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Original Paper

From Theory to Practice: Emotion Regulation in Language Learning via AI

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Abstract

The integration of AI-assisted emotion recognition and regulation into language education offers new possibilities for enhancing second language (L2) teaching and learning experiences. This paper examines the role of AI in supporting emotionally intelligent language education by connecting cognitive, emotional, and instructional aspects. Drawing on empirical research from neuroscience, educational psychology, and intelligent tutoring systems, it explores how AI can assist in emotion regulation and improve teaching strategies for both learners and instructors. The findings contribute to the application of emotion perception, teaching responses, and learning regulation mechanisms in language teaching practice.

Keywords

emotion cognition, emotion regulation, AI, second language learning, emotionally intelligent teaching

1. Introduction

In the context of globalization, bilingualism has become an important quality for individual social participation and cross-cultural communication. Neurolinguistic research (Maftoon et al., 2014) has shown that when second language learning takes place in a natural, contextual and emotionally engaging environment, the limbic system (especially the amygdala and hippocampus) is significantly involved in language processing. This finding indicates that the emotional factor and cognitive factor in language learning are both of great importance. However, the present language teaching practice still focuses more on the training of cognitive ability. The emotional experience and mood fluctuations of learners in the classroom have been given less attention (Dewaele, 2020; Shao et al., 2020; Wu & Kabilan, 2025). This dichotomy of cognition and emotion restricts the overall optimization of teaching process and the improvement of learner's individual experience to some extent.

Traditional emotion recognition usually relies on a single mode such as facial expression or text feedback. It is difficult for such feedback mode to capture the true emotional state of learners and teachers comprehensively and accurately, thus affecting the fine adjustment of personalized teaching and the quality of classroom interaction. Fortunately, with the development of AI-driven emotional computing technology, emotion recognition methods integrating multi-modal information such as voice, image and text have been gradually introduced into intelligent classrooms as well as online teaching scenes. Studies have shown that such technologies significantly improve the recognition accuracy of teachers' implicit emotions and can capture students' emotional fluctuations in the classroom in real time (Li et al., 2022; Zhao et al., 2024) . In distance learning, they have shown effectiveness in helping teachers assess students' learning conditions and adjusting their teaching methods accordingly (Zhou et al., 2024).

In recent years, the increasing need for effectiveness of using AI in education settings encourages a shift from focusing on emotion recognition to emotion regulation. For instance, the empirical research by Shi (2024) presented an AI system that combines emotion detection and personalized learning tailored for English learners. This research demonstrated that this platform significantly enhanced language learning outcomes and the emotional self-regulation skills of learners. Also, this AI platform significantly improved students' motivation to learn and emotional engagement. Moreover, Yang and Zhao (2024) conducted a qualitative study on 498 Chinese EFL learners and found that students will experience a series of positive and negative emotions in AI-assisted teaching and actively regulate their emotions through various strategies (e.g., goal adjustment and attention transfer). These two studies indicate that AI has a great influence on language learning as well as changes the way learners regulate emotions.

The integration of artificial intelligence technology into language learning scenarios promotes the advancement of emotion recognition and regulation from theoretical construction to practical application. This article focuses on the influence of emotions on second language learning. Firstly, it discusses the mechanism of different emotional states on second language learning and the empirical basis. Subsequently, the practical application of artificial intelligence-driven emotion analysis and regulation technology in language learning is explored, and the challenges it faces are analyzed simultaneously. Furthermore, based on the data from the Web of Science database (2003-2024), sort out the current research hotspots and development trends in this field. Finally, this paper indicates that in the intelligent classroom environment, an emotional regulation model led by teachers and supported by artificial intelligence should be constructed.

2. The Impact of Emotional States on Second Language Acquisition

2.1 Emotional Valence and Cognitive Processing

Second language acquisition research generally holds that emotional valence plays an important role at all stages of the language learning process. Emotions can change the way language learning is experienced and they can regulate the allocation of cognitive resources. Krashen (1982) has mentioned in the Affective Filtering Hypothesis that emotional variables such as anxiety and motivation can directly affect the learners' processing efficiency of language input.

The influence of positive and negative emotions on language learning has been pointed out by a number of studies. Studies have shown that positive emotions can enhance learners' intrinsic motivation and sense of achievement, while negative emotions can weaken learners' language comprehension and expression ability (Dornyei & Csizer, 1998; Teimouri et al., 2019). For example, studies showed that there is a stable negative relationship between verbal anxiety and academic performance (MacIntyre & Gardner, 1994; Horwitz et al., 1986; Fisher et al., 2018). Gregersen (2020) observed that learners with high anxiety tend to exhibit classroom avoidance and excessive self-correction.

From physiological aspects, Fredrickson's (2004) broaden–and–build theory proposes that positive emotions can enhance the processing of immediate information, as well as gradually expand cognitive resources. Furthermore, Tyng et al. (2017) demonstrated through electroencephalogram that negative emotions inhibit the activity of the prefrontal cortex and are key drivers of attention that impair working memory and language processing efficiency. These findings position emotional states as not merely motivational factors; instead, they are rooted in the framework of language acquisition.

Emotion and language processing share overlapping but distinct neural pathways. Wildgruber et al. (2006) identified a multistage system of emotional intonation: acoustic analysis was performed first in the right auditory cortex, followed by semantic and emotional assessments in the superior temporal gyrus and inferior frontal gyrus. Early information processing focuses on the right hemisphere, whereas higher-order cognition splits into specialized circuits. This reveals the dynamic role of emotion in language comprehension. Moreover, effective emotion regulation relies on the modulation of limbic responses in the prefrontal cortex (PFC), especially amygdala inhibition (Morawetz & Basten, 2024). Individuals with stronger PFC involvement and reduced amygdala responses showed better modulation. This provides key insights into AI-assisted language learning tools that target emotional adaptation.

2.2 Emotion, Motivation, and Learning Engagement

Under the framework of motivation theory, the second language motivation self-system proposed by Dornyei (2009) has developed a structural model consisting of three elements. Teimouri (2017) pointed out that this model covers the ideal self, the expected self and self/others expectations, revealing how the differences among different self-concepts trigger emotional responses and further affect learning behaviors. Recent research by Pavelescu (2023) and others indicates that the connection between emotions, motivations and behaviors is not a simple linear causality but follows a complex interaction path. Specifically, although goal setting may trigger emotional responses, these responses will be dynamically adjusted in the continuous learning experience, forming a cyclical mechanism of mutual influence.

Longitudinal studies consistently show that learner-related pleasures enhance the willingness to communicate. In contrast, anxiety has a negative impact on both classroom participation and extracurricular language use (Pavelescu, 2023; Alrabai, 2022). Alrabai's (2022) further clarifies that emotion regulation affects learning outcomes through two different pathways. First, it directly influences the level of motivation. Second, it indirectly has an impact on behaviors through changes in motivation (e.g., increased pleasure leading to greater persistence and thus bringing more practical opportunities). Moreover, studies have shown that self-regulated learning (SRL) strategies can effectively alleviate emotional disorders and maintain motivation (Zhang & Zou, 2022; Solhi et al., 2024). Learners who adopted meta-cognitive monitoring, cognitive re-evaluation and adaptive goal adjustment demonstrated stronger emotional resilience and sustained engagement. More importantly, this self-regulation process significantly benefits from external support systems, whether through teacher guidance or adaptive learning techniques.

These findings all reveal how emotions and motivations interact to influence learners' psychological experiences and behavioral patterns. To achieve successful language learning, it is essential to be aware of one's own emotions and learn to regulate them. Therefore, one of the core areas in developing artificial intelligence-assisted systems is to detect users' emotional responses as accurately as possible and provide real-time adaptive support for them.

3. AI-Powered Emotion Analysis and Regulation in Language Learning

3.1 Technological Evolution and Theoretical Advances

The research of educational psychology and language acquisition has promoted the development of emotion recognition and regulation technology in language learning. The Affective Filtering Hypothesis" proposed by Krashen (1982) pointed out the mediating effect of emotions on language input processing. This theoretical framework lays the foundation for affective mechanisms in second language acquisition. Later, Pavlenko's (2005) framework for bilingual emotion further shows how emotional expressions are shaped by culture-language systems. Her research revealed a systematic divergence in semantic framing and perceptual mechanisms when learners express emotions in the first and second language contexts.

The development of emotion-aware educational technology has evolved from early intelligent tutoring systems. In this area AutoTutor (Graesser et al., 2004) pioneered natural language-based teaching dialogues. AutoTutor demonstrates the sophisticated ability to detect emotional states and misunderstandings through learners' language patterns. The system dynamically adjusts its teaching strategies in the form of frame prompts, Socratic questions and so on. More importantly, it incorporates affective computing elements by monitoring conversational cues (hesitant patterns, negative wording, etc.). These features make AutoTutor an early prototype of emotion-aware AI in education.

Contemporary applications of multimodal emotion recognition technologies and generative AI in education allow for more sophisticated integration of content delivery and emotional state regulation. In recent years, emotion recognition systems have made breakthroughs in accuracy, real-time performance and adaptability. The system collects multi-source data such as integrated speech, facial expression. Through the dynamic modeling of learners' emotional states, the feature extraction and fusion processing of cross-modal data are realized. For example, the Prosody BERT model constructed by Zhao et al. (2024) has achieved excellent performance in the implicit recognition of teachers' emotions. Li et al. (2022) developed a neural network framework that combines vision and speech. And it can be used to monitor students' learning emotions in the classroom in real time.

In terms of design, theoretical frameworks such as the control value theory of Pekrun (2006) and the technology acceptance model of Davis (1989) play an important role. The control value theory suggests that affective experiences stem from learners' evaluation of task control and value. And the technology acceptance model explains how affective factors influence user adoption of technology tools. These complementary perspectives serve as guides in the design of adaptive AI systems. Artificial intelligence-driven emotion regulation mechanisms are building a more dynamic and humanized language learning system. Nowadays chatbots can even generate context-appropriate responses by modulating intonation complexity as well as information density (Zhou et al., 2024). The transition from passive emotion recognition to active emotion regulation, creating human-centered intelligent learning environments.

3.2 Emotion Recognition and Regulation in Teaching Applications

3.2.1 Emotion Regulation in Instructional Settings

The Perception-analysis-regulation Cycle proposed by D'Mello and Kory (2015) has become an important framework for the development of affective computing in intelligent language learning systems. This theory stresses a closed-loop feedback. First, the system will continuously sense the user's emotional signal. And after that it will dynamically analyze the user's cognitive state, and finally optimizing the interaction strategy accordingly.

A study with 214 adult learners demonstrated its concrete applications (Graesser et al., 2022) . By combining keystroke dynamics (WPM), facial-action-unit analysis (FACS), and dialog pattern mining, the system achieved high accuracy in detecting disengagement episodes. Subsequent strategy adjustments yielded a reduction in early termination and an improvement in post-test scores. Furthermore, the evolved version of AutoTutor system, Affective AutoTutor, integrates an emotion recognition module on the basis of the original cognitive dialogue model. This improvement can perceive learners' emotional cues (such as intonation, expression, and language features) in real time and make dynamic teaching responses. D'Mello and Graesser (2013) pointed out that the system showed stronger teaching promotion in dealing with learners with low motivation and weak knowledge, especially in improving their emotional engagement and interaction frequency.

In addition to verbal and behavioral cues, recent studies have also identified attention as a key part in emotional regulation mechanisms. The Gaze Tutor system developed by D'Mello et al. (2012) identified the mind-wandering state of learners through eye tracking technology and re-attracted their attention to return to the learning task with guided language in time. Their results show that the system has a significant positive effect on learning performance when processing tasks with high cognitive load. This study strengthens the dynamic coupling relationship of emotion,attention and behavior in the process of language learning. And it also proves the feasibility and prospective value of multi-modal recognition system in the application of AI language learning.

Furthermore, the development of Large Language Model (LLMs) also influences the AutoTutor system. The MWPTutor system developed by Chowdhury et al. (2024) embers LLMS into the teaching process of finite states. By combining rules and generation, it achieves more adaptive language interaction while ensuring the rigor of instructional design. This study reveals the practical stage of AI language system to have stronger empathy and interaction ability while retaining the controllability of teaching.

3.2.2 Cross-Cultural Challenges and Optimization in Emotion Recognition

In recent years, the research of cross-cultural emotion recognition has gradually advanced to the direction of multi-modal modeling. Gong et al. (2024) constructed a multi-stack generalized learning system (MSBLS) using EEG and EM signals to conduct cross-cultural recognition experiments in three cultural contexts (Chinese, German and French). Studies have found that different cultural groups have different brain regions activated in the process of emotional cognition, especially in the activation of the prefrontal, temporal and parieto-occipital lobes. These results reveal the cultural neural mechanism of emotion processing and provide technical support for the development of multi-modal recognition systems with cultural adaptability.

In addition to speech and brain signals, cross-cultural recognition bias of facial expressions has also become an urgent problem to be solved in the design of emotion recognition systems. Halberstadt et al. (2022) noted that teachers have an anger bias in identifying black children's emotions. In other words, they tend to misidentify their neutral expressions as angry emotions, while the error tolerance rate is higher for white children. This bias reflects the skew of the training data in the ethnic structure, and also suggests that the current AI system needs to strengthen the fairness regulation mechanism in the multicultural context.

In order to improve the interactive experience and emotional resonance ability of AI emotional systems in cross-cultural scenes, immersive technology is introduced into the optimization of emotional regulation mechanism. Shadiev et al. (2021) developed a virtual reality cross-cultural learning environment incorporating 360-degree panoramic video based on the theory of cultural convergence. Participants in the immersive situation obtained significant improvement in cross-cultural cognition, especially in emotional intelligence dimensions such as emotionality and self-control. This suggests that virtual reality environments have practical application potential in stimulating cultural acceptance willingness and enhancing cultural empathy (Shadiev et al., 2021).

Cultural differences not only affect the understanding between speakers and receivers, but also challenge the generalization ability of emotion recognition models. Laukka and Elfenbein (2021) found in their meta-analysis of 37 cross-cultural tonal emotion recognition studies that although multiple emotions can be accurately identified in cross-cultural contexts, in-group advantage effect exists widely.

That is, there is a higher recognition accuracy between the expresser and the perceiver who share the cultural background. The greater the cultural distance, the lower the recognition accuracy. This supports the dialect theory of emotion (Elfenbein et al., 2007) and suggests that we should pay attention to the cultural fit of models when building emotion recognition systems for global users (Laukka & Elfenbein, 2021).

Therefore, in cross-cultural language learning scenarios, the optimization of emotion recognition system should comprehensively consider cultural semantics, expression habits and social bias. From this perspective, future AI-assisted teaching systems are expected to introduce fine-tuned speech style models based on specific cultural groups, balance training data of race and gender, and combine immersive environments with emotional intelligence feedback mechanisms.

4. A Bibliometric Analysis of AI, Emotion, and Language Learning (2003–2024)

Figure 1, 2 and 3 respectively show the network visualization, overlay visualization and density visualization drawn based on VOSviewer. This study takes Web of Science (WOS) core collection as data source. The search formula is as follows: TS=(("emotion*" OR "affect*" OR "sentiment") AND ("language learn*" OR "second language") AND ("AI" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "adaptive system*" OR "intelligent tutor*")). A total of 186 articles and review types published between 2003 and 2024 were selected for quantitative analysis.

The network visualization reveals the connections between co-occurring keywords. It indicates the cross-research between AI and language learning covers multiple sub-fields, including model design, skill training, task execution, feedback mechanism and learner participation, etc., showing an overall trend of integration of technology application and teaching objectives. Among the keywords, "model", "skill", "feedback" and "engagement" frequently appear, constituting the core semantic network of the current research.

The overlay visualization shows the evolution of keywords over time. Keywords such as "chatbot", "integration", "engagement" and "feedback" have increased rapidly in the past three years, indicating that the research focus is gradually shifting from the "accuracy and efficiency" of AI system itself to the level of "personalized feedback" and "interactive experience". In particular, driven by generative AI (such as ChatGPT) technology, "chatbot" has become a hotspot node with the rapid increase in co-occurrence intensity in recent years.

The density map shows the most central topics in the research area. It further corroborates the above findings: "model" and "feedback", as high-frequency and high-intensity keywords, gather in the central area of heat map, showing their significant academic attention in the corpus.

The annual publication trends shown in Figure 4 show significant growth in relevant research after 2020, with a peak in 2024 in particular. This trend can be attributed to the widespread use of generative AI tools (such as the GPT series), emotion recognition models, and intelligent tutoring systems in teaching practices. AI+language learning research is entering a stage of leap from low-level model construction to high-level teaching context application.

In general, the current research on AI and language learning is undergoing a transition from technology-driven to learner-centered, with research topics gradually focusing on learners' emotional state recognition, real-time feedback mechanism, interactive teaching strategies and other directions. This trend indicates that the future AI-enabled language education will carry out more in-depth exploration in aspects of personalization, emotional intelligence, and dynamic adaptation.

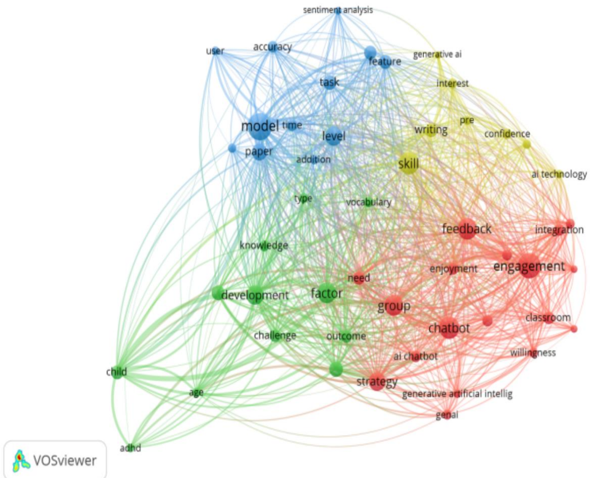

Figure 1. Network Visualization

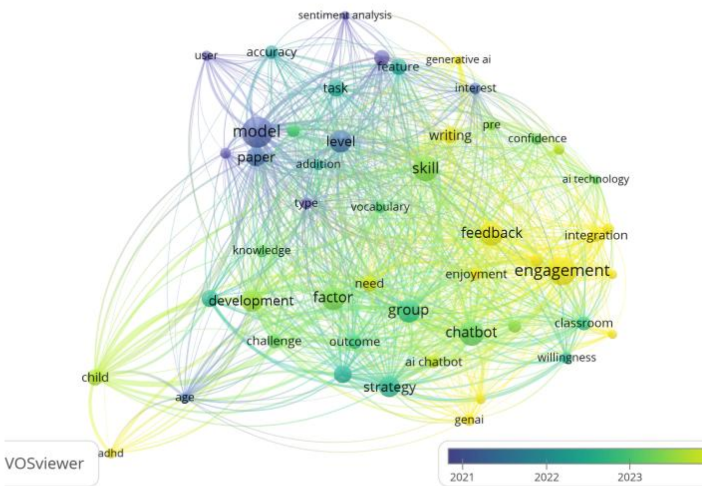

Figure 2. Overlay Visualization

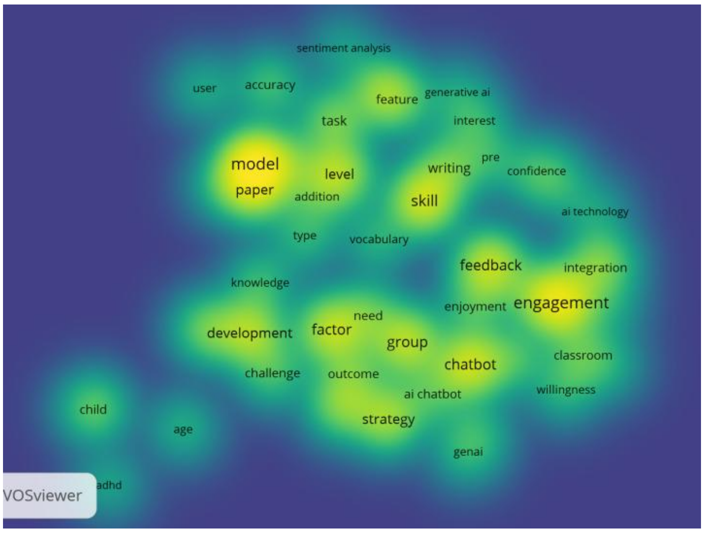

Figure 3. Density Visualization

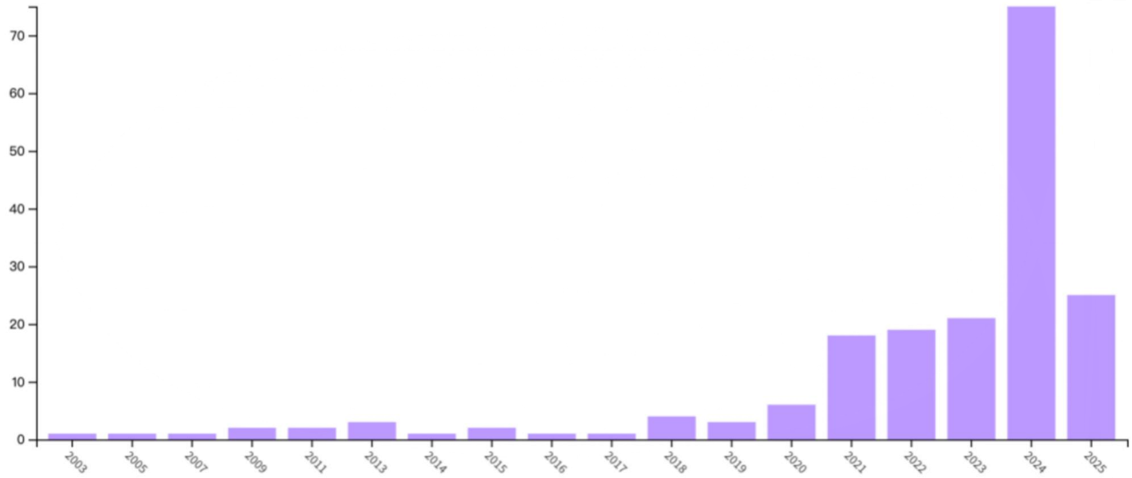

Figure 4. Annual Publication Trends

5. Toward Emotionally Intelligent Language Education: Practical Paths for AI-Based Regulation

In the development of language education systems centered on emotional intelligence, the integration of artificial intelligence emotion recognition technology plays a key role. It should not be limited to providing perceptual feedback, but should permeate all aspects of instructional design. By analyzing students' voice features, facial expressions, semantic content and behavioral data, the artificial intelligence system can determine students' emotional states in real time. Subsequently, this feedback was embedded into the teaching process (D 'mello & Graesser, 2013; Zhou et al., 2024). For example, in the design and execution of language tasks, the system can automatically adjust the task difficulty, language feedback tone or motivational cues according to the learner's anxiety level, effectively avoiding learning interruptions caused by emotional disorders.

Effective emotional perception teaching design should follow the logic of perception - judgment - reaction. In this process, the teacher is no longer just the transmitter of the teaching content, but the co-designer and implementor of the emotional regulation path. Through dynamic linkage with the AI system, teachers can arrange differentiated task forms, interaction rhythms and feedback methods according to the real-time emotional states of different students. For example, for learners with low emotional engagement, the system can help teachers introduce emotional encouraging statements in teaching activities, adjust the pace of activities, or timely push collaborative tasks. In this way, teachers can better stimulate students' willingness to participate (Anwar et al., 2023; Shadiev et al., 2021).

In addition, in the context of multicultural teaching, the AI-assisted system can also achieve a more adaptive feedback mechanism according to the differences in emotional expression in different cultural backgrounds. For example, emotion recognition bias caused by cultural misreading can be avoided by detecting linguistic style preferences and adjusting the interpretation of emotional cues (Laukka & Elfenbein, 2021). The system design provides teachers with more accurate classroom control tools, and effectively reduces teaching fracture and inefficiency caused by emotional mismatch.

In the future, the emotional perception teaching system should further integrate generative AI, big data and multi-modal recognition technology. For example, when the system detects learner fatigue, frustration, or low engagement, it can actively generate empathy language feedback and adjust the pace of the task. The system can also intelligently recommend cooperative learning and rest strategies to enhance the empathy and humanization of the teaching process. According to Zhou et al. (2024), AI systems that integrate emotion recognition and natural language generation perform more closely to real teachers in teaching interactions. It can dynamically adjust the language style and emotional tone while maintaining the advancement of the learning task. Such a system can improve learners' emotional engagement and learning perseverance.

6. Conclusion

AI-assisted emotion recognition and regulation are gradually being integrated into language teaching practices, becoming an important tool for promoting the optimization of classroom interaction and personalized learning support. This article emphasizes the significant influence of emotional factors in language learning and reviews its mechanism. Secondly, the article briefly reviews AI emotion recognition and regulation from the aspects of theory and technological evolution, and explains its application in teaching scenarios and cross-cultural challenges. Existing studies have shown that AI emotion recognition and regulation technology has demonstrated its operational value at the teaching level, whether in enhancing learning motivation or alleviating negative emotions. In addition, the article also presents the existing research hotspots and trends through Vosviewer. Finally, the AI emotional systems applied in teaching scenarios should focus more on the construction of educational equity, cultural adaptability and supporting mechanisms for teacher training. By integrating affective science, educational technology, and teaching practice, the development of the intelligent language teaching system can foster a more human-centered language learning experience.

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