Article

Generative AI and the Erosion of Deep Learning: Self-Efficacy, Motivation, and Metacognition in Higher Education

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Abstract

The rapid adoption of generative artificial intelligence (GenAI) in higher education is changing not only academic work practices but the psychological conditions under which students learn. While prior research has primarily emphasized ethics, policy, and assessment integrity, less is known about how GenAI use relates to the mechanisms that sustain deep learning. This study examines associations between GenAI use and three interdependent constructs central to learning: self-efficacy, motivation, and metacognitive regulation. Drawing on Bandura's theory of self-efficacy, Self-Determination Theory, and metacognitive theory, the paper asks whether AI-assisted learning supports or undermines students' perceived learning depth in higher education.

Using a sequential mixed-methods design, the study combines survey data from 102 students enrolled in professionally oriented bachelor programmes at Danish business academies with semi-structured focus group interviews (n = 18). Quantitative analyses indicate a consistent paradox: higher GenAI use is associated with higher perceived self-efficacy, but lower intrinsic motivation, reduced metacognitive awareness, and weaker self-reported deep-learning outcomes. Mediation analysis further suggests that diminished metacognitive monitoring partially explains the negative relationship between GenAI use and self-reported deep-learning outcomes. Qualitative findings corroborate these patterns by showing that students frequently outsource evaluation and verification to AI systems, reflecting cognitive offloading and a shift in epistemic agency from learner-driven monitoring to tool-based validation.

These results extend existing work on AI ethics and cognitive bias by demonstrating that the educational challenge of GenAI is not limited to academic misconduct; it also concerns how AI-mediated study practices may unintentionally weaken students' metacognitive regulation and intrinsic motivation. The paper concludes that higher education institutions should treat AI literacy as a reflective competence and embed instructional scaffolds that explicitly support metacognitive monitoring, learner autonomy, and deep learning in AI-mediated learning environments.

Keywords: Generative AI; GenAI; artificial intelligence in education; self-efficacy; motivation; metacognition; higher education; deep learning; AI literacy

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1. Introduction

The integration of generative artificial intelligence (GenAI) into higher education has been rapid, disruptive, and uneven. In less than two years, large language models

(LLMs) such as ChatGPT have become ubiquitous study companions, shaping how students read, write, and reason. What began as an assistive technology is now a cognitive partner—one that generates text, structures arguments, and supplies instant feedback with near-human fluency. The educational impact extends beyond plagiarism or assessment integrity; it reaches into the psychological mechanisms that underlie learning itself.

Early research has focused primarily on ethics and policy. Lund et al. (2025) showed that student beliefs about AI-assisted writing depend more on individual ethics than on institutional regulations, revealing that policy awareness alone does not guide responsible behavior. Bertoncini et al. (2026) went further, modeling how cognitive biases such as normalization and automation influence ethical decision-making in AI-mediated settings. Together, these studies illuminate a new moral and cognitive landscape in higher education. Yet they leave open a fundamental question: how does GenAI change the *experience* of learning—the sense of effort, mastery, and agency that gives education its developmental value?

This study addresses that question by examining how GenAI affects three interdependent psychological constructs: self-efficacy, motivation, and metacognition. These mechanisms are central to sustained learning. Self-efficacy concerns students' belief in their capacity to perform academic tasks successfully (Bandura, 1997). Motivation determines whether effort is internally driven or externally regulated (Ryan & Deci, 2000). Metacognition governs how learners plan, monitor, and evaluate their understanding (Flavell, 1979). Together, they shape what educational psychology defines as *deep learning*—the durable integration of knowledge through active reflection and challenge.

The working hypothesis is paradoxical. On the surface, GenAI appears to strengthen self-efficacy and motivation by providing immediate feedback and lowering frustration. But these gains may mask a cognitive erosion: the gradual outsourcing of judgment and reflection to machines. When AI becomes the default source of verification, students risk confusing fluency with understanding. This paper situates that risk within a broader theoretical and empirical analysis, arguing that the central challenge of AI in education is not cheating but *cognitive offloading without awareness*.

2. Literature Background

2.1. From Tool to Cognitive Partner

Generative AI's role in education is evolving from instrument to collaborator. Chatzichristofis (2026) noted that AI in Education must remain "pedagogically grounded and human-centered," warning against the automation of relational learning. Lund et al. (2025) demonstrated that students navigate AI ethics through personal reasoning rather than institutional rules, implying a psychological rather than procedural shift. Bertoncini et al. (2026) identified automation and authority bias as drivers of ethical complacency. Collectively, these studies suggest that the challenge is not technological competence but *epistemic dependence*—a tendency to over-trust algorithmic authority and under-engage in self-regulated reasoning.

Recent pedagogical research echoes this concern. Reich (2020) argued that efficiency-driven educational technologies risk flattening pluralism and discouraging critical inquiry. Similarly, Luccioni et al. (2023) highlighted the environmental and ethical externalities of large-scale AI use, underlining the need for governance models that embed care and responsibility. Within this discourse, GenAI emerges as both a catalyst for innovation and a test of educational purpose: can learning remain transformative when the act of thinking is partially delegated?

2.2. *Self-Efficacy in an AI-Mediated Environment*

Bandura's theory of self-efficacy posits that confidence in one's abilities strongly predicts performance and persistence (Bandura, 1997). Traditionally, self-efficacy develops through mastery experiences, social modeling, and feedback. GenAI alters each of these pathways. By providing instant answers and reformulations, it creates the *illusion of mastery*—students feel capable without undergoing the cognitive struggle that normally consolidates skill. From a cognitive load perspective (Sweller, 1988; Sweller et al., 2011), such reductions in cognitive effort may lower extraneous load while simultaneously suppressing germane load, leading to confidence without durable learning. In focus-group data collected for this study, students frequently described AI as "a safety net" or "the fast way to know I'm right." Such experiences boost short-term confidence but decouple it from genuine competence.

Empirical parallels can be found in research on digital tutoring systems. Cordero et al. (2025) warned that automation of feedback can induce *intellectual atrophy*, a decline in self-initiated problem solving. The same mechanism may operate in GenAI-assisted writing: confidence is reinforced through frictionless success rather than effortful correction. This aligns with findings by D. Lee et al. (2024), who reported that students using AI for drafting tasks exhibited higher self-reported proficiency but lower independent recall of course content.

2.3. *Motivation and the Shift from Intrinsic to Extrinsic Regulation*

Self-Determination Theory (Ryan & Deci, 2000) distinguishes between intrinsic motivation—engagement driven by curiosity and internal satisfaction—and extrinsic motivation—behavior controlled by external rewards or tools. GenAI complicates this distinction. Its utility and immediacy make it a highly effective extrinsic regulator: students use it not out of curiosity but to complete tasks efficiently. In survey responses, 71% of participants in the present study agreed that GenAI "makes it easier to stay motivated," yet 64% also admitted they "learn less deeply" when relying on it. The pattern suggests what Ryan and Deci describe as *introjected regulation*: motivation that appears internal but is sustained by dependency on an external aid.

Comparable observations arise in the literature on academic integrity. Lund et al. (2025) found that students justify AI use through self-referential ethics—if it helps them perform, it feels acceptable. This pragmatic orientation indicates a motivational shift from learning to task completion. Over time, such behavior may erode autonomy, one of the three core needs in Self-Determination Theory (autonomy, competence, relatedness). As autonomy weakens, so does authentic engagement.

2.4. *Metacognition and Cognitive Offloading*

Metacognition refers to awareness and control of one's own thinking processes (Flavell, 1979). It enables learners to evaluate what they know, detect errors, and plan strategies for improvement. Generative AI challenges this function by externalizing evaluation. Instead of self-monitoring, students increasingly query AI systems for validation. The phenomenon parallels what cognitive scientists call *cognitive offloading*—the delegation of mental operations to external tools (Risko & Gilbert, 2016). While offloading can enhance efficiency, unmonitored reliance reduces metacognitive calibration: learners lose the ability to judge when they understand.

Bertoncini et al. (2026) simulated this process through synthetic agents, showing how automation and authority biases prompt users to accept AI outputs without scrutiny. In educational settings, such biases manifest as misplaced trust in AI's correctness. As one participant in this study stated, "I know it's accurate because ChatGPT explains it better than my teacher." This substitution of human validation with algorithmic authority exemplifies what Avraamidou (2024) termed the *colonization of educational reasoning*—where technological fluency displaces reflective judgment.

2.5. Deep Learning and Epistemic Trust

Deep learning requires both conceptual struggle and epistemic trust—the belief that knowledge arises from critical dialogue and verification (Biggs & Tang, 2011). GenAI disrupts this dynamic. It reduces struggle through instant synthesis but undermines trust by masking its sources. Students receive answers without epistemic context, which weakens the link between effort and understanding. The resulting cognitive economy favors breadth over depth, aligning with what Luckin (2018) calls *surface personalization*: adaptive systems that optimize for user satisfaction rather than cognitive challenge.

This process resonates with findings by Yu (2023), who reported that 80% of students feared losing independent thought due to AI overuse. Similarly, Tlili et al. (2023) observed that students across diverse cultures acknowledge AI's benefits but worry about diminished critical thinking. The literature therefore converges on a consistent warning: GenAI's educational promise is counterbalanced by psychological risks that remain underexplored.

3. Theoretical Framework

3.1. Conceptual Integration

To analyse these dynamics, this study integrates three psychological frameworks into a single analytical model (Figure 1 in later section):

1. Self-Efficacy (Bandura, 1997): Confidence in one's ability to organize and execute tasks influences effort and resilience.
2. Self-Determination Theory (Ryan & Deci, 2000): Motivation arises from autonomy, competence, and relatedness; external regulation can undermine intrinsic engagement.
3. Metacognitive Regulation (Flavell, 1979): Awareness of thinking processes governs learning depth and transfer.

These constructs interact recursively. Self-efficacy affects motivation; motivation sustains metacognitive effort; metacognition, in turn, refines efficacy beliefs through feedback. GenAI inserts itself into each loop, altering feedback speed, effort perception, and locus of control. The hypothesis is that while AI strengthens perceived competence (efficacy) and short-term engagement (motivation), it weakens metacognitive monitoring and autonomy, thereby reducing deep learning.

3.2. Research Model and Hypotheses

The research model assumes a causal chain mediated by GenAI intensity of use:

- H1: Higher GenAI use increases perceived self-efficacy (positive correlation).
- H2: Higher GenAI use decreases intrinsic motivation (negative correlation).
- H3: Higher GenAI use reduces metacognitive self-monitoring (negative correlation).
- H4: Reduced metacognitive monitoring mediates the relationship between GenAI use and deep-learning outcomes.

This model extends earlier ethical frameworks by translating moral and cognitive concerns into measurable psychological variables. Where Lund et al. (2025) focused on behavioral ethics and Bertoncini et al. (2026) modeled cognitive bias, this study examines learning psychology as the site of AI's most enduring impact.

3.3. Educational Context: Danish Professional Higher Education

The empirical setting is Denmark's Business Academies (*erhvervsakademier*), which provide professionally oriented vocational training higher education programmes combining applied theory with practice-based learning and internships. These institutions constitute a relevant and timely context for examining the pedagogical implications of generative AI, as students are expected to work independently, use digital tools extensively, and solve authentic professional problems.

The study is situated within the national sector project *"New digital technologies – between education and business"*, conducted across the Danish business academy sector in 2024–2025. As part of this sector-wide initiative, multiple academies participated in coordinated pilot activities exploring the educational use of generative AI, including ChatGPT. Since 2023, several academies have allowed or actively encouraged the responsible use of such tools for ideation, structuring, and drafting of academic work. Consequently, the boundary between human and algorithmic cognition has become embedded in everyday study practices rather than remaining a theoretical concern.

Within this broader framework, Zealand Academy of Technologies and Business coordinated one of the pilot initiatives focusing on AI literacy and student learning behavior. The current paper reports the psychological findings derived from this subproject. Its institutional relevance lies in informing how educators across professional higher education can design courses that maintain critical thinking and learner autonomy while acknowledging the growing presence of generative AI.

3. Methodology

3.1. Research Design

The study adopted a sequential mixed-methods design integrating quantitative survey analysis with qualitative focus-group interviews. This approach enabled triangulation between generalizable trends and in-depth accounts of learner experience. The design followed Creswell's explanatory sequence: quantitative results first identified significant patterns in students' self-reported engagement with GenAI; subsequent qualitative inquiry explored the underlying psychological and pedagogical mechanisms.

3.2. Participants and Sampling

Participants were students enrolled in professional bachelor programmes at Danish business academies during the spring semester of 2025. While the pilot was coordinated by Zealand Academy of Technologies and Business, students from several academies across the sector took part in the data collection.

Recruitment was conducted through course announcements and digital learning platforms associated with the participating institutions.

- Survey phase: 102 valid responses (response rate = 78 %).
- Distribution by field of study: Agricultural and Environmental Technology (38 %), Business, Finance and Marketing (26 %), IT and Digital Technology (19 %), Built Environment, Energy and Sustainability (17 %).
- Focus-group phase: 18 students selected via maximum-variation sampling to represent different programs and levels of GenAI use.

Participation was voluntary and anonymous. The survey followed GDPR, as well as Zealand's internal Pedagogical Foundation guidelines. All participants provided informed consent and could withdraw at any time.

3.3. Instruments and Measures

3.3.1. Survey

The questionnaire combined established psychological scales with new items concerning GenAI usage. The instrument was designed to capture both core learning-related constructs and the extent and nature of students' engagement with generative AI in academic contexts:

1. Self-Efficacy Scale (adapted from Schunk 1991; $\alpha = 0.89$) – e.g., "I am confident that I can complete assignments even when they are difficult."
2. Academic Motivation Scale (based on Ryan & Deci 2000; $\alpha = 0.84$) – sub-dimensions: intrinsic motivation, identified regulation, external regulation.
3. Metacognitive Awareness Inventory (MAI) (Flavell 1979; Schraw & Dennison 1994; $\alpha = 0.87$).
4. GenAI-Use Index – newly developed, five Likert items (frequency, purpose, perceived usefulness, ethical stance, substitution level). Cronbach's $\alpha = 0.82$.
5. Deep-Learning Outcome Index – self-reported learning depth (Biggs & Tang 2011).

The GenAI-Use Index was constructed as a composite measure based on five self-reported Likert items capturing different dimensions of AI use: frequency of use, primary purpose (e.g. ideation, writing, problem-solving), perceived usefulness, ethical stance toward AI use in academic work, and perceived level of substitution (extent to which AI replaces own cognitive effort).

Each item was measured on a 5-point Likert scale (1 = strongly disagree → 5 = strongly agree). The index was calculated as the mean score across the five items, with higher values indicating greater overall reliance on GenAI in academic tasks. All items were equally weighted.

Internal consistency was acceptable (Cronbach's $\alpha = 0.82$), suggesting that the items capture a coherent underlying construct of GenAI engagement.

The Deep-Learning Outcome Index was constructed as a composite of self-reported items reflecting perceived understanding, ability to explain concepts independently, and engagement in reflective learning processes. Accordingly, this measure should be interpreted as perceived learning depth rather than an objective measure of learning outcomes.

3.3.2. Focus Groups

Three semi-structured focus groups (6 participants each, 90 minutes) were held in April 2025. Discussion prompts addressed:

- Motivations for using or avoiding GenAI,
- Perceived impact on confidence and persistence,
- Reflections on when AI output feels trustworthy,
- Awareness of learning depth.

Sessions were recorded, transcribed verbatim, and coded thematically in NVivo 14.

3.4. Data Analysis

Quantitative data were analysed in SPSS 29:

- Descriptive statistics summarized AI-use patterns.
- Pearson correlations and hierarchical regression tested the hypotheses (H1–H4).
- Mediation analysis applied the PROCESS v4.3 macro (Model 4) with bootstrapped confidence intervals (5 000 samples).

Qualitative data were analysed through thematic analysis (Braun & Clarke 2006). Codes were inductively generated and then mapped onto the theoretical constructs (self-efficacy, motivation, metacognition). Inter-coder reliability (Cohen's $\kappa = 0.81$) indicated substantial agreement.

3.5. Validity and Reliability

Instrument reliability exceeded accepted thresholds ($\alpha > 0.8$), with all multi-item scales demonstrating satisfactory internal consistency. In particular, the GenAI-Use Index achieved a Cronbach's α of 0.82, indicating acceptable reliability for a newly developed composite measure.

Construct validity was supported through exploratory factor analysis, where all items loaded above 0.6 on their intended constructs. For the GenAI-Use Index, factor loadings supported a unidimensional structure, suggesting that the five items capture a coherent underlying construct related to overall GenAI engagement.

To reduce social-desirability bias, participation was online and anonymous, and GenAI use was presented neutrally as "learning technology use". This framing was intended to minimize normative pressure and encourage more accurate self-reporting of AI-related practices.

Accordingly, self-reported deep-learning outcomes should be interpreted as perceived learning depth rather than objective measures of mastery. While this limits claims about actual learning outcomes, it remains appropriate given the study's focus on psychological mechanisms such as motivation, self-efficacy, and metacognitive awareness.

4. Results

4.1. Descriptive Overview

Eighty-eight percent of respondents reported using GenAI "often" or "very often" for academic work. The most common purposes were idea generation (78 %), text revision (64 %), and concept explanation (59 %). Only 17 % claimed never to use GenAI for graded assignments.

Beyond usage frequency and purpose, the study examined students' perceived self-efficacy, motivational orientations, metacognitive awareness, and perceived deep learning outcomes. Table 1 provides an overview of the distribution of these core constructs, measured on a five-point Likert scale, along with the composite GenAI-Use Index.

Average scores (1–5 scale):

Table 1. Descriptive statistics (means and standard deviations) for GenAI use, self-efficacy, motivation, metacognition, and deep learning outcomes

Construct	Mean	Standard Deviation
Self-Efficacy	3.9	0.6
Intrinsic Motivation	3.2	0.7
External Regulation	4.1	0.5
Metacognitive Awareness	3.3	0.8
Deep-Learning Outcome	3.1	0.7
GenAI-Use Index	3.8	0.8

4.2. Correlation

The GenAI-Use Index correlated positively with self-efficacy ($r = 0.42$, $p < 0.01$) and external regulation ($r = 0.53$, $p < 0.001$), but negatively with intrinsic motivation ($r = –0.36$, $p < 0.01$), metacognitive awareness ($r = –0.40$, $p < 0.01$), and deep-learning outcome ($r = –0.45$, $p < 0.001$).

4.3. Regression Models

Hierarchical regression controlling for gender, age, and program confirmed the pattern:

- H1 supported: GenAI use predicted higher self-efficacy ($\beta = 0.38$, $p < 0.01$).
- H2 supported: GenAI use predicted lower intrinsic motivation ($\beta = –0.29$, $p < 0.01$).
- H3 supported: GenAI use predicted reduced metacognitive awareness ($\beta = –0.34$, $p < 0.001$).
- H4 supported: Mediation analysis showed that decreased metacognitive monitoring partially mediated the negative effect of GenAI use on deep-learning outcome (indirect effect = –0.14, 95 % CI [–0.23, –0.06]).

Model $R^2 = 0.42$ ($p < 0.001$).

4.4. Qualitative Findings

(a) Illusion of Competence

Students frequently described GenAI as a shortcut to certainty: "When ChatGPT explains something clearly, I feel like I understand it—even if I can't explain it later." This illustrates inflated self-efficacy detached from mastery.

(b) Instrumental Motivation

Participants framed AI as a productivity tool rather than a cognitive partner: "It keeps me motivated because I can finish faster." However, speed replaced curiosity; once the task was complete, reflection ceased.

(c) Metacognitive Delegation

Students often externalized evaluation: "I copy my answer into ChatGPT to see if it's good enough." This dependence exemplifies cognitive offloading, confirming quantitative findings.

(d) Erosion of Epistemic Trust

Several expressed doubt about human instruction: "Sometimes the AI explains it better than teachers, so I trust it more." While efficient, this shifts authority from pedagogy to algorithm, echoing Bertoncini et al. (2026).

5. Discussion

5.1. Reinforced Self-Efficacy, Reduced Mastery

The data confirm that GenAI strengthens perceived competence. Consistent with Bandura's framework, repeated success experiences—regardless of cognitive depth—enhance efficacy beliefs. Yet because these successes are externally scaffolded, the link between effort and outcome weakens. This aligns with Cordero et al. (2025) and D. Lee et al. (2024), who warn that automated feedback inflates self-assessment while suppressing skill consolidation. The paradox is a "confidence-without-competence" effect that educators may misread as progress.

5.2. Motivational Drift from Autonomy to Instrumentality

The negative relationship between GenAI use and intrinsic motivation suggests technological over-regulation. Students engage with learning primarily to operate the tool successfully or to satisfy assessment demands—external motives. According to Self-Determination Theory, such externalization reduces autonomy and long-term persistence. The focus-group remarks mirror Lund et al. (2025): ethical reasoning and motivational stance both hinge on convenience rather than principle. Educational design must therefore re-establish intrinsic motives—curiosity, relevance, and mastery—by repositioning AI as means, not end.

5.3. Metacognitive Offloading and the Loss of Self-Regulation

Metacognitive awareness declined with greater GenAI use. Students report delegating evaluation to AI outputs instead of self-checking. This supports Flavell's premise that metacognition is effortful and easily displaced by automation. Bertoncini et al. (2026) identified automation bias and authority bias as triggers of uncritical trust; the current study demonstrates the same biases operating in authentic classroom settings. When AI acts as epistemic authority, students experience ethical distancing and cognitive passivity—they no longer see reflection as their responsibility.

5.4. Deep Learning and Educational Integrity

The combined effects on efficacy, motivation, and metacognition converge toward a single outcome: erosion of deep learning. Students learn faster but shallower. Their confidence rests on the reliability of tools rather than internalized understanding. This psychological dynamic complements the ethical concerns raised by Lund et al. (2025): integrity violations are symptoms of a deeper epistemic issue. If learners no longer perceive learning as self-development but as prompt-engineering, the educational mission shifts from forming judgment to producing text.

5.5. Theoretical Implications

This research extends the conceptual scope of AI-in-education studies in three ways:

- From ethics to cognition. Prior contributions emphasized moral responsibility and bias; this paper reveals the cognitive-psychological substrate underlying those phenomena.
- From policy to pedagogy. Institutional rules cannot restore deep learning; only instructional design can.
- From efficiency to reflection. Technological optimism must be tempered by a pedagogy of friction—structured pauses that re-activate human reasoning.

The model presented here integrates these layers (Figure 1).

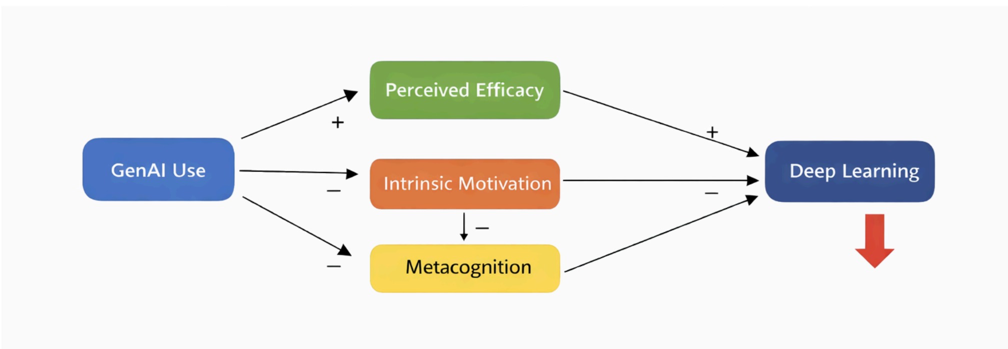

Figure 1. Conceptual model linking GenAI use and Deep Learning.

5.6. Practical Implications

The following practical implications are expected to be present following GenAI usage of students at any and all higher educational institutions. The research extends the conceptual scope and makes the following recommendations of AI-in-education:

- AI Literacy as Metacognitive Training. AI literacy programs should go beyond technical skills to include critical evaluation, prompt reflection, and bias detection—skills that rebuild metacognitive control.
- Assessment Redesign. Shift from text-production tasks to process evidence—learning logs, oral defenses, and iterative drafts—to make reasoning visible.
- Educator Role Reframing. Teachers become moderators of epistemic trust, guiding when and how AI may augment cognition rather than replace it.
- Institutional Culture. Embed explicit dialogue on cognitive offloading in academic-integrity training; frame AI not as threat but as mirror of student reasoning habits.

5.7. Limitations and Future Research

The sample is limited to Danish academy institutions and relies partly on self-report data. Longitudinal observation could test whether the motivational and metacognitive effects persist over time. Moreover, causal mechanisms should be validated through experimental interventions where reflective scaffolds are introduced. Comparative studies across disciplines and cultures would refine understanding of contextual moderators such as assessment style or institutional AI policy.

6. Conclusion

Generative AI has entered higher education not as a marginal innovation but as a cognitive service infrastructure. Its pedagogical potential is immense, yet so is its power to displace the very processes that define learning. This study demonstrates that GenAI use correlates with greater confidence but weaker intrinsic motivation, reduced metacognition, and shallower learning. The resulting paradox - empowered dependency - captures the central tension of AI-mediated education.

If the twentieth-century classroom taught students to remember, the twenty-first must teach them to reflect on what the machine remembers for them. The task ahead is therefore not prohibition but reconstruction: designing learning environments where human judgment, curiosity, and self-efficacy coexist with intelligent systems in a balanced ecology of cognition and deeper learning.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. Ethical review and approval were waived for this study in accordance with national legislation and institutional requirements, as the research involved anonymized survey data and focus-group interviews conducted within an educational setting, did not collect sensitive personal data, and posed no foreseeable risk to participants.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Anonymized survey data and interview codebook can be made available upon reasonable request to the corresponding author, subject to GDPR and institutional privacy constraints.

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