Multidisciplinary Reviews

CONFERENCE PAPER

https://doi.org/10.31893/multirev.2025ss0104

Global Challenges, Local Solutions: Engineering, Science, and Technology in Developing Regions

Psychologically responsive AI smart classroom: Technological and educational challenges

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Abstract The growth of Artificial Intelligence (AI) knowledge in teaching has catalyzed the surfacing of Psychologically Responsive AI (PRAI) smart classroom surroundings, which are able to interpret students' emotional and cognitive states and react adaptively in real time. These settings represent a transformative shift from conventional academic training systems toward emotionally and cognitively aware knowledge ecosystem. This review seriously examines the technical structure, emotional computational methodologies, and pedagogical implications surrounding the growth and use of PRAI systems. Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines, this study systematically selected and analyzed 13 peer-reviewed articles published between 2015 and 2024. Key PRAI components identified include multimodal emotion detection through facial expression analysis, voice tone processing, and physiological signal tracking; cognitive-behavioral adaptation based on learner profiles; and dynamically tailored instructional strategy driven by AI algorithms. Technically, the review highlights the significance of layered system architectures that integrate sensors, deep learning (DL)-based emotion recognition models, and real-time feedback mechanism that close the loop among student behavior and adaptive content delivery. Challenges discussed include latency and processing limitations, algorithmic bias, data privacy, and the difficulty of maintaining high predictive accuracy across culturally and psychologically diverse learners. From an educational perspective, the review explores the nuanced interplay between automation and human empathy, the evolving role of educators as interpreters of AI-generated insights, and the risk of pedagogical overdependence on affective feedback systems. By synthesizing interdisciplinary perspectives from computer science, cognitive psychology, and educational research, this review offers a consolidated overview of current PRAI innovations, identifies research gaps, and proposes ethical, inclusive, and educator-centered design directions for future implementation.

Keywords: affective computing, emotion recognition, adaptive instruction, learning analytics, deep learning models, cognitive state monitoring

1. Introduction

Rapid improvements in AI have significantly influenced different sectors, with teaching being an important area of alteration (Dimitriadou & Lanitis, 2023). One of the most innovative applications of AI in the educational context is the appearance of "smart classrooms," digitally improved learning environments that adapt to students' requirements via intelligent systems. These classrooms have progressed from basic mechanization to becoming deeply receptive, with the addition of psychological responsiveness being the latest frontier. A psychologically adaptive AI smart classroom not only adapts to learning ability but is also psycho-dynamically responsive and conscious of the emotional, behavioral and psychological conditions of students in that it is able to provide adjusted and personalized educational knowledge (Timms, 2016). This transformative idea stems from the connection among affective computing, machine learning (ML), the psychological model, and educational pedagogy. These intelligent environments can detect affective cues via different methods, including speech patterns and facial gestures, body language, biometric sensors, and even electroencephalography (EEG) signals (Li et al., 2023). If a student exhibits signs of disturbance or confusion while solving a math problem, the system can interfere by simplifying the account or by providing visual aid. Likewise, signs of disconnection can trigger changes in the pace or style of instruction to regain attention (Chen, 2022). This intervention aims to imitate the intuitive consideration and adaptability that efficient human teachers possess but with scalable precision and consistency. Despite its capability, designing and deploying psychologically responsive AI in classrooms poses a multitude of challenges (Velastegui et al., 2023). Technically, it requires a strong multimodal sensing system, running-time processing, secure data consolidating procedures, and complex AI models that can suggest fine-grained interpretations of emotions and behavior. This model must be trained on diverse datasets that represent students from various cultural, linguistic, and socioeconomic backgrounds to avoid bias and misinterpretation. The integration of insights from social and human sciences is essential to ensure ethical alignment, contextual sensitivity, and a comprehensive understanding of human behavior within educational environments. When incorporated into the real-time frame of educational decision-making, natural language processing (NLP), processor vision, and support learning algorithms are not only computationally challenging but also ethically sensitive (Shaik et al., 2022). From an instructional perspective, certain AI complements human intelligence rather than replaces it in the fundamentals of education. Moreover, these technologies should not marginalize teachers but should allow them to be interpreters and facilitators of insights obtained via AI (Murtaza et al., 2022). This requires a significant amount of reskilling and redesign of teacher education. Moreover, the educational paradigm needs to evolve to adopt a more dynamic and student-oriented approach in which psychological inconsistency is accepted as a key characteristic in the knowledge process. As these papers examine, the technical and educational challenge is a major area of focus in the fulfillment of this vision, which provides future guidance for the research and implementation approach.

2. Methods

The method involves incorporating multimodal AI systems such as voice and gesture analysis, emotion recognition, and behavioral tracking into a classroom setting to monitor students' mental health continuously. To assess emotional and cognitive cues, these systems use ML algorithms that have been trained on datasets. Both locally and through secure cloud platforms, data processing ensures privacy compliance. After that, instructors receive insights via user-friendly dashboards for adaptive teaching interventions.

2.1. Review framework: PRISMA guidelines

The PRISMA criterion was followed in this review to ensure the repeatability and transparency of the assortment and synthesis of the relevant material. Through the organization of the study identification, screening, eligibility assessment, and addition phases, PRISMA offers a systematic review methodology. The exposure for each phase, with database searches, inclusion criteria, and exclusion justification, was organized utilizing the 2020 PRISMA checklist. The studies guarantee a thorough technique, reducing bias and preserving rigor in the collection of confirmation by implementing PRISMA. The appendix includes elements that graphically depict the quantity of records found, screened, evaluated for eligibility, and added to the final review. Figure 1 presents the PRISMA flowchart. This methodological uniformity is crucial when examining new, interdisciplinary disciplines such as psychologically responsive AI in education, where the literature comes from an assortment of fields, including behavioral psychology, cognitive science, ML, and education knowledge.

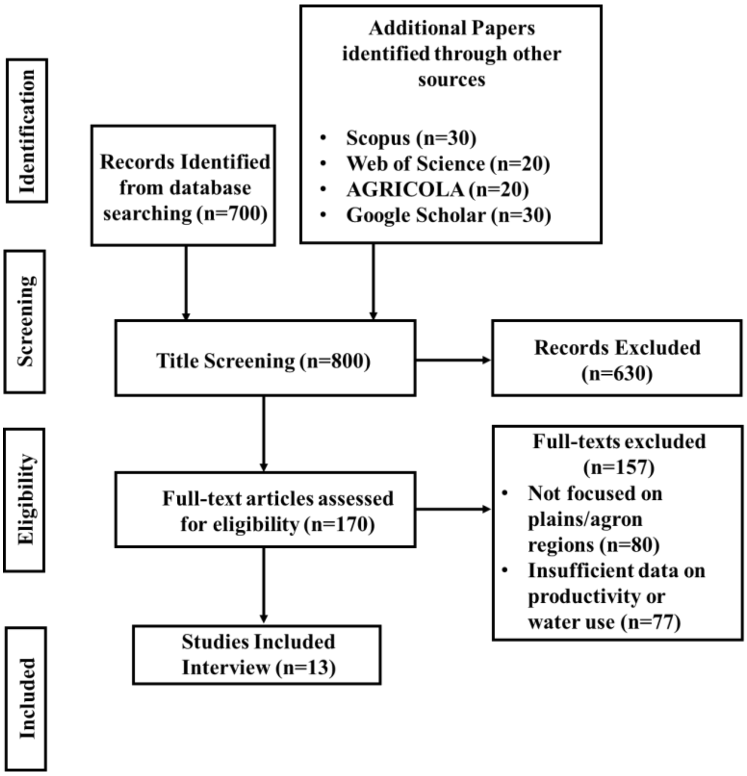

Figure 1 PRISMA architecture of the emotional model.

2.2. Search strategy and databases

To find peer-reviewed research on AI applications in psychologically receptive smart classrooms available between 2015 and 2024, a thorough search method was created, and four main academic databases were searched. Keywords such as "AI in education", "emotion-aware learning", "psychologically responsive", "affective computing", "smart classrooms", and "student behavior analytics" were among the search terms used. To increase its search scope, truncations and Boolean operators (AND, OR) were employed. For the sake of maintaining peer-reviewed rigor, Conference proceedings and dissertations were examples of gray literature omitted. After duplicate records were manually eliminated, the remaining articles were loaded into reference management software. The title and abstract of each record were assessed first, and then the complete content was screened. The objective was to guarantee that the chosen articles directly addressed the technological and psychological aspects of learning environments powered by AI.

2.3. Inclusion and exclusion criteria

Studies were accepted if they satisfied the following requirements: (1) English-language publications from 2015--2024; (2) peer-reviewed journal articles or conference proceedings; (3) AI-powered systems that react to the behavioral, emotional, or psychological states of students; and (4) theoretical modeling or application in educational settings. Articles that did not feature psychological modeling or exclusively mentioned traditional e-learning/learning management systems (LMSs) were not considered, nor were studies that lacked direct connections to classrooms or learning environments, articles that failed to provide valuable analytical insights or those lacking empirical evidence and theoretical underpinnings. The process of inclusion consisted of two stages of screening, first, the abstract and title, and second, the full-text analysis. A third reviewer was consulted whenever there was an inconsistency. This two-screening process complied with the PRISMA standards, helped reduce subjectivity and preserved relevance. Finally, 13 studies were identified as acceptable and incorporated into the review after strict filtration and quality evaluation.

2.4. Data extraction and synthesis

A standardized form for extracting data was created for each of the 13 included studies. It included the following important details: author(s), year, country, target population (e.g., school, college), type of AI technology (e.g., emotion recognition, EEG, NLP), psychological factors addressed (e.g., stress, engagement, attention), outcomes measured, and key challenges noted. Real-time emotion recognition, adaptive content delivery, behavioral feedback mechanisms, and learner modeling frameworks. A thorough grasp of the research environment was made possible by this prepared synthesis, which also made it easier to significantly examine knowledge advancement and its educational consequences in psychologically responsive AI smart classrooms.

3. Agent and multifaceted-agent system

Affective computation, emotion identification, and cognitive-behavioral versions are combined in PRAI to create expressively intelligent systems that react to the mental states of their users. Rooted in insights from social and human sciences, these systems are particularly valuable in healthcare and education, where they personalize interactions by utilizing multimodal inputs and real-time feedback. These systems, which are valuable in healthcare and education, personalize associations by utilizing multimodal inputs and real-time feedback. By aligning AI performance with human emotion, PRAI enhances engagement, fosters mental wellness, and builds adaptive learning environments.

3.1. Definition and components of the PRAI

The PRAI is the process of designing and deploying AI systems that forcefully respond to the emotional and psychological positions of their users. PRAI employs the elements of emotional computation, cognitive psychology and neuroscience to create emotionally intelligent, context-aware robots, as opposed to conventional AI, which moves solely on the basis of task-mastery or logic-driven output. The aim is to establish more useful, responsive, and empathetic relationships. PRAI is inspired by emotional computing, cognitive psychology, neuroscience, and social and human sciences in general to design emotionally intelligent and context-aware systems. At the center of PRAI is the integration of cognition and emotion, where emotional knowledge becomes a coequal determinant of behavior and decisions as opposed to a last-minute indication (Pessoa, 2017).
An important element of PRAI is multimodal emotion detection, which interprets emotional information from several channels, including textual (verbal sentiment), audio (voice tone), and visual (facial expressions) information, via DL models and data fusion methods. These factors improve the system's ability to identify difficult emotional states and promote deep relations (Harley et al., 2017). Moreover, PRAI systems are feedback driven and flexible, meaning that they can modify their performance in response to emotional feedback loops. For example, the system can initiate difficult performance, such as in presenting music or providing comforting conversation, when young people exhibit negative feelings such as dread or anxiety to improve emotional outcomes (Leite et al., 2016). In regard to the collection and processing of sensitive emotional data, privacy, consent,

and algorithmic fairness must all be cautiously calculated to avoid abuse or bias, mostly in susceptible groups such as patients or children. Table 1 lists the study objectives, limitations and directions for future work.

Table 1 Objective, limitations, and implications of PRAI systems with supporting citations.

Objective	Limitation	Citation	Implication/Need for Future Work
Build emotionally intelligent and context-sensitive AI systems	Emotional intelligence in AI is in early developmental stages; interpreting complex emotions remains challenging	Pessoa (2017)	Develop richer emotional databases and improve affective model generalization across populations
Integrate emotion and cognition for improved decision-making and learning	Difficulty in modeling dynamic interactions between cognition and emotion computationally	Pessoa (2017)	Advance computational cognitive-emotional models that are both biologically plausible and efficient
Enable multimodal emotion detection (text, voice, facial expressions)	Requires high computational power and advanced data fusion methods; multimodal data synchronization is complex	Harley et al. (2017)	Enhance personalization through adaptive algorithms that account for emotional variability and learner context
Foster empathetic and personalized interactions	Risk of overfitting AI behavior to emotional cues, leading to inappropriate or awkward interactions	Leite et al. (2016)	Introduce human-in-the-loop systems for adaptive tuning and continuous behavioral calibration
Support emotional well-being, especially for children or sensitive users	May inadvertently reinforce emotional states without human oversight if AI misinterprets cues	Leite et al. (2016)	Design safeguards and fallback mechanisms to ensure ethical AI responses

3.2. Role of affective computing and emotion recognition

The ability of robots to observe, recognize, and react to individual emotions is made possible by emotional computation, which encourages psychologically adaptive systems. In expressively sensitive settings such as education, therapy, and healthcare, this ability is extremely significant. Through the incorporation of emotion detection technology, equipment is able to grasp user feelings in real time by interpreting body language, speech tones, facial expressions, and physiological signs (Calvo & D'Mello, 2016). Humanizing AI so that it can interpret data and relate to people is the main goal of emotional computation. Emotional recognition systems achieve high categorization accuracy in a variety of scenarios by analyzing multimodal inputs for moving cues via DL models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Zhao et al., 2020). The emotion-aware system adjusts the way content is delivered in classrooms according to student moving states, increasing motivation and engagement. The integration of social and human sciences further deepens this understanding, ensuring that the development and deployment of such systems remain ethically grounded, culturally sensitive, and aligned with the complexities of human behavior and societal values. The detection of stress or despair signs in speech and behavior can help in the early analysis of mental health issues in the medical field. Affective computing ultimately lays the groundwork for more receptive and realistic human-AI communication by bridging the gap between emotional intelligence and cognitive computation.

4. Technological frameworks and architectures

Complex technology ecosystems that combine feedback systems, emotion-aware AI models, data processing pipelines, and sensing modalities into a single structural design are the foundation of PRAI smart classrooms. Three layers make up the architecture's foundation: the sensor layer, the cognitive deduction layer, and the adaptive response layer (Picard et al., 2016). Facial expressions, vocal tones, gaze direction, posture, and physiological signals are among the multimodal data that are gathered by the sense layer's network of strategy, which integrates tools from social and human sciences along with RGB and thermal cameras, microphones, EEG headsets, and heart rate sensors. These untreated inputs are sent to the layer of cognitive inference, where emotional computing algorithms use DL techniques such as CNNs and RNNs to process the data and recognize emotional and cognitive states in real time (Bosch et al., 2016).

The adaptive response layer personalizes the learning surroundings by adjusting content delivery, robot behavior, and visual feedback and affects the support strategy on the basis of detected states. The system often incorporates affective loop mechanisms, where the AI system iteratively evaluates the learner's emotions and adapts responses, fostering emotional instruction and learning retention (Zhou et al., 2019). High-volume analytics and latency-sensitive processing must be balanced, and edge cloud architectures are crucial for this. Long-term model training and storage scalability are supported by cloud communications, whereas edge devices guarantee rapid, local dispensation for instant feedback (Chen et al., 2020).

Furthermore, learning dashboards, robotic agents, data analytics engines, and AI tutors can work together seamlessly because of additional structures, such as ROS (robot operating system) and IoT middleware platforms. Cross-platform compatibility is ensured by standards such as xAPI (Experience API) and LTI (Learning Tools Interoperability) (Sampson et al., 2018). Table 2 demonstrates that architectures must assure data privacy, security, and moral use of emotional data, particularly in education, as PRAI systems become more complex. The framework aims to create an emotionally intelligent learning environment that is morally aligned, scalable, and flexible.

Table 2 Technological frameworks and architectures underpinning PRAI smart classrooms.

Component	Description	Technologies/Tools	Citation
Sensor Layer	Captures multimodal physiological and behavioral data.	RGB/Thermal Cameras, Microphones, EEG headsets, Heart rate sensors	Picard et al.(2016)
Cognitive Deduction Layer	Processes raw inputs to detect emotional/cognitive states using DL algorithms.	CNNs, RNNs, Emotion recognition algorithms	Bosch et al. (2016)
Adaptive Response Layer	Dynamically adapts content and behavior based on user's emotional state; implements affective loop mechanisms.	AI-driven feedback systems, Content delivery engines, Visual/robotic interfaces	Zhou et al. (2019)
Edge-Cloud Computing	Ensures balance between fast response (edge) and scalable storage/model training (cloud).	Edge Devices, Cloud Servers	Chen et al.(2020)
Integration Frameworks	Ensures seamless operation of AI tutors, analytics engines, robots, and dashboards.	ROS (Robot Operating System), IoT Middleware	Sampson et al.(2018)
Interoperability Standards	Supports compatibility across platforms and systems in educational environments.	xAPI (Experience API), LTI (Learning Tools Interoperability)	Sampson et al. (2018)

5. Educational Applications and Use Cases

Traditional educational techniques have been revolutionized by the integration of initial technology into education, creating more dynamic, individualized, and effective learning settings. AI, virtual reality (VR), augmented reality (AR), and learning analytics have increasingly been used in classrooms, learning management systems (regardless of whether they are studying online or in person), and online learning environments. One of the most important use cases involves the utilization of AI-powered adaptive learning platforms and the modification of the way content is delivered according to each student's performance and preferred technique of learning. In this transformation, the human and social sciences play a vital role in providing knowledge about how learners interact with technology, ensuring that educational innovations remain ethically grounded, socially inclusive, and aligned with diverse cognitive and emotional needs. This individualized strategy improves academic outcomes and student engagement (Zawacki-Richter et al., 2019). Additionally, VR and AR technologies have revolutionized experiential learning, mainly in the fields of science, engineering, and medicine. Students can practice surgery, examine architectural models, or perform chemistry experiments in VR environments without the hazard of the real world (Radianti et al., 2020). Simultaneously, learning analytics have been applied to monitor student performance and behavior in real time, enabling teachers to identify at-risk students at an early stage and provide them with focused attention (Ifenthaler & Yau, 2020).

6. Discussions

The application of wireless networks and AI in mathematics education has a narrow focus, which weakens its viability for most other academic areas or teaching practices. Although the use of digital technologies has potential in terms of personalized and adaptive learning, overall integration presupposes stable access to technical communications, which may still be a challenge in underresourced schools or areas with imperfect internet coverage (Chen, 2022).

For example, it is impossible to apply the assumption made by the study to all educational settings. As a result, the findings may not be generalizable to all educational settings, particularly those characterized by socioeconomic cultural and infrastructural inequalities that have been investigated within the psychological disciplines of social and human sciences. The other limitation is the scalability of the proposed model. The technique may be impractical where performance is required in large classrooms or where institutions have only minimum technology facilities since behavior analysis is performed in real time and requires embedded machines to work. Second, the research lacks adequate participation from critical perspectives of social and human sciences, especially concerning critical ethical issues, which include student privacy, data security and the psychological effects of always being monitored by others. Moreover, important ethical attention to the privacy of students, the safety of data, and the possible psychological effects of constant surveillance cannot be considered properly addressed in research, as these principles have become increasingly important in the era of digital spies in education (Li et al., 2023).

One of the limitations of the research conducted by Shaik et al. (2022) is the variability in the accuracy of natural language processing (NLP) models across different educational languages, contexts, and types of feedback. The review also highlights the challenges of domain-specific language, comprehending intricate student emotions, and ensuring model fairness, which are detrimental to the scalable, consistent integration of NLP into educational feedback systems.

The limitations of the research by Velastegui et al. (2023) include the small sample size, which can impose limitations on the generalizability of the findings to student populations at large. This research primarily involves the use of self-reported information, which may introduce bias in the evaluation of learning performance and psychological wellbeing. Moreover, longitudinal analysis is lacking; therefore, assessing the long-term interactive and psychological issues of the permanent application of AI to the education system is difficult.

One of the limitations of this research is the lack of empirical data regarding the use of AI in real smart classroom environments (Dimitriou & Lanitis, 2023). A major part of the discussion remains conceptual because there are no data available on large-scale implementations. The research also raises concerns about teacher preparation and training of educators to implement AI tools successfully into a wide range of instructional methods and about the challenges in assuring success in adapting new technology to existing education systems.

This paper shows that psychologically adaptive AI can change the role of education by allowing real-time versions of AI to affect the emotional and cognitive states of students. Through the incorporation of superior knowledge such as emotional computation, facial analysis and emotion recognition systems, smart classrooms are in a position to present more interesting, altered and student-centered learning experiences. Such AI-powered spaces are able to sense whether a student is stressed, bored or confused so that a teacher can slightly adjust the teaching manner and content. However, there are still few notable obstacles. The incorporation of insights from the social and human sciences is essential to ensure that, in the design and implementation of these technologies, human values are respected, social contexts, and individual differences. These fields contribute to managing important aspects of student identity, emotions, social learning space, and the ethical application of AI. These are the necessity of a correct, ethically trained AI model, strong doubts about the privacy and consent of students, and difficulty in transforming and fitting AI interventions to a wide variety of pedagogical frameworks and educational philosophies.

The inclusive and multidisciplinary approach of psychologically responsive AI (PRAI) implementation and design within the smart classroom circumvents key critical limitations that have been identified in other past research studies. The study proposal considers a broad diverse spectrum of scholarly disciplines and learning styles and makes its significance and flexibility more important than studies undertaken in the past that focused too strictly on a specific topic such as mathematics. The solutions focus on scalable low-cost technologies such as computing at the edge and custom modular system design that reduce reliance on a stable internet connection to solve infrastructure and connectivity challenges in underresourced locations. In addition to embedded device-limited models, the framework can be configured as a variable model and can be deployed in classrooms of different sizes with varying technological abilities. To discuss such weighty issues as student confidentiality, data security, mental health, and the psychological consequences of permanent surveillance areas that have been less explored in past studies, our study takes into account the knowledge of society and human sciences through the lens of sociocultural and ethical issues. This study addresses the injustices of emotion and natural language determination technologies and proactively promotes AI models that are multilingual and culturally mindful. In addition, to reduce the biases of self-reporting, our methodology recommends multimodal and long-term data collection. Our research with an in-depth analysis of the empirical data highlights practical teacher-friendly conclusions that can be applied in real classroom environments.

7. Conclusion

Psychologically responsive AI smart classrooms represent a significant and strategic increase in learning settings and make a unique contribution, adding a specialized education that caters to both students in stripe with their performance and affective indicators. These intelligent systems have the potential to enhance engagement, academic accomplishments, and feelings of well-being as they can provide, assisting knowledge experience understanding that is adaptive and student-centered. Nevertheless, their performance becomes associated with multiple challenges that should be handled. Some technological concerns should be considered, including algorithm bias, privacy issues, and system consistency. Ethical issues such as clarity in data usage and protection of the emotional safety of students are also supremely important. To have these systems socially responsible in addition to being technically competent and oriented toward human values, insights from the social and human sciences must be incorporated. Additionally, teachers need to be trained to incorporate AI tools effectively into their teaching practices. Studies of these innovations should be performed to ensure that they are properly designed and fairly deployed, and this should be accomplished through the collaboration of technologists, educators, and policymakers. Through the design of powerful ethical and operational models, mentally sensitive AI classrooms can advance favorable, efficient knowledge and observe the autonomy of the status and wellness of all students in heterogeneous learning environments.

Ethical Considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

Funding

This research did not receive any financial support.

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