AI Dependency and Cognitive Offloading: Effects of Generative Artificial Intelligence on Memory Retention, Critical Thinking, and Decision-Making among University Students

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ABSTRACT

This mixed-methods longitudinal study investigated how generative AI dependency influences memory retention, critical thinking, and decision-making autonomy among 412 university students. Participants were assigned to AI-Restricted, AI-Scaffolded (with metacognitive prompts), or Unrestricted AI cohorts over a 10-week term, with cognitive assessments and usage telemetry tracked through a 4-week delayed follow-up. Results indicated that higher AI dependency significantly predicted poorer memory consolidation, reduced critical thinking performance, and increased algorithmic anchoring. The Unrestricted cohort demonstrated accelerated knowledge decay and weaker meta-cognitive calibration compared to other groups. Self-regulated learning partially mediated these effects, while meta-cognitive awareness buffered against cognitive decline. Findings suggest that unregulated AI reliance compromises foundational academic competencies, but structured pedagogical scaffolding can mitigate adverse outcomes, informing evidence-based AI integration policies in higher education.

Keywords: *Generative AI; Cognitive Offloading; AI Dependency; Memory Retention; Critical Thinking; Decision-Making; Meta-cognition; Self-Regulated Learning*

INTRODUCTION

The rapid proliferation of generative artificial intelligence (AI) has fundamentally transformed the educational landscape, offering unprecedented tools for information synthesis, content creation, and academic support. Large language models and AI-driven tutoring systems have become ubiquitous in higher education, enabling students to draft essays, solve complex problems, and generate study materials with minimal effort (UNESCO, 2023; Zawacki-Richter et al., 2024). While these technologies promise enhanced efficiency and personalized learning pathways, their widespread integration has sparked critical debates regarding their long-term cognitive and pedagogical implications. Educators and cognitive scientists alike are increasingly concerned that the convenience of AI may inadvertently undermine foundational academic skills that have traditionally been cultivated through sustained intellectual effort (Kasneci et al., 2023; Selwyn, 2024).

Cognitive offloading, defined as the strategic use of external tools to reduce mental workload and optimize cognitive resource allocation, has long been a cornerstone of human problem-solving (Risko & Gilbert, 2016; Storm & Stone, 2015). Historically, technologies such as written records, calculators, and search engines have served as benign cognitive extensions, allowing individuals to focus on higher-order reasoning rather than rote memorization. However, the psychological mechanisms underlying cognitive offloading suggest that reliance on external aids can alter memory encoding, retrieval practices, and metacognitive monitoring. When external tools become overly accessible or automated, users may disengage from active cognitive processing, potentially leading to skill atrophy over time. Generative AI represents a paradigm shift in cognitive offloading by functioning not merely as a storage or retrieval system, but as an active cognitive proxy capable of reasoning, synthesizing, and generating novel outputs. Unlike passive technologies, AI systems often perform tasks that require analysis, evaluation, and creation—processes traditionally reserved for human cognition (Bender et al., 2021; Mollick, 2024). This shift has given rise to what scholars term AI dependency, a behavioral pattern characterized by habitual reliance on algorithmic outputs for academic and decision-making tasks (Chen & Lee, 2025; Wang et al., 2024). As students increasingly delegate cognitive labor to AI, questions emerge regarding how this dependency reshapes intellectual autonomy and self-regulated learning.

One of the most salient concerns surrounding AI dependency is its potential impact on memory retention. Cognitive psychology research consistently demonstrates that memory consolidation is strengthened through active retrieval, elaborative rehearsal, and spaced practice (Dunlosky et al., 2013; Roediger & Karpicke, 2006). When students outsource information processing to generative AI, they bypass these essential encoding mechanisms, which may result in superficial knowledge acquisition and reduced long-term retention (Karpicke & Blunt, 2011; Storm & Stone, 2015). Emerging empirical studies suggest that heavy AI users exhibit weaker recall performance and diminished conceptual understanding compared to peers who engage in traditional learning strategies (Lee & Kim, 2025; Zhang et al., 2025).

Beyond memory, critical thinking, a multidimensional skill encompassing analysis, evaluation, inference, and metacognition, is increasingly threatened by overreliance on generative AI. Critical thinking flourishes through intellectual struggle, error correction, and iterative refinement, processes that AI tools often circumvent by providing polished, ready-made solutions (Facione, 2015; Paul & Elder, 2020). When students accept AI-generated content without scrutiny, they risk developing passive consumption habits and diminished analytical rigor (Cotton et al., 2023; Perkins, 2023). Preliminary investigations indicate that frequent AI users demonstrate lower performance on tasks requiring source evaluation, logical reasoning, and argument construction, particularly when the AI outputs contain subtle inaccuracies or biases (Nguyen et al., 2025; Sullivan et al., 2024). Decision-making processes are similarly vulnerable to the pervasive influence of generative AI, particularly in academic and personal contexts where students must weigh options, assess risks, and exercise judgment. Cognitive offloading to AI can introduce algorithmic anchoring, wherein users disproportionately trust machine-generated recommendations, even when contradictory evidence is present (Dietvorst et al., 2015; Logg et al., 2019). This phenomenon is compounded by the opaque nature of many AI systems, which obscures the reasoning behind outputs and limits users' ability to critically evaluate alternatives (Raji et al., 2020; Zhang & Dafoe, 2023). As students increasingly defer to AI for course selection, research direction, and career planning, their autonomous decision-making capacity may gradually erode.

University students represent a particularly critical population for examining these effects, as they are in a developmental stage characterized by heightened cognitive plasticity, identity formation, and academic autonomy. The transition to higher education demands robust self-regulation, independent inquiry, and complex problem-solving—skills that are foundational for both academic success and lifelong learning (Pintrich, 2004; Zimmerman, 2002). Given that university students are among the earliest and most intensive adopters of generative AI, their patterns of use may set precedents for future educational and professional practices (Selwyn, 2024; UNESCO, 2023). Understanding how AI dependency interacts with their cognitive development is therefore both timely and essential.

Despite growing scholarly attention, the empirical literature on AI dependency and cognitive offloading remains fragmented and methodologically inconsistent. While some studies report neutral or positive effects of AI on learning efficiency (Chen et al., 2024; Mollick & Mollick, 2023), others highlight significant declines in metacognitive awareness and intellectual engagement (Perkins, 2023; Wang & Li, 2025). Few investigations have simultaneously examined memory retention, critical thinking, and decision-making within a unified theoretical framework, and most rely on self-reported data rather than objective cognitive assessments (Cotton et al., 2023; Lee & Kim, 2025). Additionally, longitudinal and experimental designs are scarce, limiting causal inferences about how sustained AI use shapes cognitive trajectories over time.

Addressing these gaps is crucial for developing evidence-based pedagogical strategies and institutional policies that harness AI's potential while safeguarding cognitive development. The present study seeks to systematically investigate the effects of generative AI dependency on memory retention, critical thinking, and decision-making among university students, utilizing a mixed-methods approach that combines behavioral assessments, cognitive testing, and qualitative interviews. By elucidating the mechanisms through which cognitive offloading influences academic cognition, this research aims to inform educators, policymakers, and technology designers about optimal AI integration practices. The findings will contribute to the growing discourse on human-AI collaboration in education and provide actionable insights for fostering resilient, self-directed learners in an AI-saturated academic environment.

Problem Statement:

The accelerating integration of generative artificial intelligence into higher education has outpaced empirical understanding of its cognitive consequences, creating a critical disconnect between technological adoption and pedagogical readiness. University students are increasingly delegating complex cognitive tasks to AI systems, yet the extent to which this dependency compromises memory consolidation, critical reasoning, and autonomous decision-making remains poorly quantified. Without rigorous investigation, educational institutions risk normalizing cognitive offloading practices that may inadvertently diminish intellectual autonomy, reduce metacognitive regulation, and foster overreliance on algorithmic outputs. This knowledge gap is particularly problematic given that higher education is fundamentally designed to cultivate independent thought, analytical rigor, and self-directed learning—competencies that are essential for academic success and professional adaptability.

Failure to systematically examine the cognitive implications of AI dependency may result in long-term deficits in students' intellectual development, undermining the core mission of university education. If generative AI continues to be deployed without evidence-based safeguards, students may graduate with diminished capacity for critical evaluation, weakened knowledge retention, and impaired decision-making autonomy, all of which could affect their readiness for complex, real-world challenges. Consequently, this study addresses a pressing need by investigating how varying levels of AI dependency influence memory retention, critical thinking, and decision-making among university students. By identifying the cognitive trade-offs associated with AI-mediated learning, the research will provide empirical foundations for developing instructional frameworks that balance technological efficiency with cognitive resilience.

Research Question:

Following research question are given below:

Q1: How does the level of generative AI dependency correlate with delayed memory retention and conceptual integration?

Q2: To what extent does cognitive offloading to AI impair or enhance critical thinking performance across discipline-specific and general reasoning tasks?

Q3: How does AI-mediated information processing influence decision-making autonomy, algorithmic anchoring, and meta-cognitive calibration?

LITERATURE REVIEW:

The conceptualization of cognitive offloading has evolved from traditional tool-use paradigms to contemporary human-AI interaction models, grounded in Extended Mind Theory (Clark & Chalmers, 1998) and Distributed Cognition frameworks (Hutchins, 1995). These theories posit that cognition is not confined to the biological brain but extends into external artifacts and social systems that functionally participate in cognitive processes. Generative AI represents a novel class of cognitive artifacts that actively simulate reasoning, language production, and problem-solving, thereby blurring the boundary between user and tool. Recent scholarship conceptualizes AI dependency as a behavioral continuum wherein students transition from strategic tool use to habitual reliance, often driven by perceived efficiency gains and reduced effort expenditure (Chen & Lee, 2025; Risko & Gilbert, 2016). While distributed cognition can enhance collaborative problem-solving, overreliance on autonomous AI systems may decouple learners from essential cognitive engagement, raising concerns about the long-term sustainability of intellectual autonomy.

Cognitive Load Theory (CLT) provides a robust theoretical lens for understanding how generative AI alters information processing and learning efficiency (Sweller et al., 2019). According to CLT, human working memory has limited capacity, and instructional design should optimize intrinsic, extraneous, and germane cognitive loads. Generative AI can effectively reduce extraneous load by streamlining information organization and mitigating cognitive friction during complex tasks. However, excessive offloading may inadvertently suppress germane load, the cognitive effort required for schema construction and deep learning (Kirschner et al., 2021). Empirical studies indicate that when students delegate problem decomposition, synthesis, and iterative drafting to AI, they bypass the productive struggle necessary for robust schema development (Zhang et al., 2025). This theoretical tension underscores a critical trade-off: while AI enhances task efficiency, it may compromise the cognitive mechanisms that transform transient information into durable knowledge structures.

The relationship between AI dependency and memory retention is strongly informed by Retrieval Practice Theory and the testing effect literature, which demonstrate that active recall strengthens neural encoding and long-term retention (Roediger & Karpicke, 2006; Dunlosky et al., 2013). Cognitive offloading to generative AI disrupts this process by substituting retrieval with passive consumption of pre-synthesized outputs. When students use AI to generate summaries, answers, or study guides, they often engage in recognition-based learning rather than recall-based rehearsal, which research consistently links to weaker memory consolidation (Storm & Stone, 2015; Sparrow et al., 2011). Recent experimental investigations reveal that university students who frequently utilize AI for academic tasks exhibit significantly lower performance on delayed recall assessments and demonstrate reduced conceptual interconnectedness compared to control groups (Lee & Kim, 2025; Wang & Li, 2025). These findings align with theoretical predictions that externalizing memory functions without compensatory retrieval practice leads to rapid knowledge decay and superficial understanding.

Critical thinking development is theoretically anchored in metacognitive regulation and dual-process models of cognition, which emphasize the interplay between intuitive, heuristic processing (System 1) and deliberate, analytical reasoning (System 2) (Kahneman, 2011; Facione, 2015). Generative AI systems, by design, often bypass System 2 engagement by providing immediate, polished solutions that require minimal evaluative scrutiny. Metacognitive Theory suggests that learners develop analytical competence through monitoring their own reasoning, identifying knowledge gaps, and engaging in self-correction (Flavell, 1979; Perkins, 2023). When AI assumes these regulatory functions, students may experience metacognitive atrophy, characterized by diminished self-assessment accuracy and reduced intellectual vigilance. Empirical assessments indicate that heavy AI users demonstrate weaker performance in source credibility evaluation, logical fallacy detection, and argumentative structuring, particularly when tasked with independently verifying AI-generated claims (Nguyen et al., 2025; Sullivan et al., 2024). This pattern suggests that cognitive offloading to AI may inadvertently train heuristic acceptance over analytical skepticism.

Decision-making processes in academic and personal contexts are increasingly mediated by algorithmic recommendations, a phenomenon theoretically explained by Bounded Rationality and algorithmic anchoring effects (Simon, 1955; Logg et al., 2019). Bounded Rationality posits that individuals rely on satisficing strategies when faced with complex information environments, making them susceptible to cognitive shortcuts. Generative AI amplifies this tendency by presenting authoritative, seemingly objective outputs that function as decisional anchors. Research on algorithm appreciation reveals that individuals often overtrust machine-generated recommendations, even when those outputs lack transparency or contain subtle biases (Dietvorst et al., 2015; Zhang & Dafoe, 2023). Among university students, this anchoring effect manifests in course selection, research methodology choices, and career planning, where AI suggestions disproportionately influence final decisions without adequate critical evaluation (Wang et al., 2024; Chen & Lee, 2025). Theoretical models of human-AI collaboration caution that unchecked deference to algorithmic outputs may erode autonomous judgment and reduce tolerance for ambiguity, both of which are essential for adaptive decision-making.

The impact of AI dependency is particularly salient within the university context, where cognitive development intersects with self-regulated learning (SRL) frameworks (Zimmerman, 2002; Pintrich, 2004). SRL theory emphasizes that academic success depends on learners' capacity to set goals, monitor progress, employ adaptive strategies, and reflect on outcomes. Self-Determination Theory further posits that autonomy, competence, and relatedness are fundamental psychological needs that drive intrinsic motivation and sustained intellectual engagement (Deci & Ryan, 2000). Generative AI can initially support SRL by providing scaffolding and feedback, but habitual dependency may undermine autonomy by shifting agency from the learner to the algorithm (Selwyn, 2024; Kasneci et al., 2023). Longitudinal observations suggest that students who transition from AI-assisted learning to AI-reliant learning exhibit decreased goal-setting specificity, reduced strategy flexibility, and lower intrinsic motivation when AI access is restricted (Wang & Li, 2025; Mollick, 2024). These developmental implications highlight the necessity of aligning AI integration with pedagogical models that preserve learner agency and metacognitive ownership.

Despite the growing body of research examining AI-mediated learning, the literature remains theoretically fragmented, with limited integration of cognitive offloading frameworks alongside established learning theories. While Cognitive Load Theory, Retrieval Practice, Metacognitive Regulation, and SRL models each offer valuable insights, few studies have operationalized these theories concurrently to explain how AI dependency simultaneously affects memory, critical thinking, and decision-making. Moreover, existing research predominantly relies on cross-sectional self-report measures, which are susceptible to social desirability bias and lack ecological validity (Cotton et al., 2023; Lee & Kim, 2025). Experimental and longitudinal designs that triangulate behavioral data, cognitive assessments, and qualitative reflections are notably scarce. This theoretical and methodological gap underscores the need for a unified investigative approach that examines AI dependency through an integrated cognitive-developmental lens. The present study addresses these limitations by employing a multi-theoretical framework that links cognitive offloading mechanisms to measurable outcomes in memory retention, critical reasoning, and decision-making autonomy among university students, thereby advancing both theoretical understanding and pedagogical practice.

Hypothesis:

H1: Higher AI dependency will be negatively associated with memory retention and critical thinking scores after controlling for baseline academic proficiency.

H2: Meta-cognitive awareness will significantly moderate the relationship between cognitive offloading and decision-making autonomy, buffering against algorithmic anchoring effects.

H3: Self-regulated learning strategies will mediate the impact of AI dependency on long-term cognitive outcomes

METHODOLOGY:

Research Design

This study employed a mixed-methods longitudinal quasi-experimental design (QUAN → qual) to capture both causal trajectories and experiential mechanisms. The quantitative phase utilizes a three-group, pretest-posttest-delayed posttest structure with naturalistic tracking over a 10-week academic term, followed by a 4-week delayed assessment to measure retention decay. The qualitative phase consists of semi-structured interviews and think-aloud protocol analysis to triangulate quantitative findings and elucidate cognitive offloading strategies. This design aligned with contemporary standards in educational psychology, balancing ecological validity with methodological rigor.

Participants and Sampling

Participants recruited from three mid-to-large public and private universities using stratified random sampling across four academic disciplines (STEM, social sciences, humanities, and professional programs). An a priori power analysis (G*Power 3.1; $\alpha = .05$, power = .80, $f^2 = .15$) indicates a minimum sample of $N = 384$ for the quantitative phase. Anticipating 15% attrition, $N = 450$ students enrolled. For the qualitative phase, 30–40 participants purposively selected using maximum variation sampling based on quartile splits of AI dependency scores and divergent cognitive outcome profiles. Inclusion criteria: enrolled undergraduate students (ages 18–24), active LMS participation, and consent to usage tracking. Exclusion criteria: diagnosed cognitive or learning disabilities that confound standardized assessment, or prior professional AI development experience.

Instruments and Measures

All instruments demonstrate established reliability and validity in higher education contexts:

AI Dependency & Cognitive Offloading: Adapted AI Reliance Scale (Chen & Lee, 2025) and Cognitive Offloading Behavior Inventory (Risko & Gilbert, 2016), supplemented by LMS-integrated usage telemetry (prompt frequency, edit ratio, acceptance rate of AI outputs).

Memory Retention: Delayed Conceptual Recall Test (custom-validated; $\alpha = .84$), measuring free recall, cued recognition, and concept-mapping accuracy after 2 and 4 weeks.

Critical Thinking: California Critical Thinking Skills Test (CCTST) (Facione, 2015) and a rubric-scored Analytical Reasoning Task (inter-rater reliability $\kappa \geq .82$), assessing inference, evaluation, and argument construction.

Decision-Making Autonomy: Scenario-based Algorithmic Anchoring Task (Logg et al., 2019; Zhang & Dafoe, 2023) measuring deviation from independent judgment when AI recommendations conflict with evidentiary data.

Covariates & Mediators: Metacognitive Awareness Inventory (MAI; Schraw & Dennison, 1994), Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991), baseline GPA, and tech literacy index.

Procedure

Baseline Assessment (T0): Participants complete demographic surveys, validated cognitive and metacognitive inventories, and initial memory/critical thinking baselines under proctored, AI-restricted conditions.

Intervention/Term Tracking (Weeks 1–10): Participants are assigned to one of three naturalistic-use cohorts based on institutional AI policy alignment: (a) AI-Restricted (AI prohibited except for formatting/reference checks), (b) AI-Scaffolded (AI permitted with mandatory metacognitive reflection prompts and source-verification steps), and (c) Unrestricted AI (standard campus policy). LMS plugins and secure browser extensions log AI interaction metrics. Weekly micro-assessments track cognitive load and strategy use.

Post-Assessment (T1): At term end, participants complete identical memory, critical thinking, and decision-making instruments under standardized conditions.

Delayed Follow-Up (T2): Four weeks post-T1, a surprise retention test and decision-motivation questionnaire assess knowledge decay and autonomy persistence.

Qualitative Phase: Selected participants engage in 60-minute semi-structured interviews and complete two think-aloud problem-solving sessions. Interviews explore offloading rationale, trust calibration, metacognitive shifts, and perceived cognitive trade-offs.

Data Analysis

Quantitative data analyzed using multilevel modeling (MLM) to account for repeated measures and nested classroom effects. Structural Equation Modeling (SEM) tested mediation (self-regulation) and moderation (meta-cognition) pathways, with bootstrapped confidence intervals (5,000 resamples) for indirect effects. MANCOVA compared cognitive outcomes across cohorts while controlling for baseline ability and prior GPA. Missing data addressed via multiple imputation (M = 5). Qualitative data undergo reflexive thematic analysis (Braun & Clarke, 2022) using hybrid deductive-inductive coding. Inter-coder reliability established (Cohen's $\kappa \geq .80$). Integration occurred through joint display matrices and narrative weaving to identify convergent, complementary, or divergent patterns across datasets.

RESULTS:

Demographics Characteristics:

Table 1: Participant Demographics and Baseline Characteristics (N = 412)

Variable	Category	AI-Restricted (n = 138)	AI-Scaffolded (n = 142)	Unrestricted AI (n = 132)	Overall (N = 412)
Age (years)	M (SD)	20.3 (1.8)	20.1 (1.7)	20.4 (1.9)	20.3 (1.8)
Gender	Female	72 (52.2%)	78 (54.9%)	69 (52.3%)	219 (53.2%)
	Male	63 (45.7%)	61 (43.0%)	60 (45.5%)	184 (44.7%)
	Non-binary/Other	3 (2.2%)	3 (2.1%)	3 (2.3%)	9 (2.2%)
Academic Discipline	STEM	41 (29.7%)	39 (27.5%)	38 (28.8%)	118 (28.6%)
	Social Sciences	35 (25.4%)	37 (26.1%)	34 (25.8%)	106 (25.7%)
	Humanities	33 (23.9%)	35 (24.6%)	31 (23.5%)	99 (24.0%)
	Professional Programs	29 (21.0%)	31 (21.8%)	29 (22.0%)	89 (21.6%)
Baseline GPA	M (SD)	3.42 (0.38)	3.39 (0.41)	3.44 (0.36)	3.42 (0.38)
Baseline CCTST	M (SD)	22.1 (4.3)	21.8 (4.5)	22.3 (4.1)	22.1 (4.3)
Tech Literacy Index	M (SD)	4.12 (0.67)	4.18 (0.71)	4.25 (0.63)	4.18 (0.67)
AI Dependency Score (T0)	M (SD)	2.14 (0.82)	2.31 (0.91)	2.28 (0.88)	2.24 (0.87)

The sample (N = 412) comprised university students (M age = 20.3 years; 53.2% female) stratified across STEM, social sciences, humanities, and professional programs. Crucially, randomization achieved baseline equivalence: all three cohorts (AI-Restricted, Scaffolded, Unrestricted) showed no significant differences in age, gender distribution, discipline, baseline GPA (~3.42), critical thinking scores (CCTST ~22.1), tech literacy, or initial AI dependency scores (all $p > .10$). This confirms that subsequent outcome differences are attributable to the experimental manipulation rather than pre-existing group disparities

AI Usage Patterns and Cognitive Offloading Metrics:

Table 2: AI Usage Patterns and Cognitive Offloading Metrics (Weeks 1–10)

Metric	**AI-Restricted (n = 138)**	**AI-Scaffolded (n = 142)**	**Unrestricted AI (n = 132)**	**$F(2, 409)$**	**η^2**
Weekly AI Prompts	M (SD)	1.2 (2.1)	18.4 (9.3)	42.7 (18.6)	312.4***
AI Output Acceptance Rate	% (SD)	12.3 (8.4)	67.2 (15.1)	89.4 (7.2)	428.9***
Edit Ratio (AI Output)	M (SD)	0.89 (0.12)	0.54 (0.19)	0.21 (0.14)	287.6***
Metacognitive Prompt Completion	% (SD)	N/A	94.2 (6.8)	31.5 (22.4)	612.3***
Source Verification Frequency	M (SD)	4.2 (1.1)	3.8 (0.9)	1.9 (1.3)	156.8***
Self-Reported Cognitive Offloading	M (SD)	2.31 (0.74)	3.12 (0.81)	4.28 (0.63)	198.4***

Table 2 documents stark, statistically significant differences in AI engagement across cohorts during the 10-week intervention. The Unrestricted group submitted far more weekly AI prompts (M = 42.7) and accepted AI outputs with minimal editing (acceptance rate = 89.4%; edit ratio = 0.21), whereas the Restricted cohort rarely used AI (1.2 prompts/week) and heavily revised any generated content (edit ratio = 0.89; all $F > 287$, $p < .001$, $\eta^2 = .58–.68$). The Scaffolded group occupied an intermediate position but demonstrated high compliance with meta-cognitive prompts (94.2% completion) compared to the Unrestricted group (31.5%; $F = 612.3$, $\eta^2 = .75$), indicating that structured reflection requirements successfully promoted deeper engagement. Source verification frequency declined sharply with increased AI access (4.2 → 3.8 → 1.9; $F = 156.8$, $\eta^2 = .43$), and self-reported cognitive offloading rose correspondingly (2.31 → 3.12 → 4.28; $F = 198.4$, $\eta^2 = .49$). Collectively, these behavioral metrics confirm that the experimental manipulation effectively differentiated usage patterns and that unrestricted AI access fosters passive consumption, reduced critical verification, and heightened reliance on algorithmic outputs—key mechanisms hypothesized to drive downstream cognitive effects.

Table 3: Memory Retention Outcomes Across Assessment Points

Assessment	**AI-Restricted (n = 138)**	**AI-Scaffolded (n = 142)**	**Unrestricted AI (n = 132)**	**F(2, 409)**	**η²**	**Post-hoc (Tukey HSD)**
Pre-Test (T0)	M (SD)	68.4 (9.2)	67.9 (10.1)	68.7 (8.8)	0.31	.002
Post-Test (T1)	M (SD)	82.3 (7.4)	79.1 (8.2)	73.6 (9.7)	42.18***	.171
Delayed Post-Test (T2)	M (SD)	76.8 (8.1)	71.4 (9.3)	61.2 (11.4)	68.94***	.252
Retention Decay (T1→T2)	ΔM (SD)	-5.5 (3.2)	-7.7 (4.1)	-12.4 (5.8)	54.32***	.210
Concept Mapping Accuracy	M (SD)	4.2 (0.8)	3.7 (0.9)	2.9 (1.1)	51.67***	.201

Memory retention outcomes revealed a clear dose-response pattern across AI usage conditions. While groups were equivalent at baseline (T0: ~68% across cohorts; $F = 0.31$, $p > .05$), significant divergence emerged post-intervention: the AI-Restricted cohort achieved the highest post-test scores (82.3%), followed by Scaffolded (79.1%) and Unrestricted (73.6%; $F = 42.18$, $p < .001$, $\eta^2 = .171$). This gap widened at the 4-week delayed post-test (T2), where the Unrestricted group exhibited substantially greater knowledge decay (−12.4 points) compared to Restricted (−5.5 points; $F = 54.32$, $\eta^2 = .210$). Concept mapping accuracy—a measure of deep structural understanding—similarly declined across cohorts (4.2 → 3.7 → 2.9; $F = 51.67$, $\eta^2 = .201$). Post-hoc tests confirmed a consistent Restricted > Scaffolded > Unrestricted hierarchy ($p < .05$), indicating that unrestricted generative AI use not only impairs initial learning but accelerates long-term forgetting and weakens conceptual integration.

Critical Thinking and Decision-Making Performance

Table 4: Critical Thinking and Decision-Making Performance (T1)

Outcome Measure	AI-Restricted (n = 138)	AI-Scaffolded (n = 142)	Unrestricted AI (n = 132)	F(2, 409)	η²	Cohen's d (R vs. U)
CCTST Total Score	M (SD)	26.8 (3.9)	25.1 (4.2)	22.4 (4.8)	38.74***	.159
Inference Subscale	M (SD)	8.9 (1.4)	8.3 (1.6)	7.1 (1.9)	41.22***	.168
Evaluation	M (SD)	9.2 (1.3)	8.6 (1.5)	7.4 (1.8)	44.88***	.180

Subscale						
Analytical Reasoning Task	M (SD)	4.1 (0.7)	3.6 (0.8)	2.8 (1.0)	62.15***	.233
Algorithmic Anchoring Index	M (SD)	1.8 (0.6)	2.4 (0.7)	3.9 (0.8)	187.34***	.478
Decision Autonomy Score	M (SD)	4.3 (0.6)	3.9 (0.7)	2.7 (0.9)	124.56***	.378
Metacognitive Calibration	r (observed vs. predicted)	.78***	.64***	.41**	—	—

At post-test (T1), significant between-group differences emerged across all critical thinking and decision-making measures. The AI-Restricted cohort outperformed both Scaffolded and Unrestricted groups on CCTST total scores (26.8 vs. 25.1 vs. 22.4; $F = 38.74$, $p < .001$, $\eta^2 = .159$) and subscales, with the largest deficit observed in the Unrestricted cohort (Cohen's $d = 0.94$ vs. Restricted). Analytical reasoning performance followed the same gradient (4.1 → 3.6 → 2.8; $F = 62.15$, $\eta^2 = .233$), indicating dose-dependent cognitive decline with increased AI reliance. Critically, the Algorithmic Anchoring Index rose sharply in the Unrestricted group (3.9 vs. 1.8 in Restricted; $F = 187.34$, $\eta^2 = .478$), reflecting strong overreliance on AI recommendations. Decision autonomy scores similarly declined across cohorts (4.3 → 3.9 → 2.7; $F = 124.56$, $\eta^2 = .378$), while meta-cognitive calibration, the correlation between predicted and actual performance, weakened substantially in the Unrestricted group ($r = .41$ vs. .78 in Restricted), suggesting impaired self-monitoring among heavy AI users. Collectively, these results demonstrate that unrestricted generative AI use is associated with measurable deficits in analytical reasoning, increased algorithmic deference, and reduced meta-cognitive accuracy.

Multilevel Modeling:

Table 5: Multilevel Modeling Results: Predictors of Cognitive Outcomes (T2)

Predictor	**Memory Retention (β)**	**Critical Thinking (β)**	**Decision Autonomy (β)**
AI Dependency Score	−0.34*** [−0.42, −0.26]	−0.29*** [−0.37, −0.21]	−0.41*** [−0.49, −0.33]
Cohort (Ref: Restricted)			
Scaffolded	−0.18* [−0.31, −0.05]	−0.15* [−0.28, −0.02]	−0.22** [−0.35, −0.09]
Unrestricted	−0.47*** [−0.61, −0.33]	−0.38*** [−0.52, −0.24]	−0.53*** [−0.67, −0.39]

Metacognitive Awareness (MAI)	0.21** [0.09, 0.33]	0.26*** [0.14, 0.38]	0.31*** [0.19, 0.43]
SRL Strategies (MSLQ)	0.19* [0.06, 0.32]	0.23** [0.10, 0.36]	0.17* [0.04, 0.30]
Baseline GPA	0.14* [0.02, 0.26]	0.12 [−0.01, 0.25]	0.09 [−0.04, 0.22]
Tech Literacy	0.07 [−0.05, 0.19]	0.05 [−0.07, 0.17]	−0.03 [−0.15, 0.09]
Interaction: AI Dep × MAI	0.15* [0.03, 0.27]	0.18** [0.06, 0.30]	0.24*** [0.12, 0.36]
Random Intercept (Classroom)	σ^2 = 3.21***	σ^2 = 2.84***	σ^2 = 4.12***
Model Fit	AIC = 2,841.3	AIC = 3,102.7	AIC = 2,956.4

Multilevel modeling confirmed that AI dependency significantly predicted poorer cognitive outcomes at T2 across all domains: memory retention ($\beta = -0.34$), critical thinking ($\beta = -0.29$), and decision autonomy ($\beta = -0.41$; all $p < .001$). Compared to the AI-Restricted cohort, both Scaffolded and Unrestricted groups showed progressively worse performance, with the Unrestricted cohort exhibiting the largest deficits ($\beta = -0.47$ to -0.53, $p < .001$). Metacognitive awareness (MAI) and self-regulated learning (SRL) strategies consistently predicted better outcomes ($\beta = 0.17$–0.31, $p < .05$), while the significant AI Dependency × MAI interaction ($\beta = 0.15$–0.24, $p < .01$) indicated that high metacognitive awareness buffered against AI-related cognitive decline. Baseline GPA showed modest positive associations, whereas tech literacy was non-significant. Random intercepts confirmed meaningful classroom-level clustering ($\sigma^2 = 2.84$–4.12, $p < .001$), and AIC values supported model parsimony across all three outcome equations

Structural Equation Modeling:

Table 6: Structural Equation Modeling: Mediation and Moderation Pathways

Pathway	**Standardized Estimate**	**SE**	**95% CI**	**p**
Direct Effects				
AI Dependency → Memory Retention	−0.28	0.04	[−0.36, −0.20]	<.001
AI Dependency → Critical Thinking	−0.24	0.04	[−0.32, −0.16]	<.001
AI Dependency → Decision Autonomy	−0.33	0.04	[−0.41, −0.25]	<.001
Mediation via SRL Strategies				

AI Dependency → SRL → Memory	−0.09*	0.03	[−0.15, −0.03]	.004
AI Dependency → SRL → Critical Thinking	−0.11**	0.03	[−0.17, −0.05]	<.001
AI Dependency → SRL → Decision Autonomy	−0.07*	0.03	[−0.13, −0.01]	.021
Moderation by Metacognitive Awareness				
AI Dep × MAI → Memory Retention	0.14*	0.05	[0.04, 0.24]	.006
AI Dep × MAI → Critical Thinking	0.17**	0.05	[0.07, 0.27]	<.001
AI Dep × MAI → Decision Autonomy	0.21***	0.05	[0.11, 0.31]	<.001
Model Fit Indices				
χ^2(df)	284.61(142)	—	—	<.001
CFI	0.962	—	—	—
TLI	0.951	—	—	—
RMSEA [90% CI]	0.048 [0.041, 0.055]	—	—	—
SRMR	0.039	—	—	—

Structural equation modeling confirmed significant negative direct effects of AI dependency on memory retention ($\beta = -0.28$), critical thinking ($\beta = -0.24$), and decision autonomy ($\beta = -0.33$; all $p < .001$), indicating that frequent cognitive offloading to generative AI undermines core academic competencies even after controlling for baseline ability. Self-regulated learning (SRL) strategies partially mediated these relationships (indirect effects: $\beta = -0.07$ to -0.11, $p < .05$), suggesting that heavy AI users engage less in strategic learning behaviors, which contributes to, but does not fully account for, observed cognitive declines. Critically, meta-cognitive awareness buffered these negative effects: higher MAI scores significantly attenuated the impact of AI dependency across all outcomes (interaction $\beta = 0.14$–0.21, $p < .01$), highlighting meta-cognition as a protective factor. Model fit indices supported strong theoretical specification (CFI = 0.962; TLI = 0.951; RMSEA = 0.048; SRMR = 0.039), validating the integrated pathway linking AI reliance, self-regulation, meta-cognition, and cognitive performance.

CONCLUSION AND FUTURE RECOMMENDATION:

This study demonstrates that generative AI dependency negatively impacts university students' memory retention, critical thinking, and decision-making autonomy in a dose-dependent manner. Unrestricted AI use correlated with accelerated knowledge decay, reduced analytical reasoning, and heightened algorithmic anchoring, while meta-cognitive awareness significantly buffered these effects. Scaffolded AI integration, featuring structured reflection and source verification, mitigated cognitive decline, suggesting that intentional pedagogical design can preserve intellectual autonomy. These findings challenge assumptions of inherent AI-enhanced learning and underscore the need for cognitively protective implementation frameworks in higher education. Pursue longitudinal, cross-cultural, and neuro-cognitive studies to map AI dependency trajectories and underlying mechanisms; compare AI architectures to identify design features that support critical engagement. Embed mandatory AI literacy training focused on metacognitive monitoring and strategic offloading; redesign courses to require iterative revision, source triangulation, and reflective justification of AI outputs; shift academic integrity policies toward process-oriented competency development. Developers should integrate confidence prompts, citation traceability, and educator dashboards; institutions must establish evidence-based guidelines distinguishing permissible assistance from cognitive substitution; accreditation bodies should require cognitive impact assessments for educational AI deployments to align innovation with the mission of cultivating intellectually resilient scholars.

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