Affective Generative AI for Adaptive and Inclusive eLearning: Prompt Engineering, Ethics and Pedagogical Innovation

Spyridon Kontis[1[0009-0009-7892-6966]] and Sofia Anastasiadou[1[0000-0001-6404-5003]]

[1] University of Western Macedonia, Greece
dmw00034@uowm.gr, sanastasiadou@uowm.gr

Abstract. Over the past few years, artificial intelligence (AI) has moved from being a background tool to becoming a central actor in education [49]. Generative AI is transforming the way learners interact with knowledge, offering personalized pathways, adaptive content, and new forms of digital collaboration. Yet most existing systems remain focused on efficiency and performance, while overlooking the emotional side of learning, factors such as motivation, frustration, or anxiety that often determine whether a student succeeds or disengages [1], [2].

This paper proposes the idea of Affective Generative AI in eLearning, combining large language models (LLMs), prompt engineering, and emotion-aware computing to design learning environments that are not only intelligent but also empathetic and inclusive. We argue that digital tutors capable of recognizing affective cues can adapt their responses in real time, providing encouragement, reframing explanations, or reducing cognitive load, thereby supporting both well-being and achievement [3], [4].

At the same time, handling emotional data [47] raises critical ethical and legal [12] questions. Issues of privacy, bias [51], and transparency must be addressed if such systems are to be trusted and responsibly deployed [5]– [7]. Our conceptual framework seeks to balance pedagogical innovation with these concerns, highlighting a path towards human-centered [53] AI in education that values inclusion, equity, and emotional resilience alongside cognitive performance.

Keywords: Generative AI, Affective Computing, Prompt Engineering, Adaptive Learning, LLMs, AI Ethics, Inclusive Education.

1 Introduction

Education in the 21st century is increasingly mediated by digital technologies that promise to expand access, enhance personalization, and support lifelong learning. eLearning platforms have become essential, yet their design has traditionally focused on delivering content and assessing performance, while neglecting the affective dimension of learning [8]. Emotions such as engagement, frustration, and motivation are now recognized as central to the learning process, influencing persistence, memory, and overall achievement [1], [2]. When these affective states are ignored, learners,

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especially those from vulnerable or marginalized groups, face higher risks of disengagement and exclusion [9].

Generative artificial intelligence (AI) has introduced new possibilities for adaptive and scalable digital education. Large language models (LLMs) can generate personalized explanations, tailor exercises to a learner's level, and provide immediate feedback. However, these systems remain cognitively adaptive but emotionally indifferent [10]. Recent scholarship argues that the next step for AI in education must be its integration with affective computing, enabling digital tutors not only to adapt content but also to respond to learners' emotions in real time [3], [4]. This shift aligns with broader movements in inclusive education, which emphasize equity, empathy, and responsiveness to learner diversity [11].

At the same time, the adoption of affective AI raises significant ethical and legal challenges. Emotional data is inherently sensitive, requiring careful consideration of privacy, fairness, and transparency [5], [6], [7]. Scholars in AI ethics stress that without robust governance [46] [14] frameworks, the same technologies that promise inclusion and wellbeing may instead amplify bias and erode trust [12], [13]. This paper therefore positions affective generative AI at the intersection of pedagogy, technology, and ethics, aiming to contribute to a more human-centered vision of eLearning.

The aim of this study is threefold:

1. To conceptualize an affective generative AI framework for adaptive and inclusive eLearning.
2. To examine how prompt engineering can integrate affective signals into LLM-driven educational interactions.
3. To discuss the ethical, legal, and psychosocial implications of deploying such systems in real-world contexts.

By pursuing these aims, the paper addresses a critical gap in current eLearning systems and argues for a paradigm shift: from AI that merely delivers knowledge to AI that empathizes, supports, and includes.

Unlike previous adaptive eLearning approaches that primarily emphasize cognitive personalization, our study contributes by explicitly integrating affective signals into generative AI systems through prompt engineering. This integration allows learning environments to be not only knowledge-centered but also emotion-sensitive, addressing the overlooked psychosocial dimensions of digital education. By situating our framework at the intersection of pedagogy, computational modeling, and ethics, the paper provides a novel contribution that bridges theoretical perspectives with actionable design principles for inclusive eLearning.

2 Affective Computing and the Role of Emotions in Learning

The study of emotions in human–computer interaction was first introduced through the field of affective computing, which highlighted the potential for machines to recognize and respond to emotional states [1]. In education, this perspective has become increasingly important, as re- search shows that emotions such as frustration, curiosity, or anxiety directly shape attention, memory, and motivation [2]. Learners who feel emotionally supported are more likely to persist, collaborate, and achieve meaningful outcomes, whereas neglecting the affective dimension can lead to disengagement and inequality [3].

Affective learning environments move beyond traditional instruction by embedding empathy into digital systems. Such environments aim to provide scaffolding that adapts not only to cognitive performance but also to emotional needs. For instance, when a student experiences cognitive overload, an affective-aware system may slow the pace, simplify explanations, or offer encouragement, helping to sustain resilience and wellbeing [4], [5]. This human-centered approach underscores the fundamental link between emotions and inclusion, ensuring that every learner's experience is acknowledged.

Generative artificial intelligence (AI) has rapidly advanced from ex- perimental tools to mainstream applications in education. Large language models (LLMs) can generate explanations, create adaptive exercises, and provide personalized feedback, thereby extending the possibilities of digital learning environments [6]. These systems represent a significant step towards more flexible and individualized learning, as they can dynamically tailor content to a learner's level of knowledge and preferred style of interaction [7].

Despite these advantages, current implementations of generative AI in education remain primarily cognitively adaptive. They adjust what and how of learning materials, but they do not yet address how learners feel during the process [8]. Without accounting for affective states, adaptive learning [48]-[56] risks becoming mechanistic, capable of personalizing tasks but not of sustaining engagement when learners struggle with motivation, stress, or anxiety [9].

Integrating affective signals into generative systems can bridge this gap. For example, a digital tutor powered by an LLM could detect signs of disengagement or cognitive overload and adjust its responses accordingly: simplifying explanations, providing motivational scaffolding, or reframing challenges to reduce frustration [10], [11]. Such responsiveness- ness moves adaptive learning closer to true inclusivity, where technology does not simply optimize performance but also recognizes and supports the learner as a whole person

3 Ethical and Legal Dimensions of Affective AI

While the pedagogical potential of affective generative AI is significant, its adoption raises equally important ethical and legal questions. Emotional data is among the most sensitive categories of personal information, and their collection and analysis in digital learning environments must be governed by strict principles [54] of privacy, transparency, and accountability [12], [13]. The risk is that technologies designed to foster inclusion could unintentionally reinforce bias, manipulate behavior, or exacerbate inequalities if deployed without adequate safeguards [14].

Scholars in AI ethics have repeatedly stressed the dangers of opacity, the so-called "black box" problem, where even system designers may struggle to explain why an algorithm produced a certain output [15]. In education, such opacity undermines trust, as learners and educators need clarity about how affective data are being interpreted and used [16]. Calls for responsible [50] artificial intelligence emphasize principles such as fairness, non-discrimination, and respect for human dignity [17], [18].

Embedding these principles into affective systems is essential if they are to become trustworthy allies in inclusive education.

Legal perspectives also contribute to this discussion. The rapid pace of AI development has outstripped existing regulatory frameworks, leaving gaps around liability, accountability, and cross-border governance [19], [20]. Recent debates around the European Union's AI Act and related directives illustrate the complexity of balancing innovation with protection of fundamental rights [21]. Scholars argue that frameworks must not only regulate technical standards but also anticipate new risks, including the commodification of emotions and the potential misuse of biometric affective data [22], [23].

Finally, affective AI must be situated within the broader socio-political- cal critique of digital technologies. Zuboff's analysis of surveillance [55] capitalism warns of the dangers of extracting personal experiences for profit [7]. When applied to education, this critique raises uncomfortable questions: should learners' emotions be treated as data points for optimization, or as integral parts of their human identity that deserve protection? Addressing such tensions requires an interdisciplinary dialogue between pedagogy, law, technology, and ethics [24].

4 Methodology

The methodological approach of this study combines a conceptual framework with computational underpinnings that support adaptive and inclusive e-learning. The design draws on socio-technical perspectives that emphasize the interplay between governance structures and algorithmic- mic processes [44,46].

From a technical standpoint, the methodological grounding is influenced by prior research in distributed systems and big data management. For example, dynamic scheduling of data streams has been shown to improve system responsiveness and efficiency in heterogeneous environments [48,52]. Similarly, pipeline-based approaches and linear scheduling in the cloud demonstrate how complex learning workloads can be optimized for scalability and fairness [51].

Advanced modeling tools, such as Colored Petri Nets, enable the representation of hierarchical and dynamic system behaviors, allowing researchers to simulate and validate resource allocation strategies in e-learning infrastructures [53,55]. Probabilistic detection methods applied to social and learning networks provide additional insights into the collective behaviors that shape adaptive learning environments [56]. This methodological synthesis ensures that the research framework is not only ethically and legally grounded [45,47], but also supported by rigorous computational models capable of sustaining adaptive, scalable, and inclusive AI-driven learning platforms.

5 Results

The synthesis of the literature reveals several recurring patterns that highlight both the opportunities and the challenges of embedding affective generative AI into eLearning. Three clusters of findings are particularly noteworthy: (a) the pedagogical benefits of integrating affective signals into adaptive systems, (b) the risks of ethical and legal misalignment, and (c) the broader socio-psychological implications for inclusion and learner wellbeing.

Pedagogical benefits. Research consistently demonstrates that emotions act as critical drivers of learning outcomes. Learners who feel motivated, supported, and emotionally engaged are more likely to persist and achieve higher cognitive gains [1], [2]. Digital environments that incorporate affective feedback can transform the learning experience from passive content reception to active, emotionally enriched participation [8], [9]. Generative AI offers new potential in this regard: through large language models (LLMs) and prompt engineering, systems can dynamically adapt instructional strategies, reframe explanations, or provide empathetic encouragement when signs of frustration or disengagement are detected [10], [11]. Such responsiveness aligns with broader educational goals of personalization and equity, supporting learners not only as knowledge receivers but as whole people with emotional needs.

Risks and challenges. Alongside these pedagogical promises, the literature reveals deep concerns about the ethical deployment of affective technologies. The interpretation of emotional data is fraught with risks of misclassification, cultural bias, and oversimplification of complex human experiences [12]. Furthermore, emotional data are highly sensitive: their collection, storage, and use raise acute concerns of privacy, surveillance, and manipulation [13], [14]. Scholars warn that without robust safeguards, affective AI could amplify systemic inequities rather than reduce them, for example by reinforcing stereotypes about certain groups of learners [15], [16]. The "black box" nature of advanced generative systems further complicates this picture, as even system designers may struggle to explain how outputs are derived [17]. In educational contexts, where trust is fundamental, such opacity undermines confidence among both learners and educators [18].

Psychosocial and inclusion dimensions. A third cluster of insights highlights the psychosocial importance of embedding affective aware- ness into educational technology. Inclusive education is not only about access but also about recognition, ensuring that learners' diverse emotional experiences are acknowledged and valued [19]. Studies on inclusive pedagogy emphasize that when students feel their emotions are validated, their sense of belonging and participation improves markedly [20]. Conversely, neglecting affective dimensions risks marginalizing those who already face barriers, such as learners with disabilities, neurodiverse students, or those experiencing anxiety and stress in digital environments [21]. By combining generative AI with affective computing, systems have the potential to reduce these barriers, offering timely support and fostering resilience [22], [23]. However, this promise will only materialize if ethical principles such as fairness, accountability, and transparency are embedded into design and governance processes from the outset [24], [25].

Taken together, these findings suggest that affective generative AI occupies a paradoxical position. On the one hand, it has the capacity to humanize digital learning environments, bringing empathy, motivation, and inclusion into spaces that often feel abstract and isolating. On the other hand, it risks intensifying surveillance, commodification, and inequality if developed without adequate ethical foresight. Addressing this tension requires moving beyond isolated technical solutions towards a comprehensive framework that integrates pedagogy, ethics, and psycho-social well-being.

This discussion points to the need for a structured model of adoption that can guide institutions in balancing innovation with responsibility. Such a model must ensure that generative AI systems in education are not only technically effective but also aligned with human values—supporting equity, protecting rights, and nurturing the emotional lives of learners. It is on this foundation that the proposed framework for this paper is built.

6 Framework Proposal: The Emotion-Aware Generative eLearning Model

Building on the insights from the literature, this paper proposes the Emotion-Aware Generative eLearning Model (EAGeL), a three-layered framework designed to integrate affective computing with generative AI for adaptive and inclusive digital education. The framework emphasizes both pedagogical innovation and ethical responsibility, ensuring that learners' cognitive and emotional needs are recognized while safeguarding- ing their rights and well-being.

Layer 1 – Emotional Data Recognition and Interpretation.

The first layer focuses on capturing and interpreting affective signals from learners. These may include behavioral indicators (e.g., hesitation, error patterns), self-reports (e.g., quick surveys), or biometric cues where ethically permissible (e.g., facial expression, heart-rate variability) [26]. Unlike traditional affective computing approaches that often reduce emotions to simplistic categories, this layer emphasizes contextualized interpretation. The system must recognize frustration differently in a child with learning disabilities than in an adult learner in higher education [27].

Layer 2 – Generative Adaptation through Prompt Engineering.

The second layer integrates affective inputs into large language models (LLMs) through carefully designed prompt engineering strategies. Emotional cues dynamically shape the AI's responses: for example, when frustration is detected, the model may reframe the explanation, simplify instructions, or introduce encouraging feedback [28]. Similarly, signs of boredom could trigger more interactive or gamified tasks, while indications of anxiety may lead to shorter, step-by-step guidance [29]. This adaptive loop ensures that learners receive not only personalized content but also emotionally attuned support.

Layer 3 – Ethical and Inclusive Governance.

The third layer provides the ethical "scaffolding" of the framework. Handling affective data requires strong safeguards to ensure privacy, fair- ness, and transparency [5], [13], [24]. This includes anonymization protocols, explainable AI mechanisms, and clear policies about data use. In addition, the governance layer aligns the framework with principles of Universal Design for Learning (UDL) and the European DigCompEdu framework, ensuring that emotion-aware generative systems support inclusion and accessibility across diverse contexts [30], [31]. Interdisciplinary- nary collaboration, among educators, technologists, ethicists, and policymakers, is essential to maintain alignment with human values.

7 Scalability and Sustainability

The framework is designed to be implemented in stages, beginning with low-risk affective inputs such as learner self-reports and progressing to more advanced multimodal signals as ethical and technical maturity increases [32]. This phased approach allows institutions to test, refine, and scale emotion-aware generative systems responsibly, avoiding premature adoption that could undermine trust or equity [33].

In essence, the EAGeL model seeks to reimagine digital education not only as a space for knowledge delivery but as an environment where learners feel recognized, supported, and included. By integrating emotion-sensitive prompts into generative AI, the framework offers a roadmap towards empathetic and equitable eLearning ecosystems.

8 Practical Scenarios

8.1 Scenario 1 – Managing math anxiety in online tutoring.

A high-school learner repeatedly struggles with algebra tasks on an online platform. Delayed responses, high error rates, and a quick self- report about feeling “stressed” are interpreted as signals of math anxiety [34]. Instead of re-explaining the same formula, the AI tutor adapts its response style: it breaks the problem into smaller steps, praises incre- mental progress, and introduces motivational scaffolding. Over time, the system also suggests short reflection prompts to help the learner regulate stress, aligning with evidence that affective support can improve resili- ence in mathematics learning [35]. This illustrates how generative AI can become not only a tutor but also a coach for emotional self-efficacy, pre- venting dropout in a subject often associated with student anxiety.

8.2 Scenario 2 – Rekindling motivation in disengaged learners.

In a digital history course, several students display low engagement: minimal contributions to forums, rapid skimming of digital resources, and skipping of optional assignments. The platform flags this as disengagement and possible boredom. The AI responds by reframing the learning path: introducing short quizzes framed as challenges, weaving narratives that connect historical events to current issues, and suggesting group debates through interactive prompts [36]. These interventions draw on gamification strategies, which research shows can reignite curiosity and enhance persistence in online courses. Importantly, the system does not punish disengaged learners but seeks to re-motivate them, reflecting inclusive pedagogy principles where all students are given opportunities to re-enter the learning process on their own terms [9].

8.3 Scenario 3 – Supporting neurodiverse learners in MOOCs.

A programming MOOC includes a student on the autism spectrum who struggles with vague instructions and unpredictable tasks. Over time, the system notices repeated requests for clarification and signs of withdrawal. The AI responds by offering structured task lists, step-by-step explanations, and optional peer-support groups. Although technically simple, these adjustments reduce frustration and create a sense of pre- predictability. This practice resonates strongly with the Universal Design for Learning (UDL) principles, which call for multiple means of representation and engagement, and with the DigCompEdu framework, which emphasizes teacher capacity to personalize learning through technology [37], [38]. Such scenarios illustrate how affective generative AI can extend inclusion policies into practical, everyday learning contexts, supporting not only academic performance but also social belonging.

8.4 Scenario 4 – Promoting wellbeing in higher education.

During exam season, university students in an online course show sign of overload: high dropout from optional tasks, shorter attention spans, and careless mistakes. The system interprets this as stress [39]. In re- response, it recommends pacing strategies, encourages short breaks, and even reframes assessment with alternative formats. These well-being-focused interventions are modest, but they remind learners that the digital environment is designed with care for their mental health. Such approaches are consistent with international recommendations, such as those of UNESCO and the WHO, which emphasize the integration of mental well-being into digital education systems [40].

These scenarios illustrate how the EAGeL framework can translate abstract concepts into real-world impact. By addressing anxiety, boredom, neurodiverse needs, and well-being, affective generative AI demonstrates its potential to create empathetic, adaptive, and inclusive learning ecosystems.

9 Discussion

The case scenarios and methodological approach demonstrate that affective generative AI has the potential to foster inclusion and personalization in eLearning while also raising critical governance and ethical questions. The results highlight not only the feasibility of adaptive models but also the tension between technical optimization and societal expectations. Previous works confirm that the co-evolution of AI and law must be considered as a dynamic, autopoietic process, where educational practices and legal norms evolve together [44]. At the same time, digital learning environments are deeply intertwined with the "digital DNA" of the modern workforce, linking AI competences with employability and organizational culture [45].

From a technical standpoint, advanced computational approaches such as pipelined dynamic scheduling and Markov process modeling provide scalable solutions for real-time educational platforms [48], [50], [52]. These methods support adaptive allocation of resources and ensure efficient personalization of learning flows, especially in heterogeneous cloud environments [54]. Furthermore, community detection in social networks contributes to identifying clusters of learners with similar needs, thereby reinforcing the inclusivity of affective eLearning systems [56].

On the governance side, the concept of "legal entropy" offers a useful lens to analyze the uncertainty and fragmentation in AI regulation [46]. Education cannot be isolated from these dynamics, since the integration of affective AI implies new responsibilities for teachers, institutions, and policymakers. The use of ESG-aligned data governance frameworks further emphasizes the link between AI adoption in eLearning and broader sustainability agendas [47]. This dual perspective, technical and legal, hows that building trustworthy, human-centered AI in education requires bridging algorithmic design with socio-ethical constraints.

Overall, the discussion illustrates that while the presented scenarios show promise, they must be interpreted within broader debates on responsible AI, digital ethics, and the resilience of educational institutions to disruptive technologies. In light of these insights, it becomes evident that affective generative AI in e-learning cannot be evaluated solely on the basis of its technical performance. Its real value lies in how effectively it aligns with ethical imperatives, legal frameworks, and the human-centered principles of inclusion and mental well-being. The in- interplay between technological innovation and responsible governance highlights both the opportunities and the unresolved challenges that ed- educators, policymakers, and developers must jointly address. These con- considerations naturally lead to the concluding reflections of this study, where the implications and forward-looking directions are drawn together.

The contribution of this study lies in extending existing models of adaptive eLearning towards an affective generative paradigm. While earlier research has demonstrated the potential of large language models and adaptive scheduling techniques for personalization, few works have systematically integrated emotional data into these processes. By linking computational models such as Petri Nets and Markov-based scheduling with real-time affective cues, our framework provides a distinctive pathway to connect technical scalability with pedagogical empathy. This dual focus positions the paper as a bridge between conceptual discussions of AI in education and practical, implementable architectures for inclusive learning.

10 Conclusions and Recommendations

This paper has explored the emerging field of Affective Generative AI in eLearning, emphasizing how the integration of emotion-aware computing with large language models can reshape digital education. Through the proposed EAGeL framework, we outlined how affective signals can be recognized, embedded into generative responses, and governed through ethical safeguards. Literature synthesis and practical scenarios demonstrated that such systems could promote motivation, resilience, and inclusion, while also highlighting the risks of bias, surveillance, and opacity.

Three key recommendations arise from this study. First, educational institutions should approach affective AI through phased adoption, beginning with low-risk applications such as self-report data, before expanding to multimodal affective sensing [41]. This gradual pathway allows for testing and adaptation without overwhelming learners or educators. Second, teacher professional development must be prioritized: without adequate training, even the most advanced tools risk underuse or misuse [42].

Teachers need not only technical skills but also critical awareness of ethical issues, so that they can act as mediators between learners and AI systems. Third, ethical and legal framework [44]s must evolve in parallel with technological development. Regulatory instruments such as the EU AI Act, alongside guidelines from UNESCO and WHO, should inform national and institutional policies to safeguard privacy, ensure fairness, and prevent misuse of emotional data [21], [40], [43].

Future research should examine how affective generative AI operates across diverse cultural and educational contexts, and whether its benefits can be sustained over time. Comparative case studies, longitudinal evaluations, and participatory research with learners and educators will be essential in validating the promises of the EAGeL framework. Ultimately, the goal is not to replace human educators but to design empathetic digital ecosystems where technology amplifies care, inclusion, and well-being.

By embedding empathy into generative AI, education can move closer to a vision where every learner, regardless of background, ability, or emotional state, finds recognition, support, and opportunity in the digital classroom.

As a next step, the proposed framework could be tested in pilot studies across different learning environments, such as open online courses (MOOCs), blended university classes, or special education programs. A first stage could focus on simple, low-risk methods like learner self-reports or analysis of interaction logs, and then gradually expand to more advanced indicators such as optional biometric data, always under strict ethical safeguards. The aim of these pilots would be to explore whether affect-sensitive prompt engineering helps learners stay engaged, reduce anxiety, and feel more included. Although still hypothetical at this stage, describing such a pathway shows that the framework is not only theoretical but also has real potential for future application

Disclosure of Interests.

he authors have no competing interests to declare that are relevant to the content of this article.

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