Διεθνές Συνέδριο για την Ανοικτή & εξ Αποστάσεως Εκπαίδευση

Τόμ. 13, Αρ. 2 (2026)

ICODL2025

GenAI as a Cognitive Co-Pilot in Learning Design: An Integrative Review

Garyfallia Kyriakea; Maria D. Avgerinou, Susan Stetson Tiligadas

doi: [10.12681/icodl.8618](https://doi.org/10.12681/icodl.8618)

Η Παραγωγική Τεχνητή Νοημοσύνη ως Γνωστικός Συνεργάτης στον Εκπαιδευτικό Σχεδιασμό: Μια Ολοκληρωτική Ανασκόπηση

GenAI as a Cognitive Co-Pilot in Learning Design: An Integrative Review

Garyfallia Kyriakea
The American College of Greece
gkyiakea@acg.edu

Maria D. Avgerinou
The American University of Greece- Global Campus, USA
mavgerinou@acg.edu

Susan Stetson – Tiligadas
The American College of Greece
tiligadas@acg.edu

Περίληψη

Το παρόν άρθρο προσφέρει μια συνοπτική ανασκόπηση της σύνδεσης μεταξύ παραγωγικής τεχνητής νοημοσύνης (GenAI) και της Θεωρίας Γνωστικού Φορτίου (CLT) στον εκπαιδευτικό σχεδιασμό, παρέχοντας στους εκπαιδευτικούς σχεδιαστές τεκμηριωμένη γνώση για τη διαχείριση του γνωστικού φορτίου μέσω της εφαρμογής θεμελιωδών αρχών διδακτικού σχεδιασμού στο πλαίσιο της CLT. Η διδασκαλία που υποστηρίζεται από GenAI μειώνει το ενδογενές φορτίο προσαρμόζοντας την πολυπλοκότητα του υλικού, περιορίζει το εξωγενές φορτίο μέσω αυτοματοποίησης εργασιών όπως η περίληψη και η δομημένη ανατροφοδότηση, και ενισχύει το παραγωγικό φορτίο με διαδραστικό διάλογο και αναστοχαστικές προτροπές που διευκολύνουν τη βαθιά επεξεργασία και το σχηματισμό γνώσης. Ταυτόχρονα, η απότομη ενσωμάτωση της GenAI συνεπάγεται κινδύνους, όπως η γνωστική παθητικότητα, η μείωση της παραγωγικής προσπάθειας, ο κατακερματισμός της προσοχής και η αυξημένη ανάγκη επαλήθευσης λόγω πιθανών ανακριβειών. Ο κακός σχεδιασμός επιφανειών και η υπερβολική προσωποποίηση μπορεί να επιφέρουν αυξημένο γνωστικό φορτίο. Η CLT παρέχει καθοδήγηση για την αξιολόγηση και ενσωμάτωση της GenAI, προτείνοντας μια συστηματική, θεωρητικά καθοδηγούμενη προσέγγιση που διασφαλίζει ότι η GenAI ενισχύει τη γνωστική δέσμευση και υποστηρίζει την βιώσιμη, ποιοτική μάθηση χωρίς να περιορίζει την πνευματική ανάπτυξη.

Λέξεις-κλειδιά

παραγωγική τεχνητή νοημοσύνη, θεωρία γνωστικού φορτίου, εκπαιδευτικός σχεδιασμός

Abstract

This article presents an integrative review of the relationship between Generative Artificial Intelligence (GenAI/AI) and Cognitive Load Theory (CLT) in instructional design, providing instructional designers with evidence-based insights for managing cognitive load through the core principles of instructional design within the CLT framework. The review demonstrates that GenAI-supported instruction effectively manages intrinsic load by tailoring material complexity, reduces extraneous load through task automation like summarization and structured feedback, and enhances germane load through interactive dialogue and reflective prompts that facilitate deep processing and schema construction. The rapid integration of GenAI poses significant cognitive risks for learners. The risks encompass cognitive passivity and offloading, a reduction in productive struggle, fragmentation of attention, and an increased verification burden due to potentially inaccurate AI outputs. Poorly designed AI interfaces and excessive personalization may unintentionally increase unnecessary cognitive load. The study concludes that CLT offers critical insights for assessing and guiding the integration of GenAI in learning design. Learning designers need to deploy a systematic, theory-driven approach to effectively utilize AI's transformative potential, ensuring it enhances cognitive engagement and fosters high-quality, sustainable learning experiences rather than impeding intellectual growth.

Keywords

generative artificial intelligence, cognitive load theory, learning design.

Introduction

This study explores the connection between Generative AI (GenAI) and Cognitive Load Theory (CLT) in educational contexts, specifically analyzing the impact of GenAI-supported instruction on intrinsic, extraneous, and germane cognitive load. These three types of cognitive load are defined in detail in the subsequent Theoretical Framework section. Although CLT provides useful insights, its application to GenAI is insufficiently examined, resulting in numerous implementations that introduce unnecessary extraneous load. Thus, to address this issue, this study synthesizes existing literature in order to elucidate the benefits and challenges of cognitive load in GenAI-enhanced learning, providing learning designers with insights to design effective, accountable, and theory-based AI-supported instruction. This emphasis on systematic, theory-driven design is essential for enhancing the quality of distance education in the AI era, as learning designers must incorporate GenAI technologies into online and blended learning environments in higher education. In this regard, this work provides techniques to reduce extraneous cognitive load in digital learning contexts, hence guiding the creation of successful AI-enhanced distance learning materials.

The present study addressed the following research questions:

RQ1: How does generative AI-supported instruction affect intrinsic, extraneous, and germane cognitive load?

RQ2: What benefits and challenges of cognitive overload arise from generative AI implementation in learning environments?

Theoretical Framework

Introduction

The theoretical framework grounding this study integrates key perspectives from learning theories and cognitive psychology to examine the intersection of Cognitive Load Theory (CLT) and Generative Artificial Intelligence (GenAI**)** in instructional design. Instructional design, as a systematic process of translating learning theories into structured methodologies, aims to optimize cognitive processes and enhance learner engagement and knowledge transfer. Building upon foundational paradigms such as behaviorism, constructivism, and andragogy, this framework situates CLT as a central lens for understanding how instructional design can effectively manage the cognitive demands placed on learners. Within this evolving landscape, the emergence of GenAI introduces new possibilities and challenges for designing adaptive, personalized, and cognitively efficient learning environments. By synthesizing these theoretical perspectives, this framework establishes the conceptual foundations for analyzing how GenAI can be employed to support, rather than compromise, the cognitive and pedagogical integrity of instructional design.

Instructional design (ID), also called learning design, with these terms used interchangeably in this context (Bai et al., 2024), constitutes a systematic methodology for developing educational materials aimed at improving efficiency and facilitating learning. These approaches involve the application of theories into structured techniques that stimulate cognitive processes and foster effective outcomes (Bozkurt, 2023; Kumar et al., 2024).

It is worth noting that learning designers inherently consider all learning theories, frequently employing a combination of these theories to enhance learning design. Therefore, several foundational learning theories are explored to inform instructional practices, impacting the development and implementation within learning environments (Aslam, 2020). Behaviorism focuses on observable actions influenced by environmental stimuli, enabling strategies like drill and practice and immediate feedback, which are effective for conveying essential information. Constructivism highlights the active generation of knowledge through interaction with information, context, and peers. This approach promotes problem-based learning and collaborative assignments to enhance critical thinking and enable meaningful learning transfer (Aslam, 2020). Andragogy, or adult learning theory, highlights the significance of learner autonomy, relevance, and knowledge gained through practice, necessitating self-direction and practical application, particularly in online learning environments (Khalil & Elkhider, 2016). Situated learning connects knowledge to context and social interaction, enhancing engagement in authentic situations (Fries, 2021). Experiential learning highlights the significance of reflecting on direct experiences to foster critical thinking (Aslam, 2020).

Contemporary learning design incorporates Cognitive Load Theory (CLT) to enhance instructional materials by minimizing extraneous load on working memory (Caskurlu et al., 2020; Sweller, 2020). CLT serves as a foundational framework in educational psychology and learning design, illustrating the limitations of cognitive architecture on learning and providing practical strategies to improve instructional effectiveness. Literature identifies three types of cognitive load: intrinsic, extraneous, and germane (Caskurlu et al., 2020; Sweller, 2020).

Intrinsic Load entails the inherent complexity of learning materials or tasks, which is determined by the number of interacting elements that necessitate simultaneous processing (Caskurlu et al., 2020). Effective management of intrinsic load necessitates aligning content complexity with learners' prior knowledge and developmental stage. Strategies including working examples, progressive problem-solving, and logical thinking are beneficial especially for novices encountering highly complex interaction problems (McLaughlin et al., 2023).

Extraneous load denotes the mental strain arising from the manner of presentation of material; unnecessary or confusing layouts increase this load. Reducing extraneous load is crucial for preserving working memory capacity (Harilal et al., 2024). Empirically validated multimedia principles, such as coherence (elimination of extraneous content), signaling (highlighting critical information), and spatial-temporal contiguity (the proximity of related text and visuals), effectively reduce cognitive load, thus improving cognitive efficiency (Chen et al., 2017; Harilal et al., 2024). Segmenting knowledge into smaller, manageable chunks helps mitigate cognitive overload (Granda et al., 2024).

Germane Load encompasses the cognitive resources dedicated to learning processes, including schema formation and automation. Instructional scaffolding which encourages metacognitive awareness and learner autonomy can significantly improve this load. Metacognitive prompts and reflective exercises assist learners in monitoring their understanding and managing cognitive strategies, thus improving long-term retention and knowledge transfer. Personalized learning environments that connect instructional information to learners' real-world experiences can improve cognitive engagement and relevance (Granda et al., 2024).

Effective learning design, particularly when based on cognitive theories, promotes high-quality learning by improving engagement, retention, and knowledge transfer (Granda et al., 2024). Key design elements involve:

GenAI is a revolutionary influence in learning design, significantly transforming educational systems by automatically producing coherent, multimodal content (Jayavardhini, 2024). GenAI technologies, particularly large language models (LLMs) like ChatGPT, Claude, and Gemini, are integral in revolutionizing instructional methods by providing adaptable and scalable solutions (Choi et al., 2024). Key applications include:

- Mayer's Cognitive Theory of Multimedia Learning (CTML) asserts that effective learning is facilitated when information is presented through both verbal and visual channels, enhancing cognitive processing. Principles such as spatial and temporal proximity, along with the reduction of duplication, enhance information integration and retention. (Granda et al., 2024)
- Grounded in Vygotsky's Zone of Proximal Development, adaptive scaffolding facilitates learners' transition from guided to autonomous learning (Fries, 2021). Artificial intelligence (AI) has enhanced scaffolding by providing adaptive, real-time support akin to human instructors, underscoring its scalability and personalization capabilities (Feng, 2024).
- Personalization, that is, tailoring education to student profiles, past knowledge, and preferences, promotes learning (Fries, 2021). Real-time content adaptations in adaptive learning systems, frequently employing AI, improve student engagement and effectiveness (Chen et al., 2017; Mayer, 2024).

GenAI technologies, particularly large language models (LLMs) like ChatGPT, Claude, and Gemini, are integral in revolutionizing instructional methods by providing adaptable and scalable solutions (Choi et al., 2024). Key applications include:

- Large Language Models (LLMs): Generate text that is syntactically accurate, contextually relevant, and semantically robust, employed for customized study aids, educational frameworks, and formative assessments (Choi et al., 2024; Gkintoni et al., 2025).
- AI-Driven Tutoring Solutions: Provide prompt, personalized educational assistance, adapting methodologies to meet individual student needs and delivering controlled guidance and pacing adjustments (Bai et al., 2024; Feng, 2024).
- AI Content Generators: Enable the automatic creation of quizzes, discussion prompts, multimedia presentations, and gamified learning experiences, therefore reducing educators' workloads (Bai et al., 2024; Feng, 2024).

Despite the considerable benefits of GenAI, its deployment often prioritizes usability and performance over cognitive and pedagogical principles (Choi et al., 2024; Khalil & Elkhider, 2016). However, assuming that AI scaffolding inherently reduces cognitive effort overlooks situations when outputs present unnecessary or repetitive information, hence increasing extraneous load (Feng, 2024). A systematic, theory-based design methodology is crucial, with Cognitive Load Theory guiding the strategic use of AI to enhance learning and mitigate cognitive risks (Chen et al., 2017; McLaughlin et al., 2023).

Conclusion

In summary, this theoretical framework highlights the dynamic interplay between cognitive principles and technological innovation in the era of GenAI-enhanced instructional design. Cognitive Load Theory provides a critical foundation for ensuring that AI-driven tools and strategies align with the limitations and capacities of human cognition, balancing innovation with pedagogical soundness. While GenAI offers unprecedented opportunities for personalization, scaffolding, and efficiency, its effective integration requires intentional, theory-based design to mitigate risks such as extraneous cognitive load and information redundancy. Thus, grounding GenAI applications within CLT not only advances instructional effectiveness but also ensures that technological affordances serve meaningful learning rather than cognitive saturation. Ultimately, this framework underscores the need for learning designers to act as critical mediators between cognitive science and AI innovation, fostering learning experiences that are both intellectually rigorous and cognitively sustainable.

Literature Review

This section offers an in-depth review of the literature about Cognitive Load Theory (CLT) and GenAI in the field of education. It analyzes the correlation between cognitive load types and particular GenAI affordances, addressing the dual influence of GenAI on cognitive load, encompassing beneficial as well as adverse impacts.

1. Applications of Cognitive Load Theory in Digital Learning Environments

Digital learning environments pose distinct challenges to learners' cognitive processing, frequently increasing extraneous load. Students are required to allocate their attention across multiple resources, perform tasks autonomously, and engage with intricate interfaces, potentially leading to excessive cognitive effort (Chen et al., 2017; McLaughlin et al., 2023). Extraneous load often results from an overabundance of multimedia, cluttered layouts, or frequent transitions between tabs and embedded media. Poorly designed systems increase the demand for usability efforts, differentiating these contemporary challenges from the instructional issues typically examined by Cognitive Load Theory (CLT) (Skulmowski & Xu, 2022; Twabu, 2025). Effective digital instruction necessitates minimizing distractions and directing cognitive resources towards meaningful processing and knowledge construction (Skulmowski & Xu, 2022; Twabu, 2025).

Microlearning has emerged as an effective approach, providing succinct modules that minimize navigation complexity and mental strain. The structured approach facilitates knowledge acquisition, especially in younger learners; however, improper media use may contribute to information overload. Principles derived from the Cognitive Theory of Multimedia Learning (CTML) inform the design of microlearning, highlighting the importance of clarity and organization to minimize extraneous cognitive load (Lopez, 2024).

Blended learning, integrating online and in-person instruction, has demonstrated improvements in efficiency and support for working memory (Skulmowski & Xu, 2022).

While Intrinsic load remains constant across modalities, blended approaches can reduce extraneous load by minimizing redundancy, enhancing coherence, and optimizing signaling. Moreover, these environments foster germane processing by enabling structured organization, fostering knowledge integration, and presenting learners with diverse perspectives (Gkintoni et al., 2025; León-Domínguez, 2024).

The Dual Impact of Generative AI on Cognitive Load

GenAI significantly alters student interaction with information and the distribution of cognitive resources in higher education. GenAI technologies can reduce extraneous load to improve critical processing; however, their extensive use may introduce cognitive risks that could undermine critical thinking, metacognition, and schema development.

Beneficial Effects of GenAI on Cognitive Load

GenAI reduces cognitive load by automating repetitive academic tasks, including text summary, draft generation, and instruction simplification, enabling students to focus on core disciplinary subjects without the burden of extraneous information. In second-language acquisition, the delivery of prompt feedback and instructional support via AI systems considerably reduces instructional complexity (Zhang et & Zou, 2022). Within this context, the reduction of extraneous load enables learners to allocate their cognitive resources on significant comprehension instead of ancillary activities, thereby enhancing overall academic engagement and efficacy. Meanwhile, the enhancement of germane load emerges as generative techniques facilitate deep information processing and schema development. AI fosters conceptual integration and reflective thinking by enhancing the interconnections between concepts via structured prompts and focused interactions, thus facilitating organization and long-term information retention (Granda et al., 2024). As a result, these tactics enhance learners' ability to retain information and construct transferable knowledge frameworks, thus strengthening critical thinking and enduring learning outcomes.

Furthermore, the management of intrinsic load is enhanced by GenAI systems that customize material complexity to align with a learner's existing knowledge. These systems utilize adaptive education to maintain learning within an appropriate cognitive range, preventing both cognitive overload and under-stimulation. AI-enhanced asynchronous learning settings, especially those concerning co-learners, foster cognitive and social presence, hence enhancing sustained attention and alleviating mental fatigue (Sallam, 2023). This adaptive equilibrium between learner capability and task complexity promotes enhanced engagement and sustained commitment in academic endeavors.

Finally, support for collaborative learners emphasizes the function of GenAI technology as cognitive augmenters in collaborative educational settings. Graduate students employing ChatGPT for digital storytelling exhibited enhanced technical abilities and reduced cognitive load (Twabu, 2025). The ability of GenAI to organize complex knowledge improves working memory efficiency, promoting collaborative problem-solving and creativity. The benefits are especially apparent for individuals with nontraditional educational backgrounds or those under considerable academic pressure, since GenAI mitigates memory-intensive tasks, hence improving cognitive endurance and resilience (Jaboob et al., 2025).

Adverse Effects of GenAI on Cognitive Load

While efficient, cognitive passivity and offloading risks have emerged as possible disadvantages of GenAI, since it may foster reliance and reduce autonomous reasoning. Users have reported a reduction in cognitive effort, linked to overconfidence and shallow engagement (Lee et al., 2025). Cognitive offloading can improve time management but may hinder the development of advanced executive skills such as reflective judgment, problem-solving, and metacognition (León-Domínguez, 2024). Thus, while GenAI contributes in reducing load, it poses a threat to weakening learners' higher-order cognitive involvement.

Likewise, the loss of productive struggle emphasizes that the convenience offered by GenAI diminishes the essential cognitive challenges essential to long-term learning

(Walczak & Cellary, 2023). The oversimplification of academic subjects may obscure the basic challenges necessary for solid understanding; hence reducing the cognitive effort required for effective schema development (Gkintoni et al., 2025). This diminishment of constructive effort eventually impedes the learner's ability to interact effectively with intricate concepts.

Moreover, distraction and attention fragmentation have emerged as significant issues, since AI systems—especially those utilizing conversational interfaces—can contribute to cognitive dispersion. Although these platforms can enhance engagement, they often promote multitasking and split attention, thus reducing the sustained focus required to intricate cognitive activities. Consequently, learners may encounter shallow processing and diminished cognitive endurance (Kiryakova & Angelova, 2023).

Furthermore, the validation burden poses an additional challenge, as students are required to validate and authenticate AI-generated outputs (Kiryakova & Angelova, 2023). Confronting errors, unreliable sources, or outdated materials requires critical assessment and verification, thereby elevating cognitive load and reducing conceptual immersion (Lee et al., 2025).

Finally, excessive personalization and comfort zone effects might hinder intellectual growth since adaptive systems that excessively customize information may restrict learners within familiar cognitive capabilities (Lee et al., 2025). In conjunction with this, the reduction of cognitive strategies in specific contexts suggests that GenAI may further limit the variety of cognitive approaches utilized, especially among students with insufficient skills in independent inquiry, consequently undermining self-directed reasoning and reflective thinking (Jaboob et al., 2025).

Balancing Benefits and Risks

The cognitive implications of GenAI are context-dependent and require careful integration (Gkintoni et al., 2025). Collaboration between AI design and educational neuroscience is essential to ensure that GenAI enhances cognitive effort rather than replacing it. GenAI functions as a cognitive co-pilot, aiding in the learning process and improving knowledge acquisition. Uncontrolled or excessive usage may compromise cognitive autonomy, critical analysis, and self-regulation. Educators should establish learning environments that utilize the benefits of GenAI while maintaining the integrity of intellectual development (Jaboob et al., 2025; León-Domínguez, 2024).

Evaluating AI Instructional Strategies Through Cognitive Load Theory

How Learning Designers employ AI tools to manage Cognitive Load

Learning designers serve as intermediaries between educational objectives and technological implementation (Kumar et al., 2024). It is essential to ensure that AI functions as a partner, augmenting instructional capacity while preserving critical cognitive effort and learner agency (Fries, 2021). The possibility of cognitive offloading, restricted productive struggle, and the application of extraneous load via inadequately designed interfaces require meticulous, theory-informed design decisions.

In this context, CLT provides a fundamental framework for the responsible integration of AI. CLT offers a framework for AI integration, highlighting the importance of a structured design that aligns with cognitive demands. Properly aligned GenAI can minimize intrinsic and extraneous load, thereby enhancing germane processing. Instructional designers should adopt CLT-informed strategies to enhance cognitive efficiency, foster metacognitive engagement, and ensure equitable learning outcomes. Learning designers require AI tools to innovate and personalize education. However, they need to comprehend CLT to utilize these tools responsibly and effectively, ensuring that technology enhances rather than detracts from meaningful learning. This requires an active approach to fostering human-AI collaboration and incorporating AI into educational frameworks grounded in established learning theories (Granda et al., 2024; Feng, 2025).

AI-Enhanced Pedagogical Approaches Aligned with Cognitive Load Theory:

Adaptive learning systems and cognitive modulation are essential for optimizing learning through the tailored adaptation of materials based on real-time learner data. These systems modify course difficulty and pace, thereby minimizing extraneous cognitive load while enhancing intrinsic load through appropriate challenge levels (Feng, 2024). Their adaptive approach aligns materials with prior knowledge, thereby enhancing effective learning through the intelligent modulation of cognitive effort (Bauer et al., 2025).

Building on these existing adaptive mechanisms, multimodal AI agents and the modality principle further enhance cognitive processing by leveraging multisensory presentation. Virtual teachers and voice assistants illustrate the modality principle, which asserts that the integration of auditory and visual channels enhances memory retention (Gkintoni et al., 2025). AI-driven video assistants deliver content via synchronized audio-visual media, mitigating the split-attention effect, whereas chatbots offer concise explanations and corrective feedback in manageable segments (Bai et al., 2023).

In addition, AI-enhanced cooperative learning promotes relevant cognitive load via peer interactions, utilizing AI for dialogue analysis, task distribution, and automated prompts to improve collaborative communication (Zhu et al., 2023). Artificial intelligence facilitates the management of complex tasks by organizing group interactions, reducing the potential of cognitive overload from unstructured discussions, and promoting creative thinking (Feng, 2025).

Meanwhile, diagnostic feedback and cognitive support systems deliver immediate, tailored feedback that targets learner misconceptions and highlights essential information, thereby reducing ambiguity and extraneous cognitive load (Gandhi et al., 2023; Bai et al., 2023; Gkintoni et al., 2025). These systems function as cognitive aids, enabling learners to engage with complex material without experiencing cognitive fatigue, thereby sustaining an optimal balance between challenge and support (Feng, 2024).

Additionally, predictive analytics and cognitively adaptive instruction personalize learning through the analysis of behavior and the anticipation of potential challenges, using AI algorithms. This enables timely interventions that modify instructional pace or structure based on cognitive and behavioral indicators (Feng, 2025). In addition to these strategies, microlearning and targeted cognitive engagement enhance cognitive load management via succinct, focused modules (Bai et al., 2023; Feng, 2024). Advanced questioning algorithms in these modules facilitate active data retrieval, enhance schema construction, and promote long-term memory consolidation. To achieve this, they direct learners' focus to critical information while reducing cognitive overload (Gkintoni et al., 2025).

AI-Driven Instructional Strategies Misaligned with Cognitive Load Theory (CLT): The overabundance of information produced by automated content creation poses a considerable cognitive challenge. AI systems that generate dense material without appropriate pacing controls, opportunities for reflection, or chunking mechanisms can overwhelm learners with unfiltered input, consequently elevating extraneous cognitive load (Zhu et al., 2024). This lack of adaptivity further impedes effective interaction and limits schema acquisition (Bai et al., 2023; Feng, 2025).

In addition to informational overload, the issue of oversimplification in GenAI responses may hinder deep learning processes. GenAI tools that offer overly simplistic summaries or answers diminish the necessity for elaboration, inference, or critical evaluation, promoting passive content consumption rather than active knowledge construction (Bai et al., 2023; Zhang et Zou, 2022).

Similarly, under-structured collaboration AI environments can elevate intrinsic cognitive load in the absence of instructional scaffolds, role designation, or conversational moderation. Unstructured group dynamics frequently lead to confusion and cognitive overload, especially among novice learners (Eunike et al., 2025).

Furthermore, an overreliance on predictive analytics for prompt adjustments may hinder learners' metacognitive development. Excessively interventionist instructional systems that continuously modify learning paths based on performance indicators may lead to anxiety or decision fatigue, undermining the principles of Cognitive Load Theory, which advocates for a balance between cognitive load and learner capacity (Feng, 2025). Finally, inadequately designed multimedia interfaces present risks when AI-generated environments utilize complex visuals, animations, or narration without following the principles of modality, redundancy, or coherence. Poor integration may result in divided attention or cognitive interference, hindering schema development and retention (Gkintoni et al., 2025).

Methodology

The integrative review methodology was selected for its ability to examine the intricate connection between GenAI and cognitive processes in education. Unlike systematic reviews, it integrates empirical, theoretical, and conceptual works, offering a thorough understanding in an emerging, fragmented field (Torraco, 2016; Bozkurt, 2023). This methodology addresses under-theorized domains by linking AI to cognitive outcomes (Castro-Alonso, 2020) and integrating psychology, learning design, and AI assessment (Jayavardhini, 2024). Its inclusive nature incorporates global perspectives, highlights contextual trends (Feng, 2025), and provides practical insights while outlining future research trajectories (Ayres, 2020).

Eighty-one peer-reviewed sources published between 2009 and 2025 were analyzed, with over 90% after 2017, reflecting the rise of large language models. Sources included Q1/Q2 journals as well as lower-ranked or non-indexed works for their relevance to emerging practices and regional contexts. The process followed five stages: (1) database search across Scopus, Web of Science, PubMed, ERIC, and Google Scholar; (2) screening and selection, narrowing 153 articles to 81; (3) data extraction by year, type, ranking, and significance; (4) thematic analysis, categorizing studies by CLT load types and AI functions, with inductive synthesis of sub-themes; and (5) conceptual framework construction to guide cognitively sustainable AI-enhanced design. Limitations include variable study quality, challenges measuring cognitive load in dynamic AI settings, reliance on short-term outcomes, and limited generalizability. The novelty of GenAI (2023–2025) means the literature remains sparse, requiring validation in authentic learning environments (Skulmowski & Xu, 2022).

Results

This review synthesized research on the impact of GenAI on intrinsic, extraneous, and germane cognitive load, addressing the research questions and informing effective practices for learning designers.

RQ1: How does GenAI -supported instruction affect intrinsic, extraneous, and germane cognitive load?

Intrinsic Cognitive Load

The integrative review identified Intrinsic load as reflecting the complexity of a task in relation to the prior knowledge of learners. GenAI effectively manages intrinsic load by employing adaptive scaffolding, intelligent tutoring, and progressive difficulty algorithms, which decompose complex content into manageable steps. In a study, learners utilizing AI-based scaffolding in a biology module demonstrated a 27% enhancement in concept recall relative to traditional instruction (Feng, 2024). Over-personalization may restrict exposure to challenging tasks, while AI content that assumes prior knowledge can overwhelm working memory, leading to frustration and disengagement (Huang & Chen, 2025).

Extraneous Cognitive Load

Another finding was that extraneous load results from poorly organized or irrelevant materials. GenAI alleviates this burden through the automation of low-level tasks, content summarization, and facilitation of multimodal learning, thereby reducing split-attention effects (Chen et al., 2017). Poorly designed interfaces and inconsistent AI outputs can elevate cognitive strain. Research shows that the utilization of chat-based AI resulted in a 40% increase in multitasking, which led to a reduction in comprehension. In contrast, AI-driven microlearning platforms achieved a 42% decrease in extraneous cognitive load when compared to traditional materials (Huang & Chen, 2025).

Germane Cognitive Load

Finally, the study revealed that Germane load indicates the cognitive resources allocated to schema development and metacognitive involvement. GenAI enhances relevant processing via interactive prompts, reflective exercises, and feedback, thereby facilitating deep understanding. Graduate students utilizing AI-enhanced prompting tools demonstrated a 35% increase in elaborative learning strategies (Gkintoni et al., 2025; Lee et al., 2025). Passive reliance on AI or uncritical copying of responses may restrict meaningful processing and hinder long-term retention (Chen et al., 2017).

RQ2: What benefits and challenges of cognitive overload arise from GenAI implementation in learning environments?

Benefits of GenAI in Learning

This research demonstrated that GenAI reduces cognitive load through the automation of information retrieval and synthesis, thereby assisting a variety of learners, including those who are English as a Second Language (ESL) speakers and underrepresented students (Feng, 2025). Adaptive support, including culturally responsive feedback and personalized scheduling, reduces intrinsic load. For instance, ESL learners utilizing AI-assisted vocabulary feedback exhibited a 33% enhancement in cognitive endurance and self-efficacy.

Challenges of GenAI in Learning

According to the present research, GenAI may impose additional cognitive challenges such as the need for verification of AI-generated content, limited opportunities for creative problem-solving, and split attention due to interface elements like notifications and conversation windows. Research revealed that the use of unstructured AI is linked to a 22% decrease in information retention (Skulmowski & Xu, 2022).

Discussion

The findings of this review underscore the intricate and multifaceted effects of GenAI on learning. GenAI technologies function as active influencers in the ways learners engage with content, assimilate knowledge, and extract meaning. This suggests that learning designers should recognize GenAI as a significant, yet complex, influence that can either substantially improve or unintentionally obstruct cognitive processes (Skulmowski & Xu, 2022).

Our research findings fully support the efficient utilization of AI by learning designers. The benefits presented here derive directly form the research findings, which substantiate the value of effectively utilizing AI tools in learning design. Learning designers require AI tools due to their own distinctive capacity to enhance instructional efficiency. GenAI systems efficiently manage cognitive load through the automation of tasks including summarization, feedback generation, and structured material distribution (Chen et al., 2017; Zhu et al., 2024). This can optimize learners' cognitive resources, enabling a focus on deeper and more meaningful engagement with complex subject matter. The capacity of AI to adjust content complexity in real-time and offer adaptive scaffolding, especially in demanding areas such as STEM and language acquisition, guarantees that instruction stays within a learner's zone of proximal development, effectively managing intrinsic load (Feng, 2024).

Additionally, AI tools are essential for personalizing learning experiences at an unprecedented scale. Content can be tailored according to individual performance, prior knowledge, and learning styles, which is crucial for accommodating diverse learner groups, including ESL students and those with varying learning needs (Zhu et al., 2024). This adaptive capability enables designers to develop inclusive learning environments by offering tailored support that reduces cognitive strain and enhances self-efficacy (Skulmowski & Xu, 2022).

Conclusion and Recommendations

In summary, instructional designers can enhance the integration of GenAI by aligning its application with the principles of Cognitive Load Theory (CLT). GenAI effectively manages intrinsic and extraneous load by employing segmentation, scaffolding, adaptive testing, progressive difficulty, multimodal content, and intuitive interfaces. These strategies minimize split attention and offer verification scaffolds to ensure accuracy (Bai et al., 2023; Skulmowski & Xu, 2022). To improve germane load, AI should incorporate reflective prompts, diagnostic feedback, and opportunities for productive struggle, while avoiding excessive personalization that may hinder schema development (Granda et al., 2024;

Jaboob et al., 2025). Effective pedagogical oversight requires well-defined objectives, iterative prototyping, and collaboration between educators and designers to achieve a balance between automation and engagement (Eunike et al., 2025; Kumar et al., 2024). Inclusive personalization promotes equitable learning by taking into account learners' language, pacing, and prior knowledge (Bai et al., 2023).

GenAI in education presents both supportive and challenging aspects for cognition. This approach minimizes effort, addresses complexity, and promotes schema development (Feng, 2025), while also posing risks of cognitive passivity, verification overload, and distraction (Lee et al., 2025; León-Domínguez, 2024). As a partner that enhances rather than replaces human thinking, its sustainable use necessitates strategies that balance efficiency and engagement while fostering learner agency (Bozkurt, 2023; Gkintoni et al., 2025).

Ultimately, the use of CLT provides a critical foundation for ensuring quality in distance education in the age of AI. The integration of GenAI is transforming the openness landscape, allowing designers to create adaptable distance learning materials and Open Educational Resources (OER). Learning designers must leverage GenAI's ability to manage load while sustaining the productive struggle necessary for intellectual growth, thereby supporting high-quality, cognitively sustainable digital instruction.

References

Aslam, F. (2020). Educational learning theories and their implications in modern instructional designs. Health Professions Educator Journal, 3(2), 25-31

Ayres, P. (2020). Something old, something new from cognitive load theory. *Computers in Human Behavior, 113*, 106503. https://doi.org/10.1016/j.chb.2020.106503

Bai, L., Liu, X., & Su, J. (2023). ChatGPT: The cognitive effects on learning and memory. *Brain-X, 1*(3). https://doi.org/10.1002/brx2.30

Bai, S., Lo, C. K., & Yang, C. (2024). Enhancing instructional design learning: A comparative study of scaffolding by a 5E instructional model-informed artificial intelligence chatbot and a human teacher. *Interactive Learning Environments*, 1–20.

Bauer, E., Greiff, S., Graesser, A. C., Scheiter, K., & Sailer, M. (2025). Looking beyond the hype: Understanding the effects of AI on learning. Educational Psychology Review, 37(2), 45.

Bozkurt, A. (2023). Generative AI, synthetic contents, open educational resources (OER), and open educational practices (OEP): A new front in the openness landscape. *Open Praxis, 15*(3), 178–184. https://doi.org/10.55982/openpraxis.15.3.579

Caskurlu, S., Richardson, J., Alamri, H., Chartier, K., Farmer, T., Janakiraman, S., & Yang, M. (2020). Cognitive load and online course quality: Insights from instructional designers in a higher education context. *British Journal of Educational Technology, 52*(2), 584–605. https://doi.org/10.1111/bjet.13043

Castro-Alonso, J. C. (2020). Latest trends to optimize computer-based learning: Guidelines from cognitive load theory. *Computers in Human Behavior, 112*, 106458. https://doi.org/10.1016/j.chb.2020.106458

Chen, O., Woolcott, G., & Sweller, J. (2017). Using cognitive load theory to structure computer-based learning including MOOCs. Journal of Computer Assisted Learning, 33(4), 293-305.

Choi, G. W., Kim, S. H., Lee, D., & Moon, J. (2024). Utilizing generative AI for instructional design: Exploring strengths, weaknesses, opportunities, and threats. *TechTrends*, *68*(4), 832-844.

Eunike, I. J., Serang, Y., & Silalahi, A. D. K. (2025). Does ChatGPT-enhanced collaborative learning foster critical thinking in education? A Bloom's Taxonomy perspective. *Smart Learning Environments*, *12*(1).

Feng, L. (2024). Investigating the effects of artificial intelligence-assisted language learning strategies on cognitive load and learning outcomes: A comparative study. *Journal of Educational Computing Research, 62*(8), 1741–1774. https://doi.org/10.1177/07356331241268349

Fries, L. (2021). Practicing connections: A framework to guide instructional design for developing understanding in complex domains. *Educational Psychology Review, 33*(2), 739–762. https://doi.org/10.1007/s10648-020-09561-x

Gandhi, T. K., Classen, D., Sinsky, C. A., Rhew, D. C., Vande Garde, N., Roberts, A., & Federico, F. (2023). How can artificial intelligence decrease cognitive and work burden for front line practitioners? *JAMIA open*, *6*(3). https://doi.org/10.1093/jamiaopen/ooad079

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

Granda, B. S., Inzhivotkina, Y., Apolo, M. F. I., & Fajardo, J. G. U. (2024). Educational innovation: Exploring the potential of generative artificial intelligence in cognitive schema building. *Edutec, Revista Electrónica de Tecnología Educativa(89)*, 44–63.

Harilal, C., Sokhela, C., & Walt, M. (2024). Optimising instructional design strategies to mitigate cognitive overload. *ICER, 1*(1), 75–83. https://doi.org/10.34190/icer.1.1.3095

Huang, K., & Chen, C. H. (2025). Instructional video and GenAI-supported chatbot in digital game-based learning: influences on science learning, cognitive load and game behaviours. *Journal of Computer Assisted Learning*, *41*(4), e70094.

Jaboob, M., Hazaimeh, M., & Al-Ansi, A. M. (2025). Integration of generative AI techniques and applications in student behavior and cognitive achievement in Arab higher education. *International Journal of Human–Computer Interaction, 41*(1), 353–366.

Jayavardhini, P. (2024). AI study partner: Development of an LLM and Gen AI-enhanced study assistant tool. *International Journal of Scientific Research in Engineering and Management, 8*(3), 1–5. https://doi.org/10.55041/ijsrem29626

Khalil, M. K., & Elkhider, I. A. (2016). Applying learning theories and instructional design models for effective instruction. *Advances in Physiology Education*, *40*(2), 147–156. https://doi.org/10.1152/advan.00138.2015

Kiryakova, G., & Angelova, N. (2023). ChatGPT—A challenging tool for the university professors in their teaching practice. *Education Sciences*, *13*(10), 1056.

Kumar, S., Gunn, A., Rose, R., Pollard, R., Johnson, M., & Ritzhaupt, A. (2024). The role of instructional designers in the integration of generative artificial intelligence in online and blended learning in higher education. *Online Learning*. https://doi.org/10.24059/olj.v28i3.4501

Lee, G., Shi, L., Latif, E., Gao, Y., Bewersdorff, A., Nyaaba, M., Guo, S., Liu, Z., Mai, G., Liu, T. and Zhai, X., (2025). Multimodality of AI for education: Towards artificial general intelligence. *IEEE Transactions on Learning Technologies*.

León-Domínguez, U. (2024). Potential cognitive risks of generative transformer-based AI chatbots on higher order executive functions. *Neuropsychology, 38*(4), 293.

Lopez, S. (2024). The impact of cognitive load theory on the effectiveness of microlearning modules. *European Journal of Education and Pedagogy, 5*(2), 10–24018.

Mayer, R. E. (2024). The past, present, and future of the cognitive theory of multimedia learning. *Educational Psychology Review, 36*(1), 8.

McLaughlin, P., Vaughan, B., Tripodi, N., & Kelly, K. (2023). Incorporating cognitive load theory into curriculum design for the teaching of novel clinical skills in Australian osteopathy students. Focus on Health Professional Education: *A Multi-Professional Journal, 24*(3), 68–75.

Sallam, M. (2023). The utility of ChatGPT as an example of large language models in healthcare education, research, and practice: Systematic review on the future perspectives and potential limitations. https://doi.org/10.1101/2023.02.19.23286155

Skulmowski, A., & Xu, K. M. (2022). Understanding cognitive load in digital and online learning: A new perspective on extraneous cognitive load. *Educational Psychology Review, 34*(1), 171–196.

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development, 68*(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3

Torraco, R. J. (2016). Writing integrative literature reviews: Using the past and present to explore the future. Human resource development review, 15(4), 404-428.

Twabu, K. (2025). Enhancing the cognitive load theory and multimedia learning framework with AI insight. *Discover Education*, *4*(1), 160.

Walczak, K., & Cellary, W. (2023). Challenges for higher education in the era of widespread access to Generative AI. *Economics and Business Review*, *9*(2).

Zhang, L. J., & Zou, D. (2022). Fifty years of second language writing research: Looking back and moving forward. *Journal of Second Language Writing, 55*, 101867. https://doi.org/10.1016/j.jslw.2021.101867

Zhu, B., Chau, K. T., & Mokmin, N. A. M. (2024). Optimizing cognitive load and learning adaptability with adaptive microlearning for in-service personnel. *Scientific Reports*, *14*(1), 25960.