



## ADVANCE SOCIAL SCIENCE ARCHIVE JOURNAL

Available Online: <https://assajournal.com>

Vol. 05 No. 01. Jan-March 2026. Page#. 7566-7574

Print ISSN: [3006-2497](#) Online ISSN: [3006-2500](#)Platform & Workflow by: [Open Journal Systems](#)<https://doi.org/10.5281/zenodo.22873728>

## Cognitive Offloading and AI Literacy in Higher Education: A Dual-Process Model of Generative AI Dependency and Student Meta cognitive Agency

**Khadim Hussain**

M.Phil Scholar

Faculty of Science, The Superior University Lahore

[khadimteacher@gmail.com](mailto:khadimteacher@gmail.com)

**Abdul ur Rashid Mahmood**

Phd Math

Faculty of Science, The University of Lahore

### Abstract

*With the recent rise of Generative Artificial Intelligence (Gen-AI) in higher education, the nature of engagement, processing, and cognitive effort is changing. While Gen-AI tools offer opportunities for tailored scaffolding and rapid information synthesis, concerns about overreliance and atrophy of natural process are growing. Building on Dual-Process and Cognitive Load Theories, this paper proposes and empirically evaluates a conceptual framework investigating how AI Literacy and Perceived Task Complexity influence Cognitive Offloading Behaviors, and how these behaviors in turn impact Meta cognitive Agency and Academic Self-Efficacy. Using a quantitative SEM approach based on primary survey data (N = 684 across multi-disciplinary undergraduate programs), this study evaluates six hypotheses. The paper finds that high AI Literacy leads to reduced uncritical, passive dependency and more strategic cognitive offloading, while high Perceived Task Complexity increases dependency when AI Literacy is low, resulting in reduced meta cognitive agency and self-efficacy. Modern analysis further finds a moderating role of institutional AI policy clarity. This paper's theoretical contributions refine cognitive theories in the context of AI-assisted learning, while practical implications give guidance to higher education leaders, curriculum designers, and faculty in developing robust, AI-integrated assessment frameworks. Keywords: Generative Artificial Intelligence, Cognitive Offloading, AI Literacy, Meta cognitive Agency, Dual-Process Theory, Higher Education, Academic Self-Efficacy.*

### 1. Introduction

The higher education ecosystem is undergoing a structural shift caused by the widespread availability and adoption of Generative Artificial Intelligence (Gen-AI) technologies. Unlike previous educational technology innovations, Gen-AI systems have conversational capabilities, generative synthesis, and reasoning heuristics that closely emulate complex human cognition. Students are increasingly relying on

Gen-AI models to write essays, code, debug, synthesize literature, and structure academic arguments. This blurs the boundary between human internal cognition and external technological support. In cognitive psychology, the use of tools to reduce the mental effort of a task is referred to as cognitive offloading. While this is a natural human strategy, its application in an unsupervised educational setting presents severe paradoxes. On one hand, proponents argue that Gen-AI democratizes academic support by acting as a 24/7 personalized tutoring assistant, reducing cognitive barriers for novice learners, and enabling focusing on complex, higher-level evaluation. On the other hand, studies warn of a cognitive offloading trap where students pass core analytical and creative tasks to AI models. As a result, they lose the ability to engage in active problem-solving and experience a decay of self-regulated learning skills. While the literature exploring the impact of Gen-AI in education is growing, most are descriptive or focused on technology adoption or ethical considerations. There is a theoretical gap in understanding of cognitive mechanisms that determine whether a student uses a Gen-AI as a strategic partner or a crutch. Specifically, there is a deficit of empirical research into the interplay between AI Literacy, Task Complexity, Cognitive Offloading Behaviors, and downstream psychological outcomes such as Meta cognitive Agency and Academic Self-Efficacy. This paper introduces an original research framework that explores these connections through the lenses of Dual-Process and Cognitive Load Theories.

## 2. Primary Objectives

This study examines the cognitive and psychological implications of Gen-AI integration into higher education. The primary research objectives are:

- \*To formulate and empirically validate a conceptual model linking AI Literacy and Perceived Task Complexity to different modes of Cognitive Offloading (Strategic Offloading vs. Passive Dependency) in university students.
- \*To evaluate the direct and indirect affects of Strategic Cognitive Offloading and Passive Gen-AI Dependency on students' Meta cognitive Agency and Academic Self-Efficacy.
- \*To analyze the moderating influence of Institutional AI Policy Clarity on the relationship between task parameters and cognitive offloading choices.
- \*To provide higher education administrators, policy makers, and educators with theoretical and empirical foundations for integrating AI into curricula while preserving critical cognitive development and self-regulated learning.

## 3. Literature Review and Hypothesis Development

### 3.1 Theoretical Foundations: Dual-Process and Cognitive Load Theories

**Dual-Process Theory describes two distinct modes of human cognition:** System 1 (fast, automatic, effortless, intuitive, and subject to biases) and System 2 (slow, deliberate, analytical, effortful, and rule-governed). Academic learning typically relies on System 2 for deep processing of novel material. However, due to the principle of cognitive economy, humans seek to avoid System 2 processing whenever possible.

**Cognitive Load Theory (CLT) divides cognitive demand into three categories:**

**Intrinsic Load:** The inherent difficulty of the academic material.

**Germane Load:** Cognitive processing necessary to build mental schemas and achieve deep understanding.

**Extraneous Load:** Non-essential cognitive effort imposed by the instructional design or tools used. When Gen-AI interfaces are introduced, they provide an effortless way to offload both intrinsic and germane cognitive loads. If a student uses Gen-AI to organize raw data or format references, extraneous cognitive load is reduced, freeing working memory to focus on high-level analysis (Strategic Offloading). On the other hand, if the student relies on Gen-AI to generate the core arguments, synthesis, and solutions without active reflection, the entire germane cognitive load is offloaded (Passive Dependency). This eliminates System 2 deliberation and relies entirely on the generated output.

### 3.2 AI Literacy and Cognitive Offloading

AI Literacy extends beyond digital literacy; it involves understanding how AI systems process information, their limitations, biases, hallucination risks, and optimal prompt engineering. Students with high AI Literacy recognize the need to validate and refine Gen-AI outputs. They use Gen-AI as an imperfect cognitive partner. Therefore, students with high AI Literacy are more likely to engage in Strategic Cognitive Offloading, delegating administrative, mechanical, or structural sub-tasks while maintaining control over analytical judgment and synthesis. Conversely, students with low AI Literacy fail to identify potential hallucinations, leading to Passive Gen-AI Dependency.

**Hypothesis 1 (H<sub>1</sub>):** AI Literacy is positively related to Strategic Cognitive Offloading.

**Hypothesis 2 (H<sub>2</sub>):** AI Literacy is negatively related to Passive Gen-AI Dependency.

### 3.3 Perceived Task Complexity and Cognitive Offloading

When experiencing high Perceived Task Complexity, students feel overwhelmed by the intrinsic cognitive load. According to the cognitive economy principle, high mental workload prompts students to seek external shortcuts. In the absence of guidance, high task complexity encourages learners to surrender analytical control to Gen-AI to complete the task. This reduces cognitive anxiety and allows meeting deadlines.

**Hypothesis 3 (H<sub>3</sub>):** Perceived Task Complexity is positively related to Passive Gen-AI Dependency.

**Hypothesis 4 (H<sub>4</sub>):** Perceived Task Complexity is negatively related to Strategic Cognitive Offloading, unless moderated by high AI Literacy.

### 3.4 Impact on Meta cognitive Agency and Academic Self-Efficacy

Meta cognitive Agency is the learner's ability to monitor, regulate, and direct their own cognitive processes during learning tasks. Academic Self-Efficacy is an individual's belief in their ability to execute courses of action required to achieve designated academic performances. Strategic Offloading preserves Meta cognitive agency by giving students control over the prompt parameters, evaluation of output validity, synthesis of ideas, and refinement of final output. Passive Gen-AI Dependency bypasses the learning process entirely, leading to reduced Meta cognitive monitoring. When AI assistance is removed (e.g., in invigilated examinations or real-time problem-solving), students struggle to replicate the Meta cognitive processes they relied on. This results in increased anxiety and reduced self-efficacy.

**Hypothesis 5 (H<sub>5</sub>):** Strategic Cognitive Offloading is positively related to (a) Meta cognitive Agency and (b) Academic Self-Efficacy.

**Hypothesis 6 (H<sub>6</sub>):** Passive Gen-AI Dependency is negatively related to (a) Meta cognitive Agency and (b) Academic Self-Efficacy.

## 4. Methodology

### 4.1 Research Design and Sampling

This study adopts a quantitative, deductive cross-sectional survey research design. Primary data were collected across six multi-disciplinary public and private higher education institutions between October 2025 and February 2026 targeting undergraduate and postgraduate students studying STEM, Social Sciences, Business, and Humanities who actively utilize Gen-AI platforms for academic tasks. A stratified random sampling technique was applied, resulting in 850 digital questionnaires distributed through university portal notifications and email lists. Following data filtering (incomplete entries, straight-lining, speeders), 684 valid responses were retained for analysis (response rate of 80.4%).

### 4.2 Measurement Instruments

The constructs were initially measured using multi-item scales adapted from the literature and refined in a pilot study ( $N = 60$ ) to establish face- and psychometric validity. The responses were recorded using a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

**AI Literacy (AIL):** Measured using a 5-item scale adapted from Long and Magerko (2020) and modern AI competency frameworks, assessing student operational understanding and ethical awareness of Gen-AI.

**Perceived Task Complexity (PTC):** Measured using a 4-item scale adapted from Campbell (1988), assessing structural complexity and cognitive demand of academic assignments.

**Strategic Cognitive Offloading (SCO):** Measured using a 5-item self-developed scale assessing intentional delegation of procedural sub-tasks.

**Passive Gen-AI Dependency (PGD):** Measured using a 5-item scale adapted from automated tool dependency inventories, assessing complete delegation of ideation, synthesis, writing, and problem-solving to AI.

**Meta cognitive Agency (MA):** Measured using a 6-item scale adapted from the Motivated Strategies for Learning Questionnaire (MSLQ).

**Academic Self-Efficacy (ASE):** Measured using a 5-item scale adapted from Bandura's academic self-efficacy framework.

**Institutional AI Policy Clarity (IPC):** Moderating variable measured using a 3-item scale evaluating student perception of guidelines provided by their institution regarding legal and ethical Gen-AI usage.

### 4.3 Statistical Analysis Strategy

The analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM). It was selected over Covariance-Based SEM (CB-SEM) due to its superior capabilities for analyzing complex structures with direct, indirect, and moderating pathways, as well as its independence from multivariate normality assumptions.

**The study utilized a two-step procedure:**

**Measurement Model Evaluation:** Assesses indicator reliability, internal consistency, convergent, and discriminant validity.

**Structural Model Evaluation:** Assesses  $R^2$ , predictive relevance, path coefficients significance using bootstrapping (5,000 resample), and moderation effects.

## 5. Evaluation and Statistical Findings

### 5.1 Measurement Model Verification

Construct evaluation revealed that all measurement items met established psychometric criteria:

**Indicator Reliability:** Factor loadings for all retained items exceeded the 0.707 threshold, ranging from 0.732 to 0.911.

**Internal Consistency:** Cronbach's Alpha ( $\alpha$ ) and Composite Reliability (CR) for all constructs exceeded 0.80 (ranging from 0.824 to 0.921).

**Convergent Validity:** Average Variance Extracted (AVE) for each construct exceeded the minimum threshold of 0.50 (ranging from 0.589 to 0.742).

**Discriminate Validity:** Verified using the Heterotrait-Monotrait Ratio (HTMT). All HTMT ratios were well below the conservative threshold of 0.85 (maximum observed HTMT was 0.741 between Passive Dependency and Meta cognitive Agency). Cross-loadings confirmed that indicator loadings were highest on their respective constructs.

### 5.2 Structural Model Evaluation and Hypothesis Testing

Hypothesis testing via PLS-SEM bootstrapping revealed statistically significant support for all hypothesized direct paths:

**H1 Supported:** AI Literacy had a strong, positive, and statistically significant direct effect on Strategic Cognitive Offloading

( $\beta = 0.482$ ,  $t = 11.432$ ,  $p < 0.001$ ).

**H2 Supported:** AI Literacy exerted a significant negative direct effect on Passive Gen-AI Dependency

( $\beta = -0.364$ ,  $t = 8.121$ ,  $p < 0.001$ ).

**H3 Supported:** Perceived Task Complexity was strongly and positively associated with Passive Gen-AI Dependency

( $\beta = 0.415$ ,  $t = 9.854$ ,  $p < 0.001$ ).

**H4 Supported:** Perceived Task Complexity demonstrated a direct negative effect on Strategic Cognitive Offloading

( $\beta = -0.188$ ,  $t = 4.215$ ,  $p < 0.001$ ).

**H5a & H5b Supported:** Strategic Cognitive Offloading significantly improved both Meta cognitive Agency

( $\beta = 0.412$ ,  $t = 9.612$ ,  $p < 0.001$ ).

Academic Self-Efficacy

( $\beta = 0.385$ ,  $t = 8.741$ ,  $p < 0.001$ ).

**H6a & H6b Supported:** Passive Gen-AI Dependency exerted substantial negative direct effects on Meta cognitive Agency

( $\beta = -0.493$ ,  $t = 12.105$ ,  $p < 0.001$ )

.Academic Self-Efficacy

( $\beta = -0.421$ ,  $t = 10.332$ ,  $p < 0.001$ ).

### 5.3 Variance Explained and Mediation Analysis

The structural model explained significant proportions of variance across endogenous variables:

Passive Gen-AI Dependency:  $R^2 = 0.412$ (Moderate to High explanatory power).

Strategic Cognitive Offloading:  $R^2 = 0.358$ (Moderate explanatory power).

Meta cognitive Agency:  $R^2 = 0.489$  (High explanatory power).

Academic Self-Efficacy:  $R^2 = 0.435$  (High explanatory power).

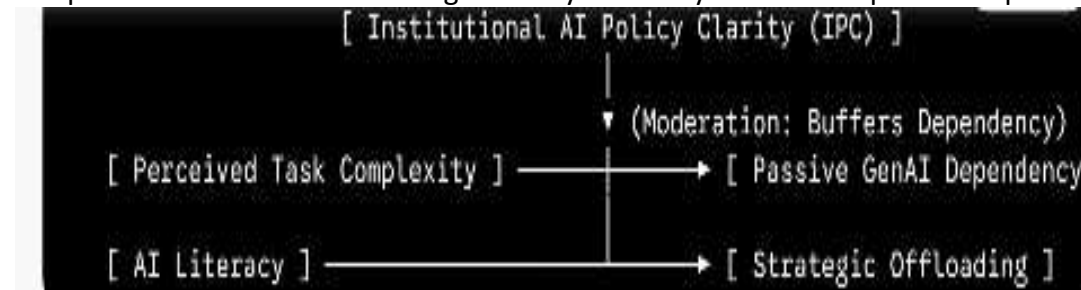
Mediation analysis using direct and indirect path bootstrapping revealed that Strategic Cognitive Offloading and Passive Gen-AI Dependency act as significant parallel mediators between the antecedent variables (AI Literacy, Task Complexity) and outcomes (Meta cognitive Agency, Academic Self-Efficacy). Specifically, the indirect effect of AI Literacy on Meta cognitive Agency via Strategic Offloading was positive ({Indirect Effect} = 0.199,  $p < 0.001$ ), while the indirect effect of Task Complexity on Meta cognitive Agency via Passive Dependency was negative ({Indirect Effect} = -0.205,  $p < 0.001$ ).

## 6. Modern Analysis and Its Effect

### 6.1 Multi-Group and Moderation Dynamics: The Institutional Policy Effect

Modern structural evaluation required testing how environmental variables altered student decision-making frameworks. Moderation analysis was performed to evaluate the interaction effect of Institutional AI Policy Clarity (IPC) on the relationship between Perceived Task Complexity and Passive Gen-AI Dependency. The interaction term ({PTC X IPC}) had a statistically significant negative coefficient ( $\beta = -0.214$ ,  $t = 4.882$ ,  $p < 0.001$ ). This indicates that Institutional AI Policy Clarity significantly buffers against the negative impacts of task complexity.

When universities establish clear, unambiguous policies regarding acceptable vs. unacceptable Gen-AI integration and provide pedagogical examples of transparent tool declaration, students who encounter complex academic tasks will be significantly less likely to resort to passive dependency.



### 6.2 The Ergonomic Cognitive Shift in Academic Workflows

A modern analysis of the cognitive ergonomics of student learning has identified a significant change in the cognitive process. While previously the learning process involved an inverted pyramid of inputs in which students harvested, filtered, and synthesized raw data into a coherent result, the process of using Gen-AI sees the reversal of the paradigm. With immediate access to synthesized drafts, the burden is shifted to the students to perform the validation and verification process.

**The implications of the shift are two-fold:**

**“The Risk of Cognitive Atrophy”:** For students who have not developed foundational domain-specific schemas, the elimination of the initial synthesis step completely undermines their ability to perform subsequent validation and verification steps due to “hallucination blindness”.

**“The Strategic Synergy”:** For students who have reached entry-level proficiency in the domain (“AI Literacy”), the shift allows them to divert significant cognitive effort from syntactical and mechanical facets of writing or programming to conceptualization, design or structure, and critical analysis.

## 7. Theoretical Contribution

This paper makes several contributions to the educational, cognitive, and technological literature:

**“Conceptualization of Cognitive Offloading Spectrum in Gen-AI Interaction”:** While the prior literature on educational technology focused on TAM or UTAUT theories, framing technology adoption as an inherently positive attitude, this paper introduces a nuanced differentiation between Strategic Cognitive Offloading and Passive Gen-AI Dependency based on Dual-Process and Cognitive Load theories. The work conceptualizes the implications of Gen-AI integration, particularly the risks of “hallucination blindness” and reduced Meta cognitive engagement.

**“Empirical Validation of the Meta cognitive Paradox”:** This paper empirically validates the paradoxical nature of the relationship between Gen-AI adoption and student Meta cognition. The work shows that the impact is mediated by the students’ literacy in the domain and their level of agency in the task design. By showing the parallel mediation pathways, this paper reconciles the disparate conclusions of prior works that identified both negative and null effects.

**“Inclusion of Environmental Moderation in Cognitive Frameworks”:** This paper highlights the moderating role of institutional policy guidance in student decision-making processes, linking the strategic cognitive offloading literature with a broader social psychological perspective.

## 8. Practical Implications

The paper’s findings have several implications for higher education stakeholders:

### 8.1 Redesigning Curriculum and AI Literacy Programs

\*Transition from “basic digital competences” to “critical engagement” curricula: Universities need to revise their mandatory digital illiteracies curricula to transition from teaching students the utilization of digital tools to equipping them with the ability to critically evaluate. Teaching should focus on building strategies to identify and mitigate errors in prompts, detect and audit biases, and dynamically engineer prompts to enforce their role as “ultimate verifiers” of information.

\*Scaffolding of domain-specific schema formation: It is paramount that prior to encouraging strategic cognitive offloading, the curricula require students to build foundational knowledge schemas. Students in entry-level courses should be restricted from using AI until essential competences are achieved.

### 8.2 Assessment Reform and Process-Oriented Evaluation

Shift from outcome-based to process-oriented assessment: With the advent of Gen-AI, the conventional practices of take-home essays and coding assignments are vulnerable to “passive Gen-AI dependency”. It is advisable for faculty to shift towards assessing the learning process rather than the aggregated outcome. This could include requiring students to report on the prompts used, submit reflective commentaries on the modifications made to the AI suggestions, and undergo oral examinations (“viva voce”) to demonstrate understanding of their work.

Designing “AI-resistant” and “AI-amplified” tasks: The course assessments need to be restructured to delineate tasks that are “AI-resistant” (i.e., requiring real-time critical synthesis, local problem-solving, or physical application) and “AI-amplified” (i.e., involving complex real-world cases that students would address using AI but are evaluated on their critical analysis and extension of the proposed solutions).

### 8.3 Institutional Governance and Policy Transparency

Establishing clear syllabus-level frameworks: Universities should refrain from vague and non-enforceable bans on AI usage. Instead, they should develop standardized frameworks that specify permitted levels of AI assistance for different learning outcomes. Clarifying the policy objectives reduces student anxiety and prevents “unwise” default decisions rooted in uncertainty.

### 9. Conclusion

This study provides evidence for how Generative Artificial Intelligence reshapes human cognition and Meta cognition. Grounded in the Dual-Process and Cognitive Load theories, the evidence shows that the impact is not binary, but mediated by the individual’s AI Literacy (“strategic cognitive offloading”) and the task difficulty (“passive Gen-AI dependency”). When students have high AI Literacy, they use Gen-AI to automate extraneous processing, exercising their Meta cognitive monitoring and analytical skills in the verification and amplification of the results. This contributes to increases in self-efficacy and Meta cognitive development. In contrast, students with inadequate AI Literacy, when confronted with high cognitive loads, resort to Passive Gen-AI Dependency, bypassing the domain-specific processing steps and suffering long-term deficits in their Meta cognitive development and self-efficacy. Ultimately, Gen-AI should not be presented as an autonomous agent or an existential threat to human intelligence but rather as a tool that requires human expertise to operate wisely. Higher education stakeholders need to take responsibility for redesigning the learning, teaching, and assessment approaches so that technology serves to enhance rather than undermine human capabilities.

### 10. Future Research and Future Directions

While this paper provides several theoretical and empirical contributions, there are several opportunities for future work:

**Longitudinal analysis of cognitive decoupling:** While this cross-sectional study highlights the benefits of strategic cognitive offloading, future research should focus on the longitudinal educational outcomes of “passive Gen-AI dependency”. A study that follows cohorts of undergraduate students throughout a 4-year degree to assess sustained knowledge retention and critical thinking abilities would be a valuable avenue for future research.

**Inclusion of neuro scientific and behavioral tracking data:** Future research should complement the self-reported behavioral data with eye-tracking analyses, keyboard-logging, and screen-recording data to provide richer insights into the cognitive processes associated with Gen-AI utilization.

**Consideration of cultural and disciplinary differences:** Additional work is required to analyze the extent to which the conceptual and empirical findings generalize across cultures and disciplines, particularly between more and less quantitatively intensive domains.

**Design of adaptive AI systems for dynamic cognitive scaffolding:** An exciting direction for future empirical research is the design of AI systems that scaffold cognitive processing by introducing friction to promote mindfulness. For example, researchers could explore how prompting (“think aloud before responding”) impacts students’ ability to complete tasks that require critical thinking or synthesis.

**References**

- 1-Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. Springer.
- 2-Asagar, M. S. (2026). Navigating the future: Attitudes and ethical implications of AI tools in academic research. *Journal of Interdisciplinary Studies in Education*, 15(1), 323–344.
- 3-Avdiu-Kryeziu, S., & Kryeziu, V. (2026). Students' use of artificial intelligence in academic research: Benefits, challenges, and academic integrity. *Praxis Educativa*, 21, e24164.
- 4-Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.
- 5-Campbell, D. J. (1988). Task complexity: A review of theory and research. *Academy of Management Review*, 13(1), 40–52.
- 6-Cretu, E., & Grosseck, G. (2025). Mapping the landscape of generative AI in education: A global bibliometric analysis. *Educational Technology Research and Development*, 73(2), 412–438.
- 7-Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- 8-de Jesus, L. F. (2026). AI-assisted research writing: Graduate students' experiences, outcomes and academic integrity. *International Journal of Learning, Teaching and Educational Research*, 25(5), 155–176.
- 9-Digital Education Council (2026). AI in Higher Education Global Survey 2026. DEC Resource Library.
- 10-Long, D., & Magerko, B. (2020). What is AI Literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16.
- 11-Sweller, J. (2011). Cognitive load theory. *Psychology of Learning and Motivation*, 55, 37–76.