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Article

Studies on How Generative AI Can Adaptively Respond to the Affective Needs of Learners: A Systematic Literature Review

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Abstract: Generative Artificial Intelligence (GenAI) has become increasingly prominent in education, providing adaptive and personalized support for learners. While prior studies have emphasized cognitive benefits such as knowledge retention and problem-solving, the affective dimensions of learning — motivation, engagement, confidence, and emotional regulation — remain comparatively underexamined. This paper presents an updated systematic literature review (SLR) on how GenAI adaptively responds to the affective needs of learners. Following PRISMA 2020 guidelines, ten peer-reviewed core studies published between 2020 and 2024 were analyzed in depth, and their findings were triangulated against thirty additional supporting sources spanning affective computing, motivational theory, mental-health-oriented chatbot research, and AI governance, for a total of forty cited references. Findings reveal five major themes: affective signal detection and adaptive feedback, reinforcement-based motivation pathways, integration of GenAI with social-emotional learning (SEL) frameworks, personalization and scaffolding strategies, and system-level governance considerations. The review identifies persistent gaps, including a scarcity of causal evidence linking affective adaptation to long-term outcomes, heavy reliance on unimodal (mostly textual) affect-sensing techniques, and underexplored teacher readiness and ethical governance structures. The paper concludes by proposing a conceptual framework for affect-adaptive GenAI and recommending longitudinal, mixed-methods research to validate and extend its role in building emotionally intelligent digital learning environments.

Keywords: Generative AI, Affective Computing, Adaptive Learning, Motivation, Engagement, Social-Emotional Learning, Systematic Literature Review

1. Introduction

Learning has never been a purely cognitive act. Decades of educational psychology research show that emotional states such as anxiety, boredom, curiosity, and confidence shape whether learners persist, disengage, or thrive [37], [38]. Motivational theories such as self-determination theory frame sustained engagement as dependent on learners' sense of autonomy, competence, and relatedness [39], while control-value theory links achievement emotions directly to learning outcomes [38]. Despite this well-established evidence base, most educational technology research — including the rapidly growing literature on Generative AI (GenAI) — has historically centered on cognitive metrics such as accuracy, retention, and task completion, leaving the affective dimension comparatively underexplored.

The emergence of large language model (LLM)-based tools such as ChatGPT has changed the scale and nature of learner–AI interaction. Unlike earlier rule-based intelligent tutoring systems, GenAI tools can generate contextually rich, conversational, and seemingly empathetic responses in real time [11], [15]. This raises an important question for educational research and practice: can GenAI systems reliably detect and adaptively respond to learners' affective states in ways that support motivation, confidence, and emotional wellbeing, without introducing new risks such as over-reliance or diminished human connection [16]? This review synthesizes the empirical and conceptual literature addressing this question.

2. Objectives of the Review

This review was conducted with the following objectives:

- To identify affect-adaptive mechanisms employed in GenAI-based educational systems.
- To examine the affective outcomes reported in existing studies (e.g., motivation, engagement, confidence, anxiety, and belonging).
- To analyze the research methodologies used to evaluate affective responsiveness in GenAI-based learning environments.
- To situate core empirical findings within the broader body of affective-computing, motivational, and governance literature.
- To identify key research gaps and propose future directions and a conceptual framework for affect-adaptive GenAI research.

3. Methodology

3.1 Review Protocol

The review followed PRISMA 2020 guidelines to ensure transparency and replicability in study identification, screening, and synthesis.

3.2 Search Strategy

Databases searched: Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Search queries included combinations such as "Generative AI" AND "education" AND "affective"; "AI tutor" AND "motivation OR engagement OR emotion"; and "Generative Artificial Intelligence" AND "adaptive learning."

3.3 Inclusion and Exclusion Criteria

Inclusion: peer-reviewed articles published between 2020–2024, focused on GenAI in education, with explicit reference to affective or motivational outcomes.

Exclusion: non-generative AI studies, purely cognitive-focused papers, editorials, and non-peer-reviewed works.

3.4 Study Selection

From an initial pool of 84 records, duplicates were removed and titles/abstracts were screened, yielding 29 articles for full-text assessment. Ten studies satisfied all inclusion criteria and were retained as the core evidence base for thematic synthesis (Figure 1).

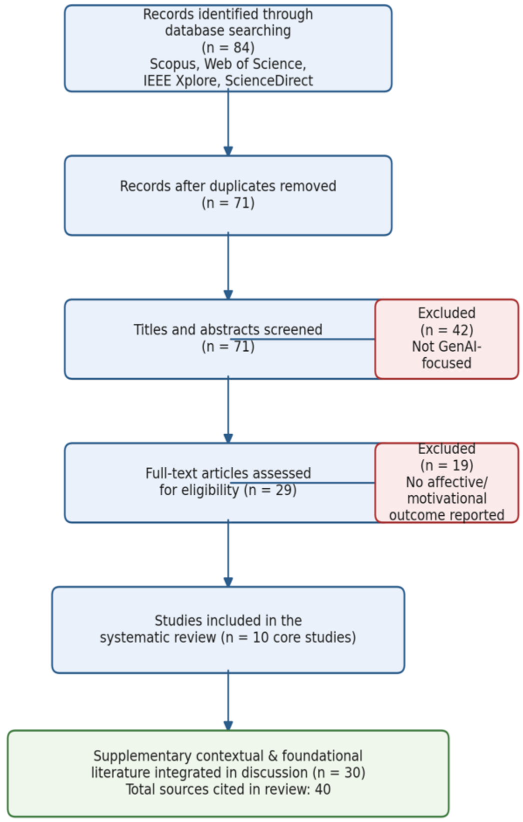

Figure 1. PRISMA 2020 flow diagram of the study identification and selection process.

3.5 Supplementary Literature Integration

Because affective computing and GenAI-in-education research spans multiple disciplines (educational psychology, human–computer interaction, and AI ethics), the ten core studies were supplemented with thirty additional peer-reviewed and institutional sources identified through targeted searches on affect detection, motivational theory, chatbot-mediated emotional support, and AI governance. This narrative-synthesis layer, common in interdisciplinary SLRs, allows the ten core empirical studies to be interpreted against a wider evidentiary and theoretical backdrop. In total, forty sources are cited throughout this review.

3.6 Data Extraction

For each core study, data were extracted on: authors and year, research focus and methodology, affective outcomes measured, and key findings and limitations. Supplementary sources were coded by thematic category (affect detection, motivation theory, wellbeing, governance, or personalization) to support narrative synthesis.

4. Results

4.1 Thematic Findings

4.1.1 Affective Signal Detection and Adaptive Feedback

A qualitative study on language education found that GenAI-generated feedback reduced learner anxiety and fostered a sense of emotional belonging through empathetic language [1]. This finding is consistent with a broader body of affective-computing research showing that both textual and multimodal signals — including facial expression, voice, posture, and physiological data — can be used to infer learner affect and drive adaptive responses [24], [25]. Deep-learning approaches to facial expression recognition have been applied to track student engagement in real time during online learning [26], [29], while multimodal fusion techniques combining heart-rate, acoustic, and behavioral data have improved recognition of concentration, confusion, and frustration beyond what any single modality can achieve [25], [27], [28]. Sentiment analysis of open-text student feedback using NLP and deep learning further illustrates how textual affect signals alone can support instructional decision-making [30]. Collectively, this literature suggests GenAI systems are currently better positioned to exploit textual and conversational affect cues than the richer multimodal signals used in specialized affective tutoring systems [23].

4.1.2 Reinforcement and Motivation Pathways

Yang [2] demonstrated that reinforcement-based adaptive strategies enhanced both cognitive and affective engagement, while context-personalized tasks increased motivation and performance [10]. These results align with self-determination theory, which holds that motivation is strengthened when learners experience autonomy, competence, and relatedness [39], and with control-value theory, which links positive achievement emotions to sustained engagement [38]. However, larger-scale syntheses caution that motivational gains are not automatic: a meta-analysis of GenAI interventions found effects on academic performance to be positive but heterogeneous across study designs [13], and research on so-called "metacognitive laziness" suggests that over-reliance on GenAI can, under some conditions, undermine self-regulated motivation and processing depth [14]. This tension — between reinforcement-driven motivational gains and the risk of passive over-reliance — is an important nuance for affect-adaptive system design.

4.1.3 Integration with Social-Emotional Learning (SEL)

A critical literature review highlighted the importance of embedding GenAI within SEL frameworks to promote ethical and responsible emotional engagement, identifying teacher oversight as a critical safeguard [3]. This resonates with foundational SEL and community-based learning theory, including the Community of Inquiry model, which frames social, cognitive, and teaching presence as jointly necessary for meaningful online learning [40]. Institutional guidance from UNESCO and the OECD likewise stresses human-centered design and teacher preparation as prerequisites for responsible affective AI use in classrooms [33], [34].

4.1.4 Personalization and Scaffolding

Postgraduate students with strong digital adaptability reported increased confidence and engagement when using GenAI [4], while scaffolding strategies were found to reduce frustration and support self-directed learning [5]. Personalized integration of GenAI into the Community of Inquiry model enhanced social, teaching, and cognitive presence in digital classrooms [6]. These findings extend classical scaffolding theory into GenAI contexts and are corroborated by controlled studies showing that adaptive, AI-generated feedback increased the depth of pre-service teachers' reflective engagement [32], and by bibliometric evidence of moderate-to-strong positive effects of GenAI on engagement across educational settings more broadly [31].

4.1.5 System-Level, Meta-Analytic, and Emotional-Wellbeing Perspectives

A systems-level analysis emphasized the need for governance and responsible adoption of GenAI in e-learning [8], while a meta-analysis confirmed cognitive benefits of GenAI and suggested that affective adaptations could further amplify outcomes [9]. Responsible development of automated feedback systems remains a key challenge [7]. Broader syntheses reinforce this picture: a systematic review of empirical GenAI-in-education research found substantial coverage of engagement and motivation outcomes but comparatively little causal evidence [11], and a large-scale meta-analysis similarly reported medium-to-large effects of GenAI on affective outcomes while calling for more rigorous experimental designs [12]. At the same time, an emerging body of work on GenAI chatbots and student wellbeing complicates a purely positive narrative: chatbot-mediated support has been associated with reduced anxiety and stronger perceived emotional support in several studies [16], [18], [19], yet other work finds that socially anxious students may over-rely on AI companionship in ways that risk greater emotional distress over time, and that chatbot use can simultaneously enhance personalized assistance while diminishing a sense of human connection [16], [17]. Domain-specific studies, such as ChatGPT-integrated nursing education, report improved motivation and knowledge retention relative to traditional lectures [20]. These wellbeing findings, together with survey evidence of AI-related anxiety among secondary school students [21] and evidence that structured chatbot-mediated writing tasks can strengthen learners' emotional-intelligence subscales [22], underscore the need for the ethical, pilot-tested governance frameworks discussed in Section 6, including assessment scales for responsible GenAI integration [35] and systematic reviews of regulatory challenges [36].

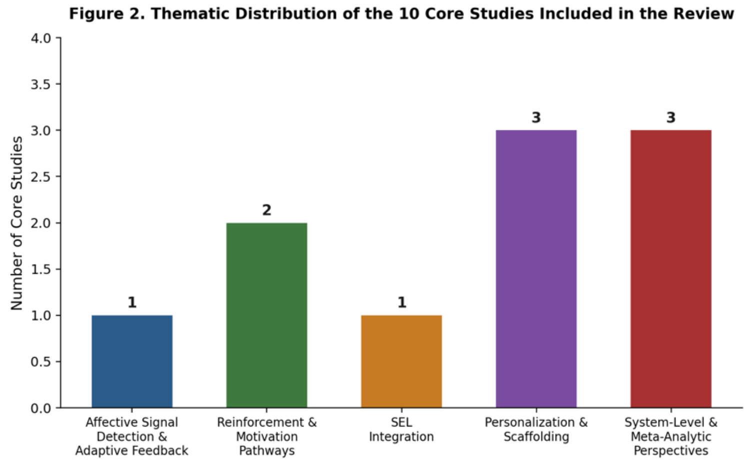

Figure 2. Thematic distribution of the ten core studies included in the systematic review.

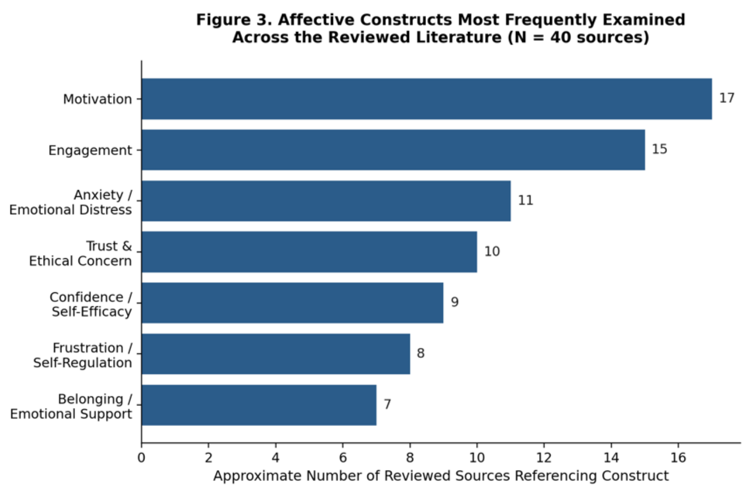

Figure 3. Approximate frequency with which key affective constructs are examined across the 40 reviewed sources, illustrating the relative research emphasis on motivation and engagement compared with wellbeing- and trust-related constructs.

4.2 Summary Table of Core Included Studies

#	Study / Focus	Method	Affective Outcomes	Key Findings	Ref
1	Enhancing Emotional Aspects (2023) — Language education	Qualitative	Anxiety, belonging	GenAI feedback reduced anxiety and enhanced belonging	[1]
2	Yang (2024) — Reinforcement & motivation	Experimental	Engagement, retention	Reinforcement-based strategies improved motivation and	[2]

				cognitive engagement	
3	SEL & GenAI (2023) — Teacher education	Literature review	SEL readiness	Teacher oversight essential for ethical affective use of GenAI	[3]
4	Postgraduate Adaptability (2024) — Higher education	Survey	Academic confidence, adaptability	Digital adaptability improved confidence with GenAI	[4]
5	Scaffolding Perspectives (2024) — Self-directed learning	Case study	Motivation, frustration	Scaffolding reduced frustration and boosted self-regulation	[5]
6	CoI Personalization (2024) — Digital classrooms	Conceptual framework	Engagement, collaboration	Personalization improved social and cognitive presence	[6]
7	Responsible Feedback (2024) — AI feedback	Framework	Trust, usability	Need for transparent, responsible GenAI feedback	[7]
8	Systems View (2024) — E-learning outcomes	Systems analysis	Governance, ethics	Calls for systemic governance models	[8]
9	Meta-analysis (2024) — Student outcomes	Meta-analysis	Motivation, performance	GenAI improved outcomes; affective benefits remain underexplored	[9]
10	GenAI in Classroom (2024) — Personalized tasks	Experimental	Motivation, performance	Context personalization enhanced motivation	[10]

Table 1. Summary of the ten core studies included in the systematic review.

4.3 Supplementary Literature by Category

Category	**Focus of Supporting Literature**	**Representative References**
Affect Detection & Sensing	NLP sentiment analysis, multimodal facial/voice/physiological affect recognition, affective tutoring systems	[23]–[30]
Motivation & Engagement Theory	Reinforcement theory, self-determination theory, control-value theory, metacognitive laziness	[13], [14], [38], [39]
Emotional Wellbeing & Mental Health	Chatbot-mediated emotional support, anxiety reduction, risks of over-reliance	[16]–[22]

Ethics & Governance	Institutional policy, teacher readiness, ethical assessment frameworks	[33]–[36]
Personalization, Scaffolding & SEL Foundations	Scaffolding theory, Community of Inquiry model, bibliometric reviews	[31], [32], [37], [40]
Meta-Analytic & System-Level Syntheses	Large-scale reviews and meta-analyses of GenAI's cognitive and affective impact	[11], [12], [15]

Table 2. Categorization of the thirty supplementary sources used for narrative synthesis and theoretical grounding.

5. Discussion

The synthesis indicates that GenAI can positively influence learners' emotional states through empathy, scaffolding, and personalization [1], [4], [5], [6]. However, when the ten core studies are read alongside the broader supporting literature, the overall evidence base appears fragmented and mostly exploratory rather than confirmatory. Reinforcement strategies and personalized learning tasks emerge as particularly effective for motivation [2], [10], [39], while scaffolding strategies reduce frustration and promote self-regulation [5], [32]. At the same time, the wellbeing literature introduces an important counterweight: the same conversational qualities that make GenAI feel emotionally responsive can also foster over-reliance or a diminished sense of human connection for some learners [16], [17].

A second cross-cutting observation concerns measurement. Most core studies rely on self-report surveys or qualitative interviews to capture affective states [1], [3], [4], while the specialized affective-computing literature has developed considerably more granular, multimodal measurement techniques [23]–[30]. This suggests an opportunity: affect-adaptive GenAI systems could be substantially strengthened by incorporating lightweight multimodal or behavioral affect-sensing signals rather than relying solely on text-based inference.

Future research must move beyond short-term experimental studies toward longitudinal, mixed-methods approaches that evaluate both immediate and sustained affective outcomes [9], [11], [12]. Moreover, the role of educators in supervising and guiding affect-adaptive GenAI cannot be overstated, especially in addressing ethical risks around data privacy, bias, and emotional manipulation [3], [33], [34], [35], [36].

6. Research Gaps

- Lack of causal evidence directly linking affective adaptations to learning outcomes [9], [11], [12].
- Limited reliance on multimodal affect sensing; most GenAI-in-education studies use only textual cues, in contrast to the specialized affective-computing literature [23]–[30].
- Few studies measure long-term outcomes such as resilience and persistence beyond a single semester or intervention [13], [14].
- Insufficient focus on teacher readiness and ethical governance structures for affect-adaptive systems [33]–[36].
- Learner dispositions such as reward sensitivity and digital adaptability remain underexplored as moderators of affective response [2], [4].
- Limited understanding of when affective adaptation helps versus when it fosters unhealthy over-reliance or reduced human connection [16], [17].

7. Proposed Conceptual Framework for Affect-Adaptive GenAI

Building on the thematic synthesis above, this review proposes a conceptual framework describing how affect-adaptive GenAI systems could be structured (Figure 4). Learner input — including text, behavioral signals, and performance data — first passes through an affective signal detection layer that draws on sentiment analysis and, where available, multimodal cues [23], [24], [30]. Detected affective states then inform adaptive response generation, in which the GenAI system produces empathetic feedback and scaffolding tailored to the learner's emotional and cognitive state [1], [5], [32]. This feeds into a personalization and SEL-aligned intervention layer that draws on social-emotional learning principles and the Community of Inquiry model [3], [40]. The framework distinguishes between resulting cognitive learning outcomes and affective outcomes such as motivation, confidence, and resilience [9], [39], while situating the entire pipeline within an overarching layer of ethical governance, teacher oversight, and privacy safeguards [33], [34], [35].

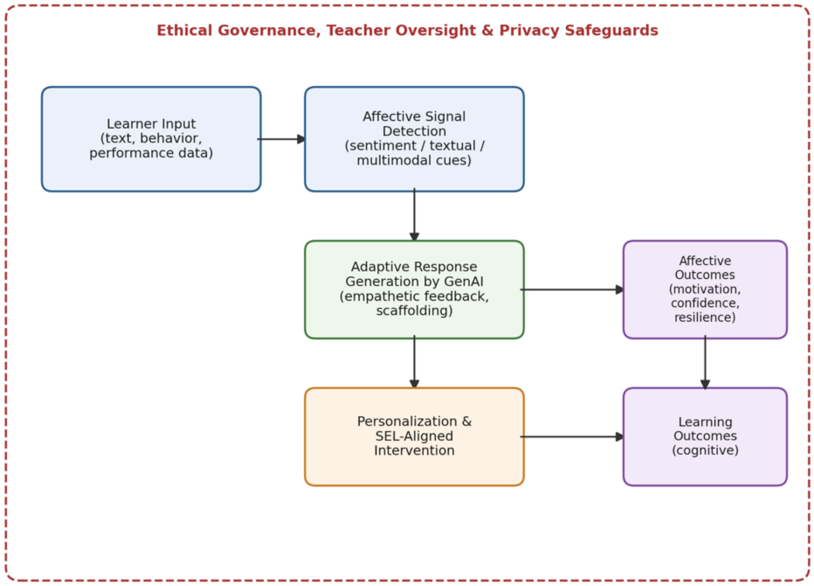

Figure 4. Proposed conceptual framework for affect-adaptive Generative AI in education.

8. Implications for Practice and Policy

For practitioners, the findings suggest that GenAI tools are most beneficial for learner affect when paired with explicit scaffolding and teacher oversight rather than deployed as a stand-alone substitute for human support [3], [5], [32]. For developers, the review highlights the value of incorporating richer affect-sensing techniques beyond text, informed by the mature affective-computing literature [23]–[30]. For policymakers and institutions, the emerging governance frameworks reviewed here — including UNESCO guidance, OECD analyses, and assessment scales such as the AIAS — provide a starting point for developing institution-specific policies on affect-adaptive GenAI use that protect learner privacy and wellbeing [33], [34], [35], [36].

9. Limitations of This Review

This review is limited by the small number of core studies (n = 10) meeting strict inclusion criteria, reflecting the relative novelty of affect-adaptive GenAI as a distinct research area. The thirty supplementary sources were selected to provide theoretical and contextual grounding rather than through an independent systematic search protocol, and the construct-frequency figures presented in Section 4 are illustrative approximations intended to convey relative emphasis in the literature rather than precise bibliometric counts. Future systematic reviews with larger core samples and formal meta-analytic techniques are needed to validate the patterns identified here.

10. Conclusion

This SLR reveals that while GenAI shows strong potential for affect-adaptive learning support, evidence is still limited and fragmented. By consolidating findings across ten core studies and thirty supporting sources, this review highlights the need for stronger empirical designs, multimodal affect sensing, and ethical governance frameworks. Ultimately, GenAI has the capacity to become an emotionally intelligent tutor that not only enhances cognition but also nurtures motivation, resilience, and engagement in learners — provided its development and deployment remain grounded in sound pedagogy, empirical evidence, and human oversight [1]–[40].

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