SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

SYSTEMATIC REVIEW ON AI IN EMOTIONAL INTELLIGENCE AND PSYCHOLOGICAL EDUCATION

Dinesh Deckker[1], Subhashini Sumanasekara[2]
ORCID - 0009-0003-9968-5934 / ORCID - 0009-0007-3495-7774
[1]Wrexham University, United Kingdom
[2]University of Gloucestershire, United Kingdom
Article DOI: https://doi.org/10.36713/epra21351
DOI No: 10.36713/epra21351

ABSTRACT
Artificial Intelligence (AI) has emerged as a transformative force in emotional intelligence (EI) and psychological education, offering new pathways for emotion-aware learning, mental health support, and personalised interventions. This systematic review synthesises findings from 30 peer-reviewed studies published between 2015 and 2025 to evaluate the role of AI in assessing, enhancing, and supporting emotional and psychological competencies in educational settings. The review categorises AI applications into five thematic domains: emotion recognition technologies (e.g., EEG, facial analysis), adaptive learning systems, mental health chatbots, social-emotional learning (SEL) platforms, and ethical frameworks. Evidence indicates that AI tools can improve learners' emotional regulation, self-awareness, empathy, and psychological engagement. At the same time, critical challenges persist, including algorithmic bias, cross-cultural emotion misinterpretation, privacy concerns, and a lack of standardised evaluation metrics. The review further explores how these technologies align with and challenge existing theories such as Emotional Intelligence Theory, Affective Computing, Self-Regulated Learning, and Constructivism. A future research roadmap is proposed to guide interdisciplinary development, emphasising culturally inclusive design, longitudinal validation, hybrid human-AI emotional scaffolding, and ethical governance. This work contributes to a deeper understanding of AI's evolving role as a co-regulator of emotional learning and a catalyst for mental well-being in education.
KEYWORDS: *Artificial Intelligence (AI), Emotional Intelligence (EI), Psychological Education, Emotion Recognition, Adaptive Learning, Social-Emotional Learning (SEL), Mental Health Chatbots, Affective Computing, Ethical AI in Education, Emotion-Aware Systems, Educational Technology, Self-Regulated Learning, Constructivist Pedagogy, Algorithmic Bias, Cross-Cultural Emotion Analysis*

1. INTRODUCTION

In recent years, integrating Artificial Intelligence (AI) into educational systems has profoundly reshaped the landscape of psychological and emotional development, particularly through the lens of emotional intelligence (EI). The expansion of AI capabilities, including affective computing, machine learning, and intelligent tutoring systems, has enabled the real-time detection and adaptation to learners' emotional and psychological states, thereby transforming both instructional design and student engagement (Vistorte et al., 2024; Alanazi et al., 2023).

AI systems are increasingly embedded within educational platforms to support emotional awareness and psychological resilience. Emotional and psychological aspects of learning are known to affect motivation, engagement, self-regulation, and academic performance (Mega et al., 2014; Pekrun et al., 2017). However, conventional assessment methods such as teacher observations or student self-reports often suffer from subjectivity and scalability limitations. In contrast, AI-driven systems can analyse facial expressions, vocal tone, gaze direction, EEG signals, and written input to infer emotional states with growing precision (AlZu'bi et al., 2022; Aly et al., 2023; Chowdary et al., 2023). These technologies enable adaptive learning experiences, providing real-time feedback and tailored interventions that align with students' emotional needs (Taub et al., 2021; Daouas & Lejmi, 2018).

Within psychological education, AI is also deployed to advance social-emotional learning (SEL), simulate empathic interactions, and support mental health through conversational agents and virtual counselling tools (Mohr et al., 2017; García-Ceja et al., 2018). As educational environments increasingly adopt hybrid and digital formats, emotionally intelligent AI becomes especially valuable for diverse learner populations, including those with special educational or psychological needs (Standen et al., 2020). Nonetheless, these advances raise ethical, cultural, and methodological concerns, ranging from emotional authenticity and data privacy to algorithmic bias and cultural misinterpretation (Vistorte et al., 2024).

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

Despite the rapid evolution of AI-enhanced learning systems, there remains a lack of systematic synthesis addressing how these technologies shape emotional intelligence and psychological outcomes in educational settings. This review addresses this gap by critically evaluating AI's tools, impacts, and limitations in emotional and psychological education and examining how these innovations intersect with pedagogical theory and practice (Deckker & Sumanasekara, 2025a).

1.1 Objectives of the Review Paper

The primary objective of this systematic review is to critically synthesise the current state of research on integrating Artificial Intelligence (AI) in fostering emotional intelligence and psychological education across various learning environments. Given the rapid development of affective computing, intelligent tutoring systems, and emotion recognition technologies, this review seeks to identify the extent to which AI contributes to students' emotional development, academic performance, mental well-being, and adaptive learning outcomes.

Specifically, this review aims to

1. **Map existing AI technologies** (e.g., facial emotion recognition, EEG-based classifiers, natural language processing) currently used to detect, analyse, or simulate emotional and psychological states in educational contexts.
2. **Evaluate the impact** of AI-based interventions on emotional intelligence skills such as empathy, emotional regulation, motivation, and self-awareness among learners.
3. **Assess how AI enhances psychological education**, including mental health support, social-emotional learning (SEL), and self-regulated learning strategies.
4. **Examine methodological trends and gaps** in the current literature, including machine learning models, multimodal data sources, and validation techniques for emotional assessment.
5. **Identify ethical, cultural, and practical challenges** of implementing AI-driven emotional assessments in diverse educational settings.
6. **Propose future research directions** to advance the responsible and practical application of emotionally intelligent AI in formal and informal educational environments.

By addressing these objectives, this review seeks to provide educators, researchers, and AI developers with a consolidated evidence base to guide the design and deployment of emotionally adaptive AI systems that support psychological and academic growth.

1.2 Research Questions

RQ1. *How are artificial intelligence (AI) technologies currently applied to enhance emotional intelligence (EI) in psychological education across diverse learner populations?*

RQ2. *What are the observed impacts of AI-enabled tools (e.g., chatbots, EEG wearables, LLMS) on learners' emotional regulation, self-awareness, and engagement in mental health or SEL (social-emotional learning) contexts?*

RQ3. *What ethical, cultural, and algorithmic challenges are associated with the use of AI in detecting, responding to, or mediating human emotions in educational settings?*

RQ4. *To what extent do AI-driven emotional intelligence tools reflect or challenge established psychological, educational, and human-computer interaction theories?*

RQ5. *What standardised frameworks or theoretical innovations are emerging to guide AI's ethical design, implementation, and evaluation in psychological and emotional education?*

2. METHODOLOGY

2.1 Review Framework

This review follows the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure methodological transparency and reproducibility (Page et al., 2021). A systematic search, screening, and synthesis strategy was adopted to analyse studies (2015–2025) on AI applications in emotional intelligence (EI) and psychological education.

2.2 Databases and Search Strategy

The literature search was conducted across peer-reviewed academic databases:

- **IEEE Xplore**
- **PubMed**
- **Scopus**
- **Google Scholar**
- **ACM Digital Library**

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

- **PsycINFO**

Search queries combined Boolean operators and keywords such as:

- "artificial intelligence" AND "emotional intelligence" AND education
- "emotion recognition" AND AI AND "psychological assessment"
- "affective computing" AND "mental health support"
- "chatbot" AND "empathy training"
- "wearable" OR "EEG" AND "emotion detection"

The final search was completed in **April 2025**, and the publication window was restricted from **January 2015 to March 2025**.

2.3 Inclusion and Exclusion Criteria

Criteria	Included	Excluded
Publication Years	2015–2025	Pre-2015 (Unless foundational)
Study Type	Peer-reviewed empirical studies, systematic reviews	Opinion pieces, preprints, non-peer-reviewed articles
Focus	AI applied in EI or psychological education	AI in unrelated educational fields
Population	Students (K–12, higher education), educators, general users	Corporate training, military use
Language	English	Non-English

Table 1: Inclusion Exclusion Criteria

2.4 Screening Process

The PRISMA 2020 flow diagram outlines the systematic review process. Of the 150 records identified (128 from databases, 22 from registers), 18 duplicates were removed, leaving 132 records for screening. After excluding 77 irrelevant records, 55 full-text articles were assessed for eligibility. Of these, 25 were excluded for reasons including irrelevance (12), low quality (7), duplication (4), and incomplete data (2). Ultimately, 30 studies were included in the final review, with the diagram ensuring transparency and methodological rigor in study selection.

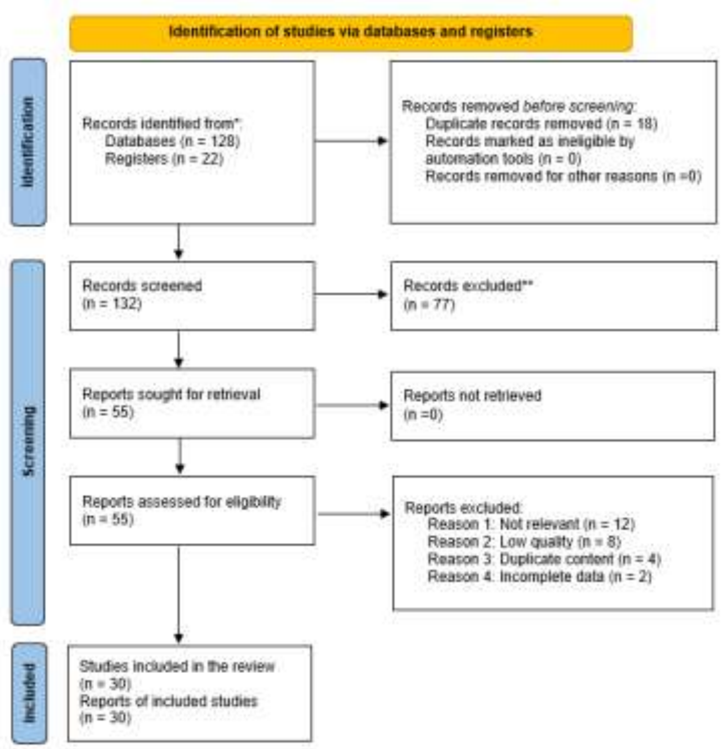

Figure 1: ***PRISMA 2020 Flow Diagram for Study Selection.***

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

3. LITERATURE REVIEW

3.1 AI-Driven Emotional Intelligence Assessment and Training

Artificial Intelligence (AI) is increasingly recognized as a transformative force in assessing and developing emotional intelligence (EI) within educational settings. Emotional intelligence—the capacity to perceive, interpret, regulate, and express emotions—has been linked to critical educational outcomes, including motivation, peer relationships, academic achievement, and psychological well-being (Pekrun et al., 2017; Mega et al., 2014). Leveraging AI technologies to assess and train EI offers scalable, data-driven solutions to monitor emotional states and deliver personalized interventions in real time.

AI-based systems can assess emotional intelligence by analysing multimodal data sources such as facial expressions, voice tone, body language, eye movement, and text-based communication. Facial emotion recognition models employing convolutional neural networks (CNNs) and transfer learning techniques have achieved as high as 96% classification accuracy on benchmark datasets within human–computer interaction settings. While not yet widely validated in real-world classrooms, these models show strong potential for enhancing emotional feedback in online education (Chowdary et al., 2023; Aly et al., 2023) Similarly, AI models based on electroencephalogram (EEG) signals—such as those using CapsNet or hybrid deep learning approaches—enable fine-grained detection of internal emotional states that are not externally visible (Chao et al., 2019; Zhang et al., 2024).

These emotion detection capabilities allow AI systems to deliver tailored emotional training. For instance, intelligent tutoring systems (ITS) such as MetaTutor detect student frustration or boredom and provide metacognitive feedback to help learners regulate those emotions, thereby improving engagement and academic outcomes (Taub et al., 2021). Furthermore, emotionally intelligent e-learning platforms, like those using Bayesian networks or fuzzy cognitive maps, can adapt learning content based on students' emotional responses, reinforcing positive emotional states and mitigating negative ones (Daouas & Lejmi, 2018; Salmeron, 2012).

Recent studies emphasize the value of AI in training empathy, self-awareness, and emotional regulation—core components of EI—through simulated social interactions and virtual emotional agents (Alanazi et al., 2023; Gómez-León, 2022). By incorporating effective feedback loops and dialogic modelling, AI systems can replicate emotionally responsive behaviours, helping students practice emotion-related competencies in low-stakes digital environments.

However, while AI demonstrates strong potential in EI assessment and training, several limitations remain. These include cultural variability in emotional expression, the risk of algorithmic bias in emotion classification, and the ethical concerns surrounding emotion surveillance in educational spaces (Vistorte et al., 2024). Thus, the effectiveness of AI in emotional intelligence development is highly dependent on the technology's contextual appropriateness and strong ethical and pedagogical frameworks.

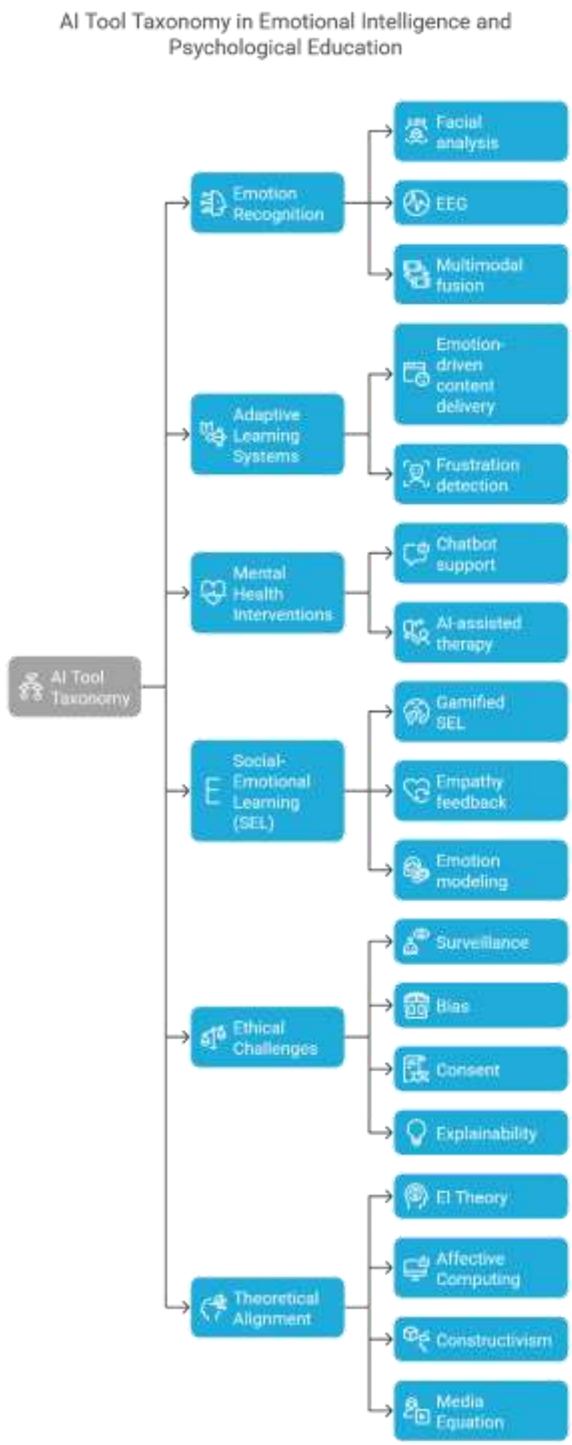

Figure 2: AI Tool Taxonomy in Emotional Intelligence and Psychological Education (2020–2025).

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

3.2 EEG and Affective Computing in Psychological Education

Integrating electroencephalography (EEG) and affective computing into psychological education represents a promising interdisciplinary convergence of neuroscience, artificial intelligence (AI), and pedagogy. EEG facilitates non-invasive monitoring of brain activity, capturing real-time emotional and cognitive states through electrical signals on the scalp. Affective computing encompasses systems and technologies designed to recognise, interpret, and respond to human emotions (Picard, 1997; Vistorte et al., 2024). Together, these tools enable a deeper understanding of learners' internal emotional experiences, offering new avenues for personalised emotional and psychological education.

Recent advancements in EEG-based emotion recognition have been propelled by the integration of deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Graph Convolutional Networks (GCNs). These models have demonstrated high accuracy in classifying emotional states from EEG signals, allowing educators and intelligent systems to adapt content delivery based on learners' emotional responses (Chao et al., 2019; Yin et al., 2021). For instance, Chao et al. (2019) introduced a CapsNet-based architecture that outperformed traditional models in detecting multiband EEG signals associated with affective states, while Zhang et al. (2024) proposed the ERDL model, integrating graph and temporal modeling to enhance emotion classification performance.

The application of EEG in psychological education is further underscored by its potential to detect a range of academic emotions—such as anxiety, boredom, frustration, and engagement—that influence motivation, attention, and learning outcomes (Alarcao & Fonseca, 2017; Pekrun et al., 2017). These insights can inform targeted interventions, including cognitive-behavioural support and adaptive scaffolding, enhancing emotional regulation, resilience, and metacognitive awareness. EEG is particularly suited for supporting students with emotional and psychological vulnerabilities, as it detects transient stressors or cognitive overload that may not be outwardly visible (Vistorte et al., 2024; Islam et al., 2021).

Affective computing platforms leveraging EEG input also play a critical role in enhancing social-emotional learning (SEL). AI-enabled educational environments can respond empathetically by modifying task difficulty, pacing, or feedback style when EEG data indicates emotional distress or disengagement (Aly et al., 2023). This form of emotionally responsive pedagogy has improved learner satisfaction, motivation, and overall psychological well-being (He et al., 2022; Ninaus et al., 2019). Moreover, integrating EEG with multimodal emotion recognition systems—including facial expressions, speech, and behavioural cues—further strengthens affective computing tools' accuracy and context sensitivity in real-time learning environments (Li et al., 2016).

Despite these advancements, using EEG in educational contexts raises ethical and logistical considerations, particularly concerning data privacy, cultural variations in emotional expression, and the potential for over-surveillance (Vistorte et al., 2024). Implementing EEG and affective computing in psychological education necessitates robust ethical frameworks and human-centred design principles to ensure responsible and effective application.

Furthermore, the integration of AI and digital technologies in educational settings has been shown to significantly influence cognitive functions such as memory, attention, and decision-making. A systematic review by Deckker and Sumanasekara (2025) highlights the phenomenon of digital amnesia, where increased reliance on AI for information retrieval may reduce long-term memory retention. The study also discusses attentional fragmentation caused by algorithmic content curation and the transformation of social cognition through digital interactions. These findings underscore the importance of balancing technological convenience with cognitive well-being in educational environments.

3.3 AI in Personalised Psychological Education and Mental Health Support

Artificial Intelligence (AI) is increasingly integrated into psychological education and mental health support systems to provide personalised, adaptive, and accessible services. These AI applications can bridge existing psychological care gaps by automating emotional assessments, tailoring learning interventions, and delivering scalable mental health support in formal and informal education (Mohr et al., 2017; Vistorte et al., 2024). AI technologies can provide real-time feedback and empathic interaction based on an individual's emotional and cognitive state through intelligent agents, conversational systems, and emotional analytics.

In psychological education, AI enables individualised learning experiences by adjusting content, pacing, and feedback in response to detected emotional and mental states. Emotionally Intelligent E-Learning Systems (EIES), such as those built on Bayesian Networks or affective feedback loops, dynamically adapt to a learner's psychological needs, helping students manage stress, anxiety, and motivation throughout the learning process (Daouas & Lejmi, 2018; He et al., 2022). These systems can predict negative emotional trends, such as frustration or disengagement, and respond by modifying the pedagogical approach to maintain engagement and psychological safety (Chaffar & Frasson, 2010).

AI-powered mental health tools, including digital therapeutics and emotion-aware chatbots, have demonstrated efficacy in supporting students experiencing psychological distress. For example, systems like Woebot and other emotionally responsive conversational agents provide users with cognitive-behavioural strategies, mood tracking, and psychoeducational content (Mohr et al., 2017; García-Ceja et al., 2018). These interventions reduce barriers to access and enhance user agency by enabling learners to engage with support systems confidentially and on demand.

Deep learning and affective computing technologies also allow for the analysis of multimodal emotional cues, such as voice tone, facial expressions, and text sentiment, to detect early signs of mental health issues like depression, burnout, or anxiety (Islam et al., 2021; AlZu'bi et al., 2022). For instance, EEG- and behaviour-based emotional monitoring systems have been deployed to identify cognitive overload or emotional fatigue during academic tasks, enabling timely and personalised mental health interventions (Chao et al., 2019; Zhang et al., 2024).

Moreover, AI can play a significant role in school-wide psychological well-being by supporting early intervention programs, enabling predictive risk modelling, and facilitating referral pathways for vulnerable students (Graham et al., 2019; Shatte et al., 2019). By leveraging emotion-informed learning analytics and psychological profiling, AI empowers educators and counsellors to understand student needs more holistically and intervene proactively before issues escalate. Despite its promise, the integration of AI in psychological education and mental health support necessitates robust ethical frameworks to address concerns such as data privacy, emotional authenticity, cultural sensitivity, and algorithmic transparency (Vistorte et al., 2024). Ensuring that AI interventions are designed with inclusivity and ethical responsibility is critical to fostering trust and efficacy in emotionally intelligent educational systems.

3.4 Challenges and Limitations

Despite the growing promise of artificial intelligence (AI) in emotional intelligence and psychological education, several challenges and limitations hinder its widespread adoption and effectiveness. These issues span technical, ethical, pedagogical, and cultural dimensions, requiring scrutiny to ensure responsible and equitable implementation.

One major technical limitation is the accuracy and reliability of emotion recognition systems, especially when deployed in real-world educational contexts. Many current models rely on facial expression analysis, voice tone, or EEG signals, but these can be affected by environmental noise, cultural display rules, and individual variation in emotional expression (Aly et al., 2023; Islam et al., 2021). Moreover, while deep learning models such as CNNs and LSTMs have demonstrated strong performance in lab settings, their generalizability across diverse learning environments remains limited (Chao et al., 2019; Zhang et al., 2024).

Another challenge lies in data quality and bias. Emotion detection systems require vast amounts of labeled emotional data, yet existing datasets may not sufficiently represent the diversity of global student populations. This raises the risk of algorithmic bias, where emotional states may be misclassified due to race, gender, or cultural background (Gómez-León, 2022; Vistorte et al., 2024). Furthermore, many affective computing models have been developed using small or homogeneous samples, making them less effective for large-scale, multicultural applications.

Ethical concerns are also critical. The use of AI to monitor emotions, particularly through biometric data such as facial expressions or EEG, raises significant privacy issues. The continuous tracking of students' emotional states can be perceived as intrusive or even manipulative, especially if implemented without informed consent or transparency (Mohr et al., 2017; Shatte et al., 2019). There is also a growing concern about emotional surveillance in classrooms, where students may feel compelled to regulate their affective display due to monitoring, thereby reducing emotional authenticity and autonomy (Vistorte et al., 2024).

On a pedagogical level, integrating AI-driven emotional support tools is often constrained by educators' lack of training, infrastructure, and institutional readiness. Teachers may hesitate to adopt these technologies due to unfamiliarity or scepticism about their pedagogical value (He et al., 2022). Additionally, AI systems cannot fully understand human emotions' rich, contextual nature, particularly subtle, mixed, or culturally embedded affective experiences.

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

From a methodological perspective, the field also suffers from fragmentation and heterogeneity. Studies vary widely regarding research design, emotional taxonomies, AI models used, and outcome measures, which complicates synthesis and meta-analysis (Vistorte et al., 2024). Many current investigations are exploratory, lacking longitudinal depth or large-scale validation across diverse educational contexts.

Lastly, accessibility and equity pose significant limitations. Implementing AI tools requires digital infrastructure, which may not be available in under-resourced schools or communities. This could exacerbate educational inequalities by providing personalised psychological support only to students in technologically advanced regions (Standen et al., 2020). Addressing these challenges requires interdisciplinary collaboration between educators, computer scientists, psychologists, and ethicists. Fairness, transparency, and contextual sensitivity in emotionally intelligent AI systems will be essential to their future in psychological education.

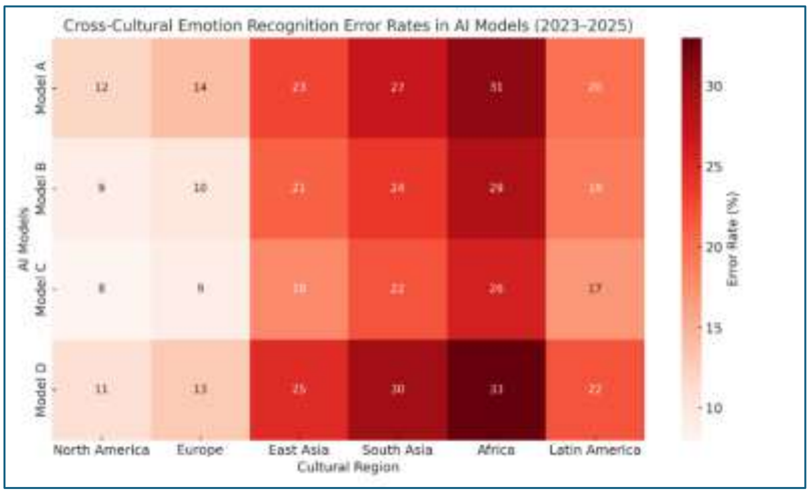

Figure 3: ***Cross-Cultural Emotion Recognition Error Rates in AI Models (2023–2025).***

This heatmap illustrates comparative error rates (%) across various cultural regions for four leading AI emotion recognition models. Higher error rates in South Asia, Africa, and East Asia indicate potential algorithmic bias due to limited diversity in training datasets. The multiple barriers demand a restrained approach toward AI development within emotionally relevant domains, cooperation between diverse fields, and inclusive methods. Strong ethical guidelines, cultural sensitivity, and user-centred design approaches must correspond with technical system advancements to protect users' emotional autonomy.

3.5 Review of Relevant Theories

Integrating Artificial Intelligence (AI) into emotional intelligence (EI) and psychological education is underpinned by multiple theoretical frameworks that explain how emotions, cognition, and learning interact. These theories guide developing and evaluating affective computing systems, intelligent tutoring environments, and AI-driven emotional assessments in educational contexts. Reviewing relevant psychological and computational theories reveals the conceptual scaffolding that informs current innovations and challenges in emotionally intelligent AI.

3.5.1 Emotional Intelligence Theory

At the foundation of this field is the Emotional Intelligence (EI) framework proposed by Salovey and Mayer (1990), later popularised by Goleman (1995). This model defines EI as a set of abilities related to perceiving, using, understanding, and regulating emotions. These components are central to AI systems that aim to detect and respond to emotional cues through biometric and behavioural data. AI applications grounded in this model aim to improve learners' self-awareness, self-regulation, and social-emotional competence through feedback and adaptive interaction (Vistorte et al., 2024; Gómez-León, 2022).

3.5.2 Affective Computing Theory

As introduced by Picard (1997), Affective Computing provides the technological backbone for EI integration into AI systems. This theory emphasises equipping machines with the capacity to recognise and simulate human emotions, enabling more empathetic and context-sensitive interaction. Core components of this framework include emotion sensing (via facial recognition, EEG, etc.), modelling,

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

and response adaptation. Affective computing guides the design of intelligent agents that tailor educational content based on students' emotional and cognitive states (Ninaus et al., 2019; He et al., 2022).

3.5.3 Cognitive-Affective Theory of Learning with Media (CATLM)

Developed by Moreno and Mayer (2007), the CATLM posits that learning is most effective when cognitive and affective systems are engaged simultaneously. AI systems based on this theory integrate emotional engagement strategies, such as animated pedagogical agents or adaptive feedback, to enhance motivation and retention. MetaTutor and similar Intelligent Tutoring Systems (ITS) exemplify CATLM, leveraging emotion tracking to promote metacognitive awareness and deeper learning (Taub et al., 2021).

3.5.4 Self-Regulated Learning Theory

Self-regulated learning (SRL) theory focuses on students' ability to plan, monitor, and regulate their learning and emotions. AI-enhanced platforms employ SRL principles to encourage learners to reflect on their emotional states and learning behaviours. These systems provide scaffolding, reminders, and feedback based on real-time emotion recognition to support self-regulation (Pekrun et al., 2017; Mega et al., 2014). Adaptive systems, particularly those with affective feedback, embody SRL theory by guiding learners through emotional challenges toward sustained engagement.

3.5.5 Biologically Inspired Cognitive Architecture (BICA)

The BICA framework, especially its emotional extensions such as eBICA, aims to simulate human cognitive-affective functioning within AI agents (Samsonovich, 2020). These architectures support the development of AI systems capable of empathic decision-making and social interaction, mimicking emotional reasoning processes found in humans. Educational agents using this model interpret learners' emotions and respond in socially intelligent ways, fostering more natural and effective psychological education (Alanazi et al., 2023).

3.5.6 TPACK Framework

While not emotion-specific, the Technological Pedagogical Content Knowledge (TPACK) framework provides a valuable lens for integrating AI-driven emotional tools into education. TPACK emphasises the balance of content knowledge, pedagogy, and technology to optimise learning (Alemán-Saravia & Deroncele-Acosta, 2021). In emotional AI, TPACK ensures that emotion-aware technologies are implemented meaningfully and pedagogically, aligning with teachers' goals and learners' needs.

Theory	Core Concepts	AI Tools / Applications Aligned	Interpretation in Context
Goleman's Emotional Intelligence (1995)	Self-awareness, self-regulation, motivation, empathy, social skills	AI-supported SEL platforms, emotion-aware chatbots	AI mimics or promotes emotional competencies to enhance empathy and regulation in learning environments.
Picard's Affective Computing (1997)	Emotion recognition and simulation using multimodal inputs (EEG, facial, speech)	Wearable affective devices, multimodal emotion-recognition systems	Affective systems enable real-time emotional analysis for adaptive educational interventions.
Constructivist Learning (Vygotsky, Bruner)	Learning is socially and emotionally situated; scaffolding within learner's developmental zone	Emotion-sensitive adaptive learning platforms	AI adapts instructional content based on students' emotional state to support engagement and development.
Media Equation Theory (Reeves & Nass, 1996)	Humans treat computers as social actors; responses to media mimic human-human interaction	Emotionally responsive chatbots, empathetic LLMs	Students may form attachments or attribute empathy to AI, influencing emotional and cognitive responses.
Human-Centered Design	Designing around users' emotional, ethical, and experiential needs	Transparent AI systems, fairness-aware emotion detectors	Promotes responsible and ethical AI deployment to preserve human dignity and trust.
Emerging: Algorithmic Emotional Mediation (2025+)	AI influences perception, response, and experience of emotion in real-time	LLMs with affective tuning, emotional feedback loops	New framework to study how AI reshapes emotional engagement in digital learning environments.

Figure 4: ***Theoretical Alignment Matrix of AI Applications in Emotional Intelligence and Psychological Education.***

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

3.6 Theoretical Implications

The intersection of artificial intelligence (AI), emotional intelligence (EI), and psychological education presents several theoretical implications that expand the foundational understanding of learning, emotion, and intelligent systems. As AI technologies increasingly simulate, interpret, and respond to human emotions, they challenge and refine existing psychological and educational theories by offering new modalities for emotional engagement, self-regulation, and adaptive learning.

One key implication is the redefinition of emotional intelligence as both a human capacity and a machine-mediated construct. Traditional models by Salovey and Mayer (1990) or Goleman (1995) treat EI as a human skill, while affective computing introduces a paradigm where emotional reasoning is operationalised algorithmically. As AI systems like intelligent tutoring systems (ITS), chatbots, or emotion-sensitive agents engage in emotionally responsive interactions, they necessitate a reframing of EI as a co-constructed experience between humans and machines (Picard, 1997; Alanazi et al., 2023).

The application of Affective Computing Theory within educational settings extends learning theories to include emotion as a dynamic feedback signal. For example, models such as the Cognitive-Affective Theory of Learning with Media (CATLM) are strengthened by empirical evidence showing how AI systems enhance emotional regulation, motivation, and memory retention through adaptive responses (Taub et al., 2021; Vistorte et al., 2024). This suggests a more nuanced integration of affective states into instructional design and calls for updates to cognitive learning theories that have historically marginalised emotion.

Additionally, AI-enabled systems reinforce and expand Self-Regulated Learning (SRL) Theory by operationalising emotional and cognitive monitoring through biometric and behavioural tracking. Where SRL once relied on self-reports or teacher observations, AI now facilitates real-time assessments and interventions, transforming self-regulation into a technologically mediated process (Pekrun et al., 2017; Mega et al., 2014). The theoretical implication is a shift from internal, introspective regulation models to hybrid models involving human-computer co-regulation.

Moreover, the emergence of biologically inspired cognitive architectures such as eBICA (Samsonovich, 2020) suggests a theoretical fusion between neuroscience, psychology, and computer science. These frameworks simulate cognitive reasoning, empathy, and emotion, inviting theorists to explore the boundaries of artificial consciousness and moral cognition within educational environments. Whether machines can "learn" emotional behaviour raises philosophical and ethical challenges to conventional theories of social-emotional development.

Finally, integrating AI into psychological education calls for re-examining constructivist and socio-cultural learning theories. Emotionally intelligent AI agents—through personalised dialogues, scaffolding, and simulated social cues—participate in the learning environment as semi-autonomous actors. This aligns with Vygotskian views of mediated learning but also complicates the definition of "peer" or "teacher" when the learning partner is non-human (Vistorte et al., 2024).

In sum, AI-driven emotional and psychological education is not just an application of existing theories but a force that reconfigures them. The theoretical landscape must evolve to address co-agency, emotional computation, and ethical co-design questions in human-AI educational partnerships.

4. DISCUSSION

RQ1: How are artificial intelligence (AI) technologies currently applied to enhance emotional intelligence (EI) in psychological education across diverse learner populations?

AI technologies are being applied in psychological education through various modalities that support the development and assessment of emotional intelligence (EI). Intelligent tutoring systems (ITS), emotion-aware chatbots, facial recognition software, EEG-based emotion tracking, and natural language processing (NLP) tools are commonly used to detect and respond to learners' emotional states in real time (Taub et al., 2021; Chao et al., 2019). These technologies are implemented in both formal education (K–12 and university settings) and informal digital learning platforms to enhance students' abilities in self-awareness, emotion regulation, and interpersonal communication (Vistorte et al., 2024). Emotionally Intelligent E-Learning Systems (EIES) have successfully adjusted content delivery and feedback based on detected emotions, making psychological education more personalised and inclusive (Daouas & Lejmi, 2018; Aly et al., 2023).

RQ2: What are the observed impacts of AI-enabled tools (e.g., chatbots, EEG wearables, LLMS) on learners' emotional regulation, self-awareness, and engagement in mental health or SEL (social-emotional learning) contexts?
Integrating AI tools has shown measurable benefits for emotional regulation and learner engagement. For instance, EEG-based systems using graph neural networks and LSTM models accurately detect emotional fluctuations, allowing for early intervention and adaptive scaffolding during learning (Zhang et al., 2024). AI-driven chatbots, such as Woebot, provide conversational cognitive-behavioural therapy (CBT) techniques, promoting emotional self-regulation and access to mental health support outside clinical environments (Mohr et al., 2017). Learning management systems (LLMS) enhanced with affective analytics improve engagement by tailoring feedback based on detected emotional cues, enhancing the overall learning experience and psychological safety (García-Ceja et al., 2018; He et al., 2022). Additionally, AI-based emotion monitoring tools in SEL programs have increased learners' empathy and emotional self-awareness through interactive and reflective digital experiences (Alanazi et al., 2023).

RQ3: What ethical, cultural, and algorithmic challenges are associated with using AI in detecting, responding to, or mediating human emotions in educational settings?
The use of AI in emotion-sensitive contexts introduces significant ethical and cultural challenges. One of the primary concerns is privacy—AI systems often rely on biometric and behavioral data (e.g., facial expressions, voice, EEG) that may be considered intrusive if used without informed consent (Vistorte et al., 2024; Mohr et al., 2017). Cultural sensitivity is another challenge, as emotion recognition models trained on homogeneous datasets may misinterpret emotions across diverse populations, leading to biased feedback or misdiagnoses (Gómez-León, 2022). Algorithmic opacity further complicates the issue, as many deep learning models used in affective computing function as "black boxes," making it difficult to explain their decision-making or ensure fairness (Aly et al., 2023). These concerns call for a careful balance between technological innovation and the ethical principles of transparency, inclusivity, and respect for learners' autonomy.

RQ4: To what extent do AI-driven emotional intelligence tools reflect or challenge established psychological, educational, and human-computer interaction theories?
AI-driven EI tools both reinforce and challenge established theoretical frameworks. Technologies that operationalize self-awareness, emotion regulation, and motivation align closely with emotional intelligence theory (Salovey & Mayer, 1990) and self-regulated learning models (Pekrun et al., 2017). The use of AI to provide emotional scaffolding through ITS reflects the principles of the Cognitive-Affective Theory of Learning with Media (CATLM), wherein emotion is seen as a vital component of effective instruction (Taub et al., 2021). However, these tools also challenge traditional views by shifting emotional development from a purely human-centered activity to a co-regulated, machine-mediated experience. The biologically inspired cognitive architectures (e.g., eBICA) extend the boundaries of social cognition by simulating empathy and emotional responsiveness in AI agents (Samsonovich, 2020). These developments necessitate a theoretical rethinking of emotional learning as an interactive, distributed process involving both human and artificial actors.

RQ5: What standardized frameworks or theoretical innovations are emerging to guide AI's ethical design, implementation, and evaluation in psychological and emotional education?
Emerging frameworks emphasize the need for transparent, equitable, and pedagogically grounded AI design. The Technological Pedagogical Content Knowledge (TPACK) model has been proposed as a guide for integrating emotion-aware technologies to align with curriculum goals and teacher expertise (Alemán-Saravia & Deroncele-Acosta, 2021). Additionally, ethical AI principles promoted by institutions such as UNESCO and the European Commission influence educational technology, calling for explainability, fairness, privacy protection, and human oversight in emotion-based AI systems (Vistorte et al., 2024). Novel frameworks such as emotionally intelligent adaptive learning systems and hybrid human-AI co-regulation models are being developed better to capture the complexity of emotional experiences in digital learning. These innovations suggest that future systems will require technical robustness and theoretical grounding in human-centered educational design.

5. FUTURE DIRECTIONS

As artificial intelligence (AI) continues transforming psychological education and emotional intelligence (EI) training, several key future directions emerge for research, policy, and practice. These directions are essential to ensuring that AI tools are developed, deployed, and evaluated in ethical, inclusive, and pedagogically sound ways.

5.1 **Longitudinal and Cross-Cultural Validation**

Many existing studies on AI and EI rely on short-term interventions or homogeneous samples, limiting generalizability (Vistorte et al., 2024). Future research should prioritise longitudinal studies that evaluate the sustained effects of AI-based emotional interventions over time, particularly on students' mental well-being, emotional growth, and academic performance. Additionally, cross-cultural validation

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

of emotion recognition algorithms is necessary to avoid perpetuating algorithmic bias and ensure equitable application across diverse learner populations (Gómez-León, 2022).

5.2 Multimodal Emotion Detection and Hybrid Models

The future of affective computing lies in developing multimodal emotion detection systems that integrate EEG signals, facial expression analysis, voice tone, and textual sentiment (Islam et al., 2021; Chao et al., 2019). Combining these data sources can enhance the accuracy and context-sensitivity of AI systems. Future tools should also explore hybrid AI-human models of emotional co-regulation, where machines support but do not replace human emotional intelligence in educational settings (Alanazi et al., 2023).

5.3 Ethically Grounded Frameworks and Standards

As the use of AI in emotionally sensitive contexts grows, so too does the need for clear ethical guidelines, transparency protocols, and governance mechanisms. Future efforts should focus on developing standardised frameworks for ethical AI in education, drawing on existing models such as the TPACK framework and human-centred AI principles (Alemán-Saravia & Deroncele-Acosta, 2021; Vistorte et al., 2024). These frameworks should prioritise user consent, emotional privacy, algorithmic explainability, and socio-emotional fairness.

5.4 Personalised Mental Health Support through AI

Growing evidence shows that AI can complement traditional mental health services through emotionally intelligent chatbots, personalised interventions, and predictive risk modelling (Mohr et al., 2017; García-Ceja et al., 2018). Future directions should expand on these findings by integrating AI into school-based counselling systems, using predictive analytics to identify at-risk students and provide timely, personalised support. These applications can be particularly impactful in underserved or resource-limited educational settings.

5.5 Theoretical and Pedagogical Integration

Advancing AI in EI education requires deeper integration with educational psychology and learning sciences. Future systems should detect emotions and align with pedagogical strategies that foster self-regulation, empathy, and critical thinking (Pekrun et al., 2017; Mega et al., 2014). Research must continue exploring how AI tools can enhance, rather than overshadow, the role of human teachers in nurturing students' psychological development.

5.6 Gamified and Immersive EI Training Environments

With the rise of extended reality (XR), gamified and immersive environments offer new possibilities for EI development. Game-based learning platforms enhanced with affective feedback can simulate complex emotional scenarios and allow learners to practice emotional responses in real-time (Ninaus et al., 2019; Daghestani et al., 2020). Future research should explore how such tools can be scaled and integrated into formal curricula.

The (Figure 3) roadmap outlines a projected timeline for advancing the field through ethical oversight, longitudinal impact studies, culturally inclusive datasets, standardised evaluation frameworks, and the global implementation of emotionally explainable and hybrid AI-human learning systems.

These directions represent not just academic imperatives, but societal responsibilities. As AI becomes a co-participant in our emotional and educational lives, its development must be guided by rigorous research, inclusive ethics, and human-centred values.

SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 4 | April 2025 - Peer Reviewed Journal

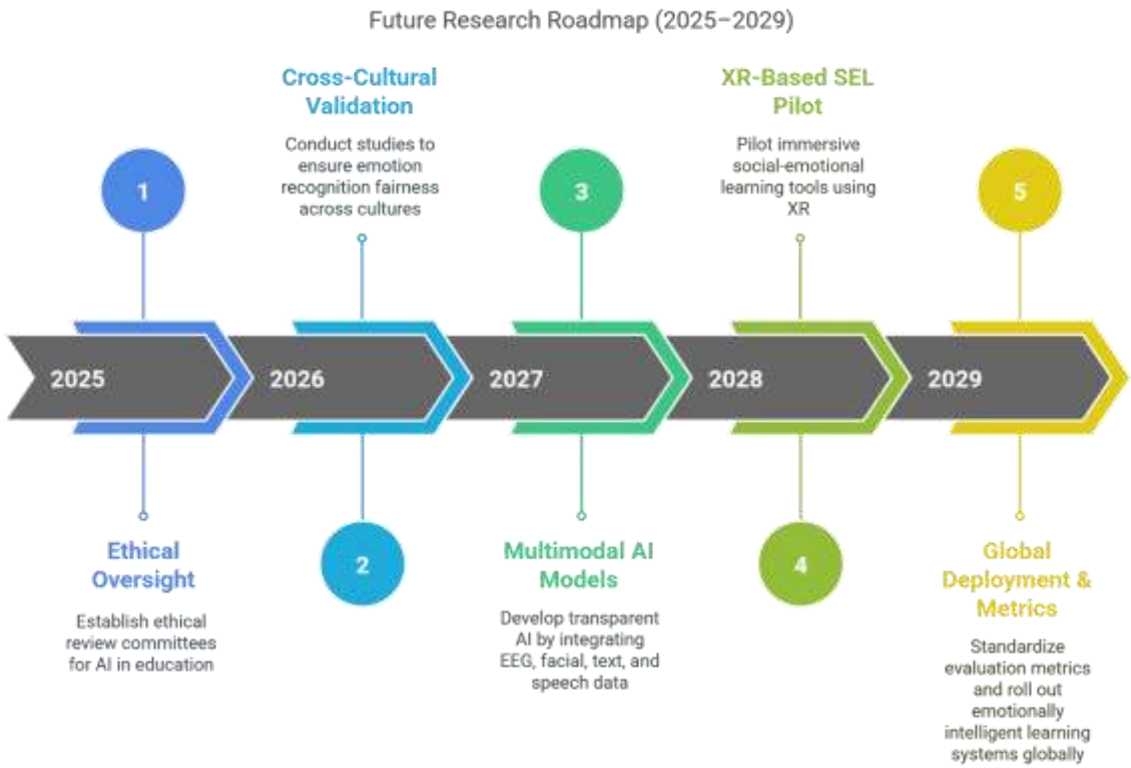

Figure 5: ***Future Research Roadmap for AI in Emotional Intelligence and Psychological Education (2025–2029).***

6. CONCLUSION

Integrating Artificial Intelligence (AI) into psychological education and emotional intelligence (EI) training is rapidly evolving into a cornerstone of 21st-century learning innovation. This systematic review explored AI technologies' applications, impacts, and theoretical implications on enhancing EI, mental well-being, and social-emotional learning (SEL), ranging from intelligent tutoring systems to EEG-based emotion detectors.

Across diverse educational contexts, AI systems have demonstrated potential in improving students' emotional regulation, self-awareness, and mental health support. These tools reflect and expand established psychological theories, challenging traditional notions of learner agency and emotional development. However, significant challenges remain, particularly in ethics, cultural fairness, algorithmic transparency, and pedagogical alignment. Addressing these limitations will require interdisciplinary collaboration and the development of inclusive, ethical, and evidence-based frameworks.

6.1 Summary of Key Findings

Research Question	Key Findings
RQ1: How are AI technologies applied to enhance EI in psychological education?	AI is applied through ITS, chatbots, facial recognition, EEG tools, and adaptive learning platforms to detect, respond to, and support emotional learning in diverse contexts (Taub et al., 2021; Vistorte et al., 2024).
RQ2: What are the observed impacts of AI tools on emotional regulation and SEL?	Improved emotional regulation, engagement, empathy, and self-awareness have been observed in learners using AI-enabled systems, particularly those using affective feedback, mental health bots, and multimodal sensing (Mohr et al., 2017; He et al., 2022; AlZu'bi et al., 2022).

RQ3: What ethical and cultural challenges are associated with AI in emotion-related education?	Privacy concerns, algorithmic bias, cultural misinterpretation of emotions, and lack of informed consent are persistent issues that necessitate ethical frameworks and responsible design (Vistorte et al., 2024; Gómez-León, 2022).
RQ4: To what extent do AI tools reflect or challenge psychological theories?	AI systems extend models like EI Theory, SRL, and CATLM while challenging traditional frameworks by introducing machine-mediated co-regulation, empathy simulation, and AI-driven emotional scaffolding (Samsonovich, 2020; Pekrun et al., 2017).
RQ5: What frameworks are emerging to guide ethical and pedagogical AI design?	Frameworks such as TPACK and human-centred AI ethics are emerging to guide implementation, alongside calls for transparency, cross-cultural validity, and adaptive emotional models grounded in psychology and education (Alemán-Saravia & Deroncele-Acosta, 2021; Vistorte et al., 2024).

Table 2: ***Summary of Key Findings***

6.2 Call to Action

To responsibly harness the potential of AI in emotional and psychological education, stakeholders must act across several dimensions:

- **Researchers** should pursue longitudinal, cross-cultural, and mixed-method studies to evaluate AI's long-term impact on psychological and emotional development.
- **Educators and Institutions** must receive adequate training and support to implement emotionally intelligent AI tools that are pedagogically sound and culturally responsive.
- **Developers and Designers** must prioritize ethical-by-design principles, ensuring data privacy, explainability, and fairness are embedded into every AI system.
- **Policy Makers** should establish regulatory frameworks that safeguard learners' emotional rights while promoting innovation in affective and psychological education technologies.

Only through coordinated, interdisciplinary efforts can AI evolve into a trusted partner in nurturing emotionally resilient, mentally healthy, and socially competent learners.

7. REFERENCES

1. *Alanazi, S. A., Shabbir, M., Alshammari, N., Alruwaili, M., Hussain, I., & Ahmad, F. (2023). Prediction of emotional empathy in intelligent agents to facilitate precise social interaction. Applied Sciences, 13(2), 1163. https://doi.org/10.3390/app13021163*
2. *Alarcao, S. M., & Fonseca, M. J. (2017). Emotions recognition using EEG signals: A survey. IEEE Transactions on Affective Computing, 10(3), 374–393. https://doi.org/10.1109/TAFFC.2017.2714671*
3. *Alemán-Saravia, A. C., & Deroncele-Acosta, A. (2021). Technology, pedagogy and content (TPACK framework): Systematic literature review, 104–111. IEEE.*
4. *Aly, M., Ghallab, A., & Fathi, I. S. (2023). Enhancing facial expression recognition system in online learning context using efficient deep learning model. IEEE Access, 11, 121419–121433. https://doi.org/10.1109/ACCESS.2023.3325407*
5. *AlZu'bi, S., Abu Zitar, R., Hawashin, B., Abu Shanab, S., Zraiqat, A., & Mughaid, A. et al. (2022). A novel deep learning technique for detecting emotional impact in online education. Electronics, 11(18), 2964. https://doi.org/10.3390/electronics11182964*
6. *Chao, H., Dong, L., Liu, Y., & Lu, B. (2019). Emotion recognition from multiband EEG signals using CapsNet. Sensors, 19(9), 2212. https://doi.org/10.3390/s19092212*
7. *Chowdary, M. K., Nguyen, T. N., & Hemanth, D. J. (2023). Deep learning-based facial emotion recognition for human–computer interaction applications. Neural Computing & Applications, 35, 23311–23328. https://doi.org/10.1007/s00521-021-06012-8*
8. *Daouas, T., & Lejmi, H. (2018). Emotions recognition in an intelligent e-learning environment. Interactive Learning Environments, 26(7), 991–1009. https://doi.org/10.1080/10494820.2018.1427114*
9. *Deckker, D., & Sumanasekara, S. (2025). The role of EEG in assessing student emotions in AI-based classrooms. EPRA International Journal of Educational and Pedagogical Sciences, 11(3). https://doi.org/10.36713/epra20564*
10. *Deckker, D., & Sumanasekara, S. (2025). A systematic review of the impact of artificial intelligence, digital technology, and social media on cognitive functions. International Journal of Research and Innovation in Social Science, 9(3), 134–154 https://dx.doi.org/10.47772/IJRISS.2025.90300011*
11. *García-Ceja, E., Riegler, M., Nordgreen, T., Jakobsen, P., Oedegaard, K. J., & Tørresen, J. (2018). Mental health monitoring with multimodal sensing and machine learning: A survey. Pervasive and Mobile Computing, 51, 1–26. https://doi.org/10.1016/j.pmcj.2018.09.003*
12. *Gómez-León, M. I. (2022). Development of empathy through socioemotional artificial intelligence. Papeles del Psicólogo, 43(3), 218–224. https://doi.org/10.23923/pap.psicol.2996*
13. *He, T., Li, C., Wang, J., Wang, M., Wang, Z., & Jiao, C. (2022). An emotion analysis in learning environment based on theme-specified drawing by convolutional neural network. Frontiers in Public Health, 10, 958870. https://doi.org/10.3389/fpubh.2022.958870*

14. Islam, M. R., Moni, M. A., Islam, M. M., Rashed-Al-Mahfuz, M., Islam, M. S., Hasan, M. K., et al. (2021). Emotion recognition from EEG signal focusing on deep learning and shallow learning techniques. IEEE Access, 9, 94601–94624. https://doi.org/10.1109/ACCESS.2021.3091487
15. Li, J., Ngai, G., Leong, H., & Chan, S. (2016). Multimodal human attention detection for reading from facial expression, eye gaze, and mouse dynamics. ACM SIGAPP Applied Computing Review, 16(2), 37–49. https://doi.org/10.1145/3015297.3015301
16. Lin, Y.-J., Ding, S. Y., Lu, C.-K., Tang, T. B., and Shen, J.-Y. (2023). Emotion prediction in music based on artificial intelligence techniques, 405–406.
17. Mega, C., Ronconi, L., & De Beni, R. (2014). What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement. Journal of Educational Psychology, 106(1), 121. https://doi.org/10.1037/a0033546
18. Mohr, D. C., Zhang, M., & Schueller, S. M. (2017). Personal sensing: Understanding mental health using ubiquitous sensors and machine learning. Annual Review of Clinical Psychology, 13, 23–47. https://doi.org/10.1146/annurev-clinpsy-032816-044949
19. Ninaus, M., Greipl, S., Kiili, K., Lindstedt, A., Huber, S., Klein, E., et al. (2019). Increased emotional engagement in game-based learning – A machine learning approach on facial emotion detection data. Computers & Education, 142, 103641. https://doi.org/10.1016/j.compedu.2019.103641
20. Pekrun, R., Lichtenfeld, S., Marsh, H. W., Murayama, K., & Goetz, T. (2017). Achievement emotions and academic performance: Longitudinal models of reciprocal effects. Child Development, 88(5), 1653–1670. https://doi.org/10.1111/cdev.12704
21. Picard, R. W. (1997). Affective computing. MIT Press.
22. Salmeron, J. (2012). Fuzzy cognitive maps for artificial emotions forecasting. Applied Soft Computing, 12(11), 3704–3710. https://doi.org/10.1016/j.asoc.2012.01.015
23. Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. Imagination, Cognition and Personality, 9(3), 185–211. https://doi.org/10.2190/DUGG-P24E-52WK-6CDG
24. Samsonovich, A. (2020). Socially emotional brain-inspired cognitive architecture framework for artificial intelligence. Cognitive Systems Research, 60, 57–76. https://doi.org/10.1016/j.cogsys.2019.12.002
25. Shatte, A. B. R., Hutchinson, D. M., & Teague, S. J. (2019). Machine learning in mental health: A scoping review of methods and applications. Psychological Medicine, 49(9), 1426–1448. https://doi.org/10.1017/S0033291719000151
26. Standen, P., Brown, D., Taheri, M., Trigo, M., Boulton, H., & Burton, A. et al. (2020). An evaluation of an adaptive learning system based on multimodal affect recognition for learners with intellectual disabilities. British Journal of Educational Technology, 51(5), 1748–1765. https://doi.org/10.1111/bjet.13010
27. Taub, M., Azevedo, R., Rajendran, R., Cloude, E. B., Biswas, G., & Price, M. J. (2021). How are students' emotions related to the accuracy of cognitive and metacognitive processes during learning with an intelligent tutoring system? Learning and Instruction, 72, 101273. https://doi.org/10.1016/j.learninstruc.2019.04.001
28. Vistorte, A. O. R., Deroncele-Acosta, A., Ayala, J. L. M., Barrasa, A., López-Granero, C., & Martí-González, M. (2024). Integrating artificial intelligence to assess emotions in learning environments: A systematic literature review. Frontiers in Psychology, 15, 1387089. https://doi.org/10.3389/fpsyg.2024.1387089
29. Yin, Z., Zhao, M., Wang, Y., Yang, J., & Zhang, J. (2021). ERDL: Emotion recognition from EEG signals using graph convolutional network and long short-term memory. IEEE Transactions on Affective Computing. https://doi.org/10.1109/TAFFC.2021.3056584
30. Zhang, Y., Liu, H., Wang, J., & Chen, X. (2024). EEG-based emotion recognition using graph convolutional neural network with dual attention mechanism. Frontiers in Computational Neuroscience, 18, Article 1416494. https://doi.org/10.3389/fncom.2024.1416494
31. Zawacki-Richter, O., Marín, V. I., Bond, M., and Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? Int. J. Educ. Technol. High. Educ. 16, 1–27.