AI-Driven Conversational Agents in Education: A Survey on Emotional and Cognitive Interventions

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Abstract

This survey paper examines the integration of AI-driven conversational agents and educational technologies aimed at addressing emotional and cognitive challenges in educational settings. The paper explores the role of artificial intelligence in supporting mental health, enhancing emotional regulation, and improving learning experiences. It provides a comprehensive overview of core concepts, including emotional challenges, cognitive regulation, and AI-driven interventions. The survey analyzes the application of conversational agents, the use of deep learning for emotion prediction, and the influence of social media, while also discussing ethical considerations. It highlights AI's role in mental health support, focusing on AI-driven empathy, emotional recognition, and cognitive modeling. The paper identifies challenges such as bias, ethical implications, and data privacy, while emphasizing opportunities for personalized and adaptive learning. Future research directions include refining AI systems for better emotional understanding, exploring GenAI-integrated teaching methods, and developing robust regulatory frameworks. These efforts aim to enhance educational practices and support student well-being through advanced AI technologies.

1 Introduction

1.1 Structure of the Survey

This survey comprehensively explores AI-driven conversational agents in educational contexts, particularly their role in alleviating emotional and cognitive challenges. It begins by emphasizing the importance of integrating artificial intelligence in education to support mental health and enhance emotional regulation. The subsequent sections define key concepts, including emotional challenges, cognition, regulation, intervention, conversational agents, educational technology, and artificial intelligence, establishing a foundational understanding of their relevance in educational settings.

The third section investigates emotional challenges and cognitive regulation in education, detailing their impact on learning outcomes and discussing intervention strategies. It also considers the social and cultural factors that influence these challenges. Following this, the survey reviews AI-driven interventions aimed at providing emotional and cognitive support, highlighting existing frameworks, technological advancements, and the incorporation of emotional processes in AI interventions.

In the fifth section, the focus shifts to the role of conversational agents and educational technology in delivering these AI-driven interventions. It examines the integration of conversational agents with educational technologies, the application of deep learning for emotion prediction, and the effects of social media. Ethical considerations surrounding the use of these technologies for emotional regulation are also addressed.

The sixth section explores the application of artificial intelligence for mental health support in education, examining AI-driven empathy, emotional recognition, and the modeling of cognitive and emotional states, while also highlighting ethical and practical challenges. The survey concludes with

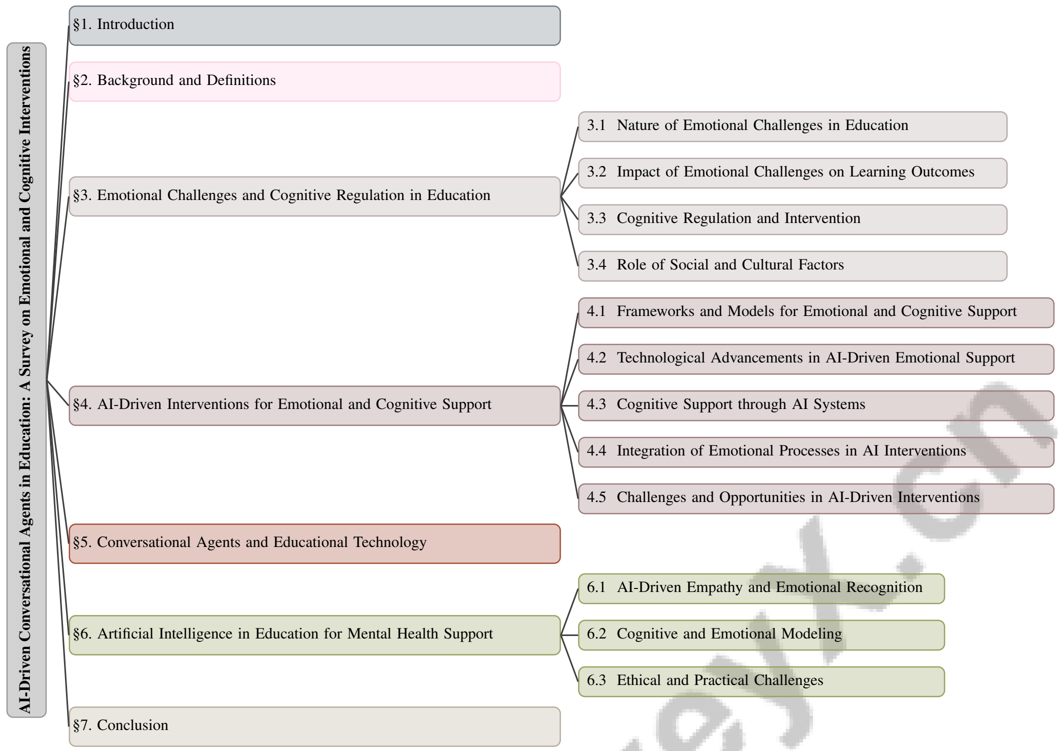


Figure 1: chapter structure

a synthesis of key findings, discussing the implications of integrating AI-driven conversational agents in education and outlining future research directions, along with their potential impact on educational practices and student well-being.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Artificial Intelligence in Education

Artificial Intelligence (AI) is transforming education by addressing students' cognitive and emotional challenges through personalized learning. Advanced large language models (LLMs), such as GPT-4, are approaching artificial general intelligence (AGI) capabilities, serving as effective thought partners that enhance human cognition through collaboration [1, 2]. The concept of 'machine psychology' highlights the importance of understanding AI behavior through its inputs and outputs, crucial for developing systems that meet human cognitive and emotional needs, thereby supporting student learning and emotional well-being [3].

AI's integration into computing education, particularly through Generative Artificial Intelligence (GenAI), necessitates a balanced approach to foster critical thinking and independent problem-solving among students [4]. The development of empathetic AI systems requires moving beyond mere emotion detection to understanding cognitive processes, enabling empathetic responses aligned with students' emotional states and learning contexts [5]. Designing AI systems capable of processing information at multiple abstraction levels involves integrating symbolic and subsymbolic information, essential for adaptive educational tools [6]. Furthermore, cognitive psychology insights can enhance AI's exploratory capabilities, fostering meaningful student engagement [7].

2.2 Significance of Empathetic AI in Education

Empathetic AI is pivotal in educational settings for fostering emotional engagement, critical for effective learning. By incorporating empathy, AI can facilitate meaningful interactions, creating environments responsive to students' emotional and cognitive needs. The Commonsense-aware

Empathetic Chatting Machine (CEM) exemplifies this by integrating commonsense knowledge to improve understanding of users' emotions and contexts [5].

Developing empathetic AI involves recognizing intrinsic motivation to generate socially engaging behaviors, adapting to the social and emotional dynamics of educational contexts [8]. However, ethical concerns arise when AI systems attempt to regulate emotions without genuine understanding, risking oversimplification of complex human experiences. While AI can produce empathetic responses, its lack of true comprehension raises societal concerns [9, 10, 11, 12, 13]. Thus, designing AI with a nuanced understanding of emotions is crucial to avoid adverse outcomes.

Incorporating empathy into AI requires understanding human cognitive and emotional processes alongside technological advancements. This integration leverages peer acknowledgment, learning engagement classification, empathetic response generation, and domain knowledge measurement to create personalized, emotionally responsive learning experiences. Enhancing online learning communities through peer interactions, utilizing LLMs for educational text classification, and implementing emotional support strategies can significantly boost student engagement, emotional well-being, and academic success [14, 10, 15, 16].

3 Emotional Challenges and Cognitive Regulation in Education

The intricate relationship between emotional challenges and cognitive regulation is crucial for cultivating effective educational environments. Emotional challenges, influenced by a myriad of internal and external factors, significantly impact students' cognitive functions and academic performance. This section delves into these challenges, their manifestation in educational contexts, and their implications for cognitive regulation, highlighting the need for targeted interventions and support mechanisms.

As illustrated in Figure 2, the figure outlines the hierarchical structure of emotional challenges and cognitive regulation in educational settings. It highlights the nature and impact of emotional challenges, cognitive regulation and intervention strategies, as well as the role of social and cultural factors. This visual representation serves to underscore the complexity of these interactions, reinforcing the argument for comprehensive support systems that address both emotional and cognitive dimensions in education.

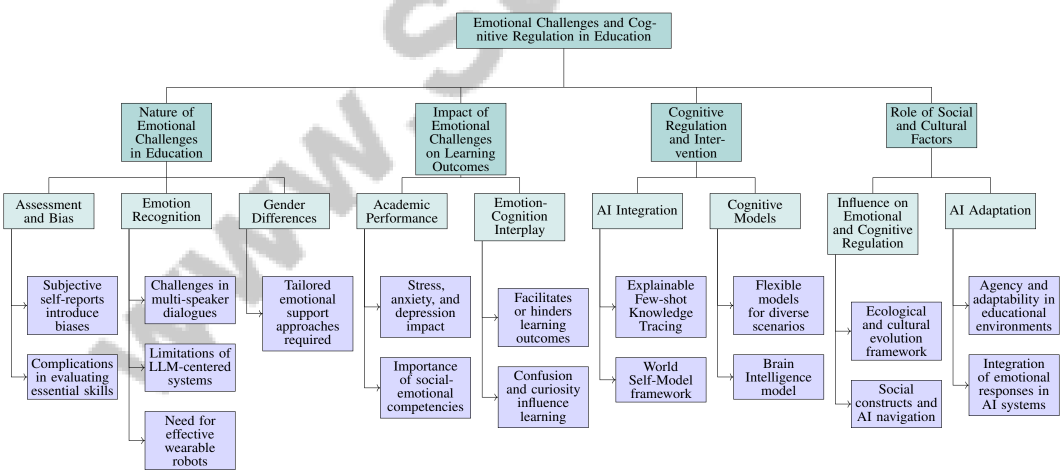


Figure 2: This figure outlines the hierarchical structure of emotional challenges and cognitive regulation in educational settings, highlighting the nature and impact of emotional challenges, cognitive regulation and intervention strategies, and the role of social and cultural factors.

3.1 Nature of Emotional Challenges in Education

Educational settings are fraught with emotional challenges arising from the interplay between cognitive processes and emotional states. Current assessment methods for social-emotional competence often rely on subjective self-reports, introducing biases that complicate the evaluation of essential skills for learning and teaching [17]. The role of emotion in human intelligence offers insights for designing robotic systems that mimic human behavior, yet conversational AI's limitations in accurately identifying human emotions pose significant challenges [18, 13].

The complexity of emotion recognition in multi-speaker dialogues necessitates sophisticated modeling of conversational context and emotional dynamics [19]. Current LLM-centered systems struggle with abstract reasoning and generalization, further complicating emotional understanding [20]. Learner-generated discussions reveal that emotions such as confusion and curiosity, alongside cognitive states like opinion, significantly influence learning processes [15]. The absence of effective wearable robots for emotional recognition limits personalized support [21]. Additionally, gender differences in emotional expression require tailored emotional support approaches [22]. Understanding LLMs' behavioral patterns is pivotal for their integration into educational contexts to support emotional and cognitive development [3].

3.2 Impact of Emotional Challenges on Learning Outcomes

Emotional challenges significantly affect academic performance, manifesting as stress, anxiety, and depression, which impede concentration, information processing, and knowledge retention. Integrating social-emotional competencies into teaching can enhance teacher-student relationships, improving emotional regulation and cognitive engagement [17, 23, 9, 14]. The emotion-cognition interplay is critical, as emotional states can either facilitate or hinder learning outcomes.

To illustrate this complex relationship, Figure 3 presents a figure that depicts the hierarchical structure of emotional challenges in education, emphasizing their impact on learning outcomes, assessment challenges, and potential technological solutions. This visual representation underscores the multifaceted nature of emotional challenges and their implications for educational practices.

Challenges in assessing social-emotional competence stem from biases in self-reported data [17]. Current AI systems' limitations in abstract reasoning and generalization hinder their ability to understand emotional dynamics in educational settings [20]. Designing systems that emulate human behavior and respond to emotional cues is crucial [18], yet the inability of conversational AI to understand emotions complicates emotional regulation efforts [13]. Emotion recognition in multi-speaker conversations requires advanced modeling to capture emotional interactions' nuances and their learning impact [19]. Emotions like confusion and curiosity shape cognitive states and academic performance [15]. The absence of effective wearable robots for emotional recognition limits personalized support [21], and gender differences in emotional expression necessitate tailored emotional regulation approaches [22].

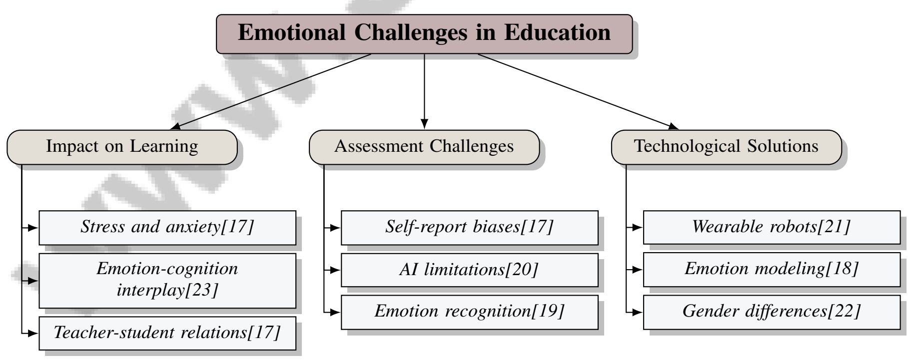


Figure 3: This figure illustrates the hierarchical structure of emotional challenges in education, emphasizing the impact on learning outcomes, assessment challenges, and technological solutions.

3.3 Cognitive Regulation and Intervention

Cognitive regulation is essential for optimizing cognitive processes and enhancing learning outcomes. The synergy between human cognitive flexibility and AI's data processing capabilities can significantly enhance educational outcomes [24]. AI-driven interventions can support cognitive regulation through adaptive, personalized learning experiences.

Li's Explainable Few-shot Knowledge Tracing method exemplifies AI integration by tracking student knowledge and predicting performance with minimal data, offering insights into cognitive states and facilitating targeted interventions [25]. Yue's World Self-Model framework enhances AI systems' ability to model learning processes and support cognitive regulation through adaptive responses [26]. The ERUDITE method monitors EEG data in real-time to adapt learning environments, maintaining cognitive engagement [27].

Fulbright's metrics of cognitive accuracy and precision evaluate the enhancement of human cognition through AI collaboration [28]. Signorelli stresses the importance of flexible cognitive models that adapt to diverse educational scenarios, supporting individual learning paths and cognitive needs [29]. Lu's Brain Intelligence model enhances AI's capabilities, fostering creativity and problem-solving skills without extensive training data [30]. Latapie's neurosymbolic architecture promotes cognitive synergy by integrating symbolic and subsymbolic information [6].

3.4 Role of Social and Cultural Factors

Social and cultural factors significantly influence emotional challenges and cognitive regulation in educational settings. The ecological and cultural evolution framework highlights human intelligence's dependence on ecological niches and cultural contexts [31]. Addressing emotional and cognitive challenges requires considering social constructs and cultural dynamics.

Mathur discusses social constructs' complexities, including ambiguity and nuanced signals, which AI systems must navigate to support emotional and cognitive regulation effectively [32]. AI agents' agency and adaptability are crucial for successful integration into diverse educational environments. Ke explores LLMs' limitations in comprehending complex emotions and cognitive processes, complicating AI integration in education [9]. Ethical concerns and data privacy issues must be addressed to support students' emotional and cognitive development effectively.

Berry emphasizes self-awareness as foundational for developing a theory of mind in AI systems, essential for understanding and responding to diverse social and cultural contexts [33]. Riva highlights LLMs' lack of social and experiential background, which shapes human cognition and influences emotional challenges [34]. Assunção proposes integrating emotional responses into AI systems to enhance exploratory behavior, recognizing the absence of emotional variation as a key obstacle [7]. This integration is vital for developing AI systems that adapt to social and cultural nuances, supporting cognitive regulation and addressing emotional challenges.

4 AI-Driven Interventions for Emotional and Cognitive Support

4.1 Frameworks and Models for Emotional and Cognitive Support

Method Name	Technological Integration	Emotional Recognition	Framework Interpretability
E[27]	Wearable Eeg Devices	Emotional States	Understandable Insights
FB[21]	Brain Wearable Device	Interpret Emotions	Cognitive Algorithms
BI[30]	Artificial Life Technology	-	Understand Concepts Autonomously
CEM[5]	Comet	Emotion Detection	Commonsense Reasoning
APT[10]	Immersive Technologies, AI	Identify Emotional States	Understandable Insights, Cognitive

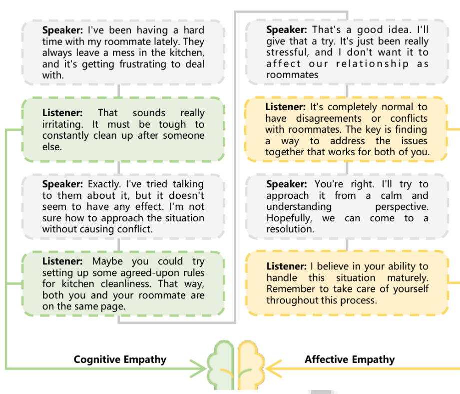
Table 1: Comparison of various AI frameworks and models for emotional and cognitive support, highlighting their technological integration, emotional recognition capabilities, and framework interpretability. This table provides a detailed overview of the methods employed in each framework, illustrating the diverse approaches to enhancing emotional and cognitive experiences in educational settings.

The development of AI frameworks for emotional and cognitive support is crucial for enhancing educational experiences. Yong's REPT system exemplifies this by integrating embodied perspective-taking with retrospective video recall in a VR environment, highlighting immersive technologies' potential to facilitate emotional understanding and cognitive engagement [10, 35, 36, 37]. Cheng's MERR dataset, combining audio, visual, and textual inputs with emotion-specific encoders, significantly advances emotional recognition capabilities, fostering students' emotional well-being and empathetic response generation [38, 39, 10, 13].

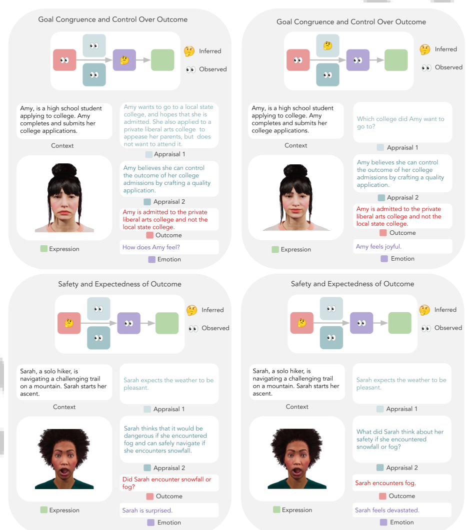
Aldrup et al.'s TRUST tool evaluates teachers' social-emotional competence, demonstrating the need for profession-specific measures to inform AI-driven support systems [17, 14, 16, 40]. Li's Explainable Few-shot Knowledge Tracing method enhances interpretability in student performance predictions, improving prediction accuracy and providing insights into student cognition and emotional states [38, 16, 41, 25, 15].

Hou's HLMA framework enables LLM-based agents to simulate human memory processes by recalling relevant memories for response generation, enhancing dialogue performance [42, 43, 34, 44, 45]. Taherisadr's ERUDITE framework integrates wearable EEG devices in an IoT system for real-time feedback, promoting adaptive learning environments [27]. Chen et al.'s Fitbot, a wearable affective robot, recognizes and responds to human emotions, showcasing wearable technologies' potential in educational settings [21].

Kelkar's Cognitive Homeostasis framework likens cognitive processes to physiological homeostasis, emphasizing regulation through structured subsystems and laying the groundwork for sophisticated AI agents [46, 47, 48, 49, 50]. Lu's Brain Intelligence model integrates memory and idea functions to foster creativity and problem-solving skills [30]. Latapie's neurosymbolic architecture merges symbolic and subsymbolic processing, essential for supporting complex cognitive tasks [6]. Sabour's CEM utilizes commonsense knowledge for empathetic responses, emphasizing empathy's importance in AI educational tools [5].



(a) Empathy in Communication: A Case Study of Cognitive and Affective Empathy[10]



(b) Goal Congruence and Control Over Outcome[51]

Figure 4: Examples of Frameworks and Models for Emotional and Cognitive Support

As illustrated in Figure 4, AI-driven interventions for emotional and cognitive support are exemplified through case studies on empathy in communication and goal congruence's influence on emotional and cognitive responses [10, 51]. Additionally, Table 1 presents a comparative analysis of different AI frameworks and models designed for emotional and cognitive support, emphasizing their integration of technology, ability to recognize emotions, and interpretability of the frameworks.

4.2 Technological Advancements in AI-Driven Emotional Support

Recent AI advancements have significantly enhanced emotional support in educational contexts. The MELD dataset, integrating audio, visual, and textual inputs from multi-party conversations, exemplifies the multimodal approach crucial for advancing emotion recognition [19]. This comprehensive understanding enables personalized support.

The Emotion-based Behavior model employs deep learning techniques like CNN, LSTM, and BERT, marking a breakthrough in emotion prediction [52]. Transformer language models such as RoBERTa-Large and DistilBERT have improved semantic fluency modeling, enhancing emotion recognition systems [53].

Bojić's work on evaluating pragmatic competence showcases LLMs' potential in generating contextually appropriate emotional responses, crucial for meaningful student engagement [54]. The Aff-Wild dataset, comprising extensive facial affect data, has been pivotal in training AI models to recognize complex emotional expressions [55]. Recent research has also enhanced LLMs' ability to understand and generate emotionally rich content, fostering supportive learning environments [56].

4.3 Cognitive Support through AI Systems

AI systems provide essential cognitive support, enhancing learning experiences through personalized educational interventions. By leveraging insights from Open Learner Modelling (OLM), these systems ensure interpretable decision-making processes, promoting a deeper understanding of learning [38, 49, 24].

The interplay between AI and human cognitive flexibility is critical for improving educational outcomes. AI-driven interventions support cognitive regulation through personalized learning experiences, as emphasized by Çukurova [24]. Li's Explainable Few-shot Knowledge Tracing method exemplifies AI's role in cognitive support by tracking student knowledge and predicting performance, enhancing personalized educational support [25].

As illustrated in Figure 5, the categorization of AI systems in cognitive support highlights three main areas: AI-driven interventions, real-time feedback, and enhanced AI capabilities. Each area encompasses specific methods and models that contribute to cognitive support in educational contexts. Yue's World Self-Model (WSM) connects perception and cognition, enabling effective modeling of student learning processes [26]. Taherisadr's ERUDITE method, integrating wearable EEG devices, offers real-time feedback on cognitive states, optimizing learning experiences [27]. Fulbright's metrics of cognitive accuracy and precision facilitate the evaluation of cognitive interventions, ensuring effective support for student learning [28].

Lu's Brain Intelligence model enhances AI capabilities, fostering creativity and problem-solving skills [30]. Latapie's neurosymbolic architecture integrates symbolic and subsymbolic processing, essential for supporting complex cognitive tasks [6].

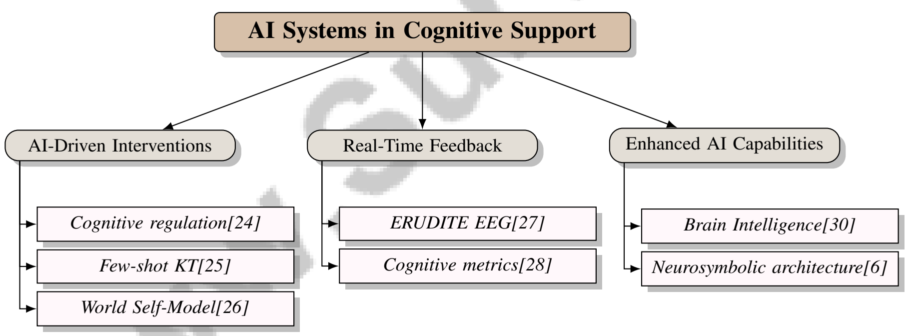


Figure 5: This figure illustrates the categorization of AI systems in cognitive support, highlighting three main areas: AI-driven interventions, real-time feedback, and enhanced AI capabilities. Each area encompasses specific methods and models that contribute to cognitive support in educational contexts.

4.4 Integration of Emotional Processes in AI Interventions

Method Name	Emotional Integration	Cognitive-Emotional Interaction	Behavioral Adaptation
EBBM[52]	Emotion Prediction	Emotion Classification Appraisal	Behavior Generation
CAB[57]	Emotional Dependencies	Cognitive Paths	Behavioral Dialogue Acts
GEE[58]	Empathy IN Communication	Simulate Emotional Context	Modify Rsa Framework
SRTA[59]	Facial Recognition	Simultaneous Processing	Modify Their Behavior

Table 2: Comparison of Various AI Methods for Emotional Process Integration, Detailing Their Approaches to Emotional Integration, Cognitive-Emotional Interaction, and Behavioral Adaptation.

Integrating emotional processes into AI interventions involves synthesizing emotion classification, appraisal, and behavior generation modules. Raza's emotion-oriented behavior model demonstrates AI's capability to generate contextually appropriate responses through emotional reasoning [52].

Hoey's BayesAct posits that effective social interaction in AI can be achieved by merging emotional reasoning with cognitive decision-making [60].

Gao's CAB model generates empathetic responses by incorporating cognitive paths, emotional dependencies, and behavioral dialogue acts, emphasizing the interplay between cognitive and emotional elements in AI interventions [57]. Huff's survey aligns LLMs with human cognitive processes, enhancing their ability to integrate emotional processes effectively [45].

Kennington's research on child language acquisition highlights the importance of social and emotional interactions in language learning, supporting the need for AI systems to incorporate emotional elements [61]. Kim's innovation in the Rational Speech Acts framework enhances response specificity and empathy by focusing on targeted input words [58].

Mishra's cognition-affect integrated model posits that emotions emerge from cognitive and affective interactions, providing a foundation for systematically integrating emotional processes into AI systems [62]. Jumelle's SRTA method leverages real-time emotional and cognitive data to inform decision-making [59]. Assunção discusses incorporating artificial emotions into deep learning methodologies, enhancing AI's ability to engage meaningfully with users [7]. Table 2 presents a comparative analysis of different AI methodologies that integrate emotional processes, highlighting their strategies for emotional integration, cognitive-emotional interaction, and behavioral adaptation.

4.5 Challenges and Opportunities in AI-Driven Interventions

AI-driven interventions in education offer both challenges and opportunities. A key challenge is the reproducibility and bias issues in current studies, which obscure the nuances of LLM behavior [3]. The lack of consensus on effective implementation strategies and the risks associated with misinformation generated by Generative AI (GenAI) further complicate the landscape [4].

Combinatorial complexity in object recognition necessitates advanced algorithms to manage vast data combinations [63]. Additionally, reliance on accurate real-time monitoring can be problematic in dynamic educational environments [64]. Attention capture by AI technologies poses long-term risks to individual autonomy and cognitive health, necessitating research to address these concerns [65].

Despite these challenges, AI-driven interventions offer substantial opportunities for enhancing educational experiences. The integration of commonsense reasoning in conversational agents, as demonstrated by CEM, enriches interactions by increasing response diversity [5]. Moreover, developing intrinsically motivated robot behaviors can sustain human interest and foster positive social interactions [8].

Opportunities also exist in refining AI systems to improve planning capabilities and reduce biases, contributing to the creation of ethically sound and effective AI tools aligned with educational goals [1].

5 Conversational Agents and Educational Technology

5.1 Integration of Conversational Agents with Educational Technologies

The integration of conversational agents with educational technologies significantly enhances personalized and adaptive learning experiences. By utilizing natural language processing and real-time data analysis, these agents create interactive educational environments. Mahboub's approach exemplifies this integration, employing real-time analysis and adaptive resource allocation to refine AI-driven interventions, allowing dynamic adjustments based on students' needs and emotional states [66]. These agents serve as intermediaries between students and educational content, offering personalized guidance and feedback. By analyzing interactions and emotional responses, they tailor experiences to individual learning styles, thus fostering a supportive learning environment. Their ability to adapt to cognitive and emotional needs through advanced memory recall and empathetic responses positions them as essential tools in contemporary education [10, 4, 67, 43].

Incorporating emotion modeling and appraisal mechanisms enhances conversational agents' understanding of students' emotional dynamics, fostering empathetic interactions. By employing a comprehensive emotional palette for empathetic response generation, supported by appraisal theory, agents analyze emotional triggers in dialogue. This capability allows them to address cognitive

AI-generated, for reference only.

and affective empathy, improving engagement quality and support [10, 56, 58]. This is vital for addressing students' diverse emotional and cognitive challenges, enhancing engagement and learning outcomes.

5.2 Deep Learning and Emotion Prediction in Conversational Agents

Deep learning enhances emotion prediction in conversational agents, improving their understanding of users' emotional states. Models like convolutional neural networks (CNNs) have been pivotal for emotion recognition, as demonstrated by experiments with the Aff-Wild dataset, which tested various deep learning models, including a baseline CNN-M architecture [55]. This dataset provides a robust foundation for training models to recognize nuanced emotional cues.

Integrating deep learning techniques enables conversational agents to predict emotions with greater accuracy and contextual relevance. Systems like Emotion-LLaMA can discern emotional cues from multimodal inputs, enhancing applications in human-computer interaction, education, and mental health support. The MERR dataset, with over 28,000 annotated samples, facilitates training models to generalize across diverse emotional scenarios, improving performance in real-world applications [39, 68, 56, 19, 36]. This capability is essential for creating interactive and empathetic conversational experiences, allowing agents to tailor responses to users' emotional and cognitive needs.

Recent models employing architectures like CNN and Long Short-Term Memory (LSTM) networks have shown significant improvements in recognizing emotions from speech, while multimodal datasets such as MELD facilitate understanding emotional nuances in conversations, leading to more effective human-agent interactions [19, 52, 69, 56]. Such adaptability enhances user engagement and satisfaction, allowing agents to respond empathetically and in alignment with users' emotional states.

5.3 Social Media and Conversational Agents in Education

Social media platforms are integral to education, offering new avenues for enhancing conversational agents' functionality. These platforms facilitate information dissemination and create interactive learning environments that improve educational outcomes. Technologies such as Large Language Models (LLMs) and Open Learner Modelling (OLM) provide valuable tools for automating educational text classification and understanding learners' cognitive and emotional states, enabling personalized learning experiences and interpretable AI frameworks [38, 15].

Conversational agents integrated with social media access real-time data on user interactions, preferences, and emotional states, allowing for personalized and contextually relevant educational support. This integration enables agents to adapt their responses based on current trends and user feedback, ensuring educational content remains engaging. By leveraging sentiment analysis and emotion detection techniques, conversational agents enhance their understanding of users' emotional states, enriching interactions and fostering supportive learning environments. Insights from social media interactions can inform educational technology design, promoting engagement and motivation through tailored communication strategies [39, 14, 10, 70, 15].

Social media's role in education extends beyond content delivery to collaborative learning and community building. Conversational agents, particularly those powered by advanced LLMs, effectively mediate social learning environments by facilitating discussions, providing real-time feedback, and encouraging active participation. Their natural language processing capabilities allow them to understand and respond to users' emotional and cognitive states, enhancing engagement and promoting collaborative learning experiences. This capability is crucial for creating inclusive educational experiences that cater to diverse learning needs and preferences [9, 15, 32].

5.4 Ethical Considerations and Emotional Regulation

The deployment of conversational agents for emotional regulation in education necessitates careful ethical considerations to ensure these technologies promote well-being without causing harm. Mathur emphasizes that integrating Social-AI systems must be approached cautiously, as these systems can influence students' emotional states and social interactions [32]. Ethical deployment involves ensuring transparency, privacy, and the prevention of manipulation or bias in emotional regulation processes.

The use of immersive technologies, such as the REPT system, underscores the importance of ethical considerations in emotional regulation. Yong highlights that while immersive experiences can enhance empathy, they must be designed to avoid causing emotional distress [37]. Striking a balance between meaningful emotional engagement and safeguarding students' emotional health is essential.

Moreover, ethical implications extend to the potential for dependency and its impact on students' autonomy. To support students in cultivating independent emotional regulation skills—rather than creating dependence on external assistance—integrating interpretable AI frameworks that enhance cognitive and affective empathy is crucial. Approaches like Open Learner Modelling can make AI representations of learners' emotions transparent, while emotional support strategies based on appraisal theory can foster nuanced empathetic responses. This promotes self-reliance in emotional management, ultimately leading to effective learning outcomes [38, 14, 10]. Designing systems that support emotional learning and resilience while respecting students' individual emotional journeys is essential.

6 Artificial Intelligence in Education for Mental Health Support

6.1 AI-Driven Empathy and Emotional Recognition

AI systems in education are increasingly equipped to recognize and respond empathetically to emotional states, leveraging advanced models to enhance interactions. Integrating cognitive architectures with large language models (LLMs) aids in developing AI that aligns with human values, crucial for effective emotional recognition [1]. The Aff-Wild benchmark is pivotal in evaluating facial affect analysis models in real-world settings, advancing emotion recognition capabilities [55]. Understanding the distinction between real and computer-generated facial expressions is essential for improving virtual avatars' emotional representation, thereby enhancing AI-driven empathy [22].

Incorporating psychological theories into LLM frameworks enhances emotion cognition methodologies, enriching AI systems' ability to recognize and respond empathetically to emotional states [56]. The CEM model exemplifies generating contextually relevant responses, increasing user satisfaction and engagement through the use of commonsense knowledge [5]. Intrinsically motivated behaviors in AI, as discussed by Scheunemann, are perceived as warmer than reactive ones, highlighting the importance of intrinsic motivation in human-AI interaction [8]. Assunção's findings on the causal link between emotional states and exploratory behavior in AI agents suggest that integrating emotional processes enhances adaptability in educational contexts [7].

6.2 Cognitive and Emotional Modeling

Modeling cognitive and emotional states in AI aims to emulate human-like understanding and responsiveness. Wolff's SP theory provides a foundational framework for natural language processing and reasoning, crucial for cognitive and emotional modeling [71]. This theory emphasizes pattern recognition and structured reasoning, facilitating nuanced human-AI interactions. Integrating cognitive functions with techniques like information compression and heuristic learning enhances AI's understanding of complex scenarios, paving the way for applications in psychology and medical diagnostics [9, 46, 49].

Mishra highlights the role of cognitive functions in emotional categorization through network analysis and neural decoding, crucial for improving AI's emotional responsiveness [62]. Hou's dynamic memory consolidation approach enhances AI's cognitive support by considering contextual relevance and recall frequency, aligning cognitive processes with human memory dynamics [43]. Zhu's Arithmetic-GPT model addresses domain-specific cognitive modeling for complex decision-making tasks, exemplifying the integration of symbolic and subsymbolic processes [72, 6].

Future research should focus on integrating emotional and cognitive processes, as suggested by Belkaid, to enhance AI systems' ability to emulate human-like behavior [18]. McGrath's discussion on multiple realizability encourages exploring diverse methodologies to improve AI's adaptability and robustness [73].

6.3 Ethical and Practical Challenges

Integrating AI for mental health support in education presents ethical and practical challenges. A key ethical concern is the oversimplification of emotional cognition, which may lead to reliance on labeled data and hinder generalization across diverse contexts [56]. The complexity and opacity of LLMs complicate understanding potential unforeseen harm as capabilities expand [3]. Societal implications, such as impacts on employment and misinformation, necessitate robust ethical frameworks for AI deployment in education [1].

Practical challenges include AI's limitations in capturing human emotions and cognitive processes. The reliance on large datasets raises privacy concerns, particularly for mental health support. Narrow topic coverage in cognitive knowledge graphs restricts AI's applicability in providing comprehensive support [56]. Enhancing interpretability tools is essential for building trust in AI systems used for mental health support. AI integration in education should empower students to develop independent emotional regulation skills, focusing on interpretable AI and redefining educators' roles to prioritize metacognitive skills [38, 24, 14, 41, 4]. This approach fosters a hybrid human-AI intelligence that enhances cognitive engagement and prepares students for an AI-ubiquitous world.

7 Conclusion

7.1 Future Directions and Research Needs

The evolving landscape of AI in education presents promising avenues for enhancing pedagogical methods and promoting student well-being through sophisticated technological solutions. Future research should focus on refining AI systems to enhance their understanding and processing of human emotions, thereby improving empathetic interactions and ensuring precise functionality. This aligns with the need to investigate the long-term efficacy of methods like REPT across various relational settings to enhance their practical application and effectiveness.

Key areas for exploration include evaluating GenAI-integrated pedagogical strategies, analyzing emerging trends in educational technology, and formulating best practices for integrating GenAI into computing education. Strengthening the synergy between cognitive architectures and large language models (LLMs) is vital for better mimicking human cognitive processes and addressing current system constraints.

Additionally, the examination of diverse semantic similarity measures and the validation of proposed methodologies across various educational contexts will enhance the adaptability of AI systems in heterogeneous learning environments. Future investigations should also emphasize longitudinal studies on LLM behavior, the application of machine psychology to multimodal models, and the development of rigorous experimental frameworks.

Improving the precision of learning state detection and evaluating the generalizability of methods like ERUDITE across diverse populations will bolster AI's role in personalized education. Ongoing exploration of data security, the resilience of emotion recognition algorithms, and the broadened application of wearable affective robots like Fitbot across varied user demographics are critical for advancing the field.

Establishing comprehensive regulatory frameworks for AI applications in children's environments and promoting interdisciplinary collaboration to address ethical concerns and developmental impacts are essential for the responsible and effective use of AI in educational settings. Furthermore, exploring diverse subject areas and integrating qualitative research methods will enrich our understanding of psychological factors in social annotation, yielding more nuanced educational insights.

Lastly, expanding the range of emotions studied and enhancing the accuracy of emotion transfer from real to computer-generated faces, potentially through machine learning advancements, will improve emotional representation in AI systems. Future research should also investigate the potential of the neurosymbolic framework for artificial intelligence and explore methods for integrating symbolic and subsymbolic processes more effectively.

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