REVIEW OF ARTIFICIAL INTELLIGENCE IN EDUCATION

DOI: https://doi.org/10.37497/rev.artif.intell.educ.v7ii.99

ARTICLE

MOTIVATING LEARNERS THROUGH PSYCHOLOGY-INFORMED LANGUAGE MODELS

Motivando Aprendizes por Meio de Modelos de Linguagem Informados pela Psicologia

Edward T. Vieira, Jr.
School of Management, Simmons University (Boston, MA, USA)
E-mail: edward.vieira@simmons.edu

Yulong Li
School of Management, Simmons University (Boston, MA, USA)
E-mail: yulong.li@simmons.edu

ABSTRACT | Purpose: This article proposes a psychology-informed conceptual architecture for large language model (LLM)-supported learner interaction. The purpose is to move educational LLMs beyond primarily transactional responses toward relational and transformational engagement that supports motivation, persistence, reflection, and conceptual growth. **Research methods:** The article uses conceptual analysis and theory integration. It synthesizes research on LLM use in education, Self-Determination Theory, empathy, cognitive dissonance reduction, intelligent tutoring systems, learner profiling, and adaptive feedback to develop a three-layer learner-engagement model. **Findings:** The proposed architecture includes three interacting layers: a Psychological Processes Layer, a Recognition Layer, and a Response Generation Layer. These layers are supported by a learner profile module that preserves continuity across interactions. Together, the model enables LLMs to recognize learner goals, preferences, emotions, and tensions; select motivational and empathic strategies; and generate adaptive, scaffolded, and reflective responses. **Discussion:** The framework suggests that psychologically informed LLMs can function as more authentic tutors or coaches by supporting autonomy, competence, relatedness, emotional safety, and productive cognitive conflict. The model has implications for K–12 education, higher education, workplace learning, AI literacy, responsible implementation, and future empirical research on learner-facing AI systems.

Keywords | Large language models; learner engagement; Self-Determination Theory; empathy; cognitive dissonance reduction; educational technology.

Qualis B1 2021-2024 CAPES

Indexed in ANPAD SPELL

GUEST PAPER
Received: 18 May 2026
Revised: 19 May 2026
Accepted: 20 May 2026
e-ISSN: 2965-4688

Corresponding Author:
Edward T. Vieira, Jr – E-mail: edward.vieira@simmons.edu

How to cite this article: Vieira, E., & Li, Y. (2026). Motivating Learners Through Psychology-Informed Language Models. *Review of Artificial Intelligence in Education,* 7(i), e099. https://doi.org/10.37497/rev.artif.intell.educ.v7ii.99

RESUMO | Objetivo: Este artigo propõe uma arquitetura conceitual, fundamentada em princípios psicológicos, para a interação entre aprendizes e modelos de linguagem de grande escala (LLMs). O objetivo é deslocar os LLMs educacionais de respostas predominantemente transacionais para formas de engajamento relacional e transformacional que apoiem motivação, persistência, reflexão e crescimento conceitual. **Métodos de pesquisa:** O artigo utiliza análise conceitual e integração teórica. Sintetiza pesquisas sobre o uso de LLMs na educação, Teoria da Autodeterminação, empatia, redução da dissonância cognitiva, sistemas tutoriais inteligentes, perfil do aprendiz e feedback adaptativo para desenvolver um modelo de engajamento do aprendiz em três camadas. **Resultados:** A arquitetura proposta inclui três camadas interativas: uma Camada de Processos Psicológicos, uma Camada de Reconhecimento e uma Camada de Geração de Respostas. Essas camadas são apoiadas por um módulo de perfil do aprendiz que preserva a continuidade entre interações. Em conjunto, o modelo permite que os LLMs reconheçam objetivos, preferências, emoções e tensões do aprendiz; selecionem estratégias motivacionais e empáticas; e gerem respostas adaptativas, estruturadas e reflexivas. **Discussão:** O modelo sugere que LLMs psicologicamente informados podem atuar como tutores ou orientadores mais autênticos, apoiando autonomia, competência, relacionamento, segurança emocional e conflito cognitivo produtivo. A estrutura tem implicações para educação básica, ensino superior, aprendizagem profissional, alfabetização em IA, implementação responsável e futuras pesquisas empíricas.

Palavras-chave | Modelos de linguagem de grande escala; engajamento do aprendiz; Teoria da Autodeterminação; empatia; dissonância cognitiva; tecnologia educacional.

INTRODUCTION

Artificial intelligence systems and especially large language models (LLMs) are increasingly deployed in education, professional training, and lifelong learning contexts (Rismanchian & Doroudi, 2025; UNESCO, 2025). We focus on LLMs defined as "… a class of pretrained neural networks scaled in both parameters and training data that enables broad-capability language understanding and generation across tasks" (Kalyan & Subramanyam, 2023). In other words, it is an artificial intelligence system trained on massive text datasets to generate, summarize, translate, understand, and predict human-language content (Kirvan & Kerner, 2025). The human interface enables interaction through plain or conversational text, allowing users to communicate with the system much as they would with another person (Graesser, 2016).

Learner interaction with LLMs may be conceptualized in three forms. Transactional interaction focuses on information exchange and immediate task completion. Relational interaction emphasizes recognition, encouragement, and connection. Transformational interaction goes further by supporting meaningful change in understanding, perspective, motivation, or self-development. A well-designed LLM can reduce learning friction by a balanced integration of these three types of interaction. However, current LLM systems used in education, which often function as tutors, assistants, guides, data analysts, or programmers, primarily emphasize transactional responsiveness, with limited evidence that everyday AI use has yet become relationally or pedagogically transformational (Bos et al., 2025).

The key difference between transactional responsiveness and transformational engagement lies in depth and intent of the communication. Transactional responsiveness is reactive and exchange-based, focusing on meeting immediate needs or expectations with clear, efficient responses, while transformational engagement is proactive and motivational, aiming to inspire intrinsic commitment, growth, and deeper connection. In other words, transactional responsiveness resolves surface-level interactions by providing what is asked for, whereas transformational engagement seeks to reshape perspectives and foster long-term enthusiasm, creativity, and alignment with broader knowledge goals. Therefore, most LLMs provide answers but do not sustain motivation; they deliver feedback but not meaningful growth. To move beyond such limitations and to facilitate learning, LLM systems for education should be designed with theories of human motivation and development at their core. This conclusion is supported by LLM usage and reported issues presented in the extant research (Tasdelen & Bodemer, 2025).

EMPIRICAL FOUNDATIONS FOR LLM ENGAGEMENT

In a structural equation modeling study of 226 university students who utilized LLMs in their coursework, Ngo, Vo, and Phan (2025) found that perceived trust and ease of use positively influenced students' attitudes toward using LLMs. Consequently, these attitudes had a significant positive effect on their intentions for initial adoption as well as long-term usage.

There appears to be a general pattern in goals for using LLMs notwithstanding an individual's professional background. The Sleegers, Elsey, and Moss (2025) study of 2,000 professionals found that the top three common uses for LLMs were: Search (72%), Explanation (56%), and Writing (56%). Seventy-five percent reported that LLMs made them more productive. The findings also suggest that reducing cognitive effort and providing flexible support for knowledge-intensive work are key factors driving LLM adoption and continued use.

A study of 114 students by Tasdelen and Bodemer (2025) found that context-personalized learning and tasks were associated with greater intrinsic motivation, interest, and learning outcomes compared to standard generic approaches.

Mejia-Domenzain and colleagues (2025) investigated how personalized content influences user learning and engagement through RELEX, an adaptive example-based learning platform for procedural writing. In a controlled experiment with 200 participants, the researchers compared personalized versus static examples. They found that users who received personalized content revised their work more frequently, produced higher-quality writing, and reported a more positive learning experience than those who received generic feedback. The findings suggest that personalization, achieved through example retrieval and adaptive annotation, enhances both writing performance and learner satisfaction by aligning instructional content with individual needs and abilities.

A review of 118 publications by Yan et al. (2023) found that approximately 75% of studied participants actively used LLMs. A consistent finding across these studies was that trust in LLM outputs is a significant factor influencing adoption. To explain users' limited trust, the authors identified fact-checking as a major concern, underscoring the importance of system reliability in educational applications. Additional common concerns reported across the studies included "low technological readiness" and a "lack of replicability and transparency."

These findings collectively indicate that relational interaction, personalization, and trust are critical yet remain underexplored dimensions in LLM-mediated learning. This conclusion is consistent with evidence that undergraduate students perceive generative artificial intelligence as a useful academic support tool, while also differing substantially in their trust, ethical judgments, and concerns about whether AI use constitutes cheating (Basch et al., 2025). With this in mind, we argue for an LLM learner-interaction architecture grounded in Self-Determination Theory (SDT), empathy (both cognitive and affective), and cognitive dissonance reduction. SDT emphasizes the psychological needs of autonomy, competence, and relatedness (Deci & Ryan, 2000). Empathy equips LLMs to recognize and respond to learner cognitive and affective information processing, while dissonance reduction enables systems to successfully guide learners through internal conflicts and effectively face challenges associated with learning new and complex content (Jung et al., 2025). Together, these frameworks can transform LLMs into an *authentic coach and tutor.* It is a partner that not only answers questions but motivates, scaffolds, and cultivates learner growth.

To operationalize these concepts, we propose a three-layer architecture supported by a learner profile module. The architecture comprises:

1. **Psychological Processes Layer:** guides motivational and empathic strategy selection based on SDT, empathy, and cognitive dissonance reduction;
2. **Recognition Layer:** detects learner input, identifies goals, preferences, emotions, and potential tensions or cognitive dissonance; and
3. **Response Generation Layer:** produces adaptive, learner-facing feedback while drawing on the learner profile module to support continuity across prompts and sessions. Working together, this architecture produces adaptive feedback, personalized choices, and scaffolded support in natural language, along with any other output relevant to the learner's prompt.

This design has multiple merits. It supports sustained motivation and engagement, personalizes interaction at psychological and emotional levels, and leverages dissonance as a driver of conceptual change. Furthermore, it addresses challenges of authenticity (How genuine the interaction feels to learners.), scalability, and learner trust (Do learners believe the LLM to be reliable and helpful?) (Ngo, Vo, & Phan, 2025).

The sections below elaborate the theoretical foundations and practical implications of integrating Self-Determination Theory (SDT), empathy, and cognitive dissonance reduction (CDR) into LLM architectures for learner interaction. We begin by examining SDT, empathy, and CDR, highlighting their importance in education and their relevance to LLM-supported engagement. Together, these three frameworks underpin the proposed conceptual foundation. Building on this base, we then introduce a three-layer LLM architecture for learner interaction and present the LLM Learner Engagement Model, which operationalizes these concepts to support learner motivation, interaction, and outcomes. This article is a conceptual framework paper intended to inform the design of learner-facing LLM systems and to guide future empirical work in digital education.

CONCEPTUAL FRAMEWORK

Self-Determination Theory in LLM Learning Systems

Self-Determination Theory or SDT, developed by Deci and Ryan (2000), is one of the most influential frameworks for understanding human motivation. It posits that individuals thrive when three basic psychological needs are met: autonomy (the sense of volition and choice), competence (the feeling of mastery and effectiveness), and relatedness (the sense of connection with others).

When these needs are satisfied, learners are more intrinsically motivated, persist longer, and demonstrate greater creativity and well-being (Ryan & Deci, 2020), which contrasts with traditional systems that only emphasize performance outcomes (Deci et al., 1999). LLMs designed with SDT in mind can create conditions where learners experience the fulfillment of these needs while interacting with the system.

Autonomy

For *autonomy*, LLMs can provide meaningful choices in how learners engage—for example, by offering different problem-solving strategies, learning modalities (visual, textual, interactive), or pacing options in the privacy of their own environments. Studies on learner-centered design show that giving learners structured choices increases their sense of agency and enhances long-term motivation (Shen & Cui, 2024; Xia, et al., 2022).

Competence

For *competence*, LLMs can deliver scaffolded feedback. For example, instead of a binary "right/wrong," an LLM could respond: "You've mastered the first two steps; let's refine the third one together." This approach builds learners' self-efficacy and reinforces the perception that effort leads to improvement. Empirical evidence suggests that competence-oriented feedback enhances persistence in challenging learning tasks (Shen & Cui, 2024; Singh & Ab Aziz, 2025; Wang et al., 2024).

Relatedness

For *relatedness*, LLMs can employ empathic language and continuity across sessions to make learners feel recognized and connected. Even simulated social presence has been shown to increase learner engagement and satisfaction. In one study, LLM tutors that incorporated relational cues (such as remembering past struggles and offering encouragement) led to higher learner trust and perceived support compared to non-relational systems (Li et al., 2025).

Embedding SDT into LLM architecture can facilitate an increased level of intrinsic motivation and relational interactions. This deeper internalization is essential for lifelong learning, where external motivators may be inconsistent or absent (Zhou et al., 2024). By aligning with SDT, LLM architectures can thus sustain quality engagement far beyond short-term tasks thus moving toward engagement that is transformational.

Empathy in LLM Learning Systems

While SDT provides the motivational blueprint for learning, LLMs can complement this by demonstrating perceptions of empathy and *relational sensitivity,* enabling authentic responses. In other words, empathy reinforces learner's sense of relatedness. Empathy can be conceptualized in two dimensions: *cognitive empathy* (the capacity to understand, think, and respond to a learner's rational perspective) and *affective empathy* (the capacity to understand, feel, and respond to a learner's emotional perspective) (Vieira, 2014). In human-based teaching, empathy is strongly correlated with a learner's perception of instructor credibility (trust and competence), persistence, and openness to challenges (Cornelius-White, 2007). Extending these insights to LLMs requires simulating empathic recognition and responsiveness to foster meaningful learner engagement.

LLMs can simulate cognitive empathy through natural language processing and sentiment analysis. For example, when a learner types, "I don't think I'll ever understand statistics," the system can detect negative sentiment, identify the self-efficacy challenge, and respond with tailored encouragement, such as "I know this feels difficult, but remember last week when you solved a similar regression problem—let's build on that success." Affective empathy can be approximated by adjusting tone, pacing, and phrasing to respond to the learner's emotional state such as offering calm, reassuring language when frustration is detected, or using energizing language when enthusiasm wanes.

Evidence suggests that empathic LLM tutors increase engagement quality and self-efficacy. For instance, in a controlled study, students who interacted with an LLM tutor displaying empathic cues reported significantly higher levels of motivation and trust compared to those working with a neutral tutor (Li et al., 2025). Empathy also helps satisfy SDT's need for relatedness. These findings suggest that although it is not a human teacher, empathic responsiveness of LLMs creates a sense of being understood, which fosters emotional safety and willingness to persevere both desired expectations in human relationships (D'Mello & Graesser, 2012; Kestin et al., 2025; Yin et al., 2025).

The merits of integrating empathy lie in the system's ability to shift from *transactional* to *relational* interaction. Traditional tutoring systems respond to queries with information. Empathic systems respond with understanding, encouragement, and adaptive support. This relational orientation strengthens learner persistence and helps prevent disengagement when challenges arise (De Gennaro et al., 2020; Fernandez-Herrero, 2024; Sharma et al., 2022).

Cognitive Dissonance Reduction in LLMs

The third pillar of the proposed conceptual framework is *cognitive dissonance reduction* or CDR. Festinger's (1957) theory of cognitive dissonance describes the discomfort people feel when they hold contradictory beliefs or when new evidence conflicts with existing attitudes and/or behaviors.

Individuals reduce the discomfort by sufficiently reconciling the dissonance through any number of strategies, such as changing one of the dissonant conditions, modifying their behaviors to align with beliefs, or seeking consonant information. In education, such dissonance is common. Students may simultaneously believe "I am not good at math" while earning good grades, or they may encounter new scientific concepts that conflict with deeply held intuitions. In educational settings, instructors can help students recognize and work through tensions between prior assumptions and new information. Such guided cognitive conflict can support conceptual change when learners become dissatisfied with existing conceptions and are able to see a new conception as intelligible, plausible, and useful (Posner et al., 1982; Cooper, 2019).

In LLM contexts, dissonance often surfaces when learners express frustration, doubt, or conflicting self-perceptions. An LLM system capable of detecting these conflicts can turn them into teachable moments. For example, a learner who insists, "I'll never understand probability," after solving several related problems presents clear cognitive dissonance. The learner's belief about incompetence conflicts with actual evidence of competence. An LLM "tutor" that acknowledges this dissonance can help the learner reframe self-perceptions by responding: "You say you cannot understand probability, but last session you successfully solved two probability problems. Let us reconcile these together.").

The value of embedding CDR lies in its role as a *growth driver*. Rather than simply providing correct answers, an LLM can encourage reflection and help learners integrate new knowledge with existing beliefs. Research in higher education shows that interventions prompting learners to reflect on inconsistencies between self-perceptions and actual performance enhance both metacognition and resilience (Mintz, 2022; Vogl, et al., 2020). Moreover, by assisting learners in reducing dissonance, LLM tutors foster deeper learning and lasting conceptual change rather than superficial memorization.

It is important to recognize, however, that dissonance must be carefully calibrated. Too much conflict can lead to discouragement or disengagement; too little falls short to engage. To promote growth, the leaner profile module of the proposed architecture is particularly critical, as it tracks learner history, affective responses, and progress. This allows the LLM to scaffold dissonance in a supportive way posing manageable challenges, acknowledging discomfort, and offering constructive pathways toward resolution (Pacaci et al., 2023).

In summary, CDR adds a unique dimension to LLM-based learning interactions. It transforms moments of cognitive conflict into opportunities for growth, enabling LLMs to function as coaches who help learners wrestle with their beliefs and assumptions, producing more resilient and self-aware learners (Bogaerts & Leake, 2006; D'Mello & Graesser, 2014).

Toward a Three-Layer LLM Architecture for Learner Engagement

We propose a three-layer architecture that integrates learner preferences and psychology, recognition of these learner characteristics, and adaptive response into a coherent, informed system (see Figure 1). In this architecture, the Psychological Processes Layer frames learner needs and tensions and selects strategies that align with SDT, empathy, and cognitive dissonance reduction. The Recognition layer addresses learner preferences and detects motivational and dissonance cues.

The Response Generation layer then delivers a concrete, supportive response that is relational in the context of the learner and nudges the person toward adaptive next steps.

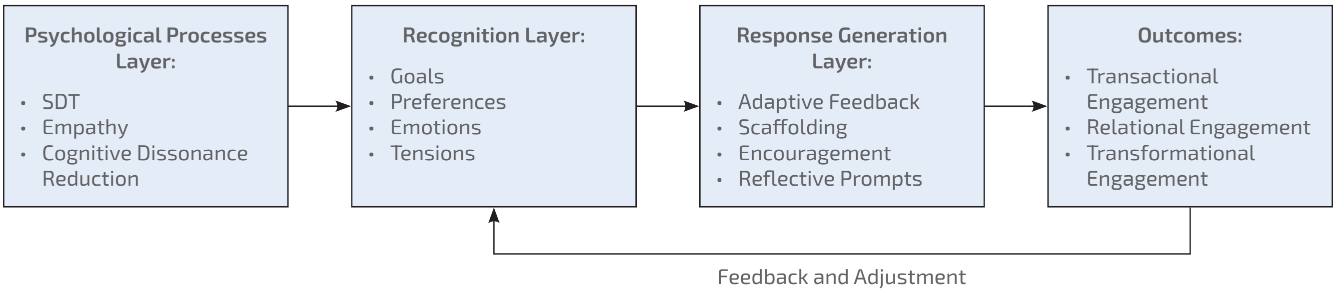

Figure 1. LLM-Learner Engagement Model

Note. The model illustrates a psychology-informed architecture for LLM-supported learner engagement. The Psychological Processes Layer draws on Self-Determination Theory, empathy, and cognitive dissonance reduction to guide motivational and relational support. The Recognition Layer identifies learner goals, preferences, emotions, and tensions. The Response Generation Layer produces adaptive feedback, scaffolding, encouragement, and reflective prompts. These processes support transactional, relational, and transformational engagement outcomes, which inform ongoing feedback and adjustment across learner interactions.

Psychological Processes Layer

The Psychological Processes Layer's support lies with the foundation of sustained engagement. Studies grounded in SDT demonstrate that when technologies meet learners' needs for *autonomy*, *competence*, and *relatedness*, both persistence and intrinsic motivation increase (Ryan & Deci, 2020; Xia et al., 2022). In practice, systems that provide meaningful choices (autonomy), scaffold mastery (competence), and communicate empathy (relatedness) tend to be more effective.

Empathic tutoring systems exemplify this integration. Affect-sensitive Intelligent Tutoring System (ITS) have shown that recognizing and responding to learner emotion increases engagement and persistence compared to content-only models (D'Mello & Graesser, 2012). Empathy operates both cognitively, understanding learners' reasoning, and affectively, acknowledging their emotions (Li et al., 2025). These dynamics shift LLM interactions from transactional exchanges to relational and transformational engagements, respectively, that sustain trust and motivation.

Cognitive dissonance reduction complements this motivational scaffolding. Festinger's CDR theory (1957) and subsequent work (Pacaci et al., 2023) demonstrate that conceptual conflict can catalyze deeper understanding. LLM systems can strategically introduce and resolve dissonance, guiding learners through reflection and reconciliation to strengthen resilience and self-awareness (Bogaerts & Leake, 2006). Thus, this layer fuses empathy, affirmation, and constructive dissonance into an adaptive motivational engine.

Recognition Layer

Learner recognition begins with two complementary inputs:

- **Learner Profile Initialization.** At the start of a session, learners specify preferences such as reading level, formatting of examples, or visual format.

- **Dynamic Learner Interaction & Continuity.** As dialogue unfolds, the system continuously updates its understanding of learner goals, emotions, and engagement patterns across multiple sessions.

Continuity is essential for perceived authenticity. A learner profile and interaction history allow the LLM to function as a consistent tutor, remembering prior struggles, acknowledging progress, and adapting challenges. Platforms that track learner history and preferences report higher engagement than those resetting each session (Shen & Cui, 2024). By capturing cognitive and affective trends, the system can time the introduction of dissonance and offer reassurance when frustration risks disengagement. This emphasis on learner-sensitive adaptation is consistent with adaptive practicing research showing that systems can integrate learner confidence and control options into adaptive mechanisms to support autonomy, self-regulated learning, and interpretability.

Response Generation Layer

Response generation represents the voice of the LLM, where empathy, motivation, and personalization converge to sustain learning momentum. This layer translates detection and motivation insights into adaptive, learner-facing feedback. Moreover, effective responses should go beyond correctness by incorporating scaffolding, encouragement, and reflective prompts aligned with the learner's emotional and motivational state (De Gennaro et al., 2020). Additionally, feedback emphasizing progress and strategy promotes longer engagement and better skill transfer (Yin et al., 2025).

Outcomes: From Transactional to Relational and Transformational Engagement

Together, the three layers form a psychologically informed tutorial ecosystem:

- **Empathy management** ensures learners feel understood.
- **Motivational processes** satisfy autonomy, competence, and relatedness while transforming dissonance into growth.
- **Adaptive responses** provide clear, encouraging, and personalized feedback.
- **Learner profiling** preserves continuity, making the LLM feel relational, authentic, and focused on learner needs.

When integrated, these components enable LLMs to function as an authentic tutor that nurtures persistence, resilience, and conceptual development by moving educational technology beyond information delivery toward relational and transformational engagement. Importantly, this is a continuous process: as learner preferences, characteristics, and/or requirements change, the LLM would adjust to the circumstances and context, thus, moving into a new cycle of deployment and engagement, as represented by the feedback loop.

Technical Implementation Considerations

Although the proposed model is conceptual rather than prescriptive, several technical approaches could support implementation of the three-layer architecture. At the Recognition Layer, learner inputs could be processed through natural language processing methods that identify sentiment, emotion, uncertainty, confidence, confusion, and motivational cues. For example, transformer-based sentiment analysis has been increasingly applied in educational contexts and can help identify affective patterns in learner language, although such detection should be interpreted cautiously and supplemented by learner confirmation rather than treated as definitive psychological diagnosis). Learner profiling could then combine stable learner preferences, such as preferred explanation style or reading level, with dynamic interaction data, such as repeated misunderstandings, confidence signals, prior feedback, and progress over time. This approach is consistent with personalized education frameworks emphasizing that learner characteristics should be measured repeatedly and used systematically to adapt instruction (Tetzlaff et al., 2021).

At the Psychological Processes and Response Generation Layers, implementation could rely on structured prompt engineering, retrieval-augmented generation, and guardrail-based response templates. Prompt engineering could specify the instructional role of the system, the learner's current state, the desired motivational strategy, the required level of explanation, and ethical constraints such as preserving learner autonomy and avoiding over-persuasion. Recent reviews suggest that prompt engineering can improve the usefulness and task alignment of LLM outputs by structuring the input conditions under which the model responds (Chen et al., 2025). Retrieval-augmented generation could also be used to ground LLM responses in course materials, rubrics, institutional policies, or approved examples rather than relying only on the model's general training data. RAG systems combine a generative model with retrieved external information, which can improve factual grounding and support more transparent, source-linked feedback in knowledge-intensive tasks (Lewis et al., 2020).

Finally, privacy-preserving mechanisms should be incorporated into learner profiling, including data minimization, role-based access, encryption, limited retention, local or institution-controlled storage, and, where appropriate, federated learning or differential privacy. Federated learning can reduce direct exposure of raw learner data, but it does not by itself guarantee privacy because model updates may still leak sensitive information; therefore, additional privacy-preserving safeguards remain necessary (Truong et al., 2021).

Together, these technical indications suggest that the proposed architecture can be implemented through a layered pipeline of learner-state detection, profile updating, theory-guided prompting, retrieved instructional grounding, monitored response generation, and privacy-aware data governance.

Why This Approach?

The growing body of research on ITS, learning analytics, and LLM-powered educational technologies underscores the increasing importance of designing systems that engage learners not only cognitively but also emotionally and motivationally. Yet, despite significant advances, several persistent gaps remain in the literature. These gaps highlight where existing work falls short and where the proposed three-layer LLM learner engagement architecture, which is rooted in SDT, empathy, and CDR, offers several design-oriented contributions. The key contributions are outlined below.

- **Integrated Psychological Foundation**. Much of the existing research applies these frameworks in isolation. For example, SDT has been shown to promote autonomy, competence, and relatedness in learning environments (Xia et al., 2022; Deci & Ryan, 2000), while empathic ITS demonstrates how affective cues enhance engagement (D'Mello & Graesser, 2012). Similarly, cognitive dissonance theory has been applied to conceptual change and productive failure research (Festinger, 1957; Pacaci et al., 2023). Yet, few educational AI frameworks explicitly integrate these three dimensions within a single learner-facing LLM architecture. The proposed framework advances the literature by explicitly combining SDT's motivational principles, empathic sensitivity, and the strategic use of cognitive dissonance reduction as growth opportunities.
- **Layered Design for Learner Interaction**. Most ITS research describes modularity but does not articulate a structured layering that distinguishes between detection, motivational interpretation, and adaptive response. Some ITS manage dialogue effectively (Graesser et al., 2005), and empathic LLMs research demonstrates how conversational scaffolding can be added (Sharma et al., 2022). Reviews of affective ITS confirm piecemeal progress across different layers (Fernández-Herrero, 2024). Yet, a unified framework that clearly separates recognition, motivational interpretation, ethical-risk management, and adaptive response generation remains underdeveloped (Baksh, 2025). The contribution here is to formalize a three-layer architecture, making psychological theory operational in LLM design.
- **Learner Profiling and Continuity**. While adaptive learning platforms and clustering methods use performance data to tailor instruction (Bergdahl et al., 2024; Contrino et al., 2024; Gkintoni et al., 2025), few systems maintain a personalized integrated learner profile that records motivational states, emotional trends, and preferences over time (Khanal & Pokhrel, 2024; Kravcik, et al., 2015; Tetzlaff et al., 2021). Studies confirm that perceived support and satisfaction of psychological needs are key to LLM literacy. Persuasive technologies highlight the importance of personalization for achievement (Brons et al., 2024; du Plooy et al., 2024; Shen & Cui, 2024). The proposed model fills this gap by positioning the learner profile as the system's long-term memory, enabling continuity across sessions, and supporting relational authenticity.
- **Cognitive Dissonance as a Growth Mechanism**. Although cognitive dissonance has been studied extensively in psychology and education (Festinger, 1957), most LLM systems treat confusion or conflict as errors to be resolved quickly rather than as productive opportunities for growth. Meta-analyses confirm that conceptual change is facilitated by cognitive conflict (Pacaci et al., 2023), and impasse-driven tutoring shows how guiding learners through contradictions fosters deeper mastery (Bogaerts & Leake, 2006). The novelty of the proposed model lies in deliberately scaffolding dissonance, transforming it into a coaching mechanism

where the LLM challenges assumptions and supports resolution, thereby fostering resilience and self-awareness.

- **Authenticity and Relational Trust**. Another consistent theme in the literature is the challenge of ensuring that learners perceive LLM interactions as authentic rather than mechanical. Research demonstrates that human-like empathic features enhance user trust and self-efficacy (Li et al., 2025), and SDT-informed designs strengthen engagement by addressing autonomy and competence (Xia et al., 2022). Empathic LLMs further illustrate that acknowledgment and encouragement reduce disengagement (De Gennaro et al., 2020). Yet few publications explicitly link authenticity with continuity mechanisms that allow LLMs to "remember" and "relate." By embedding authenticity as a design principle, the proposed model advances the field by bridging the transactional–relational gap in human–LLM interaction.

In sum, the proposed architecture addresses key limitations in the literature. It integrates motivational, affective, and cognitive conflict frameworks into a unified system; formalizes a layered structure that distinguishes recognition, motivation, and response components; emphasizes continuity through learner profiling and interaction history; reframes dissonance as a growth mechanism; and prioritizes authenticity to build relational trust. Together, these contributions position the model as an important advancement in LLMs for education, moving the field from systems that simply answer questions toward LLM coaches and tutors that motivate, support, and transform learners.

DISCUSSION AND IMPLICATIONS

The integration of SDT, empathy, and CDR into an LLM learner-interaction architecture has profound implications for educational practice, instructional design, and future research. Below we discuss strengths, challenges, and applications of the proposed architecture, while highlighting directions for innovation.

Strengths

The primary strength of this architecture is its holistic psychological grounding. Unlike conventional LLM tutoring systems that rely heavily on information retrieval and correctness checking, this model incorporates motivational, emotional, and cognitive dimensions of learning. By embedding SDT, the architecture systematically supports learner autonomy, competence, and relatedness, fostering intrinsic motivation that endures beyond the initial novelty of interacting with LLMs. In this way, the LLM becomes a transformational catalyst for enhanced learning.

A second strength is personalization at multiple levels. The architecture not only personalizes based on performance data (e.g., past quiz scores), but also on motivational needs and affective cues.

Empathy allows the LLM to adjust its tone and pacing; the learner profile module ensures continuity of recognition ("I remember last time you struggled with this concept, but you made progress"). The result is an LLM that learners perceive as authentically relational and supportive.

A third strength is the constructive use of conflict. Traditional tutoring systems often minimize or avoid learner discomfort, rushing to deliver correct answers. In contrast, by incorporating cognitive dissonance detection and reduction, this architecture reframes conflict as a productive force. Learners are encouraged to confront contradictions in their self-beliefs or understanding, fostering deeper reflection and conceptual change. This mirrors the role of effective human teachers, who often challenge students in ways that initially provoke discomfort but generate growth.

Challenges

Despite its strengths, this architecture faces several challenges. One is calibration of dissonance. As noted, too much unresolved conflict may overwhelm learners, leading to frustration and dropout. Too little may yield complacency and superficial engagement. Effective calibration requires sophisticated emotion recognition, longitudinal tracking, and adaptive scaffolding, which are features that demand significant technical development.

Another challenge is authenticity of empathy. While LLMs can simulate empathy through natural language responses and tone, they do not possess genuine affective states. Critics may argue that simulated empathy risks deception or trivialization of learners' emotions. However, research suggests that simulated social and conversational cues can improve perceived trustworthiness and engagement even when learners know they are interacting with an AI system. (Li et al., 2025). To mitigate concerns, transparency is key. That is, learners should know they are interacting with an LLM. Even though the empathy is simulated, they can still benefit from the psychological effects of empathically designed interactions.

A related ethical concern involves the boundary between motivational scaffolding and inappropriate emotional influence. Because the proposed architecture intentionally recognizes learner emotions, self-doubt, frustration, and cognitive dissonance, it must avoid using these states to pressure, over-persuade, or exploit learners when they are vulnerable. Motivational scaffolding should support learner agency by offering encouragement, choices, reflection, and constructive next steps; it should not use emotional dependence, guilt, fear, shame, urgency, or excessive personalization to steer learners toward outcomes they would not otherwise endorse. This distinction is especially important because emotional artificial intelligence raises ethical concerns about whether emotions can be accurately identified, measured, and used to predict or influence human behavior (Ghotbi, 2023). Therefore, psychologically informed LLMs should include explicit non-manipulation safeguards, such as transparent disclosure that empathic responses are machine-generated, opt-out options for emotionally adaptive features, limits on persuasive or dependency-building language, escalation pathways to human support when distress is detected, and institutional review of learner-facing prompts. In this way, the architecture preserves the positive role of empathy and cognitive dissonance reduction while ensuring that motivational support remains autonomy-supportive rather than coercive.

A further limitation is ethical data use. The learner profile module requires collecting and storing sensitive information about performance, preferences, personality traits, and emotional states. Safeguards around privacy, data security, and informed consent must be central to implementation.

Institutions adopting such systems will need policies that ensure learners feel safe, respected, and in control of their personal data.

Applications in Various Educational Contexts

The merits of this architecture extend across multiple learning levels. In K–12 education, LLM-supported learning systems could supplement classroom teaching by offering individualized support, personalized scaffolding, and AI-literacy development, particularly when designed for low-resource or underserved settings (Yang, 2026). For instance, a student struggling with fractions could receive motivationally attuned scaffolding from the LLM, freeing the teacher to address other learners.

In higher education, such LLMs could be particularly valuable for supporting nontraditional or underserved students who may lack confidence. By detecting dissonance between self-doubt and demonstrated progress, LLMs could play a role in reducing attrition and promoting equity in learning outcomes, especially in private learning contexts (Xia et al., 2022).

In workplace learning, the architecture could support continuous upskilling, particularly in fast-changing fields where learners must adapt quickly. By personalizing motivation and supporting resilience through dissonance reduction, LLMs could help employees sustain learning even under pressure.

The following points summarize selected literacy implications of the proposed architecture rather than a comprehensive implementation framework. These literacy dimensions extend from the proposed architecture and can be used for curriculum design or organizational-wide LLMs.

Illustrative Implications for LLM Literacy and Implementation

1. Foundational LLM Literacy. Foundational LLM literacy begins with understanding how LLMs function, what their outputs can and cannot provide reliably, and how prompting shapes response quality. Learners should be able to understand core generative AI terminology, distinguish between general-purpose and domain-specific models, craft purposeful prompts, and verify outputs for accuracy, bias, and completeness (Galindo-Cuesta, 2025). These competencies support informed, transparent, and academically responsible use of LLMs and align with recent work emphasizing artificial intelligence literacy through cognitive, socio-emotional, and instructor-guided forms of learner interaction.
2. Responsible Use. Responsible use requires ethical awareness, data privacy, and appropriate human oversight. Learners and institutions should understand issues of authorship, originality, confidentiality, and policy compliance while using LLMs in ways that support productivity without displacing professional or academic judgment. In this sense, responsible literacy is not only technical but also ethical and contextual.
3. Emotional and Reflective Use. Emotional and reflective use emphasizes empathic communication, critical self-reflection, and sound professional judgment when interacting with LLMs. Learners should recognize that LLMs can simulate supportive dialogue without

possessing genuine understanding, and they should use these systems not only to obtain answers but also to question assumptions, examine contradictions, and reflect on their own reasoning. This dimension is especially important for maintaining authenticity, trust, and meaningful engagement, and it is consistent with evidence that scaffolded experiential engagement with generative artificial intelligence can support learner confidence, ethical awareness, and critical evaluation of artificial intelligence-generated outputs.

4. Continuous Learning. Continuous learning recognizes that LLM literacy is not static but must evolve alongside rapid technological change. Learners and professionals should monitor new capabilities, refine their practices across tools and contexts, and maintain a reflective, lifelong-learning orientation toward the effective and ethical use of LLMs. Such adaptability is essential if LLM-supported learning environments are to remain both useful and responsible over time.

Other Considerations

Several additional issues warrant attention in future work. First, research should examine how the LLM Learner Engagement Model performs across domains and learner populations, using outcomes that extend beyond achievement to include motivation durability, resilience, and willingness to engage with challenging material. Longitudinal studies would be especially valuable in determining whether systems grounded in SDT, empathy, and cognitive dissonance reduction support lasting changes in learner attitudes and self-concepts.

Second, cultural variation deserves explicit attention. Autonomy, competence, and relatedness may be expressed differently across cultural contexts; empathic cues may be interpreted differently; and tolerance for cognitive dissonance may vary across learners and settings. Designing culturally responsive LLM systems will therefore require attention to how these dimensions are perceived and enacted across diverse educational environments.

Third, hybrid human-LLM tutorial models may offer a particularly promising direction. Rather than replacing teachers, mentors, or trainers, psychologically informed LLM systems could extend human support by providing timely, consistent, and motivationally attuned guidance during and beyond formal instructional settings.

CONCLUSION

Taken together, the literature reviewed and the framework proposed here point to a coherent model of LLM-supported learner engagement that integrates recognition, motivation, adaptive response, continuity, and sustained support. Each element is empirically supported: confusion and conflict become productive when properly scaffolded; meeting SDT needs fosters intrinsic motivation; empathic responses shift systems from transactional tutors to transformational coaches; and continuity across sessions builds trust and authenticity. Research in intelligent tutoring and LLM learning environments shows such architectures are both feasible and desirable, with the potential to transform LLMs from an information provider into a motivationally intelligent coach that cultivates resilience, persistence, and self-awareness. As LLMs evolve, architectures grounded in psychology will define the next generation of authentic, motivationally intelligent learning systems.

AI Disclosure Statement

During manuscript preparation, the authors used generative AI tools to assist with language refinement, clarity, organization, and presentation order serving to sometimes provide editorial feedback. Specifically, AI was used to help identify passages where wording could be improved, transitions could be strengthened, and the sequence of ideas could be made clearer for readers.

The conceptual framework, proposed model, theoretical interpretation, scholarly argument, and substantive conclusions are the original work of the authors and reflect the authors' years of research, study, and professional judgment. AI tools were not used to write the manuscript, generate the core conceptual framework, develop the proposed model, conduct analysis, create findings, or replace authorial interpretation.

All AI-assisted suggestions were reviewed, evaluated, revised (if deployed), and approved by the authors, who take full responsibility for the accuracy, integrity, originality, and final content of the manuscript.

REFERENCES

Baksh, S. (2025). Amplifier and risk: Extending the Community of Inquiry (CoI) for student AI use: A secondary qualitative analysis. Review of Artificial Intelligence in Education, 6, e057. https://doi.org/10.37497/rev.artif.intell.educ.v6ii.57

Basch, C., Hillyer, G., Gold, B., & Yousaf, H. (2025). Understanding artificial intelligence knowledge and usage among college students: Insights from a survey on classroom, coursework, and personal applications. Review of Artificial Intelligence in Education, 6(i), e037. https://doi.org/10.37497/rev.artif.intell.educ.v6ii.37

Bergdahl, N., Bond, M., Sjöberg, J., Dougherty, M., & Oxley, E. (2024). Unpacking student engagement in higher education learning analytics: A systematic review. *International Journal of Educational Technology in Higher Education*, *21*(63). https://doi.org/10.1186/s41239-024-00493-y

Bogaerts, S., & Leake, D. B. (2006). Focusing AI students' attention: A framework-based approach to guiding impasse-driven learning. In *Proceedings of the Nineteenth International Florida Artificial Intelligence Research Society Conference* (pp. 186-191). Association for the Advancement of Artificial Intelligence Press.

Bos, N., Lammers, K.-J., & Prince van Leeuwen, A. (2025). Exploring the role of AI in higher education: A study of usage by students and teachers in the Netherlands. *Review of Artificial Intelligence in Education, 6*(i), e040. https://doi.org/10.37497/rev.artif.intell.educ.v6ii.40

Brons, A., Wang, S., Visser, B., Kröse, B., Bakkes, S., & Veltkamp, R. (2024). Machine learning methods to personalize persuasive strategies in mHealth interventions that promote physical activity: Scoping review and categorization overview. *Journal of Medical Internet Research*, *26*, e47774. https://doi.org/10.2196/47774

Chen, B., Zhang, Z., Langrené, N., & Zhu, S. (2025). Unleashing the potential of prompt engineering in large language models: A comprehensive review. *Patterns, 6*(6), 101260. https://doi.org/10.1016/j.patter.2025.101260

Contrino, M. F., Reyes-Millán, M., Vázquez-Villegas, P., & Membrillo-Hernández, J. (2024). Using an adaptive learning tool to improve student performance and satisfaction in online and face-to-face education for a more personalized approach. *Smart Learning Environments, 11*(6). https://doi.org/10.1186/s40561-024-00292-y

Cooper, J. (2019). Cognitive dissonance: Where we've been and where we're going. *International Review of Social Psychology, 32*(1), Article 7. https://doi.org/10.5334/irsp.277

Cornelius-White, J. (2007). Learner-centered teacher-student relationships are effective: A meta-analysis. *Review of Educational Research*, 77(1), 113–143. https://doi.org/10.3102/003465430298563

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Deci, E. L., Koestner, R., & Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological Bulletin*, 125(6), 627–668. https://selfdeterminationtheory.org/wp-content/uploads/2014/04/1999_DeciKoestnerRyan_Meta.pdf

De Gennaro, M., Krumhuber, E. G., & Lucas, G. (2020). Effectiveness of an empathic chatbot in combating adverse effects of social exclusion on mood. *Frontiers in Psychology, 10*, 3061. https://doi.org/10.3389/fpsyg.2019.03061

D'Mello, S. K., & Graesser, A. C. (2014). Confusion. In L. Feldman Barrett, M. Lewis, & J. M. Haviland-Jones (Eds.), *Handbook of Emotions* (4th ed., pp. 289-305). Guilford Press.

D'Mello, S. K., & Graesser, A. C. (2012). AutoTutor and Affective AutoTutor: Learning by talking with cognitively and emotionally intelligent computers that talk back. *Association for Computing Machinery Transactions on Interactive Intelligent Systems, 2*(4), 23:1-23:39. https://doi.org/10.1145/2395123.2395128

du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. *Heliyon, 10*, e39630. https://doi.org/10.1016/j.heliyon.2024.e39630

Fernández-Herrero, J. (2024). Evaluating Recent Advances in Affective Intelligent Tutoring Systems: A Scoping Review of Educational Impacts and Future Prospects. *Education Sciences*. 14, 839. https://doi.org/10.3390/educsci14080839

Festinger, L. (1957). *A theory of cognitive dissonance.* Stanford University Press. https://doi.org/10.1515/9781503620766

Galindo-Cuesta, J. A. (2025). Glossary of generative artificial intelligence for education: A conceptual and pedagogical framework. *Review of Artificial Intelligence in Education, 6*(i), e047. https://doi.org/10.37497/rev.artif.intell.educ.v6ii.47

Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulos, C. (2025). Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. *Brain Sciences, 15*(2), 203. https://doi.org/10.3390/brainsci15020203

Ghotbi, N. (2023). The ethics of emotional artificial intelligence: A mixed method analysis. *Asian Bioethics Review, 15*(4), 417-430. https://doi.org/10.1007/s41649-022-00237-y

Graesser, A.C. (2016). Conversations with AutoTutor Help Students Learn. *International Journal of Artificial Intelligence Education* 26, 124-132. https://doi.org/10.1007/s40593-015-0086-4

Graesser, A. C., Chipman, P., Haynes, B. C., & Olney, A. (2005). AutoTutor: An intelligent tutoring system with mixed-initiative dialogue. *Institute of Electrical and Electronics Engineers Transactions on Education*, 48(4), 612-618.

Jung, M., Zhang, A., Fung, M., Lee, J., & Liang, P. P. (2025). *Quantitative insights into large language model usage and trust in academia: An empirical study. arXiv preprint arXiv:2409.09186.* https://doi.org/10.48550/arXiv.2409.09186

Kalyan, S., & Subramanyam, K. (2023). *A survey of GPT-3 family large language models including ChatGPT and GPT-4*. arXiv. https://arxiv.org/abs/2310.12321

Kestin, G., Miller, K., Klales, A., Milbourne, T., & Ponti, G. (2025). AI tutoring outperforms in-class active learning: An RCT introducing a novel research-based design in an authentic educational setting. *Scientific Reports, 15*, 17458. https://doi.org/10.1038/s41598-025-97652-6

Khanal, S., & Pokhrel, S. R. (2024). *Analysis, modeling, and design of personalized digital learning environment. arXiv preprint arXiv:2405.10476.* https://doi.org/10.48550/arXiv.2405.10476

Kirvan, P., & Kerner, S. M. (2025, October 20). *What is a large language model (LLM)?* TechTarget. https://www.techtarget.com/whatis/definition/large-language-model-LLM

Kravcik, M., Santos, O. C., Boticario, J. G., Bielikova, M., & Horvath, T. (2015). *Proceedings of the 5th International Workshop on Personalization Approaches in Learning Environments (Personalization Approaches in Learning Environments 2015).* In *23rd International Conference on User Modeling, Adaptation, and Personalization (User Modeling, Adaptation, and Personalization 2015)*. Central Europe Workshop Proceedings Workshop Proceedings. https://ceur-ws.org/Vol-1388/PALE2015-complete.pdf

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W., Rocktäschel, T., Riedel, S., & Kiela, D. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems, 33*, 9459-9474. https://proceedings.neurips.cc/paper/2020/hash/6b493230205f780e1bc26945df7481e5-Abstract.html

Li, X., Zhou, T., Hu, C., & Liu, H. (2025). The effects of the human-like features of generative AI on usage intention and the moderating role of information overload. *Scientific Reports*, *15*, 35077. https://doi.org/10.1038/s41598-025-18906-x

Mejia-Domenzain, P., Frej, J., Neshaei, S. P., Mouchel, L., Nazaretsky, T., Wambsganss, T., Bosselut, A., & Käser, T. (2025). Enhancing procedural writing through personalized example retrieval: A case study on cooking recipes. *International Journal of Artificial Intelligence in Education*, *35*(2), 330-366. https://doi.org/10.1007/s40593-024-00405-1

Mintz, S. (2022, September 8). *Leveraging cognitive dissonance to enhance student learning*. *Inside Higher Education.* https://www.insidehighered.com/opinion/2022/09/08/how-cognitive-dissonance-can-enhance-student-learning-opinion

Ngo, T. T. A., Vo, T. T. A., & Phan, M. T. (2025). The psychology of AI adoption in education: University students' intentions to use large language models for learning from a Technology Acceptance Model and Theory of Planned Behavior perspective. *Acta Psychologica*, *261*, 105789. https://doi.org/10.1016/j.actpsy.2025.105789

Pacaci, C., Ustun, U., & Ozdemir, O. F. (2023). Effectiveness of conceptual change strategies in science education: A meta-analysis. *Journal of Research in Science Teaching*, *60*(7), 1–63. https://doi.org/10.1002/tea.21887

Posner, G. J., Strike, K. A., Hewson, P. W., & Gertzog, W. A. (1982). Accommodation of a scientific conception: Toward a theory of conceptual change. *Science Education*, *66*(2), 211-227. https://doi.org/10.1002/sce.3730660207

Rismanchian, S., & Doroudi, S. (2025). *The Evolution of Research on AI and Education Across Four Decades: Insights from the AIxEd Framework*. *International Journal of Artificial Intelligence Education*. Advance online publication. https://doi.org/10.1007/s40593-025-00483-9

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, *61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860.

Sharma, A., Lin, I. W., Miner, A. S., Atkins, D. C., & Althoff, T. (2022). Human-AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support. *Nature Machine Intelligence, 4*, 1–15. https://doi.org/10.1038/s42256-022-00538-5

Shen, Y., & Cui, W. (2024). Perceived support and AI literacy: The mediating role of psychological needs satisfaction. *Frontiers in Psychology, 15*, 1415248. https://doi.org/10.3389/fpsyg.2024.1415248

Singh, H. P., & Ab Aziz, A. (2025). Impact of intelligent learning assistants on creativity of university students: A self-determination theory perspective. *Future Business Journal, 11*(122). https://doi.org/10.1186/s43093-025-00544-4

Sleegers, W. W. A., Elsey, J. W. B., & Moss, D. (2025). *Adoption and uses of large language models among U.S. tech workers.* Rethink Priorities. https://rethinkpriorities.org/research-area/usage-and-utility-of-llms/

Tasdelen, O., & Bodemer, D. (2025). Generative AI in the classroom: Effects of context-personalized learning material and tasks on motivation and performance. *International Journal of Artificial Intelligence in Education.* Advance online publication. https://doi.org/10.1007/s40593-025-00491-9

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing personalized education: A dynamic framework. *Educational Psychology Review, 33*(3), 863-882. https://doi.org/10.1007/s10648-020-09570-w

Truong, N. B., Sun, K., Wang, S., Guitton, F., & Guo, Y. (2021). Privacy preservation in federated learning: An insightful survey from the GDPR perspective. *Computers & Security, 110*, 102402. https://doi.org/10.1016/j.cose.2021.102402

UNESCO. (2025). *AI and Education: Guidance for policymakers and practitioners*. United Nations Educational, Scientific and Cultural Organization. https://unesdoc.unesco.org/ark:/48223/pf0000387654

Vieira, E. T., Jr. (2014). The Relationships Among Girls' Prosocial Video Gaming, Perspective-Taking, Sympathy, and Thoughts About Violence. *Communication Research*, 41(7), 892-912.

Vogl, E., Hoferichter, F., & Raufelder, D. (2020). The role of social relationships in students' academic motivation and achievement: A self-determination theory perspective. *Educational Psychology Review, 32*(3), 1–30. https://doi.org/10.1007/s10648-020-09544-y

Wang, Y., Wang, H., Wang, S., Wind, S. A., & Gill, C. (2024). A systematic review and meta-analysis of self-determination-theory-based interventions in the education context. *Learning and Motivation, 87*, 102015. https://doi.org/10.1016/j.lmot.2024.102015

Xia, Q., Chiu, T. K. F., Lee, M., Sanusi, I. T., Dai, Y., & Ching, C. S. (2022). A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education. *Computers & Education, 189*, 104582. https://doi.org/10.1016/j.compedu.2022.104582

Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2023). Practical and ethical challenges of large language models in education: A systematic scoping review. *British Journal of Educational Technology, 55*(1), 1–23. https://doi.org/10.1111/bjet.13572

Yang, X. (2026). CRAILF: A zero-cost Python-based gamified framework for enhancing AI literacy among rural high school students. *Review of Artificial Intelligence in Education, 7*(i), e075. https://doi.org/10.37497/rev.artif.intell.educ.v7ii.75

Yin, J., Xu, H., Pan, Y., & Hu, Y. (2025). Effects of different AI-driven chatbot feedback on learning outcomes and brain activity. *Science of Learning, 10*, 17. https://doi.org/10.1038/s41539-025-00311-8

Zhou, J., Shen, L., & Chen, W. (2024). How ChatGPT transformed teachers: The role of basic psychological needs in enhancing digital competence. *Frontiers in Psychology, 15*, 1458551. https://doi.org/10.3389/fpsyg.2024.1458551