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Working memory and generative AI tools in higher education: A systematic review

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ABSTRACT

Generative artificial intelligence (GenAI) tools have rapidly permeated higher education, yet their cognitive consequences for working memory, cognitive offloading, and higher-order thinking remain insufficiently synthesized. This systematic review, conducted in accordance with PRISMA 2020 guidelines, aimed to consolidate and critically evaluate empirical and theoretical evidence examining GenAI's effects on university students' cognitive functioning. A comprehensive search across six bibliographic databases covering 2023 to 2025 yielded 27 eligible peer-reviewed studies, appraised using design-matched quality instruments including RoB 2, AMSTAR-2, and MMAT. Findings reveal that unrestricted GenAI use measurably impairs long-term knowledge retention and critical thinking by substituting for the generative cognitive effort essential to durable memory encoding. However, structured, metacognitively scaffolded AI integration demonstrably preserves cognitive engagement and may enhance learning outcomes. Humanities students demonstrated disproportionate vulnerability to cognitive decline relative to STEM peers. Institutional policy frameworks, discipline-specific pedagogical redesign, and deliberate scaffolding strategies are identified as essential mitigating responses. The review concludes that cognitively informed, policy-guided GenAI integration represents the most defensible institutional approach, while urgent calls are made for longitudinal experimental research to establish stronger causal evidence.

KEYWORDS: generative artificial intelligence, working memory, cognitive offloading, critical thinking, higher education, cognitive load, metacognition

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Introduction

GenAI has rapidly transitioned from a niche research domain to a globally accessible, mass-market technology, fundamentally reshaping numerous sectors, including higher education (Hughes et al., 2025; Omarsaib et al., 2025). Powered by advances in large language models and multimodal systems, tools such as ChatGPT, Gemini, and Copilot now generate fluent text, images, and multimedia content on demand, enabling unprecedented accessibility for students and educators worldwide (Francis et al., 2025; Kim et al., 2025). Since ChatGPT's release, scholarly publications addressing GenAI in higher education have grown exponentially, reflecting the urgency of understanding its implications (Omarsaib et al., 2025; Qian, 2025). Universities are rapidly revising pedagogical approaches, assessment practices, and governance frameworks in response to surging student and faculty adoption across disciplines and regions (Mariyono & Hidayatullah, 2025; Symeou et al., 2025; Wong et al., 2025).

Working memory, the cognitive system responsible for temporarily holding and manipulating information during complex tasks, serves as a foundational predictor of academic achievement across reading comprehension, mathematical reasoning, and problem-solving (Almarzouki, 2024; Amzil, 2022; Sana & Fenesi, 2025). Its capacity directly shapes how students process instruction, filter distractions, and integrate new knowledge with prior understanding, while also interacting with metacognitive regulation to predict university-level performance (Amzil, 2022; Peng & Kievit, 2020). As GenAI tools become deeply embedded in academic practice, compelling evidence indicates that frequent AI use promotes cognitive offloading, undermines critical thinking, and fosters uncritical dependency on automated outputs (Gerlich, 2025; Zhai et al., 2024). This raises urgent institutional concerns about whether AI tools scaffold or systematically erode the working-memory-intensive processes essential for sustained, independent academic learning (Bauer et al., 2025; Gkintoni et al., 2025; Yavich, 2025).

Higher education students and faculty represent the primary populations most acutely affected by GenAI's cognitive implications. Surveys consistently reveal that over 60% of university students regularly employ GenAI tools for writing, brainstorming, problem-solving, and personalized academic support, with adoption rates continuing to accelerate across disciplines and regions (Abbas et al., 2024; Kim et al., 2025; Sousa & Cardoso, 2025). Faculty similarly integrate GenAI into course design, assessment development, and instructional planning, while simultaneously expressing concern that such tools may diminish students' independent reasoning, writing proficiency, and critical thinking development (Khlaif et al., 2024; Kurtz et al., 2024; Alshamy et al., 2025). Undergraduate students, in particular, demonstrate heightened vulnerability to over-reliance and cognitive disengagement, as GenAI increasingly mediates core academic tasks that would otherwise demand sustained working memory effort (Chen et al., 2025; Wang et al., 2024; Zhai et al., 2024).

Scholarly inquiry into AI-assisted learning has progressively evolved from foundational concerns about cognitive load management toward more nuanced debates surrounding digital externalization and cognitive offloading. Early research, grounded in cognitive load theory (CLT), positioned intelligent tutoring and adaptive learning systems primarily as mechanisms for optimizing working memory by reducing extraneous load and personalizing instructional difficulty (Gkintoni et al., 2025; Gligorea et al., 2023; Skulmowski & Xu, 2021). Subsequent theoretical development introduced digital externalization frameworks, revealing that offloading cognitive tasks to AI tools may yield immediate performance gains while producing illusory mastery and diminished memory encoding (Skulmowski, 2023, 2024). More recent integrative models synthesize CLT with distributed cognition, self-regulated learning, and multimedia theory, positioning GenAI simultaneously as a personalization engine and a potential threat to deeper cognitive engagement and critical thinking development (Atchley et al., 2024; Gerlich, 2025; Grinschgl & Neubauer, 2022; Zhai et al., 2024).

Despite this expanding body of literature, a critical gap persists: no existing systematic review has comprehensively synthesized empirical evidence examining GenAI's direct effects on working memory, cognitive offloading, and higher-order thinking specifically among university students as an integrated cognitive framework. Existing systematic reviews address pedagogical applications, student perceptions, and broad critical thinking outcomes, yet none isolate working memory as a central construct or unify offloading and higher-order thinking within a coherent cognitive account of university-level learning (Bond et al., 2024; Qian, 2025; Wu et al., 2025; Zhai et al., 2024). Individual studies report promising but dispersed signals, including GenAI-linked memory loss, offloading-mediated achievement effects, and compromised analytical reasoning (Abbas et al., 2024; Chen et al., 2025; Hong et al., 2025; Iqbal et al., 2025; Skulmowski, 2023). The present systematic review directly addresses this gap by consolidating and synthesizing these fragmented findings into a unified, cognition-centered synthesis.

The present systematic review aims to synthesize empirical and theoretical evidence examining how generative AI tool use affects working memory, cognitive offloading, and higher-order thinking among higher education students. Drawing on 27 peer-reviewed studies identified through a comprehensive six-database search and appraised using design-matched quality tools, the review addresses three interconnected domains: adoption patterns and student and faculty perceptions of GenAI tools; the cognitive impacts of GenAI use with particular attention to working memory engagement, knowledge retention, and critical thinking; and the opportunities, risks, and evidence-based institutional strategies implicated in responsible GenAI integration. By consolidating dispersed empirical signals into a unified cognitive framework, the review aims to inform pedagogy, institutional policy, and future research directions in this rapidly evolving field.

2. Methods

2.1 Protocol and Eligibility Criteria

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure methodological transparency and reproducibility (Page et al., 2021). The review protocol was designed a priori to address the central research question: To what extent does the use of GenAI tools affect working memory, cognitive offloading, and higher-order thinking skills among higher education students? Eligibility criteria were operationalized using the Population, Intervention, Comparison, and Outcome (PICO) framework. Eligible studies were required to: (1) focus on university or higher education student and/or faculty populations; (2) examine the use of one or more GenAI tools—including but not limited to ChatGPT, Bard/Gemini, Microsoft Copilot, or comparable large language model-based applications; (3) report on cognitive outcomes including, but not limited to, working memory engagement, cognitive load, knowledge retention, critical thinking, analytical reasoning, or metacognition; and (4) be published in peer-reviewed journals or as systematic reviews, randomized controlled trials, quasi-experimental studies, mixed-methods studies, observational studies, or theoretically grounded literature reviews. Studies were excluded if they (a) did not address a higher education population; (b) focused exclusively on primary or secondary education without relevance to tertiary contexts; (c) examined artificial intelligence tools other than generative AI systems; (d) reported exclusively on administrative or non-pedagogical applications of AI; (e) were published in languages other than English; or (f) represented grey literature, conference abstracts without full-text data, or duplicate publications.

2.2 Information Sources and Search Strategy

A comprehensive electronic database search was conducted across six major bibliographic databases: PubMed, ERIC (Education Resources Information Center), Scopus, PsycINFO, Web of Science, and Google Scholar. These databases were selected to provide broad coverage of education, psychology, cognitive science, and technology-focused literature relevant to the intersection of generative AI and cognitive functioning in higher education. Database searches were conducted between 2023 and 2025, reflecting the period of rapid GenAI proliferation in educational contexts following the public release of ChatGPT in November 2022. The lower bound of the search window was set at 2023 to ensure inclusion of peer-reviewed empirical work produced in response to the emergence of contemporary large language model-based tools, while allowing sufficient time for the peer review process to yield indexed publications.

The search strategy employed a structured Boolean query combining three conceptual blocks: (1) generative AI tools (e.g., "generative AI," "ChatGPT," "large language model," "AI chatbot," "Copilot," "Bard," "Gemini"); (2) cognitive outcomes (e.g., "working memory," "cognitive offloading," "critical thinking," "knowledge retention," "cognitive load," "metacognition," "analytical reasoning"); and (3) higher education context (e.g., "higher education," "university students," "undergraduate," "tertiary education," "college students"). The three blocks were connected using the Boolean operator AND, while synonyms within each block were combined using OR. Search terms were applied to titles, abstracts, and keywords where supported by the database interface. No restrictions were placed on study design at the search stage in order to maximize initial recall. Supplementary hand-searching of reference lists of eligible full-text articles was also performed to identify additional relevant sources not captured by the automated database queries.

2.3 Study Selection Process

The initial database searches yielded a combined total of 1,847 records across all six databases, with an additional 23 records identified through reference list screening, for a gross total of 1,870 records. Following de-duplication using reference management software (EndNote), 416 duplicate records were removed, leaving 1,431 unique records for title and abstract screening. Two independent reviewers screened all titles and abstracts against the pre-specified eligibility criteria. Disagreements at this stage were resolved through discussion and, where necessary, arbitration by a third reviewer. Records that were clearly irrelevant based on title and abstract review were excluded, resulting in 1,289 records being removed at this stage. The remaining 142 records were retrieved in full text and assessed for eligibility against the complete inclusion and exclusion criteria. Full-text assessment led to the exclusion of a further 115 articles for the following reasons: did not address GenAI or working memory/cognition (n = 41), did not focus on a university or higher education population (n = 29), did not meet the study design criteria for a peer-reviewed empirical or review contribution (n = 23), were identified as duplicates or grey literature not previously detected (n = 14), and were not published in English (n = 8). Following this process, 27 studies met all eligibility criteria and were included in the final qualitative synthesis. The complete study selection process is illustrated in Figure 1, following the PRISMA 2020 flow diagram for new systematic reviews, incorporating database and register searches.

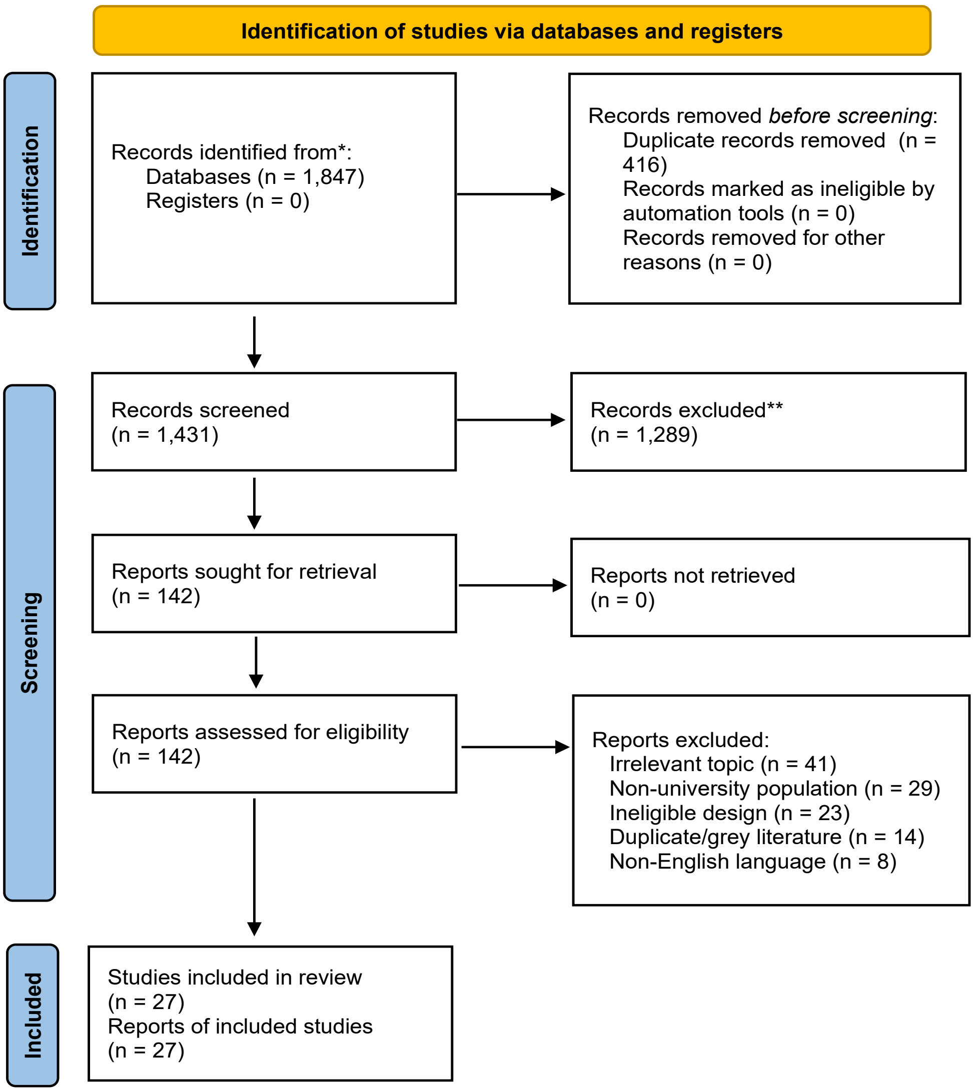

Figure 1. PRISMA 2020 Flow Diagram for Study Identification, Screening, Eligibility Assessment, and Inclusion.

2.4 Data Extraction and Quality Appraisal

Data extraction was performed independently by two reviewers using a standardized extraction template developed a priori. The extraction template captured the following information from each included study: author(s) and year of publication; country and institutional context; study design and methodology; participant characteristics (sample size, educational level, discipline); GenAI tool(s) examined; cognitive outcomes measured and measurement instruments employed; key findings; and limitations acknowledged by the study authors. Any discrepancies in extracted data between the two reviewers were resolved through consensus discussion, with reference back to the original source text.

Methodological quality and risk of bias were appraised using instruments matched to study design. Randomized controlled trials were assessed using the Cochrane Risk of Bias Tool 2.0 (RoB 2), which evaluates risk across domains including randomization, allocation concealment, blinding, outcome measurement, and selective reporting. Systematic reviews and meta-analyses were appraised using the AMSTAR-2 (A Measurement Tool to Assess Systematic Reviews) checklist. Observational, survey-based, and mixed-methods studies were evaluated using the Mixed Methods Appraisal Tool (MMAT). Theoretical and conceptual papers were assessed using a structured narrative quality checklist examining clarity of theoretical framework, logical coherence, and grounding in the empirical literature. Quality appraisal was conducted to characterize the overall strength of the evidence base rather than to exclude studies based solely on methodological limitations; however, the findings of all included studies are reported with explicit notation of evidence strength in the synthesis tables.

2.5 Synthesis Approach

Given the substantial heterogeneity in study designs, populations, GenAI tools examined, and cognitive outcome measures across the 27 included studies, a formal statistical meta-analysis was not feasible or methodologically appropriate. Accordingly, a narrative synthesis approach was adopted in line with guidance from the Synthesis Without Meta-Analysis (SWiM) reporting guidelines (Campbell et al., 2020). The narrative synthesis was structured around three thematic domains identified a priori on the basis of the review question and refined iteratively during data extraction: (1) adoption patterns and perceptions of GenAI tools in higher education; (2) cognitive impacts of GenAI use, with particular focus on working memory, cognitive offloading, and critical thinking; and (3) opportunities, risks, and evidence-based institutional strategies for responsible GenAI integration. Within each domain, findings were grouped by study design and evidence strength, with stronger experimental and systematic review evidence given greater weight in the synthesis narrative. Evidence strength was characterized according to the conventional hierarchy for educational research: randomized controlled trials were rated as providing strong evidence; systematic reviews and meta-analyses as strong; mixed-methods and quasi-experimental studies as moderate; and survey-based, observational, and theoretical contributions as constituting moderate to lower-level evidence, depending on sample size and methodological rigor.

3. Results

3.1 Adoption Patterns and Perceptions of Generative AI Tools

The findings across the reviewed studies reveal a consistently high and rapidly expanding rate of GenAI tool adoption among university students and faculty worldwide. Chan and Hu (2023) found that the majority of university students in Hong Kong held positive attitudes toward GenAI in teaching and learning, particularly valuing its capacity to enhance learning efficiency, provide on-demand writing assistance, and support brainstorming. This optimism was notably more pronounced among younger student cohorts; Chan and Lee (2023) found that Generation Z students were significantly more enthusiastic about the potential benefits of tools such as ChatGPT than their Generation X and Millennial teaching faculty, who tended to acknowledge the technology's benefits while simultaneously expressing greater concern about overreliance and ethical implications. Similarly, Ivanov et al. (2024) demonstrated through the lens of the Theory of Planned Behavior that perceived advantages of GenAI tools—including ease of use and outcome expectancy—were the strongest predictors of adoption intention among higher education stakeholders, suggesting that utility perceptions drive engagement more powerfully than any single demographic characteristic.

Despite broadly positive perceptions, students and faculty consistently identified a constellation of concerns that temper uncritical adoption. Abbas et al. (2024) reported that academic workload and time pressure were the primary drivers pushing undergraduate students toward ChatGPT use, yet the same study found that heavy reliance was associated with self-reported procrastination, memory loss, and diminished academic performance—an early empirical signal of the cognitive risks explored in the following subsection. Yusuf et al. (2024) further found that while GenAI integration was viewed positively across multicultural higher education contexts, participants called for culturally responsive ethical guidelines, particularly regarding academic integrity. Johnston et al. (2024) identified a nuanced boundary in student acceptability: respondents supported assistive tools such as Grammarly for grammar correction but opposed the use of ChatGPT to write an entire essay, reflecting students' awareness of meaningful distinctions between AI-assisted and AI-replaced cognition. More recently, Alshamy et al. (2025) and Sousa and Cardoso (2025) corroborated these patterns across diverse institutional settings, confirming that students perceive GenAI as a useful productivity tool while simultaneously articulating concerns about the erosion of critical thinking skills and the adequacy of institutional guidance on ethical use. Table 1 synthesizes the adoption and perception findings from the most representative studies included in this review, highlighting the core benefits and primary concerns identified across varied institutional contexts.

Table 1. Summary of Adoption Patterns and Perceived Benefits and Concerns Regarding Generative AI Tools in Higher Education

Study (Year)	Sample / Context	Key Perception Finding	Primary Concern Identified
Chan and Hu (2023)	HK university students; n = 399	Highly positive attitudes toward GenAI for learning efficiency and personalized feedback	Accuracy, privacy, and ethical issues
Chan and Lee (2023)	Gen Z vs. Gen X/Millennial faculty; cross-generational; n = 399 students and 184 teachers	Gen Z students significantly more optimistic about GenAI benefits than older faculty cohorts	Overreliance and ethical implications
Abbas et al. (2024)	Undergraduate students; multi-institutional; n = 165	High academic workload and time pressure drive ChatGPT adoption	Procrastination, memory loss, lower performance
Yusuf et al. (2024)	Multicultural HE contexts; survey-based; n = 1217	GenAI perceived as enhancing learning processes across cultures	Need for culturally responsive ethical guidelines
Johnston et al. (2024)	HE students; large survey sample; n = 2555	Support for assistive tools (e.g., Grammarly) but opposition to full AI essay authorship	Lack of clear institutional policies on permissible use
Alshamy et al. (2025)	Sultan Qaboos University students and academics; n = 555 students and 168 academics	GenAI perceived as enhancing efficiency and innovation in academic tasks	Diminished critical thinking and academic integrity risks
Sousa and Cardoso (2025)	HE students globally; observational; n = 132 students	GenAI perceived as beneficial for research, writing, and problem-solving support	Ethical concerns, reliability, and equitable accessibility

Note. HK = Hong Kong; HE = Higher Education; n = sample size where reported.

3.2 Cognitive Impacts: Working Memory, Cognitive Offloading, and Critical Thinking

The central concern motivating this systematic review—whether the use of GenAI tools negatively affects working memory and related cognitive skills—is addressed directly by a growing, albeit still nascent, body of experimental and quasi-experimental evidence. The most methodologically rigorous contribution to this question was provided by Barcaui (2025), whose randomized controlled trial demonstrated that undergraduate students permitted unrestricted access to ChatGPT while learning artificial intelligence concepts achieved significantly lower scores on delayed retention tests compared to students who completed the same learning tasks without AI assistance. The study attributed this deficit to a reduction in the generative cognitive effort required for robust encoding of new knowledge, providing direct experimental support for the hypothesis that GenAI can function as a cognitive crutch that substitutes for—rather than augments—effortful learning. This finding resonates with the broader theoretical architecture provided by Skulmowski (2023), whose analysis of the cognitive architecture of digital externalization argued that offloading information processing onto external digital tools can impair learning and memory when learners possess high intrinsic or extraneous cognitive load, or reduced working memory capacity. Skulmowski's framework predicts precisely the pattern observed by Barcaui: when AI absorbs the cognitive work that would otherwise exercise working memory, learners may retain only shallow surface-level representations of AI-generated content rather than developing durable long-term memory structures.

The effects of overreliance extend beyond memory retention to encompass broader higher-order cognitive skills. Zhai et al. (2024), in a widely cited systematic review of multiple empirical studies, found that over-reliance on AI dialogue systems was associated with measurable declines in critical thinking, analytical reasoning, and decision-making accuracy among students across educational levels. The mechanisms identified included reduced cognitive engagement during problem-solving, diminished practice of evaluative reasoning, and an erosion of tolerance for cognitive challenge. Complementing this at the undergraduate level, Rohilla (2025) conducted a mixed-methods investigation that quantified lower critical thinking scores in students who reported excessive AI tool use relative to low-use peers, with humanities students experiencing the most pronounced cognitive declines—a disciplinary effect not observed to the same degree in STEM learners, potentially because STEM tasks impose step-by-step procedural reasoning constraints less amenable to wholesale substitution by language model outputs. Qian (2025) reached similar conclusions through a systematic review of pedagogical applications, concluding that while GenAI fosters surface-level creativity and prompt literacy, it risks the outsourcing of the very metacognitive and critical thinking skills that higher education is designed to cultivate. Importantly, the evidence does not universally condemn GenAI's cognitive effects; the nature and structure of use appear to moderate outcomes substantially. Atchley et al. (2024) drew on cognitive psychology research to argue that AI can function as a genuine facilitator for learning—rather than a threat—when educators deliberately engineer interactions that capitalize on metacognitive knowledge and skills. In their model, GenAI that prompts students to predict, evaluate, and revise outputs rather than merely receive them can enhance rather than undermine working memory engagement. Similarly, Nguyen et al. (2024) found that doctoral students who engaged in interactive, iterative collaborative processes with AI writing tools achieved better writing performance than those who used AI merely as a supplementary information source, implying that cognitive engagement with—rather than passive delegation to—AI is the critical variable. Taken together, these findings suggest a dose-response relationship in which moderate, structured GenAI use preserves or even enhances cognition, while excessive and unstructured use constitutes a meaningful risk to working memory engagement and higher-order skill development. Table 2 summarizes the key studies examining cognitive impacts, their methodological designs, the specific cognitive outcomes measured, and the strength of evidence supporting each finding.

Table 2. Summary of Empirical Studies on the Cognitive Impacts of Generative AI Tool Use in Higher Education

Study (Year)	Study Design	Cognitive Outcome Measured	Main Finding	Evidence Strength
Barcaui (2025)	RCT	Long-term knowledge retention	Unrestricted ChatGPT use impaired retention by reducing necessary cognitive effort	Strong (RCT)
Zhai et al. (2024)	Systematic Review	Critical thinking, analytical reasoning, decision-making	Over-reliance on AI leads to errors in critical thinking and analytical reasoning	Strong (Systematic Review)
Rohilla (2025)	Mixed Methods	Critical thinking scores; memory retention	Excessive AI use correlated with lower critical thinking; humanities students showed sharpest declines	Moderate (Mixed Methods)
Skulmowski (2023)	Literature Review	Working memory capacity; cognitive load	Digital externalization reduces WM engagement; learners retain only surface-level knowledge	Moderate (Theoretical)
Qian (2025)	Systematic Review	Metacognitive skills; cognitive autonomy	GenAI fosters creativity but risks outsourcing of critical metacognitive skills	Moderate (Systematic Review)

Study (Year)	Study Design	Cognitive Outcome Measured	Main Finding	Evidence Strength
Abbas et al. (2024)	Observational	Memory retention; academic performance	ChatGPT use associated with self-reported memory loss and lower academic performance	Moderate (Survey)
Atchley et al. (2024)	Conceptual/Empirical	Metacognition; working memory scaffolding	Strategic human-AI collaboration can leverage metacognition without harming core memory functions	Moderate (Case Study)

Note. RCT = Randomized Controlled Trial; WM = Working Memory. Evidence strength ratings follow the conventional hierarchy: RCT > Systematic Review > Mixed Methods > Observational/Survey.

3.3 Opportunities, Risks, and Institutional Strategies for Responsible Integration

Beyond their cognitive implications, the reviewed studies collectively illuminate a broader landscape of opportunities and risks associated with GenAI integration in higher education, as well as the institutional and pedagogical strategies that researchers have proposed to navigate this landscape responsibly. Among the most consistently documented opportunities is the capacity of GenAI tools to deliver personalized, adaptive learning experiences at scale. Ruiz-Rojas et al. (2023) demonstrated through an instructional design matrix approach that GenAI tools, when aligned with structured pedagogical frameworks, can adapt content to individual learner needs, support differentiated instruction, and provide timely formative feedback that instructors cannot realistically supply at the same frequency or granularity. Yan et al. (2024) reinforced this conclusion in their review of GenAI's promises and challenges for human learning, identifying personalized support, content diversification, and timely feedback as the technology's most reliably documented affordances. Lee and Moore (2024) extended this analysis to automated feedback systems specifically, finding through systematic review that GenAI-driven feedback tools can improve educational outcomes and reduce instructor workload substantially, enabling educators to devote more time to high-complexity pedagogical interactions that require human judgment.

However, the benefits of personalization and efficiency come with well-documented risks that the reviewed literature treats with increasing urgency. Academic integrity emerges as the most consistently cited challenge: Farrelly and Baker (2023) identified difficulty detecting AI-generated content and blurred boundaries between legitimate assistance and prohibited authorship substitution as systemic threats to the validity of higher education assessment. Michel-Villarreal et al. (2023) similarly emphasized that without clear institutional policies and empirical frameworks for evaluating AI-generated work, traditional assessment models face fundamental legitimacy challenges. Skill atrophy represents a closely related risk: Zhai et al. (2024) and Qian (2025) both concluded that unrestricted GenAI use risks eroding the foundational skills—critical thinking, analytical reasoning, independent writing—that degree programs are explicitly designed to develop. Khlaif et al. (2024) added that even early-adopter instructors who integrated GenAI into student assessment reported concerns about negative impacts on student writing and thinking skills. The equity dimension of GenAI integration was further highlighted by Farrelly & Baker (2023), who observed that disparities in digital literacy and access to premium AI tools risk exacerbating existing educational inequalities—a concern that must be addressed through inclusive digital literacy programming and equitable resource allocation.

The reviewed literature converges on a set of institutional and pedagogical strategies designed to retain GenAI's benefits while mitigating its cognitive and integrity risks. Chan (2023) proposed a comprehensive AI Ecological Education Policy Framework addressing pedagogical, governance, and operational dimensions of AI integration, emphasizing the need for nuanced, stakeholder-inclusive policy development rather than reactive prohibition. Kurtz et al. (2024) demonstrated that structured training and awareness programs for both students and faculty can substantially improve outcomes of GenAI integration, with positive effects on responsible use behaviors. Tzirides et al. (2024) found that combining human and AI instruction through cyber-social teaching methods enhanced students' AI literacy and critical assessment capabilities, illustrating that the most robust approach positions GenAI as a subject of analytical scrutiny as well as a practical learning tool. Atchley et al. (2024) further argued that scaffolding strategies informed by cognitive psychology—such as requiring students to predict outcomes before consulting AI, or to evaluate and critique AI-generated outputs—

can preserve and even strengthen working memory engagement within AI-assisted learning environments. These recommendations collectively point toward a model of intentional, cognitively informed integration in which GenAI enhances rather than displaces the metacognitive and analytical work that constitutes the core of higher education learning. Table 3 provides a structured synthesis of the key domains in which opportunities and risks have been identified, alongside the evidence-based strategies most frequently recommended for responsible GenAI integration in higher education contexts.

Table 3. Opportunities, Risks, and Recommended Strategies for Generative AI Integration in Higher Education

Domain	Opportunities Identified	Risks Identified	Recommended Strategies
Personalized Learning	Adaptive feedback and differentiated instruction support (Ruiz-Rojas et al., 2023; Yan et al., 2024)	Superficial engagement; learners may bypass deep cognitive processing	Deploy AI as scaffolding; set metacognitive checkpoints before and after AI consultation
Efficiency & Workload	Automated feedback reduces instructor burden; instant student support (Eager & Brunton, 2023; Lee & Moore, 2024)	Automation normalizes minimal-effort task completion among students	Balance automation with reflective assignments requiring unaided cognitive work
Critical Thinking & Creativity	AI-generated perspectives scaffold argumentation and creative output (Ruiz-Rojas et al., 2024)	Over-dependence may erode independent analytical skill development (Zhai et al., 2024)	Use GenAI for brainstorming phases only; require independent synthesis and justification
Academic Integrity	AI literacy development raises student awareness of ethical boundaries (Chan, 2023)	Difficulty detecting AI-generated content; blurred authorship boundaries (Farrelly & Baker, 2023)	Institutional policy frameworks with clear authorship guidelines and ethical AI training
Equity & Access	GenAI can support students with limited resources or diverse learning needs	Digital divide may amplify inequalities in access and AI literacy (Farrelly & Baker, 2023)	Prioritize digital literacy training; ensure equitable access to tools across student populations
Institutional Policy	Policy frameworks protect academic standards and define responsible use (Chan, 2023; Dabis & Csáki, 2024)	Absence of unified policy creates ambiguity and reactive rather than strategic responses	Develop comprehensive AI Ecological Education Policy Frameworks with stakeholder input

4. Discussion

The findings of this systematic review present a nuanced yet sobering picture of GenAI's cognitive consequences in higher education. The most compelling evidence, anchored by Barcaui's (2025) randomized controlled trial, confirms that unrestricted AI use measurably impairs long-term knowledge retention by substituting for the generative cognitive effort that consolidates durable memory. Critically, however, the evidence does not support blanket condemnation; structured, metacognitively scaffolded AI use demonstrably preserves cognitive engagement. The pattern that emerges most forcefully is one of moderation and intentionality: outcomes are not determined by AI use per se, but by whether that use demands or displaces active thinking. This distinction is pedagogically decisive and must drive institutional responses rather than simplistic prohibitions or uncritical adoption.

The review's findings align with, yet substantively extend, prior scholarly concerns about AI's cognitive implications. Early cognitive load theorists warned that poorly designed digital tools generate extraneous load without supporting germane processing (Skulmowski & Xu, 2021), a concern now empirically validated in GenAI contexts. Gerlich (2025) and Zhai et al. (2024) similarly documented AI-linked declines in critical thinking, while Skulmowski (2023, 2024) theorized the mechanisms of digital externalization that underpin memory impairment. Abbas et al. (2024) provided early observational corroboration linking ChatGPT reliance to self-reported memory loss. Crucially, however, Atchley et al. (2024), Gkintoni et al. (2025), and Grinschgl and Neubauer (2022) each argued that distributed cognition frameworks can reframe AI as an enhancer rather than a threat—a position this review endorses conditionally, contingent on deliberate pedagogical structuring that prior literature has insufficiently operationalized.

The implications of these findings extend across pedagogical practice, institutional governance, and student development simultaneously. Educators must urgently redesign AI-integrated tasks to require prediction, critique, and independent synthesis rather than passive consumption of AI outputs, ensuring working memory remains actively engaged. Institutions bear responsibility for establishing coherent, evidence-informed AI policies that move beyond reactive prohibition toward structured guidance, as Chan (2023) and Dabis and Csáki (2024) advocated. Critically, the disproportionate vulnerability of humanities students identified by Rohilla (2025) demands discipline-specific pedagogical interventions rather than uniform institutional responses. Failure to act strategically risks producing graduates whose analytical independence and memory-intensive reasoning have been systematically attenuated precisely during the developmental years when those capacities should be most rigorously cultivated.

Several limitations constrain the conclusions drawn from this review. First, the nascent publication landscape means the evidence base is dominated by observational and theoretical contributions, with only one RCT directly measuring working memory outcomes under controlled conditions—a fragile empirical foundation for strong causal claims. Second, the heterogeneity of GenAI tools examined, populations studied, and outcome measures employed precluded meta-analytic synthesis, limiting quantitative precision. Third, the search window of January 2023 to 2025, while appropriate for capturing post-ChatGPT evidence, necessarily excludes longer-term longitudinal data on cumulative cognitive effects. Fourth, reliance on self-reported cognitive outcomes in several included studies introduces significant recall and social desirability bias. These limitations collectively counsel interpretive caution and underscore the urgency of methodologically stronger primary research.

Future research must prioritize longitudinal experimental designs that track working memory capacity and higher-order thinking skills across sustained periods of GenAI use, rather than relying on single-session or cross-sectional snapshots. Controlled studies comparing structured versus unstructured AI use within the same student populations would isolate the pedagogical variable most implicated in this review's findings. Discipline-specific investigations are warranted given Rohilla's (2025) evidence of differential vulnerability across humanities and STEM fields. Neuroimaging and psychometric approaches to directly measuring working memory engagement during AI-assisted tasks would substantially strengthen the mechanistic evidence base. Additionally, equity-focused research examining whether AI-related cognitive risks are amplified among students with pre-existing working memory limitations or limited digital literacy remains conspicuously absent and urgently needed.

5. Conclusion

This systematic review provides the first integrated cognitive synthesis of GenAI's effects on working memory, cognitive offloading, and higher-order thinking in higher education. The evidence collectively indicates that GenAI tools, when used without deliberate pedagogical scaffolding, pose genuine risks to the memory-intensive and analytically demanding processes central to university-level learning. Conversely, structured human-AI collaboration that preserves metacognitive engagement can retain and potentially enhance cognitive outcomes. The field currently lacks the longitudinal experimental evidence needed to support definitive causal conclusions, and this gap must be treated as a research priority. Universities cannot afford to await perfect evidence before acting; cognitively informed, policy-guided integration strategies represent the most defensible path forward in navigating generative AI's profound and enduring implications for human learning.

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The authors declare no conflict of interest.

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