

The Generative AI Cognitive Effort Paradox: When Less Effort Does Not Mean Better Learning - An Integrative Review of Cognitive Load, Productive Struggle, and Independent Learning

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Abstract

Generative artificial intelligence (GenAI) is reshaping higher education by reducing the time and effort required to access information, solve problems, and complete academic tasks. Although these capabilities can improve learning efficiency, their implications for deeper understanding and independent learning remain uncertain. This review examines the cognitive effort paradox in GenAI-supported education: the possibility that reducing unnecessary mental effort can facilitate learning while excessive cognitive delegation may weaken the processes through which knowledge is constructed and retained. Drawing on Cognitive Load Theory, desirable difficulties, self-regulated learning, and cognitive offloading research, the review distinguishes productive cognitive assistance from cognitive substitution. It examines how GenAI influences cognitive load, learning engagement, metacognitive monitoring, knowledge retention, and independent problem-solving. The synthesis suggests that the educational value of reduced cognitive effort depends on the nature of the task, learner characteristics, instructional design, and whether students remain actively involved in learning-relevant processing. An integrative conceptual framework is proposed to explain the conditions under which GenAI-supported efficiency may strengthen or constrain learning. The review offers directions for experimental research, educational assessment, and responsible GenAI integration in higher education.

Keywords: Generative Artificial Intelligence; Cognitive Load Theory; Cognitive Offloading; Productive Struggle; Desirable Difficulties; Self-Regulated Learning; Higher Education; Independent Learning

1. Introduction

Generative artificial intelligence (GenAI) is changing how students learn by providing immediate explanations, summaries, examples, and support for academic tasks. Tools such as ChatGPT can make learning more accessible, personalized, and efficient (Kasneci et al., 2023; Tlili et al., 2023). However, faster task completion does not necessarily mean better learning. Meaningful learning requires students to interpret information, evaluate alternatives, and apply knowledge independently. This creates what the present review describes as the GenAI cognitive effort paradox: while GenAI can reduce unnecessary cognitive demands, excessive

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reliance may also limit the mental effort needed for deeper understanding. Cognitive Load Theory suggests that reducing unnecessary processing can support learning (Sweller, 1988; Sweller et al., 2019), whereas the desirable difficulties perspective emphasizes that certain learning challenges strengthen long-term retention and knowledge transfer (Roediger & Karpicke, 2006; Soderstrom & Bjork, 2015). Together, these perspectives raise an important question: does GenAI improve learning by reducing unnecessary effort, or can excessive assistance weaken the cognitive processes essential for lasting understanding?

The issue also relates to cognitive offloading, whereby individuals use external resources to reduce internal cognitive demands (Grinschgl et al., 2021; S. M. F. A. Khan & Suhluli, 2025; S. M. Khan & Shehawy, 2025). Cognitive offloading is not necessarily problematic. External tools have long supported memory, calculation, and information management (Maxwell Ho & Chen, 2026). However, when a learning objective requires students to develop particular cognitive skills, repeatedly transferring those processes to GenAI may create a mismatch between successful task completion and actual competence development (Jiang & Xu, 2026).

Existing scholarship has examined the educational opportunities and challenges of large language models, including personalized support, feedback, information accuracy, assessment, and academic integrity (Kasneci et al., 2023; Shehawy & Faisal Ali Khan, 2026; Tlili et al., 2023). These contributions provide an important foundation, but a more focused synthesis is needed to distinguish cognitive effort that can productively be reduced from cognitive effort that should be preserved. Accordingly, this review addresses three questions: How does GenAI alter cognitive effort during learning? Under what conditions does reduced effort support or constrain learning? And how can educators design GenAI-supported activities that preserve productive cognitive engagement and independent learning? The review integrates CLT, desirable difficulties, cognitive offloading, and self-regulated learning to develop a framework distinguishing productive cognitive assistance from cognitive substitution. Its contribution lies in organizing these theoretical perspectives around the relationship between immediate efficiency and longer-term learning rather than assuming that either increased or reduced effort is inherently desirable.

2. Review Approach and Scope

This article adopts a critical integrative review approach. Integrative reviews are appropriate when a research problem spans several theoretical traditions and requires the development of a coherent conceptual explanation rather than only the aggregation of comparable empirical effects (Ali Khan & Islam, 2026; Sheikh et al., 2026; Snyder, 2019; Torraco, 2005). This review integrates established research on cognitive load, desirable difficulties, cognitive offloading, metacognition, and self-regulated learning with recent studies on GenAI in education. It examines how GenAI influences cognitive effort, learning processes, and the conditions under which greater efficiency may support or hinder learning. While this approach offers a broader theoretical understanding, it does not provide an exhaustive assessment of the literature or estimate overall effects. Accordingly, the proposed relationships are interpreted cautiously and presented as conceptual propositions requiring further empirical validation.

3. Theoretical Foundations

3.1 Cognitive Load Theory and GenAI-Supported Learning

Cognitive Load Theory (CLT) explains how the limited capacity of working memory influences learning. Sweller (1988) argued that excessive cognitive demands can interfere with knowledge acquisition, particularly when learners devote mental resources to activities that do not directly support understanding. Later developments distinguish demands arising from the complexity of learning material from those created by unnecessary instructional processes (Sweller et al., 2019). GenAI may help manage these demands by simplifying explanations, organizing information, and providing relevant examples. However, its educational value depends on how students use it. Seeking explanations before independently solving problems may support learning, whereas relying on complete AI-generated solutions may reduce opportunities for meaningful cognitive engagement. This distinction also reflects the expertise reversal effect, whereby instructional guidance that benefits beginners may become less useful as learners gain expertise (Tetzlaff et al., 2025). Thus, effective GenAI assistance should reduce unnecessary cognitive effort while preserving the mental processes essential for learning.

3.2 Desirable Difficulties and Productive Cognitive Effort

The desirable difficulties perspective challenges the assumption that learning conditions should always feel easy. (Gadi et al., 2026; Soderstrom & Bjork, 2015) explain that activities requiring additional effort may improve long-term learning when they engage processes that strengthen retrieval, discrimination, and knowledge reconstruction. Research on retrieval practice illustrates this distinction. (Herzallah et al., 2025; Roediger & Karpicke, 2006; Wang & Yang, 2024) found that testing can improve long-term retention even when repeated study produces stronger immediate familiarity. (Chang et al., 2024; Soderstrom & Bjork, 2015) similarly distinguish temporary performance from relatively durable learning. These findings are particularly relevant to GenAI because students can obtain polished explanations and solutions without necessarily generating or retrieving information themselves. A student who asks GenAI to answer a question may experience rapid task completion, whereas a student who first attempts an answer and then uses GenAI feedback may engage in more retrieval, comparison, and correction. However, not every difficulty is desirable (Lai et al., 2026). Confusing instructions, inaccessible explanations, and unnecessary procedural complexity can hinder learning. The educational challenge is therefore to distinguish difficulty that contributes to learning from difficulty that merely consumes resources. GenAI may be particularly valuable when used to maintain this distinction. Instead of eliminating challenges, it can provide hints, ask guiding questions, or offer feedback after an independent attempt. Such uses may reduce unproductive frustration while preserving the cognitive effort required for knowledge development.

3.3 Cognitive Offloading and Externalized Thinking

Cognitive offloading occurs when individuals use external resources to reduce demands on internal cognitive processes (Gerlich, 2025; S. M. F. A. Khan & Suhluli, 2025; Masmali et al., 2025). Everyday examples include writing reminders, using calculators, and storing information digitally. GenAI extends these possibilities by performing activities that involve

language production, interpretation, planning, and reasoning (Andreou & Christani, 2025) . Students can use it not only to retrieve information but also to organize arguments, compare alternatives, generate explanations, and propose solutions. Cognitive offloading is not necessarily harmful, as delegating routine tasks may free mental resources for more demanding learning activities (Guo & Ye, 2026). However, its value depends on the learning objective. For example, using GenAI to organize information may support critical analysis, whereas relying on it to perform the analysis may limit opportunities to develop analytical skills. Earlier research suggests that access to external information can influence memory and information retrieval (Lu et al., 2020; Sparrow et al., 2011), although these findings do not directly establish the effects of GenAI. The concern, therefore, is not cognitive offloading itself, but the delegation of mental processes that students need to develop through independent learning.

3.4 Self-Regulated Learning and Learner Agency

Self-Regulated Learning (SRL) theory emphasizes learners' ability to set goals, select strategies, monitor understanding, and evaluate progress (Khafaga & Alamer, 2026; Zimmerman, 2002). GenAI may support these processes through personalized feedback, study planning, and identifying knowledge gaps. However, excessive reliance on AI-generated responses may encourage passive learning and reduce independent judgment. From an SRL perspective, effective learning requires students to remain responsible for evaluating their understanding and deciding when further practice is needed (Cui et al., 2025). Integrating SRL with Cognitive Load Theory (CLT) and cognitive offloading provides a broader explanation: CLT addresses cognitive demands, cognitive offloading explains the delegation of mental tasks, and SRL highlights learners' control over these processes. Together, these perspectives suggest that GenAI's educational value depends on how students balance technological assistance with independent cognitive engagement.

4. GenAI and the Changing Nature of Cognitive Effort

4.1 Reduced Cognitive Effort as an Educational Opportunity

GenAI can reduce the effort involved in accessing, organizing, and understanding information by providing immediate explanations, relevant examples, and support with difficult concepts. Deng et al. (2025), in a systematic review and meta-analysis of 69 experimental studies, reported improvements in academic performance, higher-order thinking, and motivational outcomes alongside reduced mental effort, while highlighting methodological limitations and the need for stronger long-term evidence. However, reduced effort does not always indicate better learning. When GenAI simplifies complex information, it may support understanding, but when students rely on complete AI-generated answers, it may replace essential cognitive processes. Thus, the educational value of reduced effort depends on whether GenAI supports meaningful learning or substitutes for independent thinking.

4.2 Cognitive Substitution and the Risk of Passive Learning

The concern surrounding GenAI is not simply that students may use it frequently. Rather, repeated reliance may become educationally problematic when AI assistance replaces activities necessary for developing the knowledge or skills being assessed (Islam & Khan, 2024;

Shehawy & Ali Khan, 2024). Cognitive offloading research provides a basis for examining this possibility. (Dunn & Risko, 2016; Islam & Ali Khan, 2024) explain that externalizing cognitive processes changes the demands placed on internal cognition and that decisions to offload can be influenced by metacognitive judgments, which are not always accurate. In GenAI-supported learning, students may delegate explanation generation, argument development, problem decomposition, or evaluation of alternatives (Hakami, 2023; Islam & Faisal Ali Khan, 2023, 2024). Such delegation can be productive when these activities are peripheral to the learning objective. However, it may become problematic when the delegated process is itself the competence students are expected to acquire. For instance, a student learning academic writing may benefit from AI-generated feedback on argument clarity. However, repeatedly delegating the development of arguments may provide fewer opportunities to practice constructing and evaluating arguments independently. This does not establish that GenAI inevitably causes cognitive dependency. Rather, it identifies a plausible mechanism that requires careful empirical investigation. The educational risk depends on the extent of delegation, the student's existing competence, the learning objective, and whether independent practice remains part of the learning process.

4.3 Immediate Performance Versus Durable Learning

A central challenge in evaluating GenAI is distinguishing performance during AI-supported activities from learning that persists beyond those activities.

(Khalufi et al., 2025; Shehawy, Faisal Ali Khan, et al., 2025; Soderstrom & Bjork, 2015) emphasize that immediate performance can be an unreliable indicator of durable learning. Improvements observed during instruction do not necessarily represent lasting changes in knowledge or skill. This distinction is particularly relevant when students complete assignments with GenAI assistance (Islam & Khan, 2024; S. Khan & Khan, 2024). A well-structured answer may demonstrate successful use of the tool without revealing how much of the underlying knowledge the student has acquired (Sallam et al., 2024; Youssef et al., 2024). Consequently, research evaluating GenAI should distinguish between AI-assisted performance, unaided performance, delayed retention, and knowledge transfer. These outcomes are related but not interchangeable (Rana et al., 2025; Shehawy, Khan, et al., 2025). A student who produces a high-quality response with GenAI assistance may perform differently when asked to solve a comparable problem independently (Cheng et al., 2025; Medabesh & Khan, 2019; Suhululi & Ali Khan, 2022). Likewise, immediate understanding of an AI-generated explanation may not ensure that the student can retrieve or apply the information several weeks later.

The review therefore argues that assessments conducted only during AI-assisted task completion provide an incomplete picture of GenAI's educational consequences.

5. Integrative Synthesis: Productive Assistance Versus Cognitive Substitution

The preceding literature suggests that GenAI-supported learning cannot be evaluated through a simple distinction between beneficial and harmful technology use. The more relevant distinction concerns the relationship between AI assistance and the cognitive processes required for learning.

Table 1. Conceptual distinction between productive assistance and cognitive substitution

Dimension	Productive assistance	Potential cognitive substitution
Information access	GenAI helps locate and clarify relevant information	Learners accept generated information without evaluation
Conceptual understanding	GenAI provides explanations that learners actively interpret	Learners reproduce explanations without demonstrating understanding
Problem-solving	GenAI offers hints and feedback during independent attempts	GenAI completes the central reasoning process
Cognitive effort	Unnecessary processing demands are reduced	Learning-relevant processing is bypassed
Metacognition	Learners monitor understanding and identify errors	Learners equate fluent AI responses with their own competence
Self-regulation	Learners decide when and how to use assistance	AI outputs increasingly determine learning decisions
Assessment	Students demonstrate understanding independently	Performance is evaluated mainly through AI-assisted outputs

The distinction also suggests that GenAI's educational consequences are likely to depend on the relationship between assistance and learner competence. Students with limited prior knowledge may benefit from more explicit guidance, while students with greater expertise may benefit from opportunities to solve problems with less assistance. The important issue is therefore not how much GenAI assistance students receive in absolute terms, but whether the assistance is appropriately aligned with their knowledge, task demands, and learning objectives. This interpretation is consistent with CLT and the expertise reversal effect (Abdullah et al., 2025; Sweller et al., 2019; Tetzlaff et al., 2025). It also reflects the desirable difficulties perspective, which recognizes that productive learning may sometimes require effort that does not immediately improve performance (Shehawy et al., 2024; Soderstrom & Bjork, 2015).

6. Proposed Integrative Conceptual Framework

Building on the theoretical synthesis, this review proposes a framework in which GenAI assistance can influence learning through two conceptually distinct pathways. The first is a productive assistance pathway. GenAI reduces unnecessary cognitive demands, supports comprehension, and provides feedback while learners remain actively involved in processing information. Under these conditions, assistance may support cognitive engagement, self-regulation, and durable learning. The second is a potential cognitive substitution pathway. GenAI performs learning-relevant activities that students would otherwise undertake themselves. When such delegation reduces independent practice and weakens monitoring of

understanding, students may experience stronger immediate task performance without equivalent development of unaided competence as shown in Figure 1.

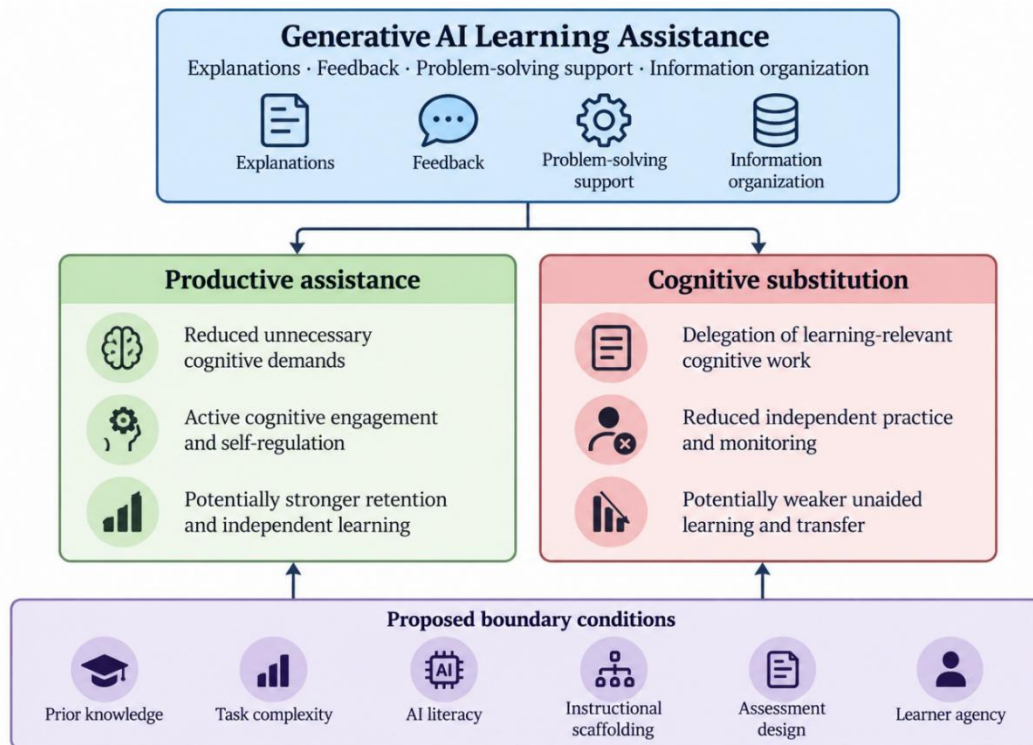


Figure 1: Conceptual Framework

Figure 1. Proposed dual-path framework for the GenAI cognitive effort paradox. Relationships are theoretical propositions, not estimated causal effects. The framework does not assume that these pathways are mutually exclusive. A student may use GenAI productively during one activity and engage in cognitive substitution during another. The same learning session may also contain both forms of interaction. This suggests that researchers should examine specific GenAI-supported learning behaviors rather than relying only on general measures of frequency of use or perceived usefulness.

The framework generates four propositions for future investigation.

Proposition 1: GenAI assistance that reduces unnecessary cognitive demands while preserving learning-relevant processing is more likely to support effective learning than assistance that removes such processing.

Proposition 2: The relationship between GenAI-assisted task performance and unaided learning outcomes depends partly on the extent to which students independently engage in reasoning, retrieval, and knowledge application.

Proposition 3: Self-regulated learning and metacognitive monitoring may help learners distinguish productive assistance from excessive cognitive delegation.

Proposition 4: Prior knowledge, task complexity, instructional scaffolding, and assessment design may influence whether GenAI-supported efficiency produces productive assistance or cognitive substitution.

These propositions are intended to guide empirical research rather than represent confirmed relationships.

7. Research Gaps and Future Research Agenda

The synthesis identifies several research priorities.

First, studies should distinguish different forms of cognitive effort. General measures of mental effort may not reveal whether GenAI has reduced unnecessary processing or learning-relevant activity. Future research could combine perceived cognitive load with behavioral indicators of explanation generation, retrieval practice, reasoning, and independent problem-solving.

Second, greater attention is needed to learning retention and transfer. Although existing experimental evidence indicates that ChatGPT-supported interventions can improve academic performance, the methodological limitations identified by (Liu, 2024; Shehawy et al., 2024) reinforce the need for assessments that distinguish AI-assisted task success from independently demonstrated learning.

Third, the role of learner agency and self-regulation requires further investigation. Students differ in their ability to judge when assistance is necessary, evaluate AI-generated responses, and recognize gaps in their understanding. These differences may help explain why similar GenAI applications produce different learning experiences.

Fourth, research should examine how instructional design changes the consequences of AI assistance. Comparing unrestricted GenAI use with guided prompting, delayed assistance, hints, self-explanation requirements, and independent retrieval activities could help identify approaches that preserve productive cognitive effort.

Finally, the literature would benefit from stronger differentiation between short-term performance and longer-term competence. A research design that measures only the quality of AI-assisted assignments cannot establish whether students have developed transferable knowledge or independent problem-solving ability.

Table 2. Research gaps and recommended future directions

Research gap	Recommended approach	Potential contribution
Cognitive effort is often treated as a general outcome	Separate unnecessary cognitive demands from learning-relevant processing	Clarify when effort reduction supports learning
AI-assisted performance may be confused with competence	Compare assisted and unaided assessments	Distinguish task completion from learning

Limited understanding of durable learning	Use delayed retention and transfer tests	Examine longer-term consequences
Cognitive delegation is insufficiently differentiated	Measure the types and extent of delegated activities	Identify productive versus potentially problematic offloading
Learner agency is not always explicitly examined	Study metacognitive monitoring and SRL	Explain individual differences
Instructional conditions vary substantially	Compare scaffolded and unrestricted GenAI use	Identify more effective pedagogical designs

8. Implications for Higher Education

Universities should evaluate GenAI not simply by improvements in task completion or student satisfaction, but by its contribution to meaningful learning. Educators can use GenAI for explanations and feedback while ensuring that students remain responsible for reasoning, critical analysis, and problem-solving. Encouraging students to attempt tasks independently before seeking AI assistance may help preserve cognitive engagement. Assessments should also distinguish AI-assisted performance from independently demonstrated competence through activities such as oral explanations, supervised tasks, and knowledge transfer exercises. Institutions should promote AI literacy that emphasizes critical evaluation, responsible use, and self-regulated learning. These recommendations offer practical directions based on the proposed framework, although their effectiveness requires further empirical validation.

9. Limitations of the Review

This review has several limitations. Its integrative approach supports theoretical synthesis but does not provide the comprehensive study identification and quality appraisal associated with a systematic review. Consequently, the discussion cannot establish the frequency or magnitude of positive and negative GenAI effects across the complete literature. The framework also combines evidence from established cognitive and educational psychology with newer GenAI research. Although this integration provides a theoretical basis for examining the cognitive effort paradox, findings from earlier technologies and general learning research cannot automatically be assumed to apply unchanged to contemporary GenAI systems.

Furthermore, GenAI technologies and educational practices continue to evolve. Differences in model capabilities, task design, student experience, and institutional expectations may affect the relevance of particular mechanisms.

The proposed framework therefore requires empirical testing across disciplines, educational levels, and learning environments.

10. Conclusion

GenAI offers opportunities to make learning more efficient through simplified explanations, immediate feedback, and task assistance. However, greater efficiency does not necessarily lead

to better learning. Its educational value depends on whether it reduces unnecessary cognitive demands while preserving essential processes such as reasoning, reflection, and knowledge application. Drawing on Cognitive Load Theory, desirable difficulties, cognitive offloading, and Self-Regulated Learning Theory, this review proposes a dual-path framework distinguishing productive cognitive assistance from potential cognitive substitution. It also highlights how prior knowledge, learner autonomy, task complexity, and instructional design may shape learning outcomes. Ultimately, GenAI should be evaluated not by how much effort it saves, but by how effectively it supports meaningful and independent learning.

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