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EFFICIENCY, ENGAGEMENT, AND COGNITIVE OFFLOADING: A REVIEW OF GENERATIVE AI IN EDUCATION

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Abstract:

This narrative review examines how generative artificial intelligence (GenAI) influences student learning through three interrelated dimensions: efficiency, engagement, and cognitive offloading. A structured search of Scopus identified 56 studies published between 2022 and 2025 that examined GenAI use in educational contexts and its implications for cognitive or learning processes. The review reveals consistent evidence that GenAI enhances task efficiency by accelerating drafting, feedback cycles, and information processing. However, efficiency gains do not uniformly translate into deeper learning, as several studies report tendencies toward surface-level completion strategies. Findings related to engagement are mixed, with perception-based studies emphasizing reduced anxiety and increased confidence, while experimental studies report variable effects on cognitive involvement. Cognitive offloading emerges as a central tension: although GenAI use is associated with reduced cognitive load and support for higher-order reasoning, concerns persist regarding over-reliance and diminished independent thinking. To interpret these patterns, this review advances a three-lens framework positioning GenAI as a mediator of cognitive effort rather than a uniformly beneficial or detrimental tool. The framework highlights the interdependence of efficiency gains, engagement dynamics, and cognitive delegation. The findings underscore the critical role of learner regulation and instructional design in shaping GenAI's educational impact. Future research should prioritize longitudinal designs, objective

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learning measures, and process-oriented methodologies to clarify long-term cognitive implications.

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Keyword:

Cognitive Engagement, Cognitive Offloading, Efficiency, Generative Artificial Intelligence, Student Learning.

Introduction

The landscape of education is being rapidly transformed by generative artificial intelligence (GenAI). Unlike previous educational technologies that primarily delivered content or provided rule-based feedback, GenAI systems, particularly large language models such as ChatGPT function as a interpretive partners in learning. Their capacity to generate text, code, and conceptual inputs reshapes how learners approach academic tasks and knowledge construction (Yan et al., 2024; Zied Bahroun et al., 2023). This shift is not just a technological upgrade but represents a fundamental change in the relationship between learners and information, with GenAI tools increasingly used for tasks to provide personalized feedback and simulating complex scenarios (Yan et al., 2024; Zied Bahroun et al., 2023).

This transformation has stirred growing concern regarding cognition, particularly in terms of how GenAI influences deep and effortful thinking associated with meaningful learning. Cognitive processes such as critical analysis, problem-solving, and metacognitive reflection, are now being both supported and potentially weakened by AI integration (Yan et al., 2024). While GenAI offers promises of enhanced efficiency, personalized learning support, and timely feedback, it also presents challenges including model imperfections, ethical dilemmas, and the risk of over-reliance that could challenge learners' intellectual abilities (Yan et al., 2024). When learners can easily delegate thinking tasks to AI, it becomes unclear whether genuine learning is taking place. Learners may develop an illusion of understanding that hides gaps in their knowledge and also skills (Yan et al., 2024).

Through a narrative review, this study develops a structured interpretation of GenAI’s educational implications. It introduces a three-lens framework: Efficiency, Engagement, and Cognitive Offloading to examine how GenAI reshapes the allocation of cognitive effort.

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Background and Theoretical Framework

Cognitive Engagement

Cognitive engagement refers to the deliberate mental effort learners invest in understanding complex concepts, mastering challenging skills, and achieving academic goals (Šedlbauer et al., 2024). It functions as a core mechanism of deep learning, distinguishing active knowledge construction from passive information reception (Sánchez-Ruiz et al., 2023). Grounded in constructivist and self-regulated learning theories (Essien et al., 2024; Kong et al., 2024; H.-Y. Lee et al., 2024), cognitive engagement encompasses higher-order processes including critical thinking, metacognition, and creative problem-solving (H.-Y. Lee et al., 2024). In addition to receiving information, engaged learners will question, analyze, and integrate new knowledge with existing understanding, a process that is essential for meaningful learning and the development of transferable competencies (Stofiana et al., 2025).

From Support Tools to GenAI

GenAI represents a fundamental shift beyond traditional supportive technologies. Its generative capabilities enable it to perform tasks previously associated with human cognition including drafting, explanation, and ideation (Sánchez-Ruiz et al., 2023; Štuikys et al., 2025). Unlike earlier educational technologies that mainly delivered content or provided rule-based feedback, GenAI systems can function as interpretive partners in learning by generating outputs that require learners to evaluate, refine, and integrate these AI-generated content with their own thinking (Yan et al., 2024; Zied Bahroun et al., 2023). This shift requires a re-evaluation of which cognitive processes remain central to learner development and also how the relationship between human cognition and machine assistance should be constructed to preserve rather than weaken learning.

Three-Lens Framework

This study examines GenAI's educational implications through three interrelated lenses: efficiency, engagement, and cognitive offloading. These lenses are analytically distinct yet operationally interconnected. Cognitive offloading may enhance efficiency, while efficiency gains may shape engagement patterns. Depending on instructional design and learner regulation, these interactions may either support reflective inquiry or encourage superficial task completion. These lenses provide an analytical structure for understanding how GenAI reallocates cognitive effort rather than evaluating the technology solely in terms of capability.

Table 1 summarizes the definition of the three lenses. This table provides the conceptual foundation for the analytical framework guiding this review.

Table 1: A Three-Lens Framework

Lens	Definition
Efficiency	Captures how GenAI streamlines task execution and enhances process performance (Magalhães Araujo & Cruz-Correia, 2024), enabling learners to attain instructional goals with reduced effort (Ahmed Kofahi & Husain, 2025) through improvements in

	speed, accuracy, and procedural consistency (Al-Obaydi & Pikhart, 2025).
Engagement	A multidimensional construct encompassing behavioral, emotional, cognitive, and social involvement (Al-Obaydi & Pikhart, 2025), reflected in active and sustained interaction with AI tools (Wu & Chiu, 2025), and driven by dynamic motivation and participatory learning (Klimova & De Campos, 2024).
Cognitive Offloading	Addresses how learners and educators intentionally transfer effort-intensive tasks such as information retrieval, error detection, or procedural problem-solving to AI systems (Nguyen et al., 2024), thereby reducing routine cognitive demands (Klar, 2025) and employing technological shortcuts (Juntarciego et al., 2025).

Lens Integration

Efficiency Lens: This lens conceptualizes GenAI as a mechanism for streamlining academic tasks. By automating repetitive or procedural components, GenAI reduces time and effort demands (Ahmed Kofahi & Husain, 2025; Al-Obaydi & Pikhart, 2025; Magalhães Araujo & Cruz-Correia, 2024). From a cognitive load perspective (Sweller, 1988), such automation may release working memory resources for higher-order reasoning. Efficiency, therefore, reflects not only speed but also the reallocation of cognitive capacity. However, the educational value of these gains depends on whether the time saved is reinvested in deeper cognitive engagement or merely accelerates surface-level task completion (Yan et al., 2024; Yunianto et al., 2024).

Engagement Lens: This lens interprets GenAI-supported learning as a process that may influence motivation and involvement. GenAI can enhance perceived competence through immediate feedback (Costa et al., 2024; Klimova & De Campos, 2024; Wu & Chiu, 2025), support autonomy via self-directed exploration, and foster interaction through collaborative tasks. However, engagement outcomes differ depending on the nature of student-AI interaction. Collaborative and reflective use where students actively question and refine AI outputs is associated with deeper cognitive processing and sustained focus (Nasr et al., 2025; Stofiana et al., 2025). In contrast, passive acceptance of AI-generated content risks disengagement, over-reliance, and a decline in critical thinking (Nasr et al., 2025; Thi et al., 2025). Therefore, engagement is not an automatic outcome of AI use but is mediated by how learners position themselves in relation to the technology.

Cognitive Offloading Lens: The Cognitive Offloading Lens addresses how learners transfer effort-intensive tasks, such as information retrieval or error detection, to AI systems (Nguyen et al., 2024). While this may reduce routine cognitive demands (Klar, 2025), excessive offloading without conceptual engagement (Elshall & Badir, 2025) may weaken schema construction and long-term retention. The educational value of offloading depends on what is offloaded and under what conditions it is offloaded. Cognitive resources for higher-order design and systems thinking can be free when AI handles routine procedural tasks (Štuikys et al., 2025). However, learners risk developing what one study terms as “epistemic dependence” which refers to a reliance on AI-generated content that undermines their own critical thinking abilities when they offload the cognitive work of analysis, evaluation, and synthesis (Essien et al., 2024). The distinction between beneficial support and harmful substitution centers on

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whether learners maintain epistemic agency by actively evaluating and integrating AI outputs rather than accepting them uncritically (Stofiana et al., 2025).

These lenses are analytically distinct yet operationally interconnected. Cognitive offloading may enhance efficiency, while efficiency gains may shape engagement patterns. Depending on instructional design and learner regulation, these interactions may either support reflective inquiry or encourage superficial task completion. Therefore, the framework provides a structured approach to examining not just whether GenAI is used, but how it is used and under what conditions its effects on learning are realized.

Methodology

This article employs a narrative review methodology to synthesize interdisciplinary research on GenAI and cognitive engagement. A narrative approach is suitable for integrating heterogeneous empirical and conceptual findings within an emerging research area (Baumeister & Leary, 1997). The literature search was conducted in Scopus, a multidisciplinary abstract and citation database known for its rigorous curation, to ensure the quality and relevance of identified sources. The search strategy was built around key conceptual clusters related to the research questions:

Population/Context: ("student" OR "learner" OR "educat*" OR "classroom") AND
Intervention/Tool: ("generative AI" OR "large language model" OR "LLM" OR "ChatGPT" OR "GPT-") AND
Outcome: ("cognitive engagement" OR "critical think" OR "metacogniti" OR "self-regulated learning" OR "problem solv*" OR "deep learning" OR "higher order thinking").

The search was limited to free to download articles published in English and focused on the period from January 2022 to November 2025. The free-to-download filter was applied to ensure full-text accessibility for comprehensive analysis. This initial search yielded 1,550 records. Following a two-stage screening process, 56 studies met the final inclusion criteria.

A two-stage screening procedure was implemented. Stage one involved title and abstract evaluation using predefined criteria. Stage two consisted of full-text screening focusing on explicit cognitive constructs or theoretical arguments related to GenAI use. Key variables were extracted into a structured framework for each of the 56 included studies, including educational context, methodology, GenAI application, and cognitive outcomes.

Results & Discussions

Methodological Patterns

This section presents the results of the narrative review including the quantitative and qualitative analyses of 56 selected articles that meet the inclusion criteria. Most included studies were published in 2025, followed by 2024, with relatively fewer studies appearing in 2023. This distribution reflects the rapidly expanding nature of GenAI research in education.

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Table 2 presents the dominant outcomes by methodology type.

Table 2: Dominant Outcomes Reported by Methodology Type

Methodology Type	Efficiency Outcomes	Engagement Outcomes	Cognitive Offloading Outcomes
Experimental	**Task acceleration** Faster execution (Rana et al., 2025; Yang et al., 2025; Zhou et al., 2024) Improved revision speed (Asamoah et al., 2024; Sánchez-Ruiz et al., 2023) Faster debugging/code generation (Štuikys et al., 2025; Yunianto et al., 2024) **LLM-specific gains** Programming task performance (Sun et al., 2025)	**Cognitive engagement** Deeper cognitive processing (Štuikys et al., 2025; Yang et al., 2025) Higher-order thinking (H.-Y. Lee et al., 2024; Zhao et al., 2025) Sustained focus (H. Li, 2023) Collaborative use and active refinement (Nasr et al., 2025) **Motivation & metacognition** Enhanced motivation/strategies (Sun et al., 2025) Learning through AI interaction (Yunianto et al., 2024) **Behavioral indicators** Frequency of LLM use (Jošt et al., 2024)	**Cognitive load reduction** Freed working memory (De La Puente et al., 2024; Naatonis et al., 2024) AI as scaffolding or a more capable other (Sun et al., 2025; Yang et al., 2025) SRL support in programming learning (Sun et al., 2025) **Offloading risks** Risk of accepting flawed AI-generated code without domain knowledge (Yunianto et al., 2024) Negative correlation between GenAI use for code generation ($\rho = -0.305$) and debugging ($\rho = -0.360$) with independent task performance (Jošt et al., 2024)
Perception-based / Mixed	**Time management** Better time management (Juntarciego et al., 2025; Wu & Chiu, 2025; Zhao et al., 2025) **Idea generation** Brainstorming and idea generation in writing tasks (Moon Hidayati Otoluwa et al., 2025; Thi et al., 2025) **Perceived productivity** Productivity gains	**Affective engagement** Reduced writing anxiety (Mekheimer, 2025; Thi et al., 2025) Lowered communication apprehension (S. Lee & Eronen, 2025) Increased confidence (L. Li & Kim, 2024) **Motivation & self-efficacy** Enhanced self-efficacy/motivation(H. Li, 2023; Yang et al.,	**Task delegation** Easier task completion (Leahy et al., 2025; Nguyen et al., 2024) **Offloading risks** Surface-level completion strategies (Al-Obaydi & Pikhart, 2025; Sun et al., 2025) Over-reliance risk (Thi et al., 2025) Plagiarism concerns and loss of authentic voice (Thi et al., 2025)

	(Chauncey & McKenna, 2023; Elshall & Badir, 2025) Tool helpfulness (Juntarciego et al., 2025) AI feedback as quicker/more accurate (Al-Obaydi & Pikhart, 2025)	2025) High satisfaction with AI tasks (Costa et al., 2024) **Interaction quality** Passive use can lead to disengagement (Nasr et al., 2025) Higher social engagement in human vs. AI peer assessment (Al-Obaydi & Pikhart, 2025)	 **Critical awareness** Students recognize need to verify AI-generated information (Costa et al., 2024) AI feedback lacks emotional engagement compared to human feedback (Al-Obaydi & Pikhart, 2025)

Efficiency vs Learning Depth

Although GenAI consistently improves task completion speed (Rana et al., 2025; Zhou et al., 2024), evidence remains insufficient to confirm that saved time leads to deeper cognitive engagement. Several studies suggest that efficiency gains may instead promote surface-level completion strategies, with students relying on AI for quick answers rather than investing in conceptual understanding (Al-Obaydi & Pikhart, 2025; Sun et al., 2025). This tension is further illustrated by findings that while GenAI accelerates information retrieval and complex problem-solving in STEM contexts (Štuikys et al., 2025), supports brainstorming and idea generation in writing tasks (Moon Hidayati Otoluwa et al., 2025; Thi et al., 2025), and enhances revision speed and debugging processes (Asamoah et al., 2024; Sánchez-Ruiz et al., 2023; Yunianto et al., 2024), its impact on learning depth depends on how it is used. Structured guidance that encourages students to articulate their own answers before receiving AI support can transform these efficiency gains into opportunities for deeper cognitive processing (H.-Y. Lee et al., 2024; Yang et al., 2025). However, experimental evidence warns that frequent LLM use for critical thinking-intensive tasks such as code generation and debugging may negatively impact learners' ability to perform independently when such tools are unavailable. This reveals a potential trade-off between immediate efficiency and long-term skill development (Jošt et al., 2024). In addition, the absence of pedagogical scaffolding may create a scenario where the speed and ease of content generation is just used to facilitate quicker task completion without fostering meaningful learning or understanding (Yunianto et al., 2024).

Engagement findings differ across methodologies. Perception-based studies frequently report reduced writing anxiety, increased confidence, and lowered communication apprehension (S. Lee & Eronen, 2025; L. Li & Kim, 2024; Mekheimer, 2025; Thi et al., 2025). Experimental studies, by contrast, examine engagement through behavioral indicators such as the frequency of LLM use for specific learning tasks, including code generation, seeking explanations, and debugging (Jošt et al., 2024; Štuikys et al., 2025). This inconsistency in measurement approaches limits direct comparison.

However, a more complex picture emerges when we examine engagement as a multi-faceted concept. Experimental studies capture cognitive engagement through indicators such as deeper processing, higher-order thinking, and sustained focus, particularly when students interact with GenAI in structured ways (H.-Y. Lee et al., 2024; H. Li, 2023; Štuikys et al., 2025; Yang et al., 2025; Zhao et al., 2025). These studies also measure engagement behaviorally by tracking how often students use LLMs for code generation, seeking explanations, or debugging (Jošt et al., 2024; Štuikys et al., 2025). Perception-based studies, by contrast, reports on the affective dimensions of engagement. Learners state reduced writing anxiety and lower communication apprehension, often because GenAI provides a non-judgmental space for practice and grammar improvement (S. Lee & Eronen, 2025; Mekheimer, 2025; Thi et al., 2025). These tools also improve motivation and self-efficacy, especially when they deliver personalized, timely feedback (H. Li, 2023; Yang et al., 2025), and learners generally express high satisfaction with AI-assisted tasks (Costa et al., 2024).

The quality of learner-AI interaction also shapes engagement outcomes. Collaborative use where learners actively question and refine AI output is associated with higher-order thinking and sustained focus (Nasr et al., 2025; Štuikys et al., 2025). In contrast, passive, AI-directed use can lead to disengagement (Nasr et al., 2025). However, experimental evidence also state a cautionary note where frequent LLM use for critical thinking-intensive tasks may negatively impact students' ability to perform independently when such tools are unavailable (Jošt et al., 2024). This finding highlights a potential trade-off between the immediate support GenAI offers and the long-term development of independent problem-solving skills.

The review reveals a dual effect of cognitive offloading. Experimental findings associate GenAI use with reduced cognitive load and freed working memory, allowing learners to focus on higher-order reasoning and problem-solving (De La Puente et al., 2024; Naatonis et al., 2024). GenAI can function as a more capable other to scaffolding learning in ways that extend learner' capabilities beyond what they could achieve independently (Sun et al., 2025; Yang et al., 2025). However, experimental evidence also warns of offloading risks. Frequent GenAI use for critical thinking-intensive tasks may negatively impact students' ability to perform independently when such tools are unavailable, revealing a trade-off between immediate support and long-term skill development (Jošt et al., 2024; Yunianto et al., 2024). Perception-based studies similarly caution against over-reliance, surface-level completion strategies, and potential cognitive atrophy (Al-Obaydi & Pikhart, 2025; Sun et al., 2025; Thi et al., 2025).

This contrast suggests that outcomes depend on learner regulation and task design. The DEQ (Domain knowledge, Ethical acumen, Query capabilities) framework indicates that learners need specific competencies to use GenAI effectively and safely (Asamoah et al., 2024). When learners lack domain knowledge or strong questioning skills, they are more likely to accept AI-generated content uncritically. As shown in Table 2, this is expressed in both experimental and perception-based studies where learners with insufficient domain knowledge risk accepting flawed AI-generated code (Yunianto et al., 2024), while perception-based studies report surface-level completion strategies and over-reliance (Al-Obaydi & Pikhart, 2025; Sun et al., 2025; Thi et al., 2025). Conversely, when GenAI is used within a structured Co-Regulated Learning (CoRL) framework, it can scaffold the very skills needed to eventually reduce dependence, turning offloading from a risk into a developmental tool (Yang et al., 2025). This is shown in studies where guided interaction promoted independent critical thinking and a reconceptualization of AI as a thinking partner rather than a shortcut (H.-Y. Lee et al., 2024; Nasr et al., 2025). Experimental evidence further shows that when GenAI functions as a more capable other, it can support self-regulated learning and reduce cognitive load while preserving learner agency (Sun et al., 2025; Yang et al., 2025).

As shown in Table 2, methodological orientation shapes reported outcomes. Experimental studies predominantly report measurable efficiency gains and cognitive load reductions, with faster task execution, improved revision speed, and freed working memory (Rana et al., 2025;

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Sánchez-Ruiz et al., 2023; Yang et al., 2025; Zhou et al., 2024). Perception-based studies, by contrast, emphasize subjective experiences and perceived learning benefits, including better time management, perceived productivity, and tool helpfulness (Juntarciego et al., 2025; Wu & Chiu, 2025; Zhao et al., 2025). However, as demonstrated above, this deviation is not simply methodological. The findings reflect a deeper pedagogical reality. The impact of GenAI is not present within the tool itself but is mediated by how it is integrated into learning.When used passively, it risks becoming a cognitive crutch that undermines independent performance (Jošt et al., 2024; Yunianto et al., 2024). However, when structured as a collaborative partner through guided interaction and co-regulated learning frameworks, it can enhance human reasoning and foster deeper learning (H.-Y. Lee et al., 2024; Nasr et al., 2025; Yang et al., 2025). This suggests that future research and practice should move beyond asking whether GenAI is effective toward investigating the specific conditions, learner competencies, and pedagogical designs that determine its influence on student learning.

Table 3 reported key pattern in GenAI outcomes across educational levels.

Table 3: Key Patterns in GenAI Outcomes Across Educational Levels

Educational Levels	Efficiency Patterns	Engagement Patterns	Cognitive Offloading Patterns
School	Faster debugging and exploration (Štuikys et al., 2025); improved grammar and deadline compliance (Juntarciego et al., 2025)	Increased curiosity and motivation through iterative prompting (Chauncey & McKenna, 2023); sustained focus (Klar, 2025)	Shared low-order cognition (Zhao et al., 2025); freeing cognitive resources for higher-order thinking (Štuikys et al., 2025)
Undergraduate	Faster task completion and drafting (Thi et al., 2025); improved revision speed (Sánchez-Ruiz et al., 2023)	Reduced writing anxiety and increased confidence (Thi et al., 2025); deeper reflection when used collaboratively (Nasr et al., 2025)	Surface-level completion risk (Al-Obaydi & Pikhart, 2025; Sun et al., 2025); over-reliance risk (Jošt et al., 2024)
Postgraduate	Research acceleration (Dai et al., 2023; Elshall & Badir, 2025); workflow optimization (Nguyen et al., 2024)	Enhanced intellectual autonomy and scholarly development (Dai et al., 2023; Klimova & De Campos, 2024)	Strategic offloading for higher-order reasoning (Essien et al., 2024); risk of epistemic dependence (Essien et al., 2024)

Developmental patterns emerge across educational levels, reflecting differences in learner maturity and task complexity. At the school level, GenAI primarily supports foundational skill development. Students benefit from faster debugging and exploration in STEM contexts (Štuikys et al., 2025), improved grammar and deadline compliance in writing tasks (Juntarciego et al., 2025), and increased curiosity through structured, iterative prompting (Chauncey & McKenna, 2023). Cognitive offloading at this stage focuses on routine tasks, freeing mental resources for higher-order thinking (Zhao et al., 2025).

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Undergraduate learners display the most varied outcomes. Efficiency gains are widely reported with faster task completion, accelerated drafting, and improved revision speed (Sánchez-Ruiz et al., 2023; Thi et al., 2025). However, the engagement pattern depends heavily on interaction quality. Collaborative, reflective use provide deeper reflection and critical thinking (Nasr et al., 2025), while passive acceptance of AI-generated content risks surface-level learning and over-reliance (Al-Obaydi & Pikhart, 2025; Jošt et al., 2024; Sun et al., 2025).

At the postgraduate level, GenAI use becomes more strategic. Learners leverage AI for research acceleration and workflow optimization (Dai et al., 2023; Elshall & Badir, 2025; Nguyen et al., 2024), with engagement characterized by enhanced intellectual autonomy and scholarly development (Dai et al., 2023; Klimova & De Campos, 2024). Cognitive offloading serves as a deliberate strategy to focus on higher-order reasoning, though the risk of epistemic dependence persists if AI outputs are not critically evaluated (Essien et al., 2024). These patterns suggest that while the indications of efficiency, engagement, and offloading shift with learner development, the fundamental tension between support and substitution remains constant across all educational stages.

Table 4 highlights cross-disciplinary variations in GenAI usage patterns.

Table 4: GenAI Outcomes by Academic Discipline

Discipline	Efficiency Patterns	Engagement Patterns	Cognitive Offloading Patterns
Humanities	**Writing process efficiency** Writing speed and deadline management (Juntarciego et al., 2025; Khampusaen, 2025; Moon Hidayati Otoluwa et al., 2025; Thi et al., 2025) Accelerated drafting and revision (Mekheimer, 2025; Thi et al., 2025) **Idea and language support** Idea generation and outlining(Hong et al., 2025; Thi et al., 2025) Paraphrasing and translation support (Thi et al., 2025)	**Affective engagement** Reduced anxiety (S. Lee & Eronen, 2025; Stofiana et al., 2025; Zhang & Wang, 2025) Improved confidence (S. Lee & Eronen, 2025; Mekheimer, 2025) Enhanced self-efficacy and motivation (H. Li, 2023; Mekheimer, 2025) **Cognitive engagement** Rhetorical development (Stofiana et al., 2025; Zhang & Wang, 2025) Deeper reflection as "thinking partner" (Nasr et al., 2025; Stofiana et al., 2025)	**Task delegation** Grammar and formatting delegation(Mekheimer, 2025; Wu & Chiu, 2025) AI as a more capable other for language development (S. Lee & Eronen, 2025) **Offloading risks** Depth vs. accuracy tension (Stofiana et al., 2025) Over-reliance and loss of authentic voice (Thi et al., 2025; Yunianto et al., 2024) Regulatory gap between awareness and enactment (Stofiana et al., 2025)
Technological	**Coding and debugging efficiency**	**Interactive and visual engagement**	**Procedural offloading** Procedural task

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	Debugging acceleration (Ahmed Kofahi & Husain, 2025; Elshall & Badir, 2025; Štuikys et al., 2025) Faster code generation and troubleshooting (Naatonis et al., 2024; Štuikys et al., 2025) Automated documentation and code commenting (Leahy et al., 2025) **Project acceleration** Expedited simulation and prototyping (Štuikys et al., 2025) Assistance with complex, multi-step problem-solving (Štuikys et al., 2025)	Interactive learning (Dahlkemper et al., 2023; Leahy et al., 2025) Complex concept visualization (Dahlkemper et al., 2023; Leahy et al., 2025; Zhao et al., 2025) **Sustained cognitive engagement** Sustained problem-solving engagement (Klar, 2025) Enhanced STEM motivation (Štuikys et al., 2025) Critical thinking through structured tasks(De La Puente et al., 2024; Zhao et al., 2025) Collaborative problem-solving as AI partner (Nasr et al., 2025)	delegation (Elshall & Badir, 2025; Naatonis et al., 2024) Reduced cognitive load for routine operations (Štuikys et al., 2025) AI as a collaborative partner for code refinement (Nasr et al., 2025) **Offloading risks** Skill atrophy risk (Elshall & Badir, 2025) Freeing resources for higher-order design and systems thinking (Štuikys et al., 2025)

As summarized in Table 4, disciplinary patterns indicate that humanities contexts emphasize writing-related efficiency, while technological disciplines highlight debugging and computational acceleration. Despite these differences, both domains exhibit similar tensions between efficiency gains and independent cognitive development. However, a closer look reveals that the nature of these tensions is shaped by the core tasks and knowledge standards of each discipline.

Humanities Disciplines

In humanities disciplines, GenAI use is predominantly oriented toward writing and language-related tasks. Efficiency gains are consistently reported in writing process efficiency such as writing speed, deadline management, and accelerated drafting and revision (Juntarciego et al., 2025; Mekheimer, 2025; Moon Hidayati Otoluwa et al., 2025; Thi et al., 2025). Learners also rely on GenAI for idea and language support especially for idea generation, outlining, paraphrasing, and translation, which streamlines the initial stages of composition (Hong et al., 2025; Thi et al., 2025). Engagement in these contexts covers both affective and cognitive dimensions. Affectively, learners report reduced writing anxiety, increased confidence, and enhanced self-efficacy and motivation, as AI tools provide a non-judgmental space for practice and feedback (S. Lee & Eronen, 2025; H. Li, 2023; Mekheimer, 2025; Thi et al., 2025). Cognitively (when used reflectively), GenAI helps learners to develop their ability to construct

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and express arguments while encouraging deeper reflection. Eventually, learners describe AI as a thinking partner that helps refine ideas and consider multiple perspectives (Nasr et al., 2025; Stofiana et al., 2025; Zhang & Wang, 2025). However, the quality of engagement depends heavily on how learners interact with the tool. Collaborative use with the tool (where learners actively question and refine AI-generated content) can promote deeper reflection and positions AI as a authentic partner in the writing process (Nasr et al., 2025). In contrast, passive acceptance of AI-generated text risks surface-level learning, over-reliance, and a loss of authentic voice (Stofiana et al., 2025; Thi et al., 2025; Yunianto et al., 2024).

This creates a distinctive cognitive offloading pattern in humanities. Learners engage in task delegation which can free cognitive resources for higher-order concerns (Mekheimer, 2025; Wu & Chiu, 2025). When used effectively, AI can function as a more capable other for language development (S. Lee & Eronen, 2025). However, this also introduces offloading risks, including a tension between depth and accuracy (Stofiana et al., 2025), over-reliance and loss of authentic voice (Thi et al., 2025; Yunianto et al., 2024), and a regulatory gap where learners recognize effective writing strategies but fail to act out independently (Stofiana et al., 2025). Learners also express concern about this tension, mentioning that over-reliance on AI could diminish their own critical thinking and writing abilities (Thi et al., 2025). The challenge, therefore, is to use AI in ways that scaffold language development without replacing the learners' own voice which requires pedagogical frameworks that encourage critical engagement with AI outputs while maintaining ownership of written work.

Technological Disciplines

In technological disciplines such as engineering, computer science, and data science, GenAI use is primarily task-oriented, focusing on problem-solving, coding, and system design. Efficiency gains are mostly reported in coding and debugging efficiency (Ahmed Kofahi & Husain, 2025; Elshall & Badir, 2025; Leahy et al., 2025; Naatonis et al., 2024; Štuikys et al., 2025). Learners also benefit from project acceleration through advanced simulation, prototyping, and assistance with complex, multi-step problem-solving (Štuikys et al., 2025). Engagement in these contexts spans interactive and visual dimensions as well as sustained cognitive engagement, including sustained problem-solving focus, enhanced STEM motivation, and critical thinking development through structured tasks (Dahlkemper et al., 2023; De La Puente et al., 2024; Klar, 2025; Leahy et al., 2025; Štuikys et al., 2025; Zhao et al., 2025). Learners who actively engage with AI as a collaborative partner for code refinement report more meaningful learning experiences (Nasr et al., 2025).

Cognitive offloading in technological disciplines involves deligating routine tasks to AI while also managing the risks that come with this delegation. Learners delegate routine tasks to AI, thereby reducing cognitive load and freeing resources for higher-order design and systems thinking (Elshall & Badir, 2025; Naatonis et al., 2024; Štuikys et al., 2025). AI can serve as a collaborative partner for code refinement (Nasr et al., 2025). However, risks occur when this offloading is not balanced with foundational skill development. Over-reliance on AI for foundational tasks may lead to skill atrophy, where learners fail to develop basic programming competencies or deep understanding of underlying principles (Elshall & Badir, 2025). Furthermore, learners with limited domain knowledge may struggle to evaluate the appropriateness of AI-generated code, potentially accepting flawed solutions without critical scrutiny. These finding highlights the importance of domain expertise as a prerequisite for effective and safe AI use in technological fields. Without it, the efficiency gains of AI may come at the cost of genuine learning and skill development.

Cross-Disciplinary Synthesis

A common pattern emerges cross both humanities and technological disciplines. The effectiveness of GenAI is mediated by the learner's ability to engage critically with its outputs. In humanities, this means maintaining authorial voice while leveraging AI for linguistic refinement and idea generation (Stofiana et al., 2025; Thi et al., 2025). As such, learners must learn to use AI as a thinking partner rather than an alternative for their own thinking (Nasr et al., 2025). In technological fields, sufficient domain knowledge is required to evaluate the appropriateness of AI-generated code and solutions. Learner's risk accepting flawed outputs and missing opportunities for genuine learning without this foundation. These patterns suggest that disciplinary norms and task structures shape both how GenAI is used and also the specific competencies learners must develop to use it responsibly. Both fields face the same underlying issue. Humanities learners may know good writing strategies but fail to apply them independently (Stofiana et al., 2025), while technology learners risk skill atrophy from over-relying on AI for basic tasks (Elshall & Badir, 2025). In each case, the danger is that AI support becomes a substitute rather than a scaffold to learning. In both cases, the challenge is the same in which ensuring that cognitive offloading enhances, rather than replaces, the development of disciplinary expertise. This requires pedagogical approaches that explicitly teach learners how to engage critically with AI. The goal is not to avoid using AI, but to use it in ways that enhance rather than diminish human cognitive development.

Table 5 synthesizes recurring tensions across lenses, reinforcing that GenAI outcomes are inherently dual edged rather than uniformly beneficial.

Table 5: Cross-Lens Tensions Identified in the Literature

Lens	Key Tension
Efficiency	Speed vs. Depth: The time saved may come at the cost of deep understanding and critical engagement.
Engagement	Enjoyment vs. Cognitive Effort: Reduced anxiety may paradoxically lead to less investment of mental effort.
Cognitive Offloading	Support vs. Substitution: The line between helpful scaffolding and harmful replacement of cognitive work is easily blurred.

The Efficiency Tension: Speed vs. Depth

The first recurring tension across the literature concerns the relationship between efficiency gains and learning depth. As synthesized in Table 2, experimental studies consistently report that GenAI accelerates task completion, improves revision speed, and enhances debugging and code generation (Rana et al., 2025; Štuikys et al., 2025; Yang et al., 2025). Similarly, perception-based studies also highlight better time management, perceived productivity, and tool helpfulness (Juntarciego et al., 2025; Wu & Chiu, 2025). However, these efficiency gains do not automatically translate into deeper learning. Several studies warn that learners may instead adopt surface-level completion strategies and use AI to finish tasks quickly without investing in conceptual understanding (Al-Obaydi & Pikhart, 2025; Sun et al., 2025). This tension plays out across both humanities and technological disciplines. In humanities, although learners benefit from accelerated drafting and idea generation, they risk losing their authentic voice if they rely too heavily on AI-generated text (Thi et al., 2025; Yunianto et al., 2024). In technology, faster code generation and debugging can free cognitive resources for higher order design but may also lead learners to accept flawed code without critical scrutiny when domain knowledge is lacking (Jošt et al., 2024). The speed vs. depth tension thus reveals that efficiency is only beneficial when the time saved is reinvested in meaningful cognitive engagement. However, this is a condition that depends heavily on both pedagogical scaffolding and learner regulation.

The Engagement Tension: Enjoyment vs. Cognitive Effort

The second tension lies in the disconnect between the affective benefits of GenAI and the cognitive demands of deep learning. Learners may feel more confident and less anxious while using GenAI. However, these positive feelings do not automatically translate into effortful engagement that leads to genuine understanding. Across perception-based studies, learners consistently report reduced writing anxiety, increased confidence, and enhanced motivation when using GenAI tools (Mekheimer, 2025; S. Lee & Eronen, 2025; Thi et al., 2025). These affective gains are valuable because they lower barriers to participation, provide a non-judgmental space for practice, and encourage learners to engage with challenging material (Costa et al., 2024; H. Li, 2023). However, this same ease of use can become a liability. When learners experience with GenAI is perceived as enjoyable and learners need to use only low effort to complete tasks, they may invest less mental effort in the learning process. Experimental evidence shows that passive, AI-directed use where learners simply accept AI outputs without questioning or refining them can lead to disengagement and undermines the development of critical thinking skills (Nasr et al., 2025). This tension is especially evident at the undergraduate level, where the same tools that reduce writing anxiety can also foster over-reliance and surface-level engagement if not used collaboratively (Jošt et al., 2024; Thi et al., 2025). The enjoyment vs. cognitive effort tension thus highlights a central challenge for educators in term of preserving the motivational benefits of GenAI while ensuring that learners remain cognitively engaged in the hard work of learning.

The Cognitive Offloading Tension: Support vs. Substitution

The third and most fundamental tension concerns the dual role of GenAI as either a scaffold for learning or a substitute for it. On one hand, experimental studies demonstrate that GenAI can reduce cognitive load by handling routine tasks, freeing working memory for higher-order reasoning and problem-solving (De La Puente et al., 2024; Naatonis et al., 2024). In addition, when used within structured frameworks, AI can function as a more capable other and scaffold the development of self-regulated learning and independent critical thinking (Sun et al., 2025; Yang et al., 2025). On the other hand, the same offloading that supports learning in one context can undermine it in another. In humanities, delegating grammar and formatting to AI may free resources for argument development, but it also creates a regulatory gap where learners recognize effective strategies yet fail to perform on them independently (Stofiana et al., 2025). In technology, procedural offloading of coding tasks can accelerate project completion, yet over-reliance on AI for foundational work leads to skill atrophy and an inability to perform without AI assistance (Elshall & Badir, 2025; Yunianto et al., 2024). The line between support and substitution is a blurred one. The outcome depends critically on learner competencies in term of domain knowledge and query capabilities, as well as task design (Asamoah et al., 2024). When learners lack the foundation to evaluate AI outputs critically, offloading becomes substitution and when they engage with AI as a thinking partner, it becomes support.

Synthesizing the Tensions: The Central Role of Cognitive Regulation

Taken together, these three tensions point to a common underlying factor which is the quality of learners' cognitive regulation in their interactions with GenAI. The speed vs. depth tension is not merely about time management but about learners' ability to regulate their learning goals and resist the temptation of superficial completion. The enjoyment vs. cognitive effort tension reflects learners' capability to maintain cognitive engagement even when the path of least resistance is available. The support vs. substitution tension centers on learners' metacognitive awareness of when and how to use AI as a tool versus when to rely on their own capabilities. This analysis suggests that the outcomes of GenAI use are not determined by the technology itself, but by the regulatory skills learners bring to their interactions with it. Learners who approach AI as a collaborative partner are more likely to experience its benefits across all three lenses (Nasr et al., 2025; Stofiana et al., 2025). In contrast, learners who use AI passively, accepting its outputs without critical scrutiny, are more vulnerable to the risks of surface learning, disengagement, and epistemic dependence (Essien et al., 2024; Nasr et al., 2025). The literature thus points to an important pedagogical requirement which is to prepare learners not just to use AI, but to use it with intention, critical awareness, and metacognitive control. This requires moving beyond technical training in prompt engineering to encourage what might be called critical AI literacy, which is the ability to evaluate AI outputs, recognize their limitations, and maintain agency over one's own learning processes (Essien et al., 2024; Stofiana et al., 2025).

Theoretical and Empirical Implications

Evidence Limitations and Inconsistencies

Although the reviewed literature ***mention***s numerous benefits of GenAI integration, the evidence base remains uneven across the three analytical lenses. Within the efficiency lens, findings consistently indicate faster task completion and improved workflow performance (Rana et al., 2025; Zhou et al., 2024). However, relatively few studies directly measure whether time savings translate into deeper cognitive engagement or improved knowledge retention. As a result, claims linking efficiency gains to learning quality remain empirically underdeveloped. Evidence within the engagement lens is especially inconsistent. Perception-based studies frequently report reduced writing anxiety, increased confidence, and enhanced motivation (S. Lee & Eronen, 2025; L. Li & Kim, 2024), whereas experimental studies operationalize engagement through behavioral indicators such as interaction frequency and persistence (Jošt et al., 2024; Štuikys et al., 2025). These different measurement approaches complicate cross-study comparison and limit conclusions regarding sustained cognitive engagement.

Within the cognitive offloading lens, theoretical tensions are particularly noticeable. Experimental studies often frame offloading as a mechanism for reducing cognitive load and supporting higher-order reasoning (Naatonis et al., 2024), while perception-based research emphasizes risks of over-reliance and diminished independent thinking (Sánchez-Ruiz et al., 2023; Sun et al., 2025; Yunianto et al., 2024). Despite these discussions, few studies differentiate between productive allocation of routine processes and harmful substitution of necessary cognitive activities. This causes the construct conceptually unclear. This lack of conceptual clarity matters because it hides the conditions under which offloading supports versus undermines learning. The central question is not whether learners offload cognitive work to AI, but what they offload, when, and with what level of critical engagement. Addressing this question requires more precise theoretical frameworks and empirical designs that can distinguish between different forms of offloading across varied learning contexts.

Conclusion

This review makes several contributions to the growing literature on GenAI in education. First, it introduces a three-lens framework: Efficiency, Engagement, and Cognitive Offloading which provides a structured way to synthesize fragmented findings across diverse methodologies, disciplines, and educational levels. By organizing the literature around these three interconnected dimensions, the framework reveals that the impact of GenAI is not uniform but depends critically on how cognitive effort is redistributed, regulated, and pedagogically structured. Second, the review identifies recurring tensions within each lens that capture the dual-edged nature of GenAI integration. These tensions move the conversation beyond simple questions of whether GenAI helps or hinders learning toward a better understanding of the conditions under which its effects are beneficial or harmful. Third, the synthesis highlights important disciplinary and developmental patterns that humanities and technological contexts shape different efficiency and engagement outcomes, while school, undergraduate, and postgraduate learners show distinct offloading patterns that reflect their evolving cognitive needs and capabilities. Together, these contributions provide researchers and educators with a coherent framework for interpreting existing evidence and designing more effective GenAI integrations.

Despite these contributions, the review also reveals significant gaps that require further investigation. Across all three lenses, there is a notable lack of longitudinal research examining how GenAI use influences cognitive independence, metacognitive skill development, and academic resilience over time. Most studies capture short-term gains or self-reported perceptions, leaving unanswered questions about whether learners who rely on GenAI develop the capacity to think and perform independently when tools are unavailable. Future research should prioritize experimental and longitudinal designs that can track sustained cognitive consequences across multiple time points. Within the efficiency lens, studies are needed that move beyond measuring speed and productivity to assess whether time savings translate into deeper learning and knowledge retention. Within the engagement lens, researchers should employ multimodal measures that combine behavioral traces, cognitive indicators, and performance metrics to distinguish between collaborative, reflective use and passive, AI-directed engagement. Within the cognitive offloading lens, experimental designs must differentiate between types of offloading either routine task delegation or conceptual task substitution to clarify when offloading enhances learning and when it undermines skill development. Addressing these gaps will require interdisciplinary collaboration and methodological innovation, but doing so is necessary for ensuring that GenAI becomes a tool that augments rather than weakens human cognitive development.

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References

Ahmed Kofahi, M., & Husain, A. (2025). ChatGPT for Operating Systems: Higher-Order Thinking in Focus. *Journal of Information Technology Education: Research*, *24*, 001. https://doi.org/10.28945/5382

Al-Obaydi, L. H., & Pikhart, M. (2025). AI partner versus human partner: Comparing AI-based peer assessment with human-generated peer assessment in examining writing skills. *Language Testing in Asia*, *15*(1), 38. https://doi.org/10.1186/s40468-025-00375-8

Asamoah, P., Zokpe, D., Boateng, R., Marfo, J. S., Boateng, S. L., Asamoah, D., Muntaka, A. S., & Manso, J. F. (2024). Domain knowledge, ethical acumen, and query capabilities (DEQ): A framework for generative AI use in education and knowledge work. *Cogent Education*, *11*(1), 2439651. https://doi.org/10.1080/2331186X.2024.2439651

Baumeister, R. F., & Leary, M. R. (1997). Writing Narrative Literature Reviews. *Review of General Psychology*, *1*(30), 311–320.

Chauncey, S. A., & McKenna, H. P. (2023). A framework and exemplars for ethical and responsible use of AI Chatbot technology to support teaching and learning. *Computers and Education: Artificial Intelligence*, *5*, 100182. https://doi.org/10.1016/j.caeai.2023.100182

Costa, A. R., Lima, N., Viegas, C., & Caldeira, A. (2024). Critical minds: Enhancing education with ChatGPT. *Cogent Education*, *11*(1), 2415286. https://doi.org/10.1080/2331186X.2024.2415286

Dahlkemper, M. N., Lahme, S. Z., & Klein, P. (2023). How do physics students evaluate artificial intelligence responses on comprehension questions? A study on the perceived scientific accuracy and linguistic quality of ChatGPT. *Physical Review Physics Education Research*, *19*(1), 010142. https://doi.org/10.1103/PhysRevPhysEducRes.19.010142

Dai, Y., Lai, S., Lim, C. P., & Liu, A. (2023). ChatGPT and its impact on research supervision: Insights from Australian postgraduate research students. *Australasian Journal of Educational Technology*, *39*(4), 74–88. https://doi.org/10.14742/ajet.8843

De La Puente, M., Torres, J., Troncoso, A. L. B., Meza, Y. Y. H., & Carrascal, J. X. M. (2024). Investigating the use of chatGPT as a tool for enhancing critical thinking and argumentation skills in international relations debates among undergraduate students. *Smart Learning Environments*, *11*(1), 55. https://doi.org/10.1186/s40561-024-00347-0

Elshall, A. S., & Badir, A. (2025). Balancing AI-assisted learning and traditional assessment: The FACT assessment in environmental data science education. *Frontiers in Education*, *10*, 1596462. https://doi.org/10.3389/feduc.2025.1596462

Essien, A., Bukoye, O. T., O'Dea, X., & Kremantzis, M. (2024). The influence of AI text generators on critical thinking skills in UK business schools. *Studies in Higher Education*, *49*(5), 865–882. https://doi.org/10.1080/03075079.2024.2316881

Hong, H., Vate-U-Lan, P., & Viriyavejakul, C. (2025). Cognitive Offload Instruction with Generative AI: A Quasi-Experimental Study on Critical Thinking Gains in English Writing. *Forum for Linguistic Studies*, *7*(7). https://doi.org/10.30564/fls.v7i7.10072

Jošt, G., Taneski, V., & Karakatič, S. (2024). The Impact of Large Language Models on Programming Education and Student Learning Outcomes. *Applied Sciences*, *14*(10), 4115. https://doi.org/10.3390/app14104115

Juntarciego, M. J. C., Gaboy, R., Delos Santos, Ma. R. H., & Collantes, L. (2025). Chat, copy, change: Prospects and risks of ChatGPT in the teaching and learning process. *Acta Scientiarum. Education*, *47*, e71533. https://doi.org/10.4025/actascieduc.v47i1.71533

Khampusaen, D. (2025). The Impact of ChatGPT on Academic Writing Skills and Knowledge: An Investigation of Its Use in Argumentative Essays. *LEARN Journal: Language Education and Acquisition Research Network*, *18*(1), 963–988. https://doi.org/10.70730/PGCQ9242

Klar, M. (2025). Using ChatGPT is easy, using it effectively is tough? A mixed methods study on K-12 students' perceptions, interaction patterns, and support for learning with generative AI chatbots. *Smart Learning Environments*, *12*(1), 32. https://doi.org/10.1186/s40561-025-00385-2

Klimova, B., & De Campos, V. P. L. (2024). University undergraduates' perceptions on the use of ChatGPT for academic purposes: Evidence from a university in Czech Republic. *Cogent Education*, *11*(1), 2373512. https://doi.org/10.1080/2331186X.2024.2373512

Kong, S.-C., Lee, J. C.-K., & Tsang, O. (2024). A pedagogical design for self-regulated learning in academic writing using text-based generative artificial intelligence tools: 6-P pedagogy of plan, prompt, preview, produce, peer-review, portfolio-tracking. *Research and Practice in Technology Enhanced Learning*, *19*, 030. https://doi.org/10.58459/rptel.2024.19030

Leahy, K., Ozer, E., & Cummins, E. (2025). AI-ENGAGE: A Multicentre Intervention to Support Teaching and Learning Engagement with Generative Artificial Intelligence Tools. *Education Sciences*, *15*(7), 807. https://doi.org/10.3390/educsci15070807

Lee, H.-Y., Chen, P.-H., Wang, W.-S., Huang, Y.-M., & Wu, T.-T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: Effect of self-regulated learning, higher-order thinking skills, and knowledge construction. *International Journal of Educational Technology in Higher Education*, *21*(1), 16. https://doi.org/10.1186/s41239-024-00447-4

Lee, S., & Eronen, J. (2025). Transforming English education in Japan by utilizing large language models for tailored learning and diverse skill development. *Discover Education*, *4*(1), 403. https://doi.org/10.1007/s44217-025-00856-1

Li, H. (2023). Effects of a ChatGPT-based flipped learning guiding approach on learners' courseware project performances and perceptions. *Australasian Journal of Educational Technology*, *39*(5), 40–58. https://doi.org/10.14742/ajet.8923

Li, L., & Kim, M. (2024). It is like a friend to me: Critical usage of automated feedback systems by self-regulating English learners in higher education. *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.8821

Magalhães Araujo, S., & Cruz-Correia, R. (2024). Incorporating ChatGPT in Medical Informatics Education: Mixed Methods Study on Student Perceptions and Experiential Integration Proposals. *JMIR Medical Education*, *10*, e51151. https://doi.org/10.2196/51151

Mekheimer, M. (2025). Generative AI-assisted feedback and EFL writing: A study on proficiency, revision frequency and writing quality. *Discover Education*, *4*(1), 170. https://doi.org/10.1007/s44217-025-00602-7

Moon Hidayati Otoluwa, Arhanuddin Salim, Kadir, Gina Nurvina Darise, Indah Wardaty Saud, & Andi Asma. (2025). Students' perceptions and effect of ChatGPT on research proposal quality across gender in Indonesia. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *14*(5), 3613–1623. https://doi.org/DOI:%252010.11591/ijai.v14.i5

Naatonis, R. N., Rusijono, R., Jannah, M., & Malahina, E. A. U. (2024). Evaluation of Problem Based Gamification Learning (PBGL) Model on Critical Thinking Ability with Artificial Intelligence Approach Integrated with ChatGPT API: An Experimental Study. *Qubahan Academic Journal*, *4*(3), 485–520. https://doi.org/10.48161/qaj.v4n3a919

Nasr, N. R., Tu, C.-H., Werner, J., Bauer, T., Yen, C.-J., & Sujo-Montes, L. (2025). Exploring the Impact of Generative AI ChatGPT on Critical Thinking in Higher Education: Passive AI-Directed Use or Human–AI Supported Collaboration? *Education Sciences*, *15*(9), 1198. https://doi.org/10.3390/educsci15091198

Nguyen, A., Hong, Y., Dang, B., & Huang, X. (2024). Human-AI collaboration patterns in AI-assisted academic writing. *Studies in Higher Education*, *49*(5), 847–864. https://doi.org/10.1080/03075079.2024.2323593

Rana, V., Verhoeven, B., & Sharma, M. (2025). Generative AI in Design Thinking Pedagogy: Enhancing Creativity, Critical Thinking, and Ethical Reasoning in Higher Education. *Journal of University Teaching and Learning Practice*, *22*(4). https://doi.org/10.53761/tjse2f36

Sánchez-Ruiz, L. M., Moll-López, S., Nuñez-Pérez, A., Moraño-Fernández, J. A., & Vega-Fleitas, E. (2023). ChatGPT Challenges Blended Learning Methodologies in Engineering Education: A Case Study in Mathematics. *Applied Sciences*, *13*(10), 6039. https://doi.org/10.3390/app13106039

Šedlbauer, J., Činčera, J., Slavík, M., & Hartlová, A. (2024). Students' reflections on their experience with CHATGPT. *Journal of Computer Assisted Learning*, *40*(4), 1526–1534. https://doi.org/10.1111/jcal.12967

Stofiana, T., Sunendar, D., Mulyati, Y., & Sastromiharjo, A. (2025). Writing with AI, thinking with Toulmin: Metacognitive gaps and the rhetorical limits of argumentation. *Ampersand*, *15*, 100242. https://doi.org/10.1016/j.amper.2025.100242

Štuikys, V., Burbaitė, R., Binkis, M., & Ziberkas, G. (2025). Developing Problem-Solving Skills to Support Sustainability in STEM Education Using Generative AI Tools. *Sustainability*, *17*(15), 6935. https://doi.org/10.3390/su17156935

Sun, D., Xu, P., Zhang, J., Liu, R., & Zhang, J. (2025). How Self-Regulated Learning Is Affected by Feedback Based on Large Language Models: Data-Driven Sustainable Development in Computer Programming Learning. *Electronics*, *14*(1), 194. https://doi.org/10.3390/electronics14010194

Sweller, J. (1988). Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Thi, X. H. N., Thien, H. V. H., Vuong, K. N., & Nguyen, T. T. (2025). Enhancing writing skills through AI-powered tools: Perceived benefits and challenges among Vietnamese EFL students. *Discover Education*, *4*(1), 472. https://doi.org/10.1007/s44217-025-00905-9

Wu, X.-Y., & Chiu, T. K. F. (2025). Integrating learner characteristics and generative AI affordances to enhance self-regulated learning: A configurational analysis. *Journal of New Approaches in Educational Research*, *14*(1), 10. https://doi.org/10.1007/s44322-025-00028-x

Yan, L., Greiff, S., Teuber, Z., & Gašević, D. (2024). *Promises and challenges of generative artificial intelligence for human learning* (arXiv:2408.12143). arXiv. https://doi.org/10.48550/arXiv.2408.12143

Yang, Y., Huang, L., Lin, W., Li, Y., Xu, Y., & Cheng, L. (2025). Enhancing Sustainable English Writing Instruction Through a Generative AI-Based Virtual Teacher Within a Co-Regulated Learning Framework. *Sustainability*, *17*(19), 8770. https://doi.org/10.3390/su17198770

Yunianto, W., Lavicza, Z., Kastner-Hauler, O., & Houghton, T. (2024). Investigating the use of ChatGPT to solve a GeoGebra based mathematics+computational thinking task in a geometry topic. *Journal on Mathematics Education*, *15*(3), 1027–1052. https://doi.org/10.22342/jme.v15i3.pp1027-1052

Zhang, H., & Wang, Q. (2025). How could GenAI work on in-service teachers' knowledge building process? An empirical study based on epistemic network analysis. *International Journal of Educational Technology in Higher Education*, *22*(1), 47. https://doi.org/10.1186/s41239-025-00544-y

Zhao, G., Sheng, H., Wang, Y., Cai, X., & Long, T. (2025). Generative Artificial Intelligence Amplifies the Role of Critical Thinking Skills and Reduces Reliance on Prior Knowledge While Promoting In-Depth Learning. *Education Sciences*, *15*(5), 554. https://doi.org/10.3390/educsci15050554

Zhou, X., Teng, D., & Al-Samarraie, H. (2024). The Mediating Role of Generative AI Self-Regulation on Students' Critical Thinking and Problem-Solving. *Education Sciences*, *14*(12), 1302. https://doi.org/10.3390/educsci14121302

Zied Bahroun, Chiraz Anane, Vian Ahmed, & Andrew Zacca. (2023). Transforming Education: A Comprehensive Review of Generative Artificial Intelligence in Educational Settings through Bibliometric and Content Analysis. *Sustainability*, *15*(12983). https://doi.org/10.3390/%20%20su151712983