	Institution
Bao-liang Lu	Shanghai Jiao Tong University
Hongjiang Zhang	Source Code Capital
Aimin Zhou	East China Normal University
Bing Qin	Harbin Institute of Technology
Xuelong Li	Northwestern Polytechnical University
Bin Liu	Beijing Institute of Technology
Yugang Jiang	Fudan University
Deshuang Huang	Tongji University
Chao Dong	Chinese Academy of Sciences
Min Chen	Huazhong University of Science and Technology

Committee include emotion modelling, emotion recognition, multimodal emotion interaction, emotion and psychological signal measurement, and artificial psychology. The Professional Committee hosted the first "Asian Academic Conference on Affective Computing and Intelligent Interaction" and published the first series of *Artificial Psychology and Digital Human Technology* in China. The Professional Committee aims to unite and organize professionals in the field of artificial psychology and affective computing in China to carry out academic exchange activities, strengthen talent training and promote the cooperation between academia and industry. It also contributes to the improvement of China's ability in scientific research, teaching and application, and the international influence in the field of artificial psychology and affective computing by undertaking social services such as knowledge popularization, offering advice and suggestions.

4.3 Top Academic Institutions

4.3.1 Important Research Institutions

This section identifies important institutions by ranking the number of publications through all authors, and the top 10 are shown in Table 4-5. The main indices involved include Citation Impact and Category Normalized Citation Impact (CNCI).

Citation Impact: The Citation Impact of a group of documents is calculated by dividing the total citations by the number of ducuments, showing the average number of citations received by a document in the group.

CNCI: The CNCI of a document is obtained by dividing its actual citation times by the expected citation times for the papers in the same type, the same publication year, and the same category. When a document belongs to more than one category, the average of the ratio of the actual citation number to the expected citation times is adopted. The CNCI of a group of documents, such as an individual, institution or country, is the average of the CNCI of each document in the group. CNCI is a valuable and unbiased index for impact that excludes the effects of publication year, category and document type. If the value of CNCI is equal to 1, the citation performance of the group of documents is comparable to the global average. If the value of CNCI is greater than 1, the citation performance of the group of documents is higher than the global average; otherwise, it is lower than the global average. If the value of CNCI equals 2, the citation performance of the group of documents is twice the global average.

As shown in Table 4-7, there are two Chinese institutions: the Chinese Academy of Sciences leading with 581 papers and Tsinghua University ranking 9th; the University of California System ranks 5th with 335 papers; and there are two institutions of the UK, France, and India, respectively, and one institution of Singapore.

4.3.2 Representative Research Institutions

(1) MIT Media Lab

The Affective Computing Group of MIT Media Lab[12] creates and evaluates new ways of bringing together Emotion AI and other affective technologies. Rosalind W. Picard is the creator of "affective computing" and also the founder and director of the group.

[12] https://www.media.mit.edu/groups/affective-computing/overview/

Table 4-7 Institutions with a Top 10 Publication in Affective Computing

No.	Name of Institution	Paper Number	Citation Impact	Citation Percentage/%	CNCI	Highly Cited Papers	h Index	Percentage in Q1 Journals/%	Country
	English Name								
1	Chinese Academy of Sciences	581	17.09	77.28	2.44	4	49	58	China
2	University of London	373	51.39	89.54	2.37	8	73	69.93	The UK
3	Centre National de la Recherche Scientifique (CNRS)	346	17.36	80.35	1.36	2	39	52.06	France
4	UDICE-French Research Universities	341	16.85	80.35	1.38	1	38	51.03	France
5	University of California System	335	38.05	84.18	2.8	4	59	59.6	The US
6	Indian Institute of Technology System (IIT System)	295	10.68	74.92	1.8	5	28	42.11	India
7	National Institute of Technology System (NIT System)	288	7.71	70.14	1.33	3	24	27.66	India
8	Nanyang Technological University	287	36.3	83.97	5.18	14	60	66.4	Singapore
9	Tsinghua University	264	20.74	82.95	2.94	2	38	63.27	China
10	Imperial College London	263	37.96	87.83	3.64	3	43	67.39	The UK

(2) Computational Intelligence Lab (CIL) of Nanyang Technological University

The CIL of Nanyang Technological University[13] is part of the College of Engineering and focuses on knowledge-intensive AI. Affective computing is one of the key research of the lab. Erik Cambria works in the lab, who is an associate professor in the School of Computer Science and Engineering of Nanyang Technological University and the founder of SenticNet, a company providing sentiment analysis service.

(3) Institute of Human-computer Interaction (HCI) and Media Integration of Tsinghua University

The Institute of Human-computer Interaction (HCI) and Media Integration of Tsinghua University[14] conducts top research in media intelligent processing, human-computer interaction, and pervasive computing. It built several academic bases, such as Key Lab of Pervasive Computing, Ministry of Education, Tsinghua University-Tencent Joint Lab for Internet Innovation Technologies, Beijing Key Lab of Intelligent Telecommunication Software and Multimedia, Tsinghua University Computer Department - Huawei Terminal Intelligent Interaction Technology Innovation Joint Laboratory, Tsinghua University (Computer Department) - Shenlan Technology Machine Vision Joint Research Center, etc. In recent years, it led many important projects in this discipline (e.g., key R&D plan of the "13th Five-Year", "973" project, key project of NSFC, etc.), and published a large number of academic papers in top journals and conferences with several articles winning the best paper awards. It also received 10 national science and technology awards, which had a significant impact on the transformation of scientific and technological achievements. There are two main research directions: ① harmonious human-computer interaction, e.g., affective computing, voice interaction, large scale interaction, brain-computer interface, interaction efficiency and optimization, new terminal natural interaction interface, etc.; ② pervasive computing environment, e.g., pervasive computing models, active service, embedded system, context awareness, smart room and Internet of things, etc.

(4) The National Laboratory of Pattern Recognition

The National Laboratory of Pattern Recognition at the Institute of Automation, Chinese Academy of Sciences studies the mechanism and effective computing methods of human pattern recognition, with specific interests in the basic theory of pattern recognition, image processing and computer vision, and speech and language processing to provide key technologies for developing intelligent systems, and a scientific basis for exploring the nature of human intelligence. The researches in image processing and computer vision are mainly on the analysis and understanding of visual patterns, including 3D vision and scene analysis, object detection and recognition, video analysis and semantic understanding, medical image analysis, biometric image recognition, remote sensing image analysis, document image analysis, multimedia computing, etc.

The researches in speech and language processing are mainly on the analysis and understanding of auditory patterns, including speech recognition, discourse comprehension, oral interpretation, emotion interaction, Chinese processing, information retrieval, etc. Currently, the lab conducts more than 400 research projects, including the National Key Research and Development Program, the major project of "New Generation Artificial Intelligence" in Science and Technology Innovation 2030, the National Natural Science Foundation of China's major, key and general programs, National Science Fund for Distinguished Young Scholars and innovation group

⑬ https://www.ntu.edu.sg/cil/about-us
⑭ https://www.cs.tsinghua.edu.cn/jgsz/yjsgjzdsys/jsjkxyksxrjjhymtjcyjs.htm

project, international cooperation projects, enterprise cooperation projects, etc. Some well-known scholars, such as academician Tan Tieniu and researcher Tao Jianhua are in the research team.

(5) Affective Information Processing Lab (AIPL)

AIPL, affiliated with the School of Biological Sciences and Medical Engineering, Southeast University, and the Key Laboratory of Child Development and Learning Science, Ministry of Education, was founded by Prof. Zheng Wenming in 2004. AIPL focuses on the research of affective computing, pattern recognition, computer vision, machine learning, and their applications in the development of children's intelligence, education, and medical treatment, etc. The lab is deeply engaged in affective computing and hosts many national and provincial level projects including the "973" project and the project supportde by the key Program of the National Natural Science Foundation of China. It has published more than one hundred papers in the *IEEE Transactions* series and top conferences in the field of computing such as IEEE ICCV, IEEE CVPR, European Conference on Computer Vision (ECCV), Conference and Workshop on Neural Information Processing Systems (NIPS), International Joint Conference on Artificial Intelligence (IJCAI) and AAAI Conference on Artificial Intelligence. Some of the research results won 1 national second prize for technical invention.

(6) Institute of Affective Computing and System Architecture, Hefei University of Technology

The Institute of Affective Computing of Hefei University of Technology was established in 2011, mainly engaged in the basic theoretical research of higher intelligence, affective computing, and large-scale knowledge acquisition, with advanced intelligent robots with emotion (such as nursing robots) as core applications. It led and participated in many projects such as the National Natural Science Foundation of China, Provincial Natural Science Foundation of Anhui, and the National "973" pre-research project.

4.3.3 Emerging research institution

Research Center for Multi-Modal Intelligence of Zhejiang Lab is an emerging research institution affiliated with Zhejiang Lab.

Founded on Sep. 6, 2017, Zhejiang Lab focuses on five areas including intelligent sensing, artificial intelligence, intelligent computing, intelligent networks, and intelligent systems. The Research Center for Multi-Modal Intelligence of Zhejiang Lab is an emerging innovative research institution in affective computing with 27 publications in the field in the last four years (2019-2022). It focuses on the studies on basic theories and key technologies such as multimodal unified representation and relevant understanding, visual knowledge representation and visual intelligence, multimodal knowledge evolution, and multimodal intelligent analysis, and R&D of flagship platforms for multimodal content generation, multimodal sensing, affective computing, and emotionally intelligent human-computer dialogue system.

Researcher Li Taihao, Deputy Director of the Research Center, is mainly engaged in the research on affective computing and multimodal intelligence. He is a student of Professor Ren Fuji, the Member of the Japanese Academy of Engineering, the Member of the European Union Academy of Sciences, the Vice President of the Chinese Association for Artificial Intelligence, and the Director of the Lab of Affective Computing and Advanced Intelligence at the University of Tokushima. Li Taihao was a postdoctoral researcher at the intersection of artificial intelligence and brain science in the Verne Caviness Lab at Harvard University. He has been involved in an innovative long-term project for the provincial talent attraction program of Zhejiang Province.

4.4 Ecosystem Analysis

4.4.1 Collaborative Network of Scholars

The Derwent Data Analyzer tool is used to analyze the collaboration of authors of the publications in affective computing. By setting the number of publications of an author greater than or equal to 30 and the number of collaborative publications greater than or equal to 3, the scholar collaboration network is able to identify the collaboration of the same team or different teams. The result is presented in Figure 4-4.

As shown in the Figure, Bjoern Schuller from the Imperial College London had many collaborations with Zixing Zhang from the University of Munich in Germany, Fabien Ringeval from the Université Grenoble Alpes and Florian Eyben from the University of Munich in Germany. Professor Shangfei Wang from the Institute of Advanced Technology of the University of Science and Technology of China collaborated with Qiang Ji from the Rensselaer Polytechnic Institute in affective computing based on facial expressions; and Professor Fuji Ren from the National Tokushima University of Japan collaborated with Professor Xiao Sun from the Hefei University of Technology of China in context affective computing and speech affective computing.

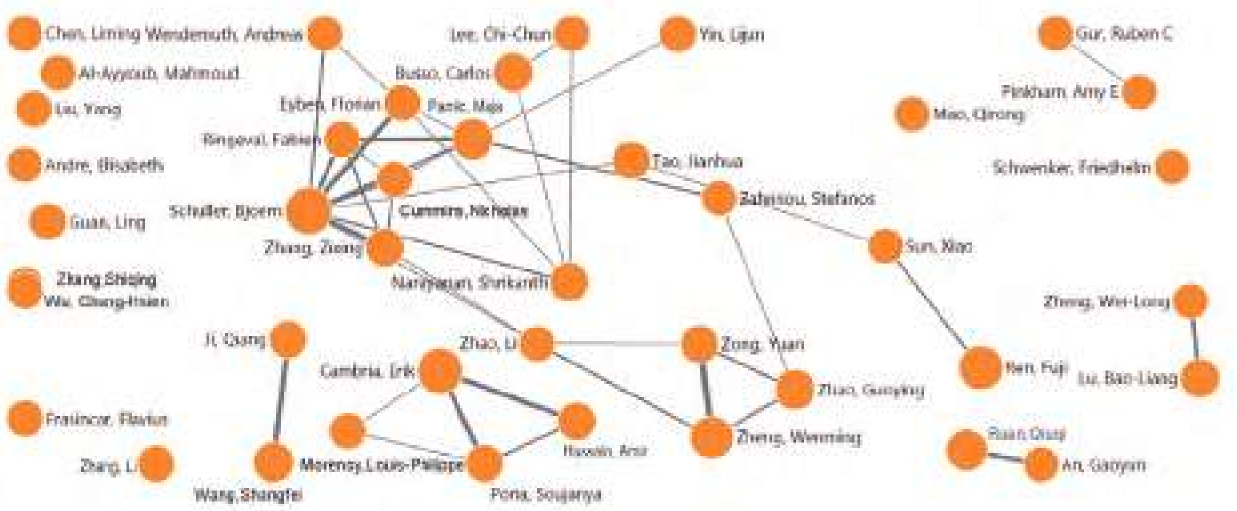

Figure 4-4 Collaborative Network of Scholars in Affective Computing

4.4.2 Citation Network Analysis

This section analyzes the authors of 27,877 affective computing papers for direct citations. In order to highlight the key authors, 40 authors with at least 30 publications are selected for the analysis. The results are shown in Figure 4-5, among which the authors within the same color clusters have strong correlation and succession in research content.

4.4.3 Keywords Co-occurrence Analysis

Word frequency is the occurrence number of a word in the document being analyzed. In the research of science measurement, word frequency dictionaries can be created by subject area, providing a quantitative analysis of scientists' creative activities. Word frequency analysis is a method to study the development trend and research hotspots in a field through the frequency distribution of keywords or subject words that can express the core content of a paper. The keywords co-occurrence analysis (co-word analysis) is a technique to identify relationships and interactions between keywords through counting the occurrence number of them in the same set of documents by pairs.

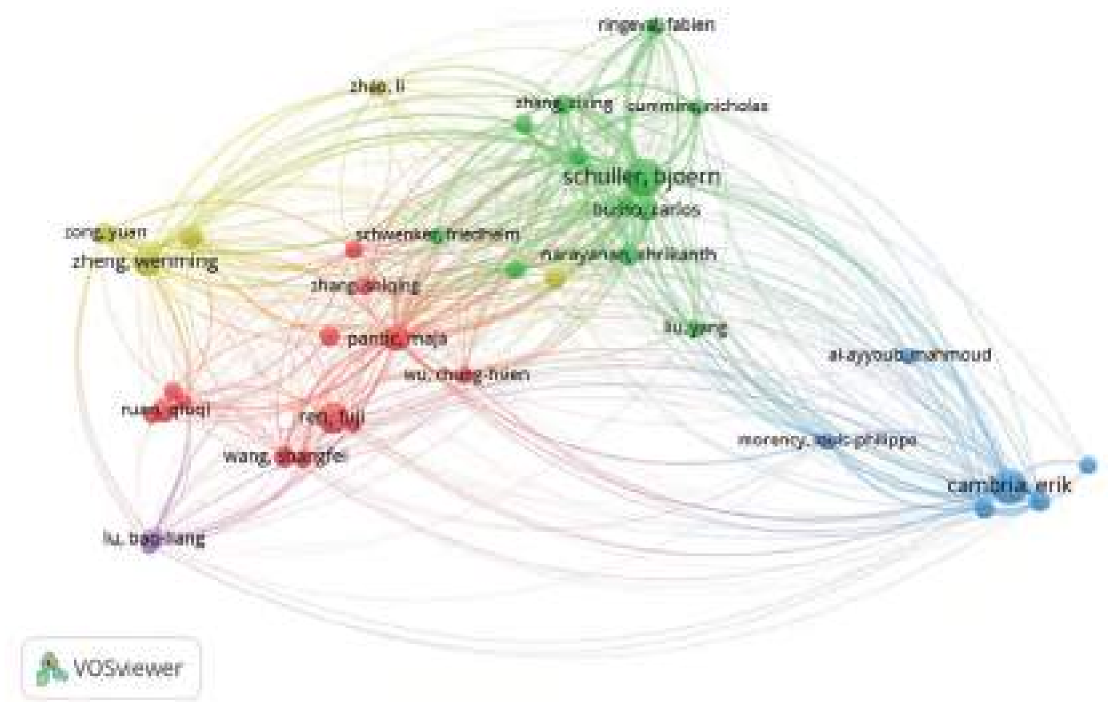

Figure 4-5 Citation Network of Scholars

(1) Word Frequency Analysis

According to the word frequency analysis on the keywords of authors as shown in Table 4-8, the technical subject words are co-occurring with the top-ranked technical subject words.

(2) Keywords Co-occurrence Analysis

Based on keywords co-occurrence analysis, this section, considering all the papers as a dataset, screens authors' keyword fields automatically and manually by using the Thomson Data Analyzer and then clusters core subject words by using the VOSviewer. The keywords are clustered by a certain co-occurrence frequency and co-occurrence intensity set according to the size of the paper dataset. According to expert interpretation, each cluster is named and interpreted separately to identify and analyze the themes of a journal.

27,877 papers are screened by authors' keyword fields automatically and manually, and 613 keywords with frequencies greater than 20 are selected from the 36,436 keywords for cluster analysis. Five clusters are obtained by clustering the core subject words with the highest co-occurrence intensity in these papers, which are listed in Table 4-9 and Figure 4-6.

The average citation of core subject words represents the average citation of papers containing these words since they are published. The average association strength is the correlation among core subject words: the higher the subject association strength, the stronger the co-occurrence among core subject words the more concentrated the research, otherwise, the lower the co-occurrence the more dispersed the research.

The "affective computing study in affective disorders" leads in average citation, indicating the current influence of crossover research between affective computing and the medical field, especially in the identification of affective disorders and depression. The "multimodal sentiment analysis based on deep learning" has the largest average association strength, indicating the highest concentration of research.

Table 4-8 Top 20 Word Frequency Analysis on Keywords of Authors in Affective Computing

No.	Record Number	Technical Subject Words	Top-ranked Technical Subject Words (Co-occurrence number)	Duration/ Year	Rate for the Last Three Years/%
1	6,305	Sentiment Analysis	Opinion Mining [866]; Machine Learning [757]; Twitter [656]	2006-2023	19
2	3,711	Emotion Recognition	Affective Computing [328]; Feature Extraction [283]; EEG [272]	1997-2022	21
3	2,121	Affective Computing	Emotion Recognition [328]; Machine Learning [153]; Emotion [122]	2000-2023	13
4	1,598	Machine Learning	Sentiment Analysis [757]; Natural Language Processing [214]; Emotion Recognition [175]	2002-2023	26
5	1,554	Facial Expression Recognition	Feature Extraction [129]; Deep Learning [120]; Face Recognition [89]	1997-2023	14
6	1,508	Deep Learning	Sentiment Analysis [485]; Emotion Recognition [243]; Machine Learning [172]	2012-2022	36
7	1,117	Opinion Mining	Sentiment Analysis [866]; Natural Language Processing [143]; Machine Learning [135]	2006-2022	10
8	1,020	Natural Language Processing	Sentiment Analysis [648]; Machine Learning [214]; Opinion Mining [143]; Deep Learning [143]	2006-2023	29
9	970	Emotion	Affective Computing [122]; Facial Expression [76]; Emotion Recognition [66]	1999-2022	12
10	918	Feature Extraction	Emotion Recognition [283]; Sentiment Analysis [169]; Facial Expression Recognition [129]	2003-2022	34
11	852	Twitter	Sentiment Analysis [656]; Machine Learning [129]; Social Media [116]	2011-2022	17
12	697	Social Media	Sentiment Analysis [490]; Twitter [116]; Machine Learning [83]	2009-2022	20
13	682	Speech Emotion Recognition	Deep Learning [58]; Feature Extraction [53]; Emotion Recognition [37]	2006-2023	27
14	658	Social Cognition	Schizophrenia [184]; Theory of Mind [161]; Emotion Recognition [157]	2002-2022	15
15	571	Text Mining	Sentiment Analysis [431]; Opinion Mining [83]; Machine Learning [74]	2006-2022	15
16	556	Facial Expression	Emotion Recognition [155]; Emotion [76]; Affective Computing [42]	1998-2022	14
17	533	Classification	Sentiment Analysis [184]; Machine Learning [86]; Emotion Recognition [70]	2003-2022	19

(Continue)

No.	Record Number	Technical Subject Words	Top-ranked Technical Subject Words (Co-occurrence number)	Duration/ Year	Rate for the Last Three Years/%
18	515	Schizophrenia	Social Cognition [184]; Emotion Recognition [83]; Theory of Mind [65]	1998-2022	9
19	504	EEG	Emotion Recognition [272]; Affective Computing [71]; Emotion [43]	2004-2022	22
20	459	Convolutional Neural Network	Deep Learning [114]; Facial Expression Recognition [83]; Sentiment Analysis [77]	2003-2022	27

Table 4-9 Five Research Themes in Affective Computing

No.	Research Theme	Number of Core Subject Words	Average Citation	Average Association Strength
1	Use natural language processing (NLP) techniques for affective computing and opinion mining	153	10.41	197.80
2	Facial expression and micro-expression recognition	134	15.89	178.77
3	Affective computing study in human-computer interaction	121	18.69	110.38
4	Affective computing study in affective disorders	30	33.5	165.59
5	Multimodal sentiment analysis based on deep learning	81	9.8	260.95

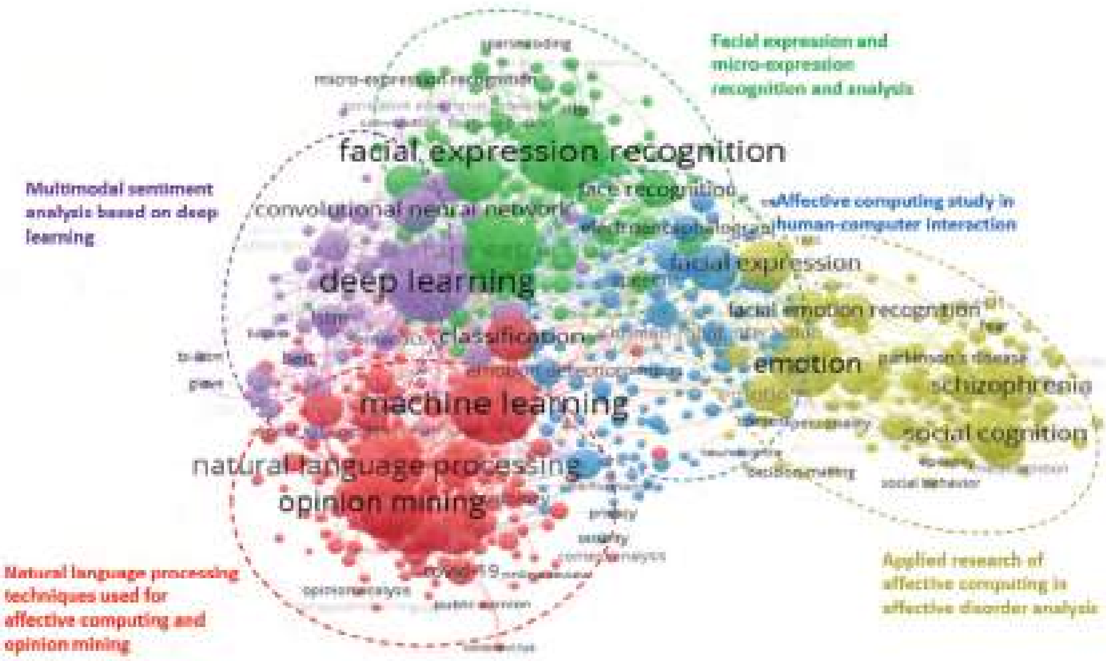

Figure 4-6 Five Research Themes in Affective Computing

Chapter V
Applications

5.1 Overview

Affective computing develops in recent years with increasing demands arising from education, health, business, industry, media, social governance and other fields, especially when the number of technology-enabled enterprises has seen a significant growth after 2007, as shown in Figure 5-1[15].

In education and training, effective use of affective computing technologies such as emotion recognition will be helpful for users in adjusting course content and pace according to the affective state to improve learning efficiency. Due to the impact of COVID-19, offline education shifted to online education, which brought a challenge for teachers to timely obtain students' feedback. In this context, technologies such as artificial intelligence and affective computing are expected to improve the teaching experience and learning experience of online education.

In terms of life and health, many psychological and physical symptoms can be initially identified and diagnosed through emotion recognition. Emotional artificial intelligence (EAI) is not yet widely used in healthcare, but there have been many research attempts and experience accu-

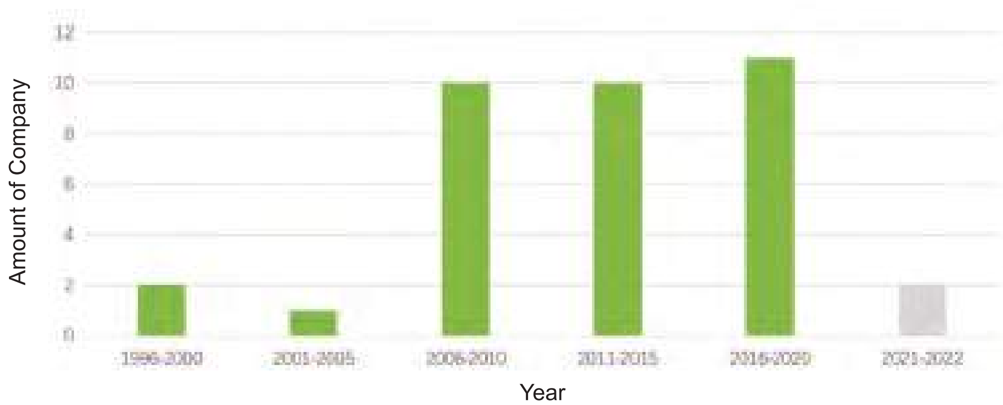

Figure 5-1 Trend of Global Affective Computing Enterprises

[15] Figure 5-1 to Figure 5-9 are all sourced from the Deloitte Science Acceleration Center (as of 2022).

mulations in the assessment and treatment of autism, bipolar disorder, depression and many other disorders. As people pay more attention to health concept, psychological health and mental health are gradually being widely emphasized. It will be the trend applying affective computing in biomedical field. Affective computing is expected to be applied to the early identification of psychological illness, and to assist in the intervention treatment and patient rehabilitation under the premise of maintaining patient privacy and reducing the sense of stigma.

Digital economy has created a boom in online consumption and online services. Using affective computing to further capture business value or improve service efficiency and quality in consumers' perception has also become a research direction for academia and business. For example, it is possible to predict consumers' preferences based on their online comments by using the sentiment text mining technology.

Industrial design, as an important tool to promote the country's industry, should not only achieve basic practicality in product design, but also constantly integrate new ideas and thinking in order to relieve life and work pressure and meet spiritual needs of people through more design language and design forms. In particular, as products are extremely rich and competition is getting fiercer currently, the emotional element has become an important and unique element in industrial design. Affective interaction in product design is a high-level information conveying process from the designer to the product and then to the public. The integration of affective computing with industrial design makes it possible to improve product functionality by recognizing and analyzing emotions.

Emotion, as a psychological experience, has a strong linguistic power, and is easy to be transformed into a psychological characteristic shared by social groups through transmission and communication. In the development of technology media, using affective computing to effectively analyze and reasonably guide public emotion will help in social stability, corporate development, and public problem solving. As the government promotes the informatization and digitization processes, affective computing is applied in many scenarios in public governance, such as social media and social emotion monitoring, post-disaster psychological assistance, lie detection in criminal interrogation, security of important places, etc. The development of psychological and consciousness science, cognitive neuroscience, computer science, and ergonomics, as well as the rapidly growing market demand, will expand the applications of affective computing.

From the market perspective, in recent years, the popularization and application of affective computing technology rely on the efforts of numerous enterprises. They start with strategic layouts in different fields based on their own technologies and development programmes. For example, BrainCo, a unicorn enterprise in the field of education and training, Hikvision, a technology company focused on technological innovation, and SensorStar and Robobind, representative start-ups, all have emerged in improving the efficiency of education and teaching and implementing individualized education through the R&D and popularization of intelligent systems or software. Expper Technologies, Softbank Robotics, UBTECH and other companies are committed to the R&D and multi-scenario application of intelligent robots. Emotibot, a representative start-up in affective computing market, has developed well in commercial service, smart finance, smart healthcare, and other areas with a variety of products together with affective computing technology. Representative start-ups in the affective computing market, such as Behavioral Signals, audEERING, CMCross, Talkwalker, Converus, and Discern Science, cooperate with companies and the government by virtue of their cutting-edge technologies and patents, to transform their technological advantages to product advantages. Unicorn enterprises such as Emotiv, Smart Eye, NVISO, and Affectiva enhance the market competitiveness of their products through technology R&D to spur their development. Intel, HiPhiGo, New Oriental, Facebook, Taobao, Du Xiaoman Financial, Sina, and other well-known enterprises have also entered the market. Universities led by Massachusetts Institute of Technology also apply the affective computing technology to education, healthcare, commerce, industry, media, social governance, and other areas through industry-academy cooperation.

Based on an extensive collection of domestic and foreign products and services which apply affective computing technology, and reference to user comments, industry evaluations, news media reports, etc., some representative products and services applied in education, healthcare, commerce, industry, media, and social governance are selected, and their corresponding enterprises are sorted out and analyzed. Figure 5-2 shows the enterprises with representative products and services in major application areas, and Figure 5-3 shows the capital scale of these enterprises. It can be seen that most are start-ups established for a shorter time and smaller size, while unicorn enterprises and established companies with sound capital base account for nearly the same, respectively.

The White Paper sorts out and analyzes representative products and services from each company and their key application technologies. As can be seen from Appendix 4, the application technology types of affective computing are various, covering speech affective computing, behavior affective computing, physiological signal affective computing, text affective computing, and multimodal affective computing, while the products and services mostly relates to technical platforms and systems, and a few are intelligent robots. The audience of products and services are still companies and institutions, not targeting at individuals and households. From Figure 5-4, 5-5, and 5-6, the application of affective computing technology in the market are dominated by unimodal application.

Affective computing is promising in respect of market demand, R&D and popularization. However, many people are skeptical of the application of affective computing technology. Some legal and ethical issues may arise in the application of affective computing technology, such as the attribution and protection of data, users' personal privacy, potential conflicts between people's free will and affective computing application, and equality issues. The conflicts between the universality and complexity of affection and the rigidity of model training and the limitation of technology application make people worry about the popularization of the technology in daily life and its integration into many scenarios. With the popularization and application of affective computing technology, it is necessary to formulate relevant laws and regulations and reasonably restrict the use of norms. Figure 5-7 shows that enterprises with different market sizes have developed in the main application areas of affective computing to varying degrees, so it is urgent to improve information security capabilities.

Figure 5-2 Representative Enterprises in Major Application Areas

Figure 5-3 Capital Scale of Representative Enterprises

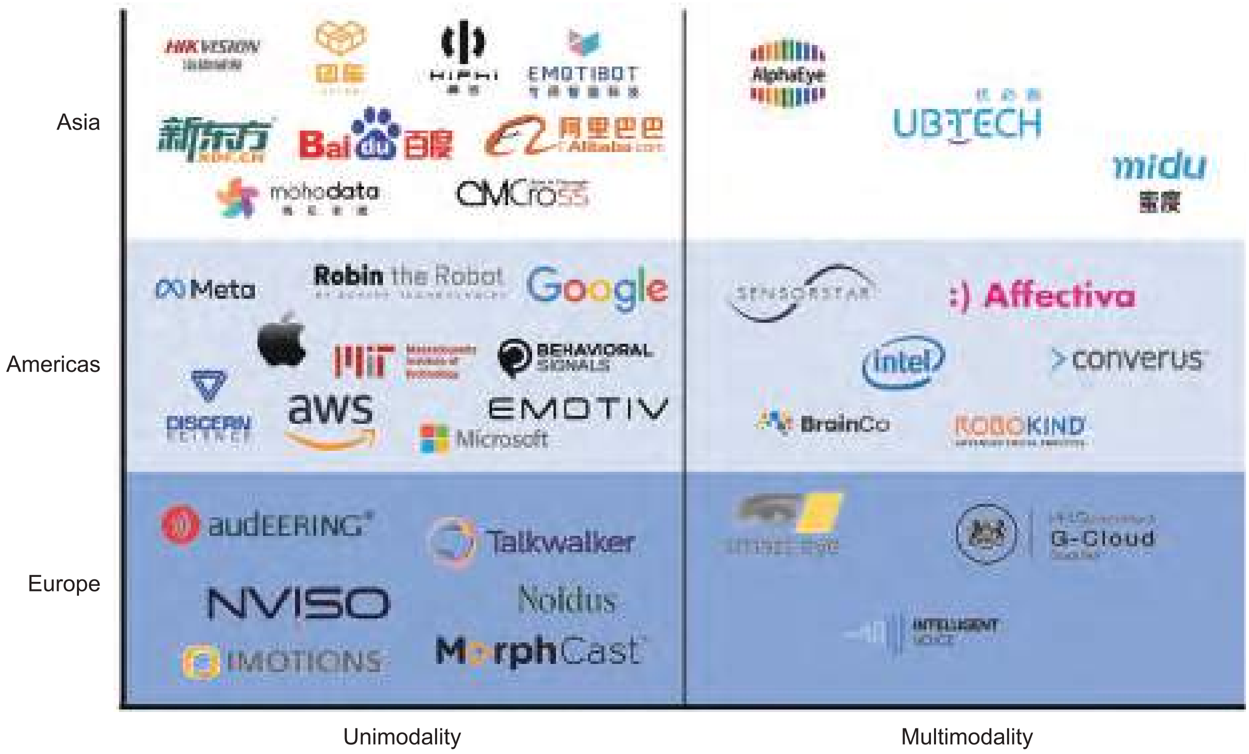

Figure 5-4 Global Representative Affective Computing Companies by Region

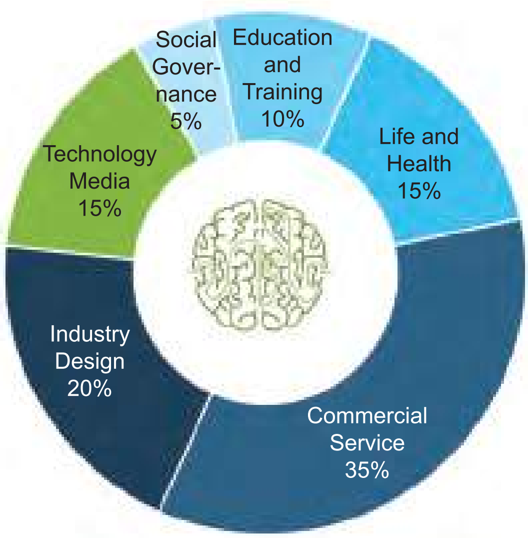

Figure 5-5 Proportion of Global Unimodality Application of Affective Computing Technology by Area

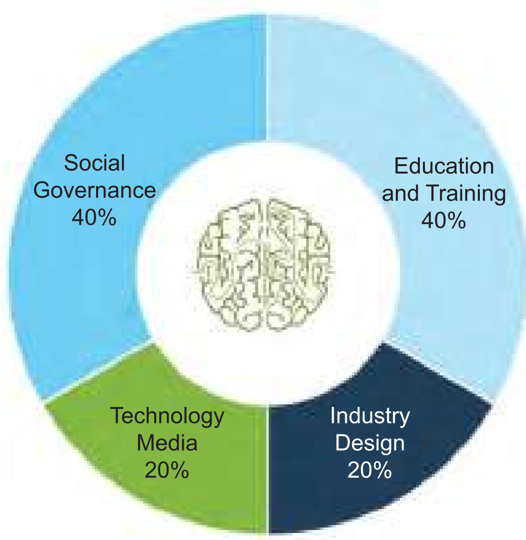

Figure 5-6 Proportion of Global Multimodality Application of Affective Computing Technology by Area

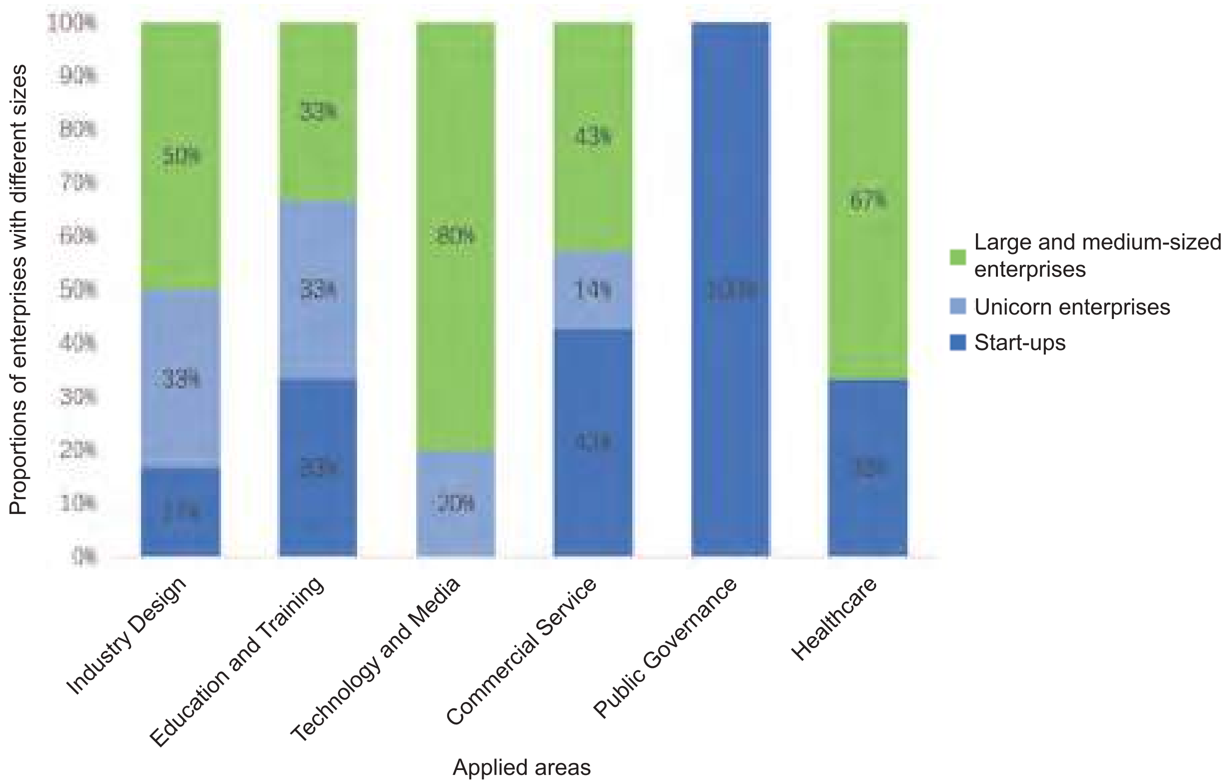

Figure 5-7 Affective Computing Development and Application of Global Representative Companies

5.2 Industry Application

In recent years, the rapid development of perceptual intelligence technology and information science technology has laid a good foundation for the R&D and application of affective computing. Affective computing has been applied to education and training, Life and Health, commercial service, industrial manufacturing, technology media, social governance and other fields. The representative Chinese enterprises of affective computing technology application are mainly located in Shanghai and Hangzhou, while Shenzhen and Beijing are closely behind (see Figure 5-8). Up to now, there are about 3,000 patent application for invention relating to affective computing in China, most of which are applied after 2018. Among globally major representative enterprises of affective computing, unicorn enterprises and large and medium-sized enterprises are more proactive in protecting affective computing technology patents (see Figure 5-9).Affective computing technology is developing rapidly in China, attracting more and more attention, and the market prospect is very promising.

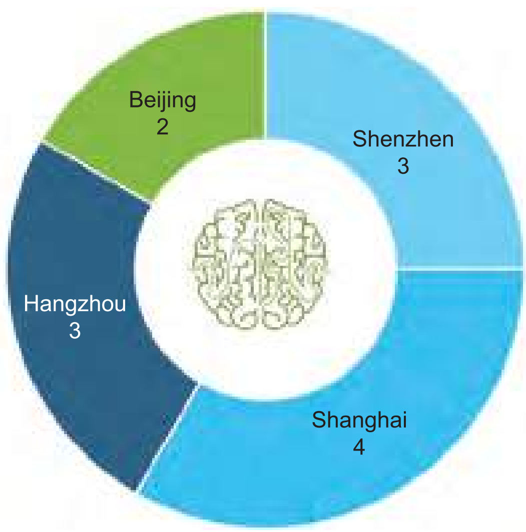

Figure 5-8 Cities of Chinese Affective Computing Companies

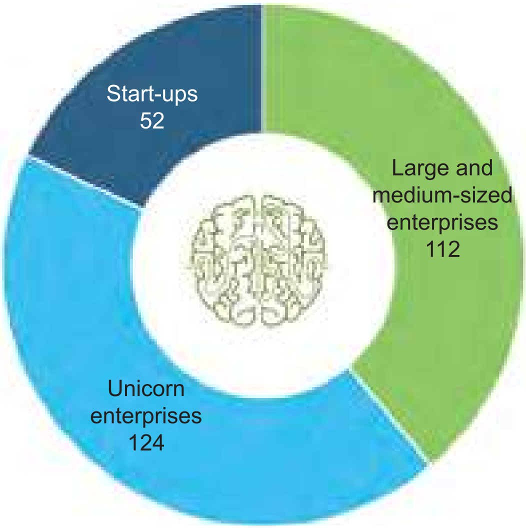

Figure 5-9 Patents of Global Representative Affective Computing Enterprises

5.2.1 Education and Training

At present, the gradual integration of AI and education has provided unprecedented opportunities for teaching innovation and education reform. Affective computing may identify, perceive, understand, and express human emotions through computer systems. It constantly promotes the development of education and training in terms of improving perception and understanding learning emotions, enhancing affective interaction, and promoting human-computer collaboration.

Globally, affective computing technology is mainly applied to: ①help enhance the contextualization of online teaching, promote the affective interaction between teachers and students, and improve the teaching quality; ②develop and improve the evaluation of study engagement in smart education, measure students' capabilities reasonably, and adjust study content and environment automatically and appropriately; ③promote the emotional perception of special groups.

China has attached great importance to education informatization and smart education, successively issuing plans for the development of education informatization and modernization. The Ministry of Education issued the *Outline for Tenth Five-Year Development Plan of Education Informatization* in 2002, followed by the *Ten Year Development Plan (2011-2020) of Education Informatization* (2012), the *Development Plan of New Generation Artificial Intelligence* (2017), the *Education Informatization 2.0 Action Plan* (2018), the *Implementation Plan for Accelerating Education Modernization (2018-2022)* (2019), the *China's Education Modernization 2035* (2019), and the *Guiding Opinions on Promoting the Construction of New Educational Infrastructure and Building a High-Quality Education Support System* (2021), etc. All these provide strong policy support for the application of affective computing technology in education and training.

In the context of Internet, education patterns are mostly the combination of online and offline class. The application of AI technology in offline classes is of great value, for example, improving the refinement of teaching evaluation by the school, assisting teachers in teaching design, and providing individualized learning guidance for students. Similarly, in the increasingly popular online class, affective computing technology can be used to understand students' emotional changes, and even their concentration and understanding (see Figure 5-10). As the text affective computing technology is more mature, affective analysis can be used in a variety of text interaction areas (such as discussion zone, survey feedback, chat room, BBS, etc.) in online education such

Figure 5-10 Evaluate and Understand Students' Emotional State in Class through Facial Expression Recognition Algorithm

as massive open online course (MOOC), and can also be used to analyze students' emotional changes during learning after class to implement individualized teaching. Due to the diversification of educational contexts and the complexity of educational environment under the background of normalization of epidemic situation, the application forms of affective computing technology vary.

5.2.2 Healthcare

Affective computing has gained more attention in healthcare industry. By analyzing and evaluating various types of data sources, the emotion categories of users or patients receiving medical services can be identified and intervened accordingly, to improve the quality of medical services. Due to the particularity of healthcare industry, the data sources used in affective computing are more diverse, including clinical data, drug reviews, physiological signals, questionnaires, etc. With the integration of affective computing technology into healthcare industry, both related academic research and practical application are constantly developing.

It is widely accepted that the affective state is closely related to individual physical and mental health. Correlating emotion recognition results with biological signals and the daily activities of individuals can reveal different patterns of influence, which has extensive and profound research value. Currently, global affective computing technology is applied to the preliminary screening, diagnosis, intervention, and efficacy evaluation of diseases; healthcare and emotional regulation of sub-health population; the improvement of medical service and management. The earliest application of affective computing technology in the field of healthcare is the screening and treatment of affective disorders, such as autism, emotional and cognitive disorders. With its sensitivity to emotion capture and accuracy of recognition, affective computing has become a powerful assistant to existing medical means. With the more mature technology, the R&D of products represented by emotional comfort and emotional support for the elderly is gradually increasing now. The affective and cognitive states of sensitive people, such as loneliness, anxiety and depression, are monitored and evaluated through their speech, facial expression, body movements, physiological signals and text output, and to timely intervene in or send feedback. In addition, based on the comments and sentiments of patients or their families, the analysis of affective tendency is conducted to understand the honest thoughts of patients and improve the quality of medical services.

The practice and application of affective computing in healthcare industry in China are expanding, mainly covering health monitoring, treatment of diseases (such as mental disorders) and rehabilitation care. At present, the application of affective computing in healthcare is limited, but it is predicted that there will be more integration of affective computing and healthcare, with the development of artificial intelligence (AI), cognitive neuroscience, ergonomics and other subjects.

5.2.3 Commercial Service

Affective computing technology is widely used in commercial service, involving intelligent navigation, robot precision marketing, intelligent customer service, financial forecasting and many others. Businesses are more willing to try such technologies to promote their commerce.

At present, robots have incorporated many aspects of people's lives. Affective computing technology enables robots to achieve affective interaction like human beings, improving user experience and satisfying different users' needs. Precision marketing and target advertising use the strong recording and analysis capabilities of affective computing technology to know users' preferences and affective states accurately. Based on users' preferences, spending power, and emotions, information can be provided to targeted users (see Figure 5-11). Providing high-quality personalized information and suggestions to consumers based on their needs is one of effective means to promote the purchase.

Figure 5-11 Salesclerks Help Customers Select Perfume through Affective Computing Devices (Source: Emotiv official website)

At the present stage, intelligent customer service is the most common application of affective computing in the global commercial service. Enterprises that traditionally employ staffs for customer service are facing the plight of rising labor costs, while traditional customer service robots are criticized for their standardization, inflexibility and other shortcomings. Intelligent customer service combines the merits of the above two. Through analyzing the speech in the call, it can identify the behavior and perceptual characteristics, and guide the customer service staffs to talk with better empathy and professionalism.

The financial service is indispensable to the commercial service industry. Deep learning and big data can identify risks more effectively to prevent and resolve financial risks. For example, the rise and fall of the stock market index can be predicted through the collection and analysis of unstructured text data such as media reports and company news, and the index prediction model based on financial text sentiment analysis. It is found that the sentiment analysis can effectively improve the accuracy of prediction model, which indicates the effectiveness of text affective computing and deep learning model in the financial area.

5.2.4 Industry Design

The application of affective computing in the industry design area mainly focuses on automotive and humanoid robot.

In the intelligent drive field, affective computing technology is mainly applied in driver monitoring system (DMS). The previous driver status monitor is more passive, that is, the driver status is indirectly judged based on the steering wheel rotation and vehicle trail. With the development of affective computing technology, active monitoring is gradually adopted now, that is, drivers' physiological signs and behavior are directly monitored, including implicit physiological signal monitoring and explicit behavior monitoring. Implicit physiological signal monitoring may reflect drivers' mental state and behaviors by measuring their EEG, ECG, and other physiological indicators. Although this method is highly accurate, it needs "contact measurement", which has greater limitations in the driving process. In contrast, the explicit behavior monitoring captures and recognizes drivers' facial expression changes (such as the movement of eyes and head) through the camera, to infer their emotions, mental state, and behaviors. This is noncontact detection, which has less interruption to drivers. Moreover, with the growing of image processing software and hardware in recent years, the speed and accuracy of measurement are significantly improved. Therefore, the explicit behavior monitoring has been widely used. Affective computing can help to infer drivers' concentration, reduce traffic accidents caused by road rage, and prevent drivers from the tendency of testiness, compulsion and aggression through warning or adjusting the vehicle interior environment, forming a closed-loop mental health intervention strategy for drivers and passengers.

With the development of modern science and technology, in addition to industrial robots, humanoid robots are indeed emerging. Humanoid robots are those designed and manufactured by imitating human beings' shape and behaviors, and can make judgement and decisions by collecting and analyzing the information of things outside. Nowadays, most humanoid robots are used for visitor guidance, FAQ and other simple tasks. Affective interaction is one of the aspects of robot intelligence. Most existing humanoid robots recognize emotions based on human facial expressions and other visual information using perceptual modules, cameras and other devices. Human interaction is typically represented by expressing affective state through facial expressions, but humans are not accustomed to communicating with robots like this. More humanoid robot designers have noticed affective factors. However, to achieve smoother human-robot affective interaction, it is necessary to understand human beings' affective characteristics when communicating with humanoid robots and continue to explore capture and recognition of human emotions. Figure 5-12 shows humanoid robots work in the vaccine research center.

Figure 5-12 Humanoid Robots Work in the Vaccine Research Center

5.2.5 Technology Media

With the popularity of the Internet, social media platforms have become one of the main channels for people to express their views. Public sentiment represents public opinions and attitudes towards various issues and events in social life. Its formation is regular, that is, with "affection" as the internal driving force, generally going through three stages (affective generation, affective propagation, and affective coupling), which runs through the whole process of individual affective generation and propagation, group affective outburst and collective behavior occurrence.

There are numerous researches on the preference of online public sentiment by analyzing the text affective data of online users. Public sentiment may be triggered by policy implementation, domestic and international situations, new product release, and public emergencies. It has become a reliable way for academia, public management institutions, and enterprises to understand real public ideas by using content analysis and sentiment analysis methods, and combining psychological and sociological research methods such as conflict psychometry and social network analysis to capture the public sentiment trend and conduct daily affective monitoring of social media users, affective analysis of network public opinion on specific events, management of public opinion on corporate brand, advertising/video affective computing, etc. In addition, with the rapid development of AI technology, affective computing technology has gradually been applied to interactive video, interactive advertising, even games, movies and other fields.

Sentiment analysis can automatically detect the emotions reflected by writing (such as Twitter, Facebook, e-mail.) through computer programs. Emotion analysis can be performed at three different levels: document level, sentence level, and aspect level. On social media, information dissemination is a process where users highly participate in and interact, and emotions have an important impact on it. Social media platform is one of the main vehicles for communication, on which users can express their emotions in a variety of ways. The rising social network platforms are creating a large amount of data all the time, and posts, comments and "likes" all implicate emotions.

In recent years, the application of affective computing technology in the field of technology and media has gradually increased. On the whole, however, the application is not extensive and mostly focused on public sentiment monitoring, still in the stage of exploration and development, and the affective computing technology used in public sentiment monitoring is mainly text affective computing. In fact, with the rise of short video platforms such as TikTok and Kwai, public sentiment has become a cross-media comprehensive content of words, emoticons, pictures and videos, making the spread of public events more diversified and complex. Multimodal affective computing is required to provide more information for public sentiment management and control, thereby improving the accuracy and reliability of decisions.

5.2.6 Social Governance

Due to the wide application of AI technology in various industries, the digital, informational and intelligent management and control level of government departments has been improved.

As for law enforcement field, law enforcement agencies use affective computing technology to judge the danger level of specific public or the credibility of their confession, which uses sentiment analysis as supplementary evidence on the basis of experience of law enforcement personnel. As shown in Figure 5-13, in criminal investigation, interrogation and other security-related work, it is crucial to judge the authenticity of the interrogated person's words. Wearable devices, eyeball scanning and tracking, webcams and other new tools are being used to collect facial micro-expression, body language and speech data. Then analyzing emotional changes and speech clues by using the non-autonomous reactions and unforgeability of physiological signals and facial micro-expression to help judge the credibility of the confession.

Many countries begin to use affective computing technology to improve the scientificity and effectiveness of national defense security, such as threat detection at border checkpoints, security monitoring in public places. In recent years, terrorism has been a concern of governments all over the world, and social networks such as Twitter have also become an information source for tracking and identifying terrorism. Sentiment analysis, text mining and other technologies are applied to analyze the unstructured content of information, providing a new channel to cope with the social threat caused by terrorism.

Affective computing has broad prospects in the field of intelligent security. The computers can capture, classify and recognize human facial expression, speech, gestures, physiological signals, etc., through which the computers can timely

Figure 5-13 Early Warning System

understand the emotional changes of the target, and give early warning for abnormal and dangerous behaviors, and implement countermeasures to help the construction of intelligent security. For example, by shooting videos with special cameras, based on people's facial expressions as well as the vibration frequencies and amplitudes of their body movements, parameters such as aggression, pressure, and tension, can be calculated to analyze people's mental state, screen suspects, give early warning, and implement other measures to help to build an all-round digital and intelligent campus security system.

Chapter Ⅵ Future Trend

6.1 Next-stage Technology Trend Prediction

AI has been closer to human cognitive model and intelligence level till now. However, scientists need to continue their research in such fields as dataset, strategy, modeling, bionics and application pattern to realize the digitalization of human mind and affection, as well as the development goal of AI “IQ and EQ”. The latest achievements in these areas will be the key to the future development of new generation AI.

6.1.1 Construction of High-quality and Large-scale Dataset

At present, in the world’s major datasets in respect of emotional intelligence, the data-based information can be divided into text data, speech data, image/video data and others.

Currently, there is a need to build larger and higher quality datasets for Chinese language in text datasets. Speech datasets and image/video datasets are generally higher quality and larger in size. However, the main challenge of image/video datasets is the efficient implementation of computing power to match the massive data processing. The difference between images and videos is the duration of the content. In essence, both images and videos rely on visual recognition technology for expression recognition to achieve computer affective computing. At present, the development of emotion recognition technology for images has been basically mature through scientific and technological research. But its development and application for videos are still in front of challenges. An ordinary video contains 24 consecutive time points (frames) of images per second. The computer judges the emotions of characters in the video by analyzing each frame with its extraordinary hashrate and sorting them by time. This leads to the problem that emotion recognition for video content needs to fully consider the dynamics of emotion over time and the uncertainty of emotion type caused by this dynamic fluctuation. At the same time, human emotions are not homogeneous at every point in time. Therefore, the overall emotion recognition of dynamic and multi-emotion type fusion state in video, especially in the process of long-term monitoring, requiring highly hashrate and effective data transmission.

The existing physiological datasets mainly include the dataset for emotion analysis using physiological and audiovisual signals of Queen Mary University of London (DEAP dataset), MAHNOB-HCI dataset by Mohammad Soleymani, Computer Science Lab of University of Geneva, etc., the Emotion EEG Dataset by the team led by SJTU Prof. Bao-Liang Lu (SEED), etc. These datasets have generally smaller size, which limits the training of deep learning algorithms to some extent. Therefore, larger scale emotional physiological datasets need to be constructed to break this limitation.

At present, there are two important features that distinguish humans from machines. First, humans are in a scenario where multiple modalities coexist in the social environment, and this feature is specifically to express intentions and emotions through language, expressions, speech, and behaviors. Second, humans have the ability to switch between modalities in processing emotions for emotional reasoning, and can switch between different modalities to find clues, and through mutual correlation for ambiguity elimination and emotional reasoning. Therefore, the establishment of a multimodal large-scale emotion dataset can help develop more human-like emotion intelligence technology and achieve more accurate emotion recognition.

6.1.2 Zero/Small Sample Learning and Unsupervised Learning

In recent years, deep learning has made great breakthroughs in the field of affective computing research. Deep learning enables the learning of complex problems very well. However, one of the biggest drawbacks of deep learning is that it requires a large amount of manually labeled training data, which is costly in terms of labor. Current models rely too much on large amounts of labeled data, and their performance is greatly affected by the amount of labeled data. Even if the data is labeled, their accuracy may be affected by subjective factors. Therefore, there is a need to develop more effective small-sample learning algorithms as well as unsupervised deep learning algorithms, especially to simulate the human cognitive process of never-seen objects, develop zero-sample learning methods, and complete learning by knowledge transfer between training and test classes, so as to promote the application of affective computing in a wider range of scenarios. This is a very worthwhile research direction.

6.1.3 Multimodal Fusion Technology Innovation

Multimodal fusion is based on multimodal representation and combines information from multiple modalities for emotion classification. Based on whether related to a specific deep learning model, there are generally two major categories: model-independent fusion methods and model-based fusion methods. The former does not depend on a specific deep learning method, while the latter uses deep learning models to solve multimodal fusion problems explicitly.

Model-independent fusion methods can be divided into early fusion (feature-based fusion), late fusion (decision-based fusion), and hybrid fusion (fusion based on a mixture of the first two). Early fusion integrates features immediately after feature extraction (usually only the representation of each modal feature needs to be connected), late fusion performs integration after the output results of each model (e.g., output classification or regression results), and hybrid fusion combines the output of early fusion method and unimodal predictors. Each of the three fusion methods has advantages and disadvantages. Early fusion can better capture the relationships between features but tends to overfit the training data. Late fusion can better handle the overfitting problem but does not allow the classifier to train all data simultaneously. Although the hybrid multimodal fusion method can be used flexibly, many current structures require careful design of when and what modalities and how they can be fused, which requires the researcher to consider carefully depending on the specific application and the research.

Model-based fusion methods address multimodal fusion from the perspective of implementation techniques and models, and there are three commonly used approaches: Multiple Kernel Learning (MKL), Graphical Models (GM), and Neural Networks (NN). The advantages of these approaches are that they can easily exploit the spatial and temporal structure of the data. They are particularly suitable for time-dependent modeling tasks, and allow embedding the knowledge of human experts into the models, making them more interpretable. Their disadvantage is that they are computationally expensive and more difficult to train in reality.

In addition, scientists have proposed a multistage multimodal emotional fusion method. The specific process is to first train a unimodal model, then splice it with another modal feature in an implicit state and train a bimodal model, and so on to obtain a multimodal model. In conclusion, multimodal fusion technology can effectively utilize the synergy and complementarity of different modal information to enhance emotional understanding and expression, improve model robustness and performance. This is an important direction for future research.

6.1.4 Multi-model Reasoning

The output of a single model may be unreliable or even incorrect, leading to wrong decisions. To avoid this, jointly multi-model reasoning is an effective solution. Multi-model fusion can effectively combine the advantages of multiple models and make full use of the complementarity between models to overcome the limitation of incomplete information representation of a single model and make the decision more stable and robust. The adoption of appropriate fusion methods is the key to joint multi-model decision making. Among them, the more representative Dempster-Shafer evidence theory is a generalization of Bayes Theorem to subjective probability and is widely used because of its ability to model uncertain knowledge. The Dempster-Shafer combination rule allows beliefs from different sources to be combined to obtain new beliefs that consider all available evidence, so it can well handle the information fusion problem.

6.1.5 Cognitive Neuroscience-inspired Affective Computing

Although we have accumulated a wealth of theoretical and applied skills in emotional mindfulness, the specific roles and influences of human emotional mindfulness in consciousness processes, evolutionary processes, and interactions have generally been shrouded in mystery. For example, according to James-Lange theory, emotions affect human autonomic nervous system, but the biological basis of this effect and the evolutionary implications behind it have not been completely uncovered. Then, it becomes an open question whether such influence mechanism needs to be considered when machines own emotional mindfulness to improve the overall effectiveness of the machine systems.

The cognitive processes, neural mechanisms and anatomical basis of human brain for emotional processing provide key insights for the development of affective computing models. Just like the convolutional neural network architecture inspired by the biological visual processing, the reinforcement learning method inspired by the behavioral theory of psychology, and the impulse network model inspired by neuroplasticity, etc., the affective computing models and algorithm innovations inspired by cognitive neuroscience will provide the opportunity to enable machines with the intelligent and sensitive responsiveness of functional brain-like and performance super-brain. Thus, the deepening research in the field of cognitive neuroscience will ultimately be related to the development process of affective computing and even the AI. The effective interface between the two disciplines has also become an important theme of concern for many major science projects represented by the Human Brain Project.

6.1.6 Cross-cultural Emotion Recognition

With the increasing population migration and cultural exchange across regions, emotional messages with multiple cultural backgrounds are emerging. For example, in Shanghai office buildings, white-collar people can often use mixed Chinese and English phrases to express various workplace stories, which contain a lot of dual language and culture from Chinese and English countries. For such emotional messages, the sample size of the current regional affective dataset is far from enough. This further leads to the bias of existing various affective computing in identifying the emotions of relevant population.

At present, there are two ways to solve the above issue from the technical point of view: one is to artificially collect more data and fuse them to form a more comprehensive affective dataset of cross-cultural and cross-ethnic people; the other is to further use deep learning based on the existing dataset, through the interactive application of affective computing for various people in different scenarios and environments to realize self-iteration and dataset improvement, making it more comprehensive. In terms of efficacy, it is clear that the latter is more relevant for application.

6.1.7 Data and Knowledge-driven Technological Innovation

For human individuals, the understanding of data must activate other information associated with it, which is a potential knowledge or common sense, and the human brain can combine data and knowledge skillfully, which can realize more general, intelligent and economical computation for complex problems. Professor Wu Fei of Zhejiang University believes that future scientific computing or AI computing must be a combination of subject experts and data driven to form scene-based AI or solve the task of the scene. Affective computing will also gradually enter the era driven by both data and knowledge: on the one hand, it needs to acquire knowledge from data to subsequently make decisions and services based on knowledge; on the other hand, it cannot only discover knowledge from data, but also use knowledge to guide the computing process.

6.2 Next-stage Industry Application Outlook

As an advanced cognitive process, thinking not only includes rational reasoning and decision-making, but also a large number of emotional factors. At present, the R&D of various intelligent interaction technologies are pursuing to make machines “more intelligent and warmer”. In fact, the ability to recognize, analyze, understand and express emotions should also be indispensable to intelligent machines. In addition to the increasing involvement and influence in daily education and training, healthcare, commercial service, industrial manufacturing, technology and media, and social governance, affective computing technology will be used in smart service, virtual reality, science and art integration and other frontier fields in the future. More and more institutions, enterprises, and media intend to use this technology to solve real-life problems in order to better serve the public.

6.2.1 Smart Service

In order to cope with the increasingly prominent problem of aging population, AI-based intelligent companionship system for the elderly has emerged. In the field of senior health management, the R&D is more focusing on intelligent service devices such as signal sensors, wearable detection devices, smart nursing beds, health service robots and others that provide interactive home health detection, physical condition assessment, and emergency assistance services for the elderly In particular, the affective computing technology is used to comprehensively detect the emotional state of the elderly and provide emotional companionship for them, to reduce their loneliness, and to provide early monitoring and early warning of diseases such as depression.

The subfield of human-computer interaction has also become a research focus. With various voice assistants and chat robots gradually participating in the lives of the general public, the R&D focus has shifted from improving the logic and accuracy of conversations to strengthening the emotional interaction in conversations. In real conversations, emotion is one of the important information exchanged by human beings. In the intelligent dialogue, if the machine can understand human emotions and integrate them into the dialogue, it will further improve the intelligence of the dialogue content.

In the future, in the field of management, affective computing will be used to obtain the emotions of leaders and employees, to intervene and coordinate them to improve the overall efficiency of the enterprise. In the field of commercial service, we can interpret customers' emotions through their comment texts, and conduct precise marketing, to build our own brand while satisfying customers' needs. In the field of healthcare, based on the results of patients' emotional data analysis, the diagnosis and prediction of psychological diseases can be made, and supplemented with active intervention. The application scenarios of human-centered smart service industry will continue to grow. The R&D of emotion cognition is the key to promote human-computer affective interaction, and an important driver to promote the popularization of smart services. In the near future, machines will be more intelligent while being warmer and more humane. Through the human-computer dialogue system, smart nursing system, emotional soothing system and others equipped with emotional perception, intelligent robots can take on the tasks of management, housekeeping, nursing and other services. While meeting people's emotional needs, they can alleviate the increasingly pressure of human resource shortage.

6.2.2 Virtual Reality

In the virtual cyberspace, intelligent interaction technology based on affective computing will play an increasingly important role. These intelligent beings, called social robots, can post information products and interact with people on social media through natural language analysis and social network behavior algorithms. Currently, the participation and influence of intelligent interaction technology in the network are increasing. More and more political, economic and media organizations are using it to attract traffic, change public discourse, and even adjust the trend of public opinion. Unlike the physical emotional robots in real world, one of the "characteristics" of online social intelligences is to imitate human cognition and communication behaviors to be a "netizen" with unique insights. With the continuous progress of technology, robots, as a new "human species" active on social networks, are becoming more and more distinctive in their personality characteristics.

With the development of VR technology, people's perception of virtual scenes has been enhanced, and AR applications have gradually expanded from the initial military field to commercial applications. The main application of AR in the VR field is to provide immersive interaction and improve people's information access in virtual scenes. In the real world, people often feel lonely and insecure due to insufficient perception of the virtual environment or the inability to accurately express themselves, which has also become an important factor affecting users' usage. Affective computing can make the design of AR interface smarter and better understanding people's emotions, thus deepening people's perception. When the system accurately calculates users' emotions, needs and expectations, personalized digital experience comes into being. In the near future, it will be a new experience when users wear AR glasses, their retinas will be filled with content that is completely customized according to their emotions and needs.

6.2.3 Social Security

Human-to-human communication is inevitably accompanied by the transmission and resonance of emotions. People express emotions through facial expressions, body movements, voice, and intonation, and perceive and understand each other's emotions through visual and auditory senses.

However, presentative emotions can be hidden or disguised. With the technological development, AI and human-computer interaction based on technologies such as emotion recognition systems and deep learning algorithms would play an important role in future social governance such as intelligent monitoring, crime risk assessment, and criminal interrogation.

After more than 10 years of development, the detection and recognition of micro-expressions have made great progress. However, most of the current micro-expression analysis is conducted based on micro-expression samples collected in the laboratory or under controlled environment. How to design a system that can detect, recognize and analyze naturally occurring micro-expressions, and how to obtain macro-expression data more easily to improve the performance of micro-expression recognition systems are still urgent issues to be addressed. It can be seen that there are still many technical barriers to the practical promotion and application of micro-expression analysis. The gradual maturity of affective computing can help with the development and application of such technologies.

In defense security, emotional AI devices such as facial expression capture helmets, physiological sensing patches and bracelets can provide more accurate, objective, convenient and real-time morale assessment and psychological diagnosis. The U.S. Army has developed a sensor system that can be embedded in the future “warrior” uniform, which can monitor the heartbeat, metabolic energy consumption on the move, inner skin temperature, and reaction sensitivity of the soldier wearing it. The British Ministry of Defense is also developing the carry-on physiological monitoring subsystem and a “new generation of warrior” warfighter system that can provide the psychological tension, heat status and sleep level. Emotional AI devices can be applied to multiple scenarios such as psychological service warning and battlefield psychological crisis intervention for soldiers.

At the same time, affective computing will help build smart cities, making cities warm, thinkable and evolvable. Only when affective computing is applied to all aspects of urban life can we truly realize the humanization and digitalization of cities.

6.2.4 Financial Decision Making

In the financial sector, as the credit business moves from offline to online, processes and tasks such as credit review and customer service can be completed by intelligent robots. Voice robots equipped with affective algorithms can not only interact with users naturally, but also “read” users’ emotions when talking, so that most users cannot tell that they are talking to machines. Affective computing can also identify the changes of speech speed, tone and energy based on the analysis of user’s voice, and analyze the speaker’s emotion, hesitation, etc., through which it can determine the probability of the speaker lying. Although the current personal credit system has been relatively perfect, it is impossible to comprehensively record and collect the financial credit risks related to individual lenders, which leads to the fact that major banks usually need to establish their own credit rating systems when dealing with individual credit customers. If staffs only judge the credit risk of customers based on credit rating results, the subjective judgment error may result in serious bad bank debts. Technologies such as affective computing can analyze a customer’s emotional state and moral level based on data such as the voice tone during the customer’s presentation to inform lending decisions.

The stock market is highly influenced by the external environment and public sentiment. In recent years, the sentiment of stock market investors has been widely studied,and the theoretical basis of stock market sentiment comes from behavioral finance, which combines the interdisciplinary disciplines of finance, psychology, and human behavior. The basic idea is that stock price trends are not entirely determined by companies, but are largely shaped by investors sentiment, due to the irrationality of investors who have a variety of judgment criteria for their investment decisions. The study of investors sentiment helps to understand the emotional preferences and cognitive biases of investors. At the same time, effective and rapid sentiment analysis can help predict the stock market trends.

6.2.5 Science and Art Integration

Currently, in the digital era, multimedia data such as images, audio and video have become the main part of data, and it is especially important to extract useful information from multimedia data and to retrieve and mine it effectively. For example, in the scenario of recommending music to users, the resource management and search efficiency of audio is particularly important. Traditional music search retrieves the corresponding content by matching text (e.g., song title, artist name, or lyrics). Searching in music databases and presenting the corresponding content to users are still essentially text-based matching search. Among the high-level semantic features of music, emotion is a more advanced feature, so the emotional features of music can be considered in retrieval techniques to improve the matching between users and music, which is the main task of computerized music emotion analysis. Based on data models, computer technology is used to automatically identify the emotional features in music, and statistical or machine learning methods are used to fit and model the emotion of music and quantify the emotional part of music.

AI-generated texts now go beyond the requirements of writing, and it can write emotionally rich, beautifully phrased poems and songs using machine learning algorithms. Researchers are beginning to work on giving machines IQ while trying to improve their EQ. AI-generated text is essentially based on the machine's ability to learn from data and calculate the optimized parameters of a large number of text representation tensor, combined with NLP, knowledge mapping, convex optimization and other techniques. The machine learns the implicit writing techniques of these poets and writes high quality poems even better than a human.

In addition, in order to meet the market demand, affective computing technology has also been applied to other fields of science and art integration, such as script and novel creation for film and television, and advertising planning.

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Appendix

1. The published articles of top 20 countries by year in the field of affective computing

No.	Country	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	China	1	1	-	4	4	2	3	20	33	71	80	114	115	107	126	144	193	315	398	468	506	777	865	835	1 019	567
2	USA	5	8	6	12	7	23	28	36	33	55	73	87	94	99	124	139	205	217	305	322	347	442	442	389	397	147
3	India	-	-	1	-	-	-	-	1	1	1	6	6	27	12	28	37	79	105	249	294	366	360	356	374	406	260
4	UK	1	1	1	3	4	6	18	28	17	34	36	37	43	50	74	72	89	90	180	158	220	235	203	198	221	88
5	Germany	-	-	3	4	-	3	7	11	18	20	26	46	40	47	59	52	86	93	121	100	142	149	128	119	139	49
6	Japan	2	6	5	15	7	4	9	9	14	19	30	34	34	22	35	39	48	64	72	86	88	119	119	97	130	30
7	Italy	-	-	1	-	2	1	1	3	3	9	10	15	12	17	26	38	46	73	109	94	92	110	125	118	128	58
8	Australia	-	-	1	1	2	1	2	5	6	7	12	17	26	21	28	40	62	55	59	73	90	104	121	117	125	69
9	Spain	-	-	-	1	1	2	3	3	4	7	13	12	26	13	32	41	53	46	64	72	74	92	110	128	120	65
10	Canada	-	1	-	2	5	-	3	5	6	4	17	12	19	19	37	38	63	49	64	80	77	95	104	86	88	47

(Continue)

No.	Country	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
11	South Korea	-	-	-	2	-	1	4	15	17	13	22	18	30	21	16	32	35	44	45	58	53	97	101	100	133	59
12	France	-	1	1	2	1	2	2	6	9	6	11	19	27	18	29	27	52	53	72	55	68	92	84	86	82	37
13	Nether-lands	-	-	1	3	1	5	5	6	8	10	13	15	24	21	35	40	30	41	62	51	44	50	65	51	69	29
14	Turkey	-	-	-	-	-	-	-	-	1	3	4	5	8	4	9	14	21	28	40	51	77	88	85	79	70	30
15	Saudi Arabia	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	8	12	26	23	44	51	77	74	124	110
16	Singa-pore	1	1	-	1	-	1	2	-	1	2	3	12	9	10	18	22	19	38	34	45	46	58	49	53	61	23
17	Malaysia	-	-	-	-	-	-	1	-	1	-	6	5	7	2	5	10	17	36	40	48	42	47	46	56	65	39
18	Pakistan	-	-	-	-	-	-	-	-	-	1	1	2	3	1	2	1	3	10	14	24	41	50	84	80	91	41
19	Brazil	-	-	-	-	-	-	1	1	3	1	3	2	2	4	8	11	15	21	27	51	33	75	67	48	48	27
20	Greece	-	1	-	-	1	-	2	7	6	6	15	27	24	23	23	13	26	24	30	35	30	35	18	29	33	15

2. Q1 journals in affective computing

Journal Name	Web of Science
Frontiers in Psychology	Psychology, Multidisciplinary
IEEE Transactions on Affective Computing	Computer Science, Cybernetics/Computer Science, Artificial Intelligence
Expert Systems with Applications	Computer Science, Artificial Intelligence/Engineering, Electrical & Electronic/Operations Research & Management Science
Psychiatry Research	Psychiatry
Knowledge-Based Systems	Computer Science, Artificial Intelligence
Information Processing & Management	Computer Science, Information Systems/Information Science & Library Science
IEEE Transactions on Multimedia	Computer Science, Software Engineering/Computer Science, Information Systems/Telecommunications
Information Sciences	Computer Science, Information Systems
Pattern Recognition	Computer Science, Artificial Intelligence/Engineering, Electrical & Electronic
Neuroscience and Biobehavioral Reviews	Neurosciences/Behavioral Sciences
Psychological Medicine	Psychology/Psychology, Clinical/Psychiatry
Journal of Affective Disorders	Clinical Neurology/Psychiatry
Applied Soft Computing	Computer Science, Interdisciplinary Applications/Computer Science, Artificial Intelligence
Decision Support Systems	Operations Research & Management Science/Computer Science, Information Systems/Computer Science, Artificial Intelligence
Future Generation Computer Systems-The International Journal of Escience	Computer Science, Theory & Methods
Information Fusion	Computer Science, Theory & Methods/Computer Science, Artificial Intelligence
Artificial Intelligence Review	Computer Science, Artificial Intelligence
Computers in Human Behavior	Psychology, Experimental/Psychology, Multidisciplinary
IEEE Transactions on Image Processing	Engineering, Electrical & Electronic/Computer Science, Artificial Intelligence
Schizophrenia Bulletin	Psychiatry
International Journal of Human-Computer Studies	Computer Science, Cybernetics/Ergonomics/Psychology, Multidisciplinary
IEEE Transactions on Cybernetics	Automation & Control Systems/Computer Science, Artificial Intelligence/Computer Science, Cybernetics

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Journal Name	Web of Science
Neuroimage	Neurosciences/Neuroimaging/Radiology, Nuclear Medicine & Medical Imaging
IEEE Transactions on Pattern Analysis and Machine Intelligence	Engineering, Electrical & Electronic/Computer Science, Artificial Intelligence
Journal of Child Psychology and Psychiatry	Psychology/Psychology, Developmental/Psychiatry
IEEE Transactions on Knowledge and Data Engineering	Engineering, Electrical & Electronic/Computer Science, Artificial Intelligence/Computer Science, Information Systems
Neural Networks	Computer Science, Artificial Intelligence/Neurosciences
Journal of Big Data	Computer Science, Theory & Methods
IEEE Intelligent Systems	Engineering, Electrical & Electronic
Engineering Applications of Artificial Intelligence	Engineering, Multidisciplinary/Automation & Control Systems/Computer Science, Artificial Intelligence/ Engineering, Multidisciplinary
Brain	Clinical Neurology/Neurosciences
IEEE Journal of Biomedical and Health Informatics	Medical Informatics/Computer Science, Interdisciplinary Applications/Computer Science, Information Systems/ Mathematical & Computational Biology
Research in Autism Spectrum Disorders	Education, Special/Rehabilitation
Biological Psychiatry	Neurosciences/Psychiatry
ACM Transactions on Multimedia Computing Communications and Applications	Computer Science, Theory & Methods/Computer Science, Software Engineering
Comprehensive Psychiatry	Psychiatry
IEEE Transactions on Neural Networks and Learning Systems	Engineering, Electrical & Electronic/Computer Science, Theory & Methods/Computer Science, Hardware & Architecture/Computer Science, Artificial Intelligence
Translational Psychiatry	Psychiatry
Computers in Biology and Medicine	Engineering, Biomedical/Biology/Computer Science, Interdisciplinary Applications/Mathematical & Computational Biology
Computer Vision and Image Understanding	Engineering, Electrical & Electronic
Human Brain Mapping	Neuroimaging/Radiology, Nuclear Medicine & Medical Imaging
European Archives of Psychiatry and Clinical Neuroscience	Clinical Neurology/Psychiatry
Information Systems Frontiers	Computer Science, Theory & Methods/Computer Science, Information Systems

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Journal Name	Web of Science
American Journal of Psychiatry	Psychiatry
International Journal of Human-Computer Interaction	Computer Science, Cybernetics/Ergonomics
Journal of King Saud University-Computer and Information Sciences	Computer Science, Information Systems
Journal of Neuroscience	Neurosciences
Electronic Commerce Research and Applications	Computer Science, Information Systems
Internet Research	Computer Science, Information Systems
IEEE Transactions on Instrumentation and Measurement	Engineering, Electrical & Electronic
Journal of the American Academy of Child & Adolescent Psychiatry	Psychiatry
International Journal of Computer Vision	Computer Science, Artificial Intelligence
Journal of Abnormal Psychology	Psychology, Clinical
European Neuropsychopharmacology	Clinical Neurology
IEEE Transactions on Circuits and Systems for Video Technology	Engineering, Electrical & Electronic
Applied Acoustics	Acoustics
Computer Systems Science and Engineering	Computer Science, Theory & Methods
Neuropsychology Review	Neurosciences
ACM Computing Surveys	Computer Science, Theory & Methods
Molecular Autism	Genetics & Heredity
Journal of Biomedical Informatics	Computer Science, Interdisciplinary Applications
Artificial Intelligence in Medicine	Engineering, Biomedical
Complex & Intelligent Systems	Computer Science, Artificial Intelligence
Emotion Review	Psychology, Multidisciplinary
Computer Methods and Programs in Biomedicine	Engineering, Biomedical
Information & Management	Computer Science, Information Systems
IEEE Internet of Things Journal	Engineering, Electrical & Electronic
International Journal of Intelligent Systems	Computer Science, Artificial Intelligence
Wiley Interdisciplinary Reviews, Data Mining and Knowledge Discovery	Computer Science, Theory & Methods
ACM Transactions on Intelligent Systems and Technology	Computer Science, Artificial Intelligence

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Journal Name	Web of Science
Computers & Education	Computer Science, Interdisciplinary Applications
Journal of Intellectual Disability Research	Education, Special
IEEE Transactions on Intelligent Transportation Systems	Engineering, Electrical & Electronic
Neuropsychopharmacology	Neurosciences
IEEE Computational Intelligence Magazine	Computer Science, Artificial Intelligence
Psychiatry and Clinical Neurosciences	Clinical Neurology
Advanced Engineering Informatics	Engineering, Multidisciplinary
British Journal of Psychiatry	Psychiatry
Journal of Computational Science	Computer Science, Theory & Methods
IEEE Network	Engineering, Electrical & Electronic
Human-Centric Computing and Information Sciences	Computer Science, Information Systems
Asian Journal of Psychiatry	Psychiatry
IEEE Transactions on Information Forensics and Security	Engineering, Electrical & Electronic
European Psychiatry	Psychiatry
Computer Communications	Engineering, Electrical & Electronic
Journal of the American Medical Informatics Association	Health Care Sciences & Services
ACM Transactions on Internet Technology	Computer Science, Software Engineering
Acta Psychiatrica Scandinavica	Psychiatry
Bipolar Disorders	Clinical Neurology
IEEE Transactions on Systems Man Cybernetics-Systems	Computer Science, Cybernetics
Depression and Anxiety	Psychiatry
International Journal of Medical Informatics	Health Care Sciences & Services
Measurement	Engineering, Multidisciplinary
Computers & Industrial Engineering	Engineering, Industrial
International Journal of Neural Systems	Computer Science, Artificial Intelligence
Journal of Organizational and End User Computing	Computer Science, Information Systems
IEEE Signal Processing Magazine	Engineering, Electrical & Electronic
American Journal of Geriatric Psychiatry	Geriatrics & Gerontology
IEEE Journal of Selected Topics in Signal Processing	Engineering, Electrical & Electronic

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Journal Name	Web of Science
Journal of Anxiety Disorders	Psychiatry
Computer Science Review	Computer Science, Theory & Methods
IEEE Transactions on Visualization and Computer Graphics	Computer Science, Software Engineering
Information and Software Technology	Computer Science, Software Engineering
Science China-Information Sciences	Engineering, Electrical & Electronic
Communications of the ACM	Computer Science, Theory & Methods
Current Directions in Psychological Science	Psychology, Multidisciplinary
Psychological Science	Psychology, Multidisciplinary
British Journal of Psychology	Psychology, Multidisciplinary
Addiction	Substance Abuse
Aggression and Violent Behavior	Criminology & Penology
IEEE Transactions on Industrial Informatics	Engineering, Industrial
Clinical Psychological Science	Psychology
Biological Psychiatry-Cognitive Neuroscience and Neuroimaging	Neurosciences
Psychological Bulletin	Psychology
Journal of Neurology Neurosurgery and Psychiatry	Clinical Neurology
International Journal of Eating Disorders	Nutrition & Dietetics
Developmental Cognitive Neuroscience	Neurosciences
Journal of Psychiatry & Neuroscience	Neurosciences
International Psychogeriatrics	Geriatrics & Gerontology
Current Psychiatry Reports	Psychiatry
Alzheimers Research & Therapy	Clinical Neurology
Computers in Industry	Computer Science, Interdisciplinary Applications
ACM Transactions on Knowledge Discovery from Data	Computer Science, Software Engineering
Alexandria Engineering Journal	Engineering, Multidisciplinary
Neuropsychobiology	Neurosciences
Neural Regeneration Research	Neurosciences
IEEE Transactions on Fuzzy Systems	Engineering, Electrical & Electronic

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Journal Name	Web of Science
Internet Interventions-The Application of Information Technology in Mental and Behavioural Health	Health Care Sciences & Services
Proceedings of the IEEE	Engineering, Electrical & Electronic
Journal of Network and Computer Applications	Computer Science, Software Engineering
Brain Behavior and Immunity	Neurosciences
Data Mining and Knowledge Discovery	Computer Science, Information Systems
MIS Quarterly	Computer Science, Information Systems
Journal of Management Information Systems	Computer Science, Information Systems
Journal of Computing in Civil Engineering	Engineering, Civil
Integrated Computer-Aided Engineering	Engineering, Multidisciplinary
Revista de Psiquiatría y Salud Mental	Psychiatry
European Journal of Psychotraumatology	Psychology, Clinical
Brain Stimulation	Clinical Neurology
European Journal of Neurology	Clinical Neurology
Virtual Reality	Computer Science, Software Engineering
Artificial Intelligence	Computer Science, Artificial Intelligence
CAAI Transactions on Intelligence Technology	Computer Science, Artificial Intelligence
Artificial Intelligence	Computer Science, Artificial Intelligence
Nature Reviews Neuroscience	Neurosciences
Progress in Neurobiology	Neurosciences
International Journal of Electronic Commerce	Computer Science, Software Engineering
Empirical Software Engineering	Computer Science, Software Engineering
International Journal of Neuropsychopharmacology	Clinical Neurology
Jama Psychiatry	Psychiatry
American Psychologist	Psychology, Multidisciplinary
Current Opinion in Neurology	Clinical Neurology
Pain	Clinical Neurology
Current Neuropharmacology	Neurosciences
IEEE-CAA Journal of Automatica Sinica	Automation & Control Systems
Sleep	Clinical Neurology

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Journal Name	Web of Science
Body Image	Psychology, Multidisciplinary
Journal of Parallel and Distributed Computing	Computer Science, Theory & Methods
Ain Shams Engineering Journal	Engineering, Multidisciplinary
Engineering Science and Technology-An International Journal-Jestech	Engineering, Multidisciplinary
Current Opinion in Psychology	Psychology, Multidisciplinary
CNS Neuroscience & Therapeutics	Neurosciences/Pharmacology & Pharmacy
Annals of Clinical and Translational Neurology	Clinical Neurology/Neurosciences
Big Data	Computer Science, Theory & Methods
IEEE Transactions on Mobile Computing	Computer Science, Information Systems/Telecommunications
Psicothema	Psychology, Multidisciplinary
Neuroscientist	Clinical Neurology
Current Opinion in Neurobiology	Neurosciences
Current Neurology and Neuroscience Reports	Clinical Neurology
Trends in Cognitive Sciences	Neurosciences
IEEE Wireless Communications	Engineering, Electrical & Electronic
Annual Review of Psychology	Psychology
Journal of Information Technology	Computer Science, Information Systems
IEEE Transactions on Emerging Topics in Computing	Computer Science, Information Systems
Perspectives on Psychological Science	Psychology, Multidisciplinary
Behavior Therapy	Psychology, Clinical
Nature Human Behaviour	Neurosciences
Computer Networks	Engineering, Electrical & Electronic
Computer Standards & Interfaces	Computer Science, Software Engineering
General Hospital Psychiatry	Psychiatry
Annals of Behavioral Medicine	Psychology, Multidisciplinary
Child and Adolescent Psychiatry and Mental Health	Psychiatry
Physical and Engineering Sciences in Medicine	Engineering, Biomedical
Molecular Neurobiology	Neurosciences

(Continue)

Journal Name	Web of Science
Journal of Pain	Clinical Neurology
IEEE Transactions on Network Science and Engineering	Engineering, Multidisciplinary/Mathematics, Interdisciplinary Applications
Computers and Electronics in Agriculture	Agriculture, Multidisciplinary/Computer Science, Interdisciplinary Applications
Archives of Computational Methods in Engineering	Computer Science, Interdisciplinary Applications/ Engineering, Multidisciplinary/Mathematics, Interdisciplinary Applications
International Journal of Geographical Information Science	Computer Science, Information Systems/Geography/ Geography, Physica/Information Science & Library Science
IEEE Transactions on Big Data	Computer Science, Theory & Methods
International Journal of Social Psychiatry	Psychiatry
Journal of the Association For Information Systems	Computer Science, Information Systems/Information Science & Library Science
Journal of Grid Computing	Computer Science, Theory & Methods
Computational Visual Media	Computer Science, Software Engineering
IEEE Transactions on Vehicular Technology	Engineering, Electrical & Electronic/Telecommunications
ACM Transactions on Software Engineering and Methodology	Computer Science, Software Engineering
Nature Neuroscience	Neurosciences
Psychological Science in the Public Interest	Psychology, Multidisciplinary
Neuron	Neurosciences
Psychotherapy and Psychosomatics	Psychiatry
IEEE Transactions on Robotics	Robotics
Sleep Medicine Reviews	Clinical Neurology
Journal of the Franklin Institute-Engineering and Applied Mathematics	Engineering, Multidisciplinary
World Psychiatry	Psychiatry
Journal of Intelligent Manufacturing	Engineering, Manufacturing
Molecular Psychiatry	Neurosciences
IEEE Transactions on Signal Processing	Engineering, Electrical & Electronic
IEEE/ASME Transactions on Mechatronics	Engineering, Mechanical
Fuzzy Sets and Systems	Computer Science, Theory & Methods

(Continue)

Journal Name	Web of Science
Lancet Psychiatry	Psychiatry
Frontiers in Cellular Neuroscience	Neurosciences
International Journal of Robotics Research	Robotics
IEEE Journal on Emerging and Selected Topics in Circuits and Systems	Engineering, Electrical & Electronic
Human-Computer Interaction	Computer Science, Theory & Methods
Journal of Environmental Psychology	Environmental Studies
Business & Information Systems Engineering	Computer Science, Information Systems
Computer-Aided Design	Computer Science, Software Engineering
IEEE Transactions on Biomedical Circuits and Systems	Engineering, Electrical & Electronic
IEEE Journal on Selected Areas in Communications	Engineering, Electrical & Electronic
Behavioral Medicine	Behavioral Sciences
European Journal of Psychology Applied to Legal Context	Psychology, Multidisciplinary/Law
IEEE Transactions on Reliability	Computer Science, Hardware & Architecture/Computer Science, Software Engineering/Engineering, Electrical & Electronic
Computer-Aided Civil and Infrastructure Engineering	Computer Science, Interdisciplinary Applications/ Construction & Building Technology/Engineering, Civil/ Transportation Science & Technology
IEEE Transactions on Industrial Electronics	Automation & Control Systems/Engineering, Electrical & Electronic/Instruments & Instrumentation
Neurobiology of Disease	Neurosciences
Review of General Psychology	Psychology, Multidisciplinary
Journal of Positive Psychology	Psychology, Multidisciplinary
npj Parkinsons Disease	Neurosciences
Computers Environment and Urban Systems	Environmental Studies/Geography/Regional & Urban Planning
Fuzzy Optimization and Decision Making	Computer Science, Artificial Intelligence/Operations Research & Management Science
Biosystems Engineering	Agriculture, Multidisciplinary
Simulation Modelling Practice and Theory	Computer Science, Software Engineering
IEEE Transactions on Medical Imaging	Computer Science, Interdisciplinary Applications/ Engineering, Biomedical/Engineering, Electrical & Electronic/ Imaging Science & Photographic Technology/ Radiology, Nuclear Medicine & Medical Imaging

(Continue)

Journal Name	Web of Science
Bulletin of the Menninger Clinic	Psychology, Psychoanalysis
International Journal of Mental Health Nursing	Nursing
IEEE Transactions on Dependable and Secure Computing	Computer Science, Hardware & Architecture/Computer Science, Information Systems/Computer Science, Software Engineering
IEEE Communications Magazine	Engineering, Electrical & Electronic/Telecommunications
Sustainable Computing-Informatics & Systems	Computer Science, Hardware & Architecture
Journal of Statistical Software	Computer Science, Interdisciplinary Applications/Statistics & Probability
International Journal of Mental Health and Addiction	Psychiatry/Psychology, Clinical/Substance Abuse
Mathematics and Computers in Simulation	Computer Science, Software Engineering/Mathematics, Applied
Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement	Psychology, Multidisciplinary
Psychological Trauma Theory Research Practice and Policy	Psychiatry/Psychology, Clinical
IEEE Transactions on Sustainable Computing	Computer Science, Hardware & Architecture
Psychiatric Rehabilitation Journal	Rehabilitation
Neurobiology of Stress	Neurosciences
Journal of Happiness Studies	Social Sciences, Interdisciplinary

3. Collaboration details of the top 20 countries in the field of affective computing

No.	Collaboration Country	Number of Collaboration Articles																			
		China	USA	India	UK	Germany	Japan	Italy	Australia	Spain	Canada	South Korea	France	Netherlands	Turkey	Saudi Arabia	Singapore	Malaysia	Pakistan	Brazil	Greece
1	China	6 905	540	54	256	58	212	41	169	32	106	41	44	23	12	44	123	20	38	5	4
2	USA	540	4 085	90	199	158	36	103	110	49	129	57	91	93	39	36	58	9	23	47	17
3	India	54	90	3 075	53	9	12	13	26	13	16	23	17	6	10	38	35	12	8	2	2
4	UK	256	199	53	2 136	243	35	110	103	80	52	9	77	136	23	55	50	25	30	26	39
5	Germany	58	158	9	243	1 482	36	65	38	34	39	7	55	80	17	3	11	5	3	13	16
6	Japan	212	36	12	35	36	1 145	2	16	13	25	6	15	11	5	5	15	13	1	3	1
7	Italy	41	103	13	110	65	2	1 111	20	50	19	9	62	43	12	7	34	3	8	5	7
8	Australia	169	110	26	103	38	16	20	1 062	21	26	10	19	21	11	26	28	21	19	11	3
9	Spain	32	49	13	80	34	13	50	21	996	13	9	36	37	11	17	9	3	5	22	15
10	Canada	106	129	16	52	39	25	19	26	13	933	8	37	16	9	32	8	2	11	16	3

(Continue)

No.	Collaboration Country	China	USA	India	UK	Germany	Japan	Italy	Australia	Spain	Canada	South Korea	France	Netherlands	Turkey	Saudi Arabia	Singapore	Malaysia	Pakistan	Brazil	Greece
		Number of Collaboration Articles																			
11	South Korea	41	57	23	9	7	6	9	10	9	8	925	13	4		16	1	8	45	2	2
12	France	44	91	17	77	55	15	62	19	36	37	13	852	36	4	9	2	6	15	15	10
13	Netherlands	23	93	6	136	80	11	43	21	37	16	4	36	684	16		8	3	1	9	13
14	Turkey	12	39	10	23	17	5	12	11	11	9		4	16	634	7	5	6	2	1	1
15	Saudi Arabia	44	36	38	55	3	5	7	26	17	32	16	9		7	565	1	21	82	1	3
16	Singapore	123	58	35	50	11	15	34	28	9	8	1	2	8	5	1	515	3	2		1
17	Malaysia	20	9	12	25	5	13	3	21	3	2	8	6	3	6	21	3	481	30		3
18	Pakistan	38	23	8	30	3	1	8	19	5	11	45	15	1	2	82	2	30	460	3	
19	Brazil	5	47	2	26	13	3	5	11	22	16	2	15	9	1	1			3	457	
20	Greece	4	17	2	39	16	1	7	3	15	3	2	10	13	1	3	1	3			425

4. Representative products and applied technologies in the field of affective computing

Company Name	Representative Products or Services	Applied Technology
Hikvision	Smart classroom behavior management system	"Huiyan" provides statistics and analysis of students' behavior and expressions in the class captured by the camera, and provides timely feedback on abnormal behavior.
Mohodata	Strategic Intelligence Service	Emotional tendency analysis of massive text content based on NLP technology
MorphCast	Interactive video platform	Facial emotion recognition and analysis technology
MIDU	Sina Yuqingtong	Use NLP technology and audio and video processing technology to monitor negative public opinion and users' negative emotions on the Internet
Affectiva	Media analysis solution	Emotional AI technology
Talkwalker	Consumer intelligence platform	Affective computing technology based on text analysis.
NVISO	Driver Monitoring System (DMS)	Real-time eye-tracking of drivers through optical cameras and infrared cameras in cars to monitor drivers' fatigue and concentration in real time.
Robokind	Zeno robot	Enhance children's emotional processing skills by detecting and interpreting the voices, expressions, and behaviors of children with autism through affective computing technology.
Emotiv	Neurotechnology of Electroencephalography (EEG)	The core technology is a head-mounted device that measures the electrical activity generated by the brain when neurons are firing, and then analyzes and provides insight into the corresponding emotions.
audEERING	entertAIn play electronic products	Voice Activity Detection (VAD) captures the player's voice data and then analyzes the voice parameters using AI models.
UBTECH	ROSA robot	High-performance servo drive and control algorithm, motion control algorithm, service robot-oriented computer vision algorithm, intelligent robot autonomous navigation and positioning algorithm, ROSA robot operating system application framework, voice and other core technologies.
Intelligent Voice	LexiQal based on its unique session analysis technology	NLP technology and sophisticated searching technology
Entertech	Cloud computing platform	Multimodal physiological signal sensor and cloud-based multi-dimensional analysis algorithm
CMCross	Biometric identification system for management and passengers	Biometric SDK engine
BrainCo	Concentration enhancement system	The technology to detect brain activities to monitor and quantify students' concentration levels

(Continue)

Company Name	Representative Products or Services	Applied Technology
Emotibot	Robot dialogue system, sentiment analysis model, commercialized AI SaaS platforms	27 Chinese and English NLP modules, facial emotion recognition, emotional attendance, language emotion understanding technology
Behavioral Signals	Dialogue system solution	AI-Mediated Conversations (AI-MC) uses customer voice data to match the most appropriate customer service agent through AI sentiment algorithm
Ningbo Alpha Eye	Alpha Eye analysis and identification warning system	“Face + Emotion” acquisition, person-witness matching and “Face + Emotion” matching technology
New Oriental	AI Double Teacher Classroom	“AI technology + MOOC teaching” model, “Huiyan System” based on facial expression recognition
Meta	Brain-computer interface hardware EMG wristband	Use Meta-developed “co-learning algorithm” to help devices recognize EMG signals
Baidu Finance	Du Xiaoman Financial	Overall perception based on multi-scale feature representation fuses speech emotion recognition.
SoftBank Robotics	Pepper, the first social humanoid robot capable of recognizing human faces and basic human emotions	The robot can quickly recognize and interact with objects in multiple modes using sensory module, touch loss sensor, led and microphone, and can navigate autonomously in all directions using infrared sensor, bumper, inertial device, 2D and 3D cameras and sonar.
Discern Science	AVATAR automated virtual agent for real-time truth assessment	The transformative initiative that high techs including specialized sensor, AI, machine learning extended reality (XR) and 5G drive threat/spoof detection.
Intel	Class software	Based on AI technology, Class integrates with Zoom for body language and facial expression recognition.
Expper Technologies	Robin, an interactive companion robot	Mathematical Model – Markov Decision Process
HiPhiGo	HiPhiGo emotional intelligent travel partner	Detect user emotions through various sensors in the cabin, and use voice recognition technology provided by Nuance to understand user commands and recognize user emotions.
Hyundai Motor	Little Big e-Motion	Emotion Adaptive Vehicle Control Technology
FlyingBinary	G-Cloud public sector cloud computing platform	Demonstrate that citizen conversations on web platforms comply with the General Data Protection Regulation (GDPR) based on natural language analytics, and simultaneously measure social sentiment and visualize the data on Tableau software.

Acknowledgement

Affective computing is a key technology that is indispensable for realizing machine anthropomorphism. As a major component of the new generation of artificial intelligence, the leap from single modality to multiple modality and beyond will be an important point to achieve total intelligence and integration of human-machine intelligence.

During the preparation of the White Paper, the engagement team received guidance and assistance from several scholars, experts and industry professionals. They have selflessly given various resources with the common goal of promoting affective computing development and application, regardless of the rewards. The engagement team hereby express sincere gratitude to these contributors.

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We do believe that more talents will join the development and transformation team of affective computing in the future. The engagement team will continue to act as a platform builder and contribute to advancing the development of affective computing technology in China!

Engagement team of Affective Computing White Paper
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