Simen Owen Academic Proceedings Series

Vol. 1 2025

Review Open Access

Psychological Adaptation and Affective Feedback in AI-Enhanced Education: A Systematic Review

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Abstract: This review synthesizes current research at the intersection of artificial intelligence (AI), education, and psychology, with a particular focus on the psychological mechanisms underlying learner adaptation. Evidence from affective computing illustrates the pedagogical value of multimodal emotion recognition, while meta-analyses of large language model (LLM)-based tutoring systems reveal both the potential for enhanced engagement and the risks of cognitive dependency. Empirical studies on adoption further highlight the mediating roles of self-efficacy, motivation, and anxiety in sustaining learner interaction with AI tools. Case analyses identify progressive adaptation, emotional regulation, and transparency as critical enablers of effective learning experiences. The review concludes that ethically grounded, human-centered AI design is indispensable for cultivating resilient, adaptive, and learner-centered educational ecosystems.

Keywords: artificial intelligence in education; affective computing; psychological adaptation

1. Introduction

In recent years, the convergence of artificial intelligence (AI), education, and psychology has accelerated, reshaping the ways in which learning is delivered, observed, and supported. This evolution in educational paradigms mirrors broader trends observed in pedagogical development across disciplines, where instructional methods have continuously adapted to balance tradition with innovation and to meet learners' changing cognitive and affective needs [1]. In online and blended learning environments, AI systems now capture rich behavioral traces-clickstreams, gaze patterns, and keystrokes-alongside increasingly sensitive affective signals, including facial expressions and vocal prosody, to infer learners' cognitive and emotional states and enable timely, data-informed interventions [2]. Concurrently, advances in natural language processing (NLP) have produced conversational learning assistants, such as large language model (LLM)-powered chatbots, that scaffold problem solving, simulate tutoring dialogues, and provide on-demand formative feedback. Meta-analytic evidence indicates that these dialogic tools can enhance student engagement across behavioral, cognitive, and affective dimensions [3], and, when effectively integrated into instruction, can yield measurable improvements in learning outcomes [4]. Collectively, affect-aware analytics and LLM-based support promise more adaptive, motivating, and personalized learning experiences.

However, these benefits are heterogeneous and highly contingent on both design features and learner characteristics. Syntheses of classroom and laboratory studies show that chatbots are more effective when prompting active sense-making-e.g., requesting rationales, encouraging self-explanations, and offering tiered hints-than when merely providing answers [3,4]. Technology-adoption research grounded in the Unified Theory

Received: 09 August 2025
Revised: 03 October 2025
Accepted: 15 October 2025
Published: 20 October 2025

of Acceptance and Use of Technology (UTAUT) further underscores that factors such as student anxiety, perceived usefulness, effort expectancy, and social influence shape both initial uptake and sustained use of tools like ChatGPT [5]. These adoption determinants interact with pedagogical context: features that facilitate one learner's progress may challenge another's self-efficacy or raise concerns about surveillance and academic integrity, thereby diminishing engagement [5]. Such evidence reinforces a central premise of this review: students' psychological mechanisms-emotion, motivation, self-efficacy, and anxiety-mediate and moderate the educational effects of AI.

The sensing dimension of this ecosystem has matured substantially. Comprehensive reviews of automated emotion recognition (AER) in online learning reveal robust pipelines that integrate visual, audio, and interaction data to classify engagement, confusion, boredom, and frustration with sufficient reliability for real-world deployment [2]. Complementing these technical advances, affective-computing research in education delineates theoretical links between emotion dynamics and learning processes, clarifying which affective states-such as engaged concentration-facilitate learning and which-such as unresolved confusion-impede it [6]. Crucially, both strands highlight context sensitivity: cultural display norms, camera placement, lighting, task type, and prior knowledge all influence signal quality, classification accuracy, and the pedagogical validity of any AI-driven intervention [2,6].

From a psychological perspective, three mechanisms are particularly salient. Cognitive load is one: AI-generated explanations can reduce extraneous load by clarifying instructions or decomposing complex problems, yet may inadvertently increase intrinsic load if they introduce unfamiliar constructs too rapidly, underscoring the need to align granularity with learners' prior knowledge [6]. Self-efficacy is another: responsive, hint-first support validates partial understanding, calibrates challenge, and builds competence beliefs, whereas solution-first responses may undermine agency and foster overreliance [3,4,6]. Anxiety is a third: adoption studies reveal that anxiety shapes intentions and persistence with AI tools, interacting with perceived usefulness and ease of use [5]. While AI can mitigate anxiety by demystifying tasks and offering nonjudgmental practice opportunities, it can also exacerbate it through webcam monitoring or uncertainty about accuracy and fair use [5,6]. These mechanisms help explain why seemingly similar AI features produce divergent outcomes across students and instructional contexts.

A human-centered design perspective naturally follows: AI should function as a regulative layer that tunes instructional conditions in response to psychologically interpretable signals, rather than as an oracle that replaces judgment. Practically, this implies a two-loop architecture. In the inner loop, affect-aware analytics and conversational scaffolds adjust task framing in real time-pacing, hinting, and exemplar selection-to regulate emotion, support metacognition, and sustain productive struggle [2,3,6]. In the outer loop, instructors and learners review aggregate patterns to recalibrate goals and redesign tasks, while adoption factors-perceived usefulness, effort expectancy, facilitating conditions, and anxiety-are addressed through onboarding, transparency, and opt-in controls over data capture [5,6]. Meta-analyses indicate that such integration is most effective when LLMs are embedded in assessment-for-learning routines (e.g., structured self-explanations, feedback comparison, reflective prompts) rather than used solely as answer generators [3,4].

This review makes three contributions. First, it synthesizes evidence from AER and affective-computing research to clarify when and how affective signals meaningfully inform pedagogical decisions, moving beyond detection accuracy to educational impact [2,6]. Second, it distills meta-analytic findings on LLM-based tutoring and feedback to identify design patterns that enhance engagement and learning transfer-structuring prompts for reasoning, constraining outputs to hints and exemplars, and pairing AI feedback with self-assessments to foster metacognitive monitoring [3,4]. Third, it integrates technology-adoption insights to explain variation in outcomes across learners and institutions, highlighting actionable levers-reducing anxiety via transparency and learner agency, and scaffolding self-efficacy through progressive help disclosure and autonomy-supportive prompts-that align with human-centered principles [5,6]. Throughout, case analyses illustrate the psychological mechanisms explicitly-for instance, contrasting emotion-informed versus generic pacing, or hint-first versus solution-first LLM dialogues-and tracing their downstream effects on cognitive load, persistence, and satisfaction.

In sum, AI in education is best conceptualized as a psychologically mediated intervention: its effectiveness depends on how it modulates learners' emotion, cognition, and motivation within context. By foregrounding these mechanisms, this review provides both theoretical grounding and practical guidance for designing the next generation of digital learning systems-systems that are not only intelligent but also empathetic, transparent, and learner-centered.

2. Literature Review

Recent scholarship converges on a clear theme: AI is no longer merely an instructional add-on but an integral component of students' everyday lifeworlds and institutional support systems. Empirical and review evidence in higher education suggests that, when embedded with structured care pathways and human oversight, AI can enhance student well-being and academic flourishing, while simultaneously reshaping teachers' roles and professional development requirements within a "dual-teacher" ecology (human teacher × machine teacher). This section synthesizes recent findings across four domains: (a) student well-being, (b) emotion/affect recognition for scalable triage, (c) generative-AI mental-health support, and (d) teacher capacity and governance.

A 2025 mini-review collates studies demonstrating that AI tools-ranging from writing and study assistants to analytics that surface learning risks-can bolster perceived academic efficacy and reduce stress by delivering timely, personalized support and low-friction access to resources [7]. At the same time, it cautions that uncritical or excessive reliance on AI may induce technostress and social displacement, particularly when AI substitutes rather than augments peer or teacher interaction. The implication for psychologically informed practice is clear: AI should function as an adjunct to human care, with transparent design, human checkpoints for sensitive decisions, and evaluation of well-being outcomes alongside academic metrics [7].

Two recent evidence maps examine how AI senses and models learners' emotions in classroom and online settings. A systematic review in Frontiers in Psychology documents multimodal pipelines-facial expression analysis, voice prosody, gaze/keystrokes, and interaction logs-integrated via classical machine learning and deep architectures to infer engagement, confusion, frustration, and boredom. Importantly, the review highlights limitations regarding ecological validity (lab tasks versus authentic classrooms), cross-cultural biases in training data, and inconsistent reporting of consent and privacy protocols [8]. A 2024 scoping review in Journal of Imaging complements this work by tracing the shift from single-modality facial classifiers toward real-time, multi-sensor fusion and temporal modeling, which better captures affective dynamics during the "messy middle" of learning, such as feedback and assessment loops. It emphasizes the need for interpretable features, calibration across devices and lighting conditions, and teacher-facing dashboards that translate affective cues into actionable pedagogical decisions (e.g., when to pause, regroup, or offer alternative explanations) [9]. Together, these reviews support the feasibility of emotion-aware analytics for cohort-scale triage, while underscoring that such systems must augment-not replace-teacher judgment [8,9].

Moving from sensing to intervention, an open trial with college students evaluated a generative-AI mental-wellness chatbot and found it feasible and acceptable for learners experiencing anxiety or depressive symptoms [10]. While the single-arm design precludes causal inference, the findings align with an emerging practice model: chatbots can serve as first-line, anonymous, always-available support that (i) provides psychoeducation and coping strategies, (ii) performs initial screening using validated scales, and (iii) routes at-risk students to human counselors through "warm handoffs." For institutions facing coverage gaps in traditional counseling, this adjunctive model reconciles scale with care; research priorities include randomized evaluations, safety monitoring, and equity analyses across subgroups [10].

The "dual-teacher" era introduces new considerations for roles, professionalism, and governance. A 2025 systematic review in Computers and Education: Artificial Intelligence synthesizes evidence on teacher adoption of AI and the professional development (PD) ecosystems required for effective orchestration [11]. It reports strong teacher interest in AI-assisted feedback, assessment, and lesson planning; early pilots of real-time analytics for classroom orchestration; and a persistent gap between teachers' PD needs (data literacy, prompt design, ethics) and available programs. The review argues that sustaining a "co-teaching" model-where AI acts as an assistive colleague-requires co-design with teachers and students, validation of analytics for reliability and fairness, and explicit governance regarding when to override AI recommendations, disclose AI use, and safeguard student data [11]. This framework maps neatly onto a triadic teacher-student-machine relationship and supports the broader shift toward collaborative, interaction-rich pedagogy.

Integrating these strands yields four design principles for psychologically informed AI-enabled education. First, adopt human-in-the-loop pipelines: emotion analytics should surface interpretable cues and uncertainty estimates, with teachers retaining decision authority [8,9,11]. Second, connect detection to support: couple affect sensing with tiered interventions (self-help content, nudges to peer/teacher contact, or referrals to counseling) to avoid "monitoring without care" [7,10]. Third, protect dignity and trust: implement privacy-preserving data practices, explicit consent, opt-out pathways, and bias audits, particularly for facial and voice analytics in diverse classrooms [8,9,11]. Fourth, invest in capacity and culture: align PD with authentic classroom tasks (feedback, differentiation, formative assessment) and recognize teachers' professional agency in shaping AI-supported learning [11].

In sum, current evidence suggests that AI can help institutions move beyond labor-intensive, low-coverage mental-health workflows toward proactive, scalable support, while deepening-not diminishing-the centrality of human relationships in learning. When framed as a supportive companion for students, an assistive colleague for teachers, and a carefully governed component of student-support ecosystems, AI has the potential to enhance both academic and psychological outcomes at scale.

3. Learner Psychological Adaptation in AI Education

3.1. Problem Landscape

Learners' psychological adaptation to AI-enhanced education is shaped by a complex interplay of challenges. Recent large-scale surveys and empirical studies highlight the key difficulties students face during this transition.

Concerns about academic integrity remain one of the most prominent barriers. According to Turnitin's 2025 international survey, over half of students-approximately 63%-explicitly consider submitting a fully AI-generated assignment as cheating [12]. This reflects a tension between students' recognition of AI's potential utility and their apprehension about violating academic norms. Such normative and ethical stress fosters hesitation and resistance, undermining trust in AI tools as legitimate learning aids.

Longitudinal research in UK higher education shows that students experience a mix of enthusiasm and unease when engaging with AI. While many incorporate generative AI into their coursework, they report significant anxiety regarding the rapid pace of technological change and the overwhelming diversity of available tools [13]. Students often worry that overreliance on AI could diminish the originality and quality of their work, and they emphasize the need for explicit, curriculum-embedded guidelines to support responsible use. Importantly, learners consistently note that "human connection remains essential," highlighting the relational gap left by automated systems [13]. These findings suggest that rapid technological adoption can increase cognitive load and destabilize emotional well-being, particularly when institutional support mechanisms are unclear.

Beyond perception and anxiety, insufficient practical competence constitutes another major barrier. Evidence indicates that although student interest in generative AI is high, many lack the skills required to apply it effectively [14]. In particular, students struggle with decomposing tasks, crafting effective prompts, and critically evaluating outputs. This gap creates a state best described as "using AI but not using it well," which undermines learning efficiency and diminishes self-efficacy, reinforcing cycles of frustration and underperformance.

Collectively, these three domains illustrate how learners' problem landscape is structured by distinct yet interconnected stressors. Normative and ethical pressures stem from concerns about cheating and academic misconduct [12]. Capacity and control pressures arise from insufficient skills to fully harness AI's potential [14]. Relational and emotional pressures reflect anxieties about information overload and the absence of meaningful interpersonal interaction [13]. These pressures interact, eroding learners' sense of agency, reducing sustained adoption of AI tools, and compromising both performance and well-being.

3.2. Determinants & Mechanisms

Learners' adaptation to AI in education is influenced by a complex interplay of factors operating across individual, technological, and contextual dimensions. Recent reviews provide a structured framework for analyzing these determinants and their effects on students' perceptions, behaviors, and outcomes [15,16].

At the individual level, demographic and psychological traits significantly shape adoption patterns. Younger learners tend to be more open to experimenting with emerging technologies, reflecting greater exposure to digital tools and lower resistance to change [15]. Learning preferences also affect adaptation: students who favor autonomous exploration and problem-based approaches are more likely to experiment with AI tools, whereas those who prefer structured, teacher-directed environments may approach AI more cautiously. Digital literacy and self-efficacy act as crucial mediators. Learners with strong ICT skills are more likely to have positive initial experiences with AI, reducing uncertainty and accelerating adaptation, whereas those with weaker competencies may struggle, reinforcing perceptions of difficulty and anxiety [15].

At the tool and task level, usability and transparency are decisive. Learners' engagement with AI is strongly influenced by perceived ease of use and usefulness [16]. Systems with intuitive interfaces, transparent processes, and timely feedback foster trust and reduce cognitive load, whereas opaque "black box" designs can increase skepticism. Personalization and interactivity further enhance learner comfort and motivation. AI tools that adapt to learners' goals and prior knowledge provide tailored support, helping to establish stable usage patterns and psychological ease. Similarly, systems that simulate interactive dialogue or offer responsive feedback help bridge the gap between human interaction and machine delivery, mitigating feelings of alienation [16].

The educational environment provides the context in which individual and system factors are enabled or constrained. Institutional culture and policy-such as clear academic integrity guidelines, curriculum integration strategies, and assessment frameworks-shape how students perceive risks and opportunities associated with AI adoption [16]. Explicit boundaries between ethical and unethical uses increase students' confidence in experimenting with AI tools. Teachers play a pivotal role: their attitudes, modeling, and scaffolding influence both immediate adoption and long-term metacognitive regulation.

Educators who demonstrate AI use in supportive ways empower students to develop effective strategies, while those who discourage or neglect AI may reinforce uncertainty and fear [15]. Disciplinary differences further shape adaptation. Students in computer science or AI-related programs, encountering AI tools in authentic, task-relevant contexts, adapt more quickly, whereas students in humanities or social sciences may prioritize ethical considerations and originality, leading to more cautious adoption [16].

Taken together, these factors operate along a conceptual pathway: individual traits × system characteristics × educational environment → shape learners' perceived usefulness, ease of use, and emotional responses (e.g., anxiety, curiosity, trust) → influence adoption intentions and usage strategies (e.g., integration into planning, prompt design, output evaluation) → feed back into learning outcomes and broader psychological adaptation, including self-efficacy, academic belonging, and well-being [15,16]. This cyclical pathway underscores that adaptation is dynamic, with feedback loops capable of amplifying positive experiences under supportive conditions or reinforcing resistance and anxiety when conditions are suboptimal.

4. Learners' Affective Feedback Studies

4.1. Multimodal Approaches in Affective Computing

Affective computing has emerged as a central component in the design of intelligent learning environments, providing systematic methods to capture and interpret learners' emotions through multiple data channels. Emotions are rarely expressed through a single modality; instead, they manifest simultaneously across facial expressions, speech, and digital interactions. By integrating these signals, multimodal affective computing aims to generate a more holistic and accurate understanding of learners' affective states, thereby enabling real-time, adaptive educational interventions.

Visual modalities are the most widely used in current practice. Cameras embedded in classrooms or online platforms can detect facial expressions such as frowning, smiling, or gaze aversion. These micro-expressions serve as reliable indicators of confusion, enjoyment, or distraction. Raised eyebrows, tightened lips, and gaze shifts can reveal cognitive overload or disengagement even in silent learners. In large or remote learning contexts, automated visual detection is particularly valuable, compensating for the lack of direct interpersonal observation.

Auditory modalities complement visual signals by analyzing speech features such as pitch, tone, tempo, and volume. Emotional states often manifest through vocal prosody, independently of spoken content. Excitement is typically reflected in higher pitch and faster tempo, whereas boredom or fatigue often appears in monotonous and slower speech. Integrating voice analytics into e-learning platforms offers a means to monitor engagement and motivation during discussions or oral participation.

Behavioral modalities provide an additional dimension, drawing from interaction logs such as keystroke dynamics, mouse clicks, touch gestures, and navigation patterns. Although primarily functional, these inputs can serve as proxies for affective states. For instance, rapid or forceful typing may indicate frustration, whereas long pauses or erratic cursor movements may suggest confusion or disengagement. When analyzed longitudinally, behavioral cues provide low-intrusion yet valuable insights into learner attention and persistence.

A practical example is iFLYTEK's "Zhixuewang" platform, which integrates facial recognition with behavioral interaction data to analyze students' affective states in real time. By synchronizing expression data with keystroke and mouse activity, the system delivers continuous, objective, and dynamic emotion tracking. This multimodal integration reduces reliance on subjective teacher observation and offers timely feedback loops that support adaptive learning strategies.

Recent empirical studies underscore the potential of multimodal approaches. Evidence demonstrates that real-time integration of facial expressions, body posture, and digital interaction logs can produce superior accuracy compared to single-channel methods [17]. Crucially, research highlights that emotion recognition is more robust when evaluated under authentic classroom conditions rather than in laboratory simulations.

At the same time, multimodal affective computing raises ethical concerns. The collection of sensitive data-including facial videos, voice signals, and behavioral logs-poses risks of misuse [18]. Privacy-preserving strategies such as differential privacy and encryption have been shown to maintain high recognition accuracy while substantially enhancing learner trust and willingness to engage with the system. This underscores the necessity of balancing technical advancement with responsible data governance.

In conclusion, multimodal affective computing enhances emotion recognition in education by integrating visual, auditory, and behavioral channels. This integration improves both the timeliness and accuracy of emotion detection, supporting personalized and adaptive learning beyond what human observation alone can achieve. Nevertheless, its effectiveness depends on careful attention to privacy, inclusivity, and ethical data use [17,18]. The ongoing challenge is to balance comprehensive affect sensing with the protection of learners' rights in increasingly data-driven educational environments [19].

4.2. Advantages and Limitations

The application of affective computing in educational contexts offers several significant advantages. Foremost among these is real-time emotional monitoring. Unlike traditional observational methods, which rely heavily on teachers' subjective interpretations and are limited in scale, affective computing systems provide continuous, objective insights into learners' emotional states. This objectivity improves the accuracy of feedback and ensures that interventions are timely and evidence-driven. Furthermore, the scalability of affective computing enables institutions to deploy these tools across large classes or entire online platforms, ensuring that every learner receives monitoring and support. In this way, affective computing fosters more inclusive and personalized learning pathways, enhancing both motivation and engagement [20].

Another key advantage is its capacity to reduce human bias. Teachers may unintentionally misinterpret learners' emotions due to personal assumptions, fatigue, or cultural differences. Automated affective systems can mitigate such bias by relying on algorithmic interpretations of multimodal data, including facial expressions, vocal cues, and behavioral inputs. This establishes a standardized approach to emotion recognition that, when properly calibrated, effectively complements human expertise.

Despite these benefits, several limitations warrant careful attention. A primary challenge lies in the detection of complex or mixed emotions. Emotional states are often layered-for instance, anxiety combined with anticipation-which can produce conflicting facial or behavioral signals. Current algorithms frequently misclassify such states, limiting interpretive depth and potentially resulting in inappropriate interventions. Technical challenges, such as facial occlusion, further complicate accurate recognition [21]. Although advanced feature-fusion and residual-attention network models improve robustness under occlusion, recognition accuracy still declines under non-ideal conditions. This highlights the need for models capable of adapting to diverse, real-world educational environments.

A second limitation involves special populations and inclusivity. Learners with speech impairments, mobility constraints, or cultural variations in emotional expression may fall outside the calibration range of current systems. In such cases, affective computing may produce biased or less reliable outcomes, raising concerns about fairness. Addressing this issue requires algorithms that are sensitive to cross-cultural differences and resilient to atypical or constrained input modalities.

Perhaps the most pressing concern relates to privacy and ethical considerations. Emotional data are inherently sensitive, reflecting deeply personal states. Learners have expressed concerns regarding how their cognitive-affective data are collected, visualized, and potentially misused [19]. Ethical risks include surveillance anxiety, stigmatization, and inadvertent disclosure of private feelings, which can undermine trust and acceptance-particularly in online learning environments where learners have limited control over data processing. Privacy-preserving strategies, such as differential privacy and federated learning, have demonstrated the potential to mitigate these risks while maintaining acceptable recognition accuracy [20]. Although some utility may be sacrificed, these approaches illustrate how technical solutions can balance performance with ethical responsibility, thereby enhancing learner confidence and the long-term sustainability of affective computing in education.

In summary, affective computing presents considerable promise for educational practice by enabling real-time, objective, and scalable emotional monitoring. Nonetheless, challenges remain, including accurate recognition of mixed emotions, inclusivity for diverse learner populations, and protection of privacy. Addressing these issues will require both technical innovations, such as more robust multimodal fusion architectures, and strong governance mechanisms to safeguard learners' rights. Current evidence indicates that the future success of affective computing in education depends not only on advancing algorithmic accuracy but also on achieving a careful balance between technological utility and ethical responsibility [19-21].

4.3. Key Findings and Emerging Patterns

Across successful implementations of AI in education, certain mechanisms consistently emerge as critical enablers of learner adaptation [22]. Progressive adaptation reduces barriers to initial engagement by providing structured entry points, such as "novice guidance modes" or scaffolded instructions [23]. These features gradually introduce learners to system functionality, decreasing cognitive load and facilitating a smoother transition into AI-mediated learning environments. Equally important are emotional compensation mechanisms [24,25]. When learners experience frustration-whether due to technical difficulties or performance setbacks-the system can respond by simplifying tasks, offering encouragement, or dynamically adjusting content difficulty. Research on multimodal emotion recognition indicates that accurate detection of affective states enables AI systems to deliver timely emotional compensation, thereby reinforcing both motivation and persistence [26]. Together, these mechanisms illustrate that psychological adaptation cannot be separated from affective engagement: sustainable AI use requires attention to both behavioral and emotional dimensions.

Conversely, failed cases often result from a combination of technical flaws and neglect of learner diversity. Errors such as speech misrecognition, unstable connectivity, or delayed system responses directly undermine trust in AI tools and provoke negative emotions such as frustration and anger. These responses not only reduce motivation but also prolong the adaptation cycle, decreasing the likelihood of continued engagement. Ignoring learner diversity further exacerbates these challenges. AI educational products that do not account for differences in age, cognitive pace, learning preferences, or accessibility needs create higher adaptation barriers [27]. Younger learners may struggle with complex interfaces, while older learners may find rapid digital interactions difficult to navigate. Research indicates that adopting human-centric explainable AI principles is essential for overcoming these barriers, as transparent and personalized explanations help diverse learners understand and trust AI-driven recommendations [28]. These findings highlight the necessity of technical robustness and inclusive design as prerequisites for effective AI education.

Recent advancements in educational AI suggest promising strategies to address these shortcomings, particularly through multimodal affective sensing and transparency-oriented design. Traditional single-channel emotion detection approaches-such as relying solely on facial expressions-often yield inaccurate results in real-world learning contexts. In contrast, multimodal methods integrate multiple data streams, including vocal tone, facial cues, and physiological signals such as heart rate or galvanic skin response, providing a more reliable and holistic assessment of learners' emotional states [26]. This enhanced capability allows systems to capture subtle emotional dynamics and deliver feedback better aligned with learners' needs.

At the same time, transparency has become a core principle in adaptive learning design. Rather than presenting opaque recommendations, AI tools increasingly explain the reasoning behind their actions, such as why a particular learning path was suggested or why task difficulty was adjusted. Data-centric multimodal explainable AI frameworks combine technical and human-centered explanations, enhancing learner trust and comprehension [27]. Furthermore, explanations tailored to individual learner profiles can mitigate resistance and reduce confusion, particularly for users less familiar with AI-driven systems [28].

In summary, the integration of progressive adaptation and emotional compensation explains why some AI education implementations succeed, while technical flaws and insufficient attention to learner diversity clarify why others falter. Emerging innovations—including multimodal emotion recognition [26], data-centric transparency frameworks [27], and human-centric explainability—provide robust strategies to address these challenges [28]. Collectively, they offer a forward-looking pathway for designing emotionally intelligent and psychologically adaptive AI systems capable of supporting sustainable learner engagement.

5. Conclusion

The convergence of AI, education, and psychology highlights both the transformative potential and the complex challenges of deploying intelligent systems in learning contexts. This review demonstrates that learners' psychological mechanisms-emotion, motivation, self-efficacy, and anxiety-are not peripheral factors but central mediators of AI intervention outcomes. Evidence from affect-aware analytics indicates that emotional signals can meaningfully inform pedagogical decisions, but only when interpreted responsibly and embedded within human-centered feedback loops. Similarly, large language model-powered tutors have proven effective in enhancing engagement and learning performance, yet their benefits depend on scaffolding strategies that promote learner agency rather than cognitive dependence.

Adoption studies further underscore that student diversity, usability, and institutional culture shape adaptation trajectories as much as technical design. Concerns over academic integrity, technostress, and privacy remain significant barriers to trust and long-term sustainability. Case analyses show that mechanisms such as emotional compensation, progressive adaptation, and transparent explainability are decisive for maintaining engagement across age groups, cultural contexts, and learning domains. Conversely, technical flaws, opaque system designs, or neglect of inclusivity undermine learners' confidence and exacerbate cognitive and emotional strain.

Looking forward, the most promising innovations lie in multimodal affective sensing, transparency frameworks, and explainable AI tailored to diverse learners. However, technological advances must be accompanied by ethical governance, including privacy-preserving mechanisms, opt-in data practices, and professional development ecosystems that enable teachers to orchestrate AI alongside pedagogy. By adopting a human-centered stance, AI can evolve from a set of tools into a psychologically adaptive layer of education-supporting well-being, sustaining motivation, and enriching learning at scale.

In sum, the future of AI in education hinges on designing systems that are not only intelligent but also empathetic, transparent, and learner-centered. Aligning technological innovation with psychological insight and ethical responsibility allows educational AI to move beyond efficiency, fostering resilience, agency, and flourishing among learners worldwide.

References

1. L. Yang, “The evolution of ballet pedagogy: A study of traditional and contemporary approaches,” *Journal of Literature and Arts Research*, vol. 2, no. 2, pp. 1–10, 2025, doi: 10.71222/2nw5qw82.
2. S. Yu, A. Androsov, H. Yan, and Y. Chen, "Bridging computer and education sciences: A systematic review of automated emotion recognition in online learning environments," *Computers & Education*, vol. 220, p. 105111, 2024. doi: 10.1016/j.compedu.2024.105111.
3. Y. M. E. Heung, and T. K. Chiu, "How ChatGPT impacts student engagement from a systematic review and meta-analysis study," *Computers and Education: Artificial Intelligence*, vol. 8, p. 100361, 2025. doi: 10.1016/j.caeai.2025.100361.
4. R. Deng, M. Jiang, X. Yu, Y. Lu, and S. Liu, "Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies," *Computers & Education*, vol. 227, p. 105224, 2025. doi: 10.1016/j.compedu.2024.105224.
5. T. Budhathoki, A. Zirar, E. T. Njoya, and A. Timsina, "ChatGPT adoption and anxiety: a cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT)," *Studies in Higher Education*, vol. 49, no. 5, pp. 831-846, 2024. doi: 10.1080/03075079.2024.2333937.
6. R. Yuvaraj, R. Mittal, A. A. Prince, and J. S. Huang, "Affective Computing for Learning in Education: A Systematic Review and Bibliometric Analysis," *Education Sciences*, vol. 15, no. 1, p. 65, 2025. doi: 10.3390/educsci15010065.
7. B. Klimova, and M. Pikhart, "Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review," *Frontiers in Psychology*, vol. 16, p. 1498132, 2025. doi: 10.3389/fpsyg.2025.1498132.
8. A. O. R. Vistorte, A. Deroncele-Acosta, J. L. M. Ayala, A. Barrasa, C. López-Granero, and M. Martí-González, "Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review," *Frontiers in psychology*, vol. 15, p. 1387089, 2024. doi: 10.3389/fpsyg.2024.1387089.
9. C. Llurba, and R. Palau, "Real-Time Emotion Recognition for Improving the Teaching-Learning Process: A Scoping Review," *Journal of Imaging*, vol. 10, no. 12, p. 313, 2024. doi: 10.3390/jimaging10120313.
10. J. A. Reyes-Portillo, A. So, K. McAlister, C. Nicodemus, A. Golden, C. Jacobson, and J. Huberty, "Generative AI-Powered Mental Wellness Chatbot for College Student Mental Wellness: Open Trial," *JMIR Formative Research*, vol. 9, no. 1, p. e71923, 2025.
11. X. Tan, G. Cheng, and M. H. Ling, "Artificial intelligence in teaching and teacher professional development: A systematic review," *Computers and Education: Artificial Intelligence*, vol. 8, p. 100355, 2025. doi: 10.1016/j.caeai.2024.100355.
12. R. Haubt, "AI in Education Writing and the Role of Turnitin,".
13. J. Fisher, L. K. Falk, and M. Mittelman, "STUDENT PERCEPTIONS OF AI IN UNIVERSITY STUDIES," *Journal of International Business Disciplines*, vol. 20, no. 1, 2025.
14. A. Almassaad, H. Alajlan, and R. Alebaikan, "Student perceptions of generative artificial intelligence: Investigating utilization, benefits, and challenges in higher education," *Systems*, vol. 12, no. 10, p. 385, 2024. doi: 10.3390/systems12100385.
15. S. Shifa, S. Hameed, H. Suhail, and A. Kiren, "Emotional Intelligence Meets Artificial Intelligence Affective Computing and Student Well-Being Online Classrooms," *The critical review of social sciences studies*, vol. 3, no. 3, pp. 271-289, 2025.
16. O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education-where are the educators?," *International journal of educational technology in higher education*, vol. 16, no. 1, pp. 1-27, 2019.
17. A. Kapoor, and R. W. Picard, "Multimodal affect recognition in learning environments," In *Proceedings of the 13th annual ACM international conference on Multimedia*, November, 2005, pp. 677-682. doi: 10.1145/1101149.1101300.
18. E. Benamar Hilal, "Understanding Private Tutoring Online Platforms: A Deep Dive into Online Education Marketplaces," 2025.
19. V. M. Corza-Vargas, R. Martinez-Maldonado, B. Escalante-Ramirez, and J. Olveres, "Students' Ethical, Privacy, Design, and Cultural Perspectives on Visualizing Cognitive-Affective States in Online Learning," *Journal of Learning Analytics*, vol. 11, no. 3, pp. 24-40, 2024.
20. M. Benouis, E. Andre, and Y. S. Can, "Balancing Between Privacy and Utility for Affect Recognition Using Multitask Learning in Differential Privacy-Added Federated Learning Settings: Quantitative Study," *JMIR Mental Health*, vol. 11, no. 1, p. e60003, 2024.
21. Y. Chen, S. Liu, D. Zhao, and W. Ji, "Occlusion facial expression recognition based on feature fusion residual attention network," *Frontiers in Neurorobotics*, vol. 17, p. 1250706, 2023. doi: 10.3389/fnbot.2023.1250706.
22. P. D. Simon, and L. M. Zeng, "Behind the scenes of adaptive learning: A scoping review of teachers' perspectives on the use of adaptive learning technologies," *Education Sciences*, vol. 14, no. 12, p. 1413, 2024.
23. Z. Salma, R. Hijón-Neira, C. Pizarro, and A. Abdul Moqeet, "Effectiveness of Robot-Mediated Learning in Fostering Children's Social and Cognitive Development," *Applied Sciences*, vol. 15, no. 7, p. 3567, 2025. doi: 10.20944/preprints202503.0634.v1.
24. J. Wang, and W. Fan, "The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: insights from a meta-analysis," *Humanities and Social Sciences Communications*, vol. 12, no. 1, pp. 1-21, 2025. doi: 10.1057/s41599-025-04787-y.
25. N. Kosmyna, E. Hauptmann, Y. T. Yuan, J. Situ, X. H. Liao, A. V. Beresnitzky, and P. Maes, "Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task," *arXiv preprint arXiv:2506.08872*, vol. 4, 2025.

26. Y. Wu, Q. Mi, and T. Gao, "A comprehensive review of multimodal emotion recognition: Techniques, challenges, and future directions," *Biomimetics*, vol. 10, no. 7, p. 418, 2025. doi: 10.3390/biomimetics10070418.
27. M. Mosleh, M. Devlin, and E. Solaiman, "Transparent Adaptive Learning via Data-Centric Multimodal Explainable AI," *arXiv preprint arXiv:2508.00665*, 2025.
28. S. Maity, and A. Deroy, "Human-Centric eXplainable AI in Education," *arXiv preprint arXiv:2410.19822*, 2024. doi: 10.35542/osf.io/k5u9b.