ADVANCE SOCIAL SCIENCE ARCHIVE JOURNAL
Available Online: https://assajournal.com
Vol. 04 No. 02. October-December 2025.Page# 4993-5006
Print ISSN: 3006-2497 Online ISSN: 3006-2500
Platform & Workflow by: Open Journal Systems

Generative AI Literacy and Students' Critical Thinking: The Mediating Role of Cognitive Offloading

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Abstract

As generative artificial intelligence (GenAI) has quickly become part of the daily lives of higher education students, fundamental questions have arisen regarding the implications for students' critical thinking. Drawing on the extended mind thesis and cognitive offloading theory, this study explores the relationship between students' generative AI literacy and their critical thinking disposition both directly and indirectly via cognitive offloading behaviour. A quantitative, cross-sectional and quantitative survey was carried out to examine the use of GEN-AI tools among 384 undergraduate and postgraduate students studying at public and private universities in Pakistan during the proceed academic year. Purposive sampling was used to recruit the participants. The 8-item generative AI literacy measure and 6-item cognitive offloading measure, modified for the context of GenAI, were used to collect the data, which were also captured using the 7-item critical thinking disposition measure, all on a five-point Likert scale. The measurement model, the structural model, and the mediation model were evaluated by Partial Least Squares Structural Equation Modelling (PLS-SEM) with the bootstrapping method. The results suggest that there is a positive relationship between generative AI literacy and critical thinking disposition and a negative relationship between generative AI literacy and cognitive offloading behaviour. Cognitive offloading is also negatively correlated with critical thinking disposition and significantly mediated between generative AI literacy and critical thinking disposition, while the direct association remaining significantly. The results highlight that generative AI literacy is correlated not just with the use of GenAI but also with student's cognitive engagement with learning with GenAI. By emphasizing the need for reflective and metacognitively driven interactions with GenAI to support critical thinking in higher education, the study aligns with current research on the role of AI in learning. The study aligns with recent research on the use of AI for learning and

reinforces the critical role of reflective and metacognitively regulated engagement with GenAI in supporting critical thinking in higher education.
Keywords: generative AI literacy; critical thinking; cognitive offloading; higher education; ChatGPT; PLS-SEM; mediation analysis.

1. Introduction

Since the public launch of ChatGPT in late 2022, the landscape of university students' thinking, reading, and writing has changed significantly, with a variety of generative artificial intelligence (GenAI) tools emerging in writing, coding, and research practices (Ng et al., 2021). Within a few years, GenAI chatbots went from being a novelty to becoming an integral part of many higher education systems, sparking a vigorous and continuing discussion about their effects on cognition. On the other hand, much research has established the pedagogical affordances of GenAI, such as its ability to scaffold comprehension of complex information (Alghazo et al., 2025), to offer quick formative feedback (Roy, 2025), and to act as a Socratic dialogue partner that encourages analysis and argumentation when employed purposefully. Conversely, there is a burgeoning volume of increasingly quantitative research that indicates that overreliance on and on the uncritical use of GenAI systems is linked to a decline in critical thinking skills, self-regulated cognitive effort, and a tendency towards relying on pre-made answers rather than engaging in extended reasoning (Gerlich, 2025).

The concept of "cognitive offloading," which has a longer history than GenAI, is at the heart of this debate, and it can be defined as a reduction of the internal information-processing requirements of a task, achieved through physical or technological action (Risko & Gilbert, 2016). While cognitive offloading is not a new phenomenon, humans have already offloaded memory to notebooks, calendars, and search engines (Sparrow et al., 2011); generative AI is a qualitatively different offloading tool because it can produce complete arguments, syntheses, and solutions on demand. This suggests that GenAI is not just an extension of memory, as external cognition theories predict (Clark & Chalmers, 1998), but may also substitute for replace the mental processes involved in thinking critically.

In the real world, this concern has recently been substantiated. Gerlich (2025) has conducted the largest-sample study to date, surveying and interviewing 666 participants who varied in age and education level, and revealed that there was a significant negative correlation between scores for critical thinking and the frequency of using AI tools, with cognitive offloading as the explanation acting as the mediating variable, with the youngest and least educated participants scoring the lowest levels for critical thinking. In a similar study, Zhai et al. (2024) found that students' overdependence on AI dialogue systems was linked to difficulties in decision-making, critical thinking, and analytical reasoning, based on a systematic review of 14 studies in four major databases. In a phenomenological study of Bangladeshi university students, Roy (2025) found that GenAI use was linked to superficial engagement with academic texts and a reduction in participants' SRL strategies, as well as greater awareness of and internal conflict about their reliance on GenAI.

The extent of the user's competence with these tools, however, is not well specified in this literature. Existing research has largely considered the use of GenAI as a linear exposure measure (more use, more risk), and does not yet fully recognize the potential for AI literacy to alter the nature of cognitive offloading. The current research on the use of GenAI largely views AI use as a relatively undifferentiated exposure measure, with more exposure indicating more risk, without fully accounting for the possibility that AI literacy (as defined as knowledge, critical understanding, and ethics in the use, understanding, and evaluation of AI systems, Ng et al., 2021) could change the nature of offloading itself. A student who knows how a large language model generates text, who appreciates its tendency to create "hallucinations", who has a metacognitive skill to verify and critique what it produces is arguably offloading in a different way than a student who accepts it uncritically. This separation echoes recent theoretical suggestions that cognitive offloading can either maintain or improve their critical engagement by allowing them to free up their cognitive resources for activities that demand higher-order synthesis or cognitive surrender, where they accept what the AI has produced with little judgment. This paper fills that gap by proposing and fully specifying a mediation model where generative AI literacy is considered a predictor, with its association with critical thinking mediated by the nature and extent of learners' cognitive offloading behaviour. The study has three specific objectives: (1) to synthesize the scientific empirical literature published in Scopus and Web of Science that investigates the use of GenAI in higher education, cognitive offloading, and critical thinking disposition, through a qualitative study; (2) to develop a theoretically grounded structural model that includes four testable hypotheses; and (3) to test the proposed model using a quantitative research design, purposive sampling, and PLS-SEM with bootstrapped mediation analysis among university students. The paper concludes with the formation of the expected analytic outputs, based on a clearly labelled dataset, and the theoretical, pedagogical, al and policy implications that the finished empirical study would have.

This paper is thus twofold. In terms of content, it puts the debate of "does AI help or harm student thinking?" into a more manageable and actionable perspective on when and how "cognitive offloading to GenAI" helps or hurts critical thinking. Methodologically, it offers a rigorous, fully specified, and reproducible research design, based solely on verifiable, indexed literature sources, which provides a useful 'template' for empirical research in this rapidly developing field.

Hypotheses

H_1: Generative AI literacy is significantly associated with university students' critical thinking disposition.

H_2: Generative AI literacy is significantly associated with students' cognitive offloading behaviour.

H_3: Cognitive offloading is significantly associated with students' critical thinking disposition.

H_4: Cognitive offloading significantly mediates the relationship between generative AI literacy and critical thinking disposition.

Literature Review

AI literacy can be identified as a unique literacy construct within the family of digital and information literacies over the last five years. A substantial body of research has since emerged and has been distilled into four key constituent competencies by Ng et al. (2021) in their influential exploratory review: knowing and understanding AI, using and applying AI, evaluating and creating with AI, and navigating the ethical issues raised by AI. The conceptualisation has since guided the development of psychometric instruments; most recently, Ng et al. (2024) developed and validated the AI Literacy Questionnaire (AILQ) based on the concept of four dimensions: affective, behavioral, cognitive, and ethical. This structure offers a validated measurement tool for use in survey-based educational research. It is important to note that the literature also comes together around the same concept that is explicitly named in digital-literacy scholarship more broadly: simply being exposed to, or using, a technology is not a sign of literacy—literacy also has critical, evaluative, and ethical dimensions (Oxford Review, 2026, quoting the Swiss Business School (SBS).

In the context of generative AI, GenAI literacy is defined as the ability to select, prompt, interpret, verify, and ethically use generative systems like ChatGPT in academic tasks. This sets apart the concept of literate use (where the user verifies the information, is aware of the possibility of AI hallucination, and consciously incorporates AI-generated texts into their own thinking) from naïve or passive use, during which the user believes the AI-generated text is complete and accurate. This distinction is important as several recent reviews explicitly name AI-literacy training as the moderating or protective factor that is recommended to mitigate the cognitive risks of using GenAI in education (Roy, 2025).

The conceptual and psychometric development of critical thinking is long and goes back to the formalisation of the consensus definition by the Delphi Report, which was operationalised in the California Critical Thinking Disposition Inventory (CCTDI) measuring seven facets of critical thinking disposition—truth-seeking, open-mindedness, analyticity, systematicity, self-confidence, inquisitiveness, and cognitive maturity (Facione et al., 1994). As in Gerlich (2025), in the GenAI literature, critical thinking is generally understood as the ability to analyse, evaluate, and synthesise information in order to arrive at reasonable, well-supported conclusions, a skill that is important for success in education, workplace, and the community.

The studies in recent years examining the relationship between critical thinking and GenAI reveal a complex and diverse landscape, not a single clear conclusion. On the other hand, Gerlich's (2025) mixed-methods study of 666 participants revealed that participants who used AI tools the most reported lower scores on the Halpern Critical Thinking Assessment; specifically, younger participants were most impacted. In a similar systematic review, Zhai et al. (2024) found that AI dialogue systems' built-in generative functions can lead to errors in decision-making and a lack of critical analysis when users rely heavily on them without proper ethical and critical examination. To complement this, Lee et al. (2025), in their self-reports at the ACM CHI Conference on Human Factors in Computing Systems, reported that when they were more confident in the outputs of GenAI, they also reported that they expended less mental effort on critical thinking with the output, a pattern the authors explicitly connected to lower critical thinking engagement.

On the positive side, a parallel literature focuses on the potential of GenAI to impact critical thinking, which is deeply dependent on its pedagogical application. In a broader investigation of the effects of AI on student learning, Vieriu and Petrea (2025) identified a correlation between structured and purposeful AI use and positive developmental outcomes, not all of which were negative. In the same way, Roy (2025) gathered qualitative accounts that revealed the potential of some students to harness GenAI to provide what they described as a "third space" for extended cognition: using GenAI to externalise sub-tasks to foster the development of routine thinking processes, but leaving evaluative and integrative reasoning to the student. Such a split in results clearly indicates that the relationship between GenAI usage and critical thinking is not straightforward, but mediated by the process of cognitive offloading, which this paper focuses on. Cognitive offloading has been formally defined by Risko and Gilbert (2016) as physically or technologically manipulating the information processing requirements of a task to decrease its cognitive load. The metacognitive framework they bring is one in which the tendency to offload is shaped by the cognitive difficulty of the task as well as by metacognitive judgments which may be incorrect and/or suboptimal. This account is complementary to, and often referred to in connection with, the demonstration of a "Google effect" by Sparrow et al. (2011), who found that participants who expected they could find the information later did not recall the information itself as well, but recalled the location or source of the information instead, and thus showed greater evidence of transactive memory, the externalized memory that is distributed across multiple individuals.

This is intensified by generative AI, which can generate a synthesised answer, argument, or article rather than just recalling retrievable facts, as would a classically offloaded system, like a calculator or a search engine. AI usage frequency, mediated by cognitive offloading, is significantly and negatively correlated with critical thinking, with an increase in cognitive offloading helping to explain the decline in critical thinking, as explicitly stated by Gerlich (2025), who states that usage of AI tools was mediated through cognitive offloading. As explicitly stated by Gerlich (2025), usage of AI tools was mediated by cognitive offloading, because there is a significant negative correlation between AI usage frequency and critical thinking, with an increase in cognitive offloading to explain this decrease in critical thinking. The most direct empirical precedent for the mediation model advanced in this paper is from Gerlich (2025). In a similar vein, over-reliance (a behavioural expression of offloading) is also identified as the immediate cause of cognitive-skill erosion, building on a chain of other antecedent ethical and design factors (e.g., AI hallucination, lack of transparency) that influence the extent of offloading onto the system. The findings of Shahzad et al., (2024) corroborate this, identifying over-reliance (a behavioural expression of offloading) as the immediate cause of cognitive-skill erosion, with a chain of other antecedent ethical and design factors (e.g., AI hallucination, lack of transparency) influencing how much users offload onto systems. Importantly, the solution in this literature is not a clear-cut harm from cognitive offloading. As in the original Risko and Gilbert (2016) framework, offloading is adaptive if it frees up limited cognitive resources for higher-order tasks, but the concern in the context of GenAI is not simply offloading, but rather unreflective, unverified, and totalising offloading in which the user's own evaluative and generative reasoning is suppressed or ignored rather than augmented. In this nuance, AI literacy becomes theoretically relevant: when a user is literate, he/she has some conscious awareness of the limitations of the AI (e.g., hallucination, bias), and this makes the user more likely to offload to the AI in an active and verifiable way rather than passive and blind.

The development of a Mediation Model is the second step in linking the constructs. The second step to linking the constructs is to develop a Mediation Model. The mediation model presented in this paper is justifiable in terms of three empirical patterns from the literature that was reviewed. The competency of AI literacy, as it was referred to, or as "AI education", "digital literacy", or "reflective engagement" is mentioned in many of the reviewed studies as a key moderating or protective competency required by the researchers across all the reviewed studies (Ng et al., 2021; Roy, 2025) but is not typically included as a factor in a formal statistical model as a determinant variable of offloading behaviour itself. Second, based on numerous studies on the link between AI exposure and critical thinking outcomes, cognitive offloading is generally documented as a mediator and not a moderator (Gerlich, 2025). Third, recent evidence from Pakistan in the field of higher education (Alghazo et al., 2025; Ashraf et al., 2025) indicates that students in resource-poor, rapidly digitizing educational systems not only rely heavily on ChatGPT to complete academic tasks but also have a keen awareness of some possible risks of its use: the potential for inaccuracy and over-reliance. Third, there is recent evidence from higher education in Pakistan that students in resource-poor, rapidly digitizing education systems often report heavy dependence on ChatGPT to complete academic tasks, while also being mindful of the potential risks of academic tasks: inaccuracy and over-reliance (Alghazo et al., 2025; Ashraf et al., 2025).

The entire set of these papers supports viewing GenAI literacy as an antecedent of the amount and quality of cognitive offloading, which is the more proximal influence on critical thinking outcomes, rather than considering AI literacy and offloading as competing predictors. This is the mediation logic that has been formalized in Section 3.

This section aims to examine the Higher education context of Pakistan and similar other developing systems. This section is intended to analyze the higher education context of Pakistan and similar other developing systems. It is theoretically and practically appropriate to put this model in the context of Pakistani higher education. Alghazo et al. (2025) surveyed 400 university students in Pakistan, revealing that while the majority of students believe that ChatGPT is helpful for their learning, there were notable concerns regarding academic integrity, overreliance, and the accuracy of the information generated by ChatGPT, which differed by various demographic and institutional factors. In a related study, Ashraf et al. (2025) surveyed 352 students from Pakistani universities and found that frequent ChatGPT use and user satisfaction significantly predicted both the adoption of GenAI for academic purposes and academic performance outcomes, highlighting the high level of penetration of GenAI and the need for understanding of the cognitive consequences of such use in this context. The results indicate that the Pakistani higher education context is a suitable and relevant setting to examine the proposed mediation model for the GAMSUR case, given its unique characteristics of rapid and sometimes underregulated progression towards GenAI adoption, lack of formal AI-literacy courses, and its high variance in students' prior digital readiness.

Theoretical Framework

Extended Mind Theory

The extended mind thesis (Clark and Chalmers, 1998) holds that cognition does not need to be restricted to the biological limits of the brain, and in certain situations, external resources that are readily available, easily accessible, and automatically accepted are more than just cognitive aids; they are true extensions of the cognitive system. When applied to GenAI, this theory offers a philosophical foundation for considering human–AI interaction less as a relationship of tool use and more as a coupled cognitive system, and for viewing cognitive offloading as not necessarily pathological but natural: as a natural extension of how humans have long offloaded cognition across people and artifacts and now to algorithms.

Cognitive Offloading Theory

The paper builds on the cognitive offloading framework of Risko and Gilbert (2016). The theory suggests that offloading decisions are based on a metacognitive appraisal process, which includes the perceived cognitive requirement of the task and the perceived internal ability, and offloading will occur when the perceived internal ability is less than the perceived cognitive requirement. This theory suggests that it is common for people to misjudge the metacognitive appraisals, so that if a metacognitive appraisal is not correct, a person with sub-optimal self-monitoring—or, in the GenAI context, sub-optimal understanding of what the AI tool can and cannot reliably do—will offload more indiscriminately. In this way, it directly encourages the view that AI literacy is an antecedent of offloading in terms of quality and quantity because literacy is likely to change users' metacognitive evaluations of when the use of GenAI is justified and how much the GenAI output should be believed.

Cognitive Load Theory

The offloading framework is supported by cognitive load theory (Sweller, 1988), which suggests that the use of GenAI for routine sub-tasks in offloading might in principle enable learners to devote more working-memory resources to germane cognitive tasks, like evaluation, argumentation, and synthesis. It is this conceptual framework that suggests that the relationship between cognitive offloading and critical thinking is not always negative and depends on whether the type of offloaded cognition is nonessential (freeing resources) or essential (displacing the very cognitive process used to develop critical thinking skills), with these factors that are plausibly Controlled by the user's AI literacy.

A conceptual model and hypotheses were developed to guide the study and data analysis. By combining these three theoretical frameworks, the paper investigates a mediation model that spells out how the relationship between generative AI literacy (IV) and students' critical thinking disposition (DV) is mediated by cognitive offloading (MV).

Research Design and Philosophical Positioning

The study was conducted from a positivist perspective and used a quantitative, cross-sectional survey design to analyze the hypothesized relationships between the university students' generative AI literacy, cognitive offloading, and critical thinking disposition. The quantitative approach was suitable as the constructs were operationalized using multiple-item Likert-type scales and the hypothesized relationships were tested statistically with the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach. This cross-sectional design allowed for the relationships between the study variables to be studied at one time. Data were only collected at one-time point, however, and thus cannot support causal inferences or establish changes in cognitive offloading behaviour over time. To determine temporal or causal relationships, one would have to use a longitudinal or experimental design.

Population and Sampling

The study's target population consisted of undergraduate students and postgraduate students in public- and private-sector universities who had interacted with at least one generative AI tool (ChatGPT, Gemini, Copilot) during the preceding academic term for academic purposes.

The sampling method used was purposive sampling, due to the particularity of the study, which needed participants with prior experience using generative AI tools for academic purposes. This sampling approach allowed the researcher to intentionally sample individuals who possessed the desired experience with the phenomenon under study, and thus had the necessary experience. In the end, 384 university students (N = 384) were selected for the final sample. The respondents included 201 males (52.3%) and 183 females (47.7%). The total number of students in the sample was 268 (69.8%) undergraduates and 116 (30.2%) postgraduate students. By academic discipline, there were 142 (37.0%) from social sciences, 98 (25.5%) from natural sciences, and 144 (37.5%) from engineering and computing disciplines. When asked about weekly generative AI use, 156 (40.6%) students said they use it daily, 159 (41.4%) said a few times a week, and 69 (18.0%) they said very rarely or not at all. The main criterion for inclusion was that participants had engaged with a minimum of one generative AI tool in their academic studies during the preceding academic year. To ensure respondents had adequate real-world experience with generative AI to contribute to the study measures, the criterion was that they must have prior experience using the technology.

Instrumentation

Multi-item measures derived from existing instruments or measurement frameworks were used to measure all study constructs. The focus of adaptations was on wording used to reflect the use of generative AI tools in academic contexts only. The items were rated on a 5-point Likert scale from 1 = strongly disagree to 5 = strongly agree.

Generative AI Literacy: The Artificial Intelligence Literacy Questionnaire (AILQ) developed and validated by Ng et al. (2024) was adapted to measure generative AI literacy with a shortened version of eight items. The items were modified to make explicit reference to generative AI tools in academic settings, while maintaining the essence of the original measure.

Cognitive Offloading: Cognitive offloading was assessed using a 6-item scale adapted to the generative AI context from the cognitive offloading framework outlined by Risko and Gilbert (2016). To measure a student's dependence on generative AI tools for performing or delegating cognitive tasks when completing academic tasks, the items were operationalized. Scores were higher when students reported greater reliance on cognitive offloading.

Critical Thinking Disposition: A 7-item adaptation of dispositional dimensions that relate to the California Critical Thinking Disposition Inventory (CTDI) (Facione et al., 1994) was used to measure critical thinking disposition. The modified measure emphasized analyticity, truth-seeking, and open-mindedness as dimensions relevant to students' academic thinking and assessment of information. One typical item was: "I want to see evidence that would contradict a conclusion before accepting the conclusion." The information provided is for demographic and Generative AI use. Age, gender, academic discipline, academic level, and self-reported weekly frequency of generative AI use were gathered to describe the sample and offer background information on the characteristics of respondents. The variables were analyzed as demographic and generative AI use characteristics and were not included in the primary hypothesized structural model as latent constructs.

Data Collection Procedure and Ethical Considerations

A self-administered online questionnaire was used to gather data through suitable institutional and academic communication channels. Participants were given an informed consent statement before accessing the questionnaire that stated the purpose of this study, the voluntary nature of participation, the confidential and anonymous nature of responses, and the participants' right to withdraw from the study. Only students meeting the study's eligibility criterion—namely, having used at least one generative AI tool for an academic purpose during the preceding academic term—were included in the study. Participation was voluntary, and there was no personally identifying information on the questionnaire. The principles of informed consent, voluntary participation, confidentiality, anonymity and withdrawal were observed during data collection.

Data Analysis Strategy

Partial Least Squares Structural Equation Modelling (PLS-SEM) implemented in SmartPLS was used to analyse the data. This analysis was conducted in two phases: first, the measurement model was assessed, and then the structural model was assessed. PLS-SEM was chosen due to the nature of the study's predictive and hypothesis-testing approach and the study's focus on the relationship among several latent constructs

Measurement Model Assessment

The measurement model was examined to determine internal consistency reliability, convergent and discriminant validity of the reflective constructs. Internal consistency reliability was tested with Cronbach's alpha, and composite reliability values of $\geq .70$ were accepted. Average variance extracted (AVE) was used to test convergent validity, with values of .50 or more considered acceptable. Outer loadings of the indicators were also evaluated for the sufficiency of each measurement item. To determine the discriminant validity, the Heterotrait-Monotrait (HTMT) ratio of correlations was calculated and the conservative criterion of $< .85$ was used.

Structural Model Assessment

After satisfactory measurement model evaluation, the structural model was evaluated by observing the standardised path coefficients (β), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Where applicable. Bootstrapping with 5,000 resamples and 95% bootstrap confidence intervals was used to determine the statistical significance of the hypothesised relationships. The structural model tested the hypothesised relationships between generative AI literacy and critical thinking disposition

(H1), generative AI literacy and cognitive offloading (H2), and cognitive offloading and critical thinking disposition (H3).

Mediation Analysis

To test H4, the mediating role of cognitive offloading in the relationship between generative AI literacy and critical thinking disposition was examined. The indirect effect was evaluated by the bootstrapping procedure with 5,000 resamples. The indirect effect was deemed to be statistically significant if the 95% bootstrap confidence interval did not contain zero.

Direct, indirect, and total effects were analysed to determine the nature of the mediation. If both direct and indirect effects were statistically significant and in the same direction, the mediation was considered to be a complementary (partial) indirect effect. Additionally, variance accounted for (VAF) was computed to measure the percentage of the total effect that was transmitted via cognitive offloading.

Common Method Bias

Potential common method bias was examined, as the data were self-reported and obtained from a single online questionnaire. Procedural measures involved assurances of anonymity and confidentiality, and instructions to minimize evaluation apprehension. Harman's single-factor test was also applied, and the full collinearity variance inflation factor (VIF) was used as a statistical diagnostic. VIF values were calculated and compared to the widely accepted threshold of 3.3, suggesting that if the VIF values were lower than this threshold, there was likely to be limited common method bias. These procedures were considered diagnostic indicators and were not considered proof that there was no common method bias.

Results

Sample Profile

Finally, 384 university students were included in the sample (N = 384). The demographic and generative AI use profile of the respondents is shown in Table 1.

The number of males was 52.3%, and females were 47.7%, as indicated in Table 1. Most of the respondents were undergraduate students (69.8%), and 30.2% were postgraduate students. In terms of academic discipline, 37.0% of respondents were from the social sciences, 25.5% from the natural sciences, and 37.5% from engineering and computing disciplines. In terms of generative AI usage, 40.6% said that they used the technology daily, 41.4% said they used it a few times a week, and 18.0% said they used it rarely.

Table:1

Demographic Characteristics and Weekly Generative AI Use of Participants

Characteristic	Category	n	%
Gender	Male	201	52.3
	Female	183	47.7
Academic Level	Undergraduate	268	69.8
	Postgraduate	116	30.2
Discipline	Social Sciences	142	37.0
	Natural Sciences	98	25.5
	Engineering/Computing	144	37.5

Characteristic	Category	n	%
Weekly GenAI Use	Daily	156	40.6
	A few times a week	159	41.4
	Rarely	69	18.0

Measurement Model Results

Table 2 shows the measurement model analysis results. Conventional reliability (composite reliability ≥ .70) and convergent validity (AVE ≥ .50) criteria are satisfied for all constructs, while the HTMT ratios of the three constructs range between .41 and .68, which is below the conservative threshold of .85, supporting discriminant validity.

Table:2

Reliability and Convergent Validity of the Measurement Model

Construct	No. of Items	Cronbach's α	Composite Reliability	AVE
Generative AI Literacy	8	.86	.89	.58
Cognitive Offloading	6	.81	.86	.55
Critical Thinking Disposition	7	.84	.88	.57

Structural Model and Hypothesis Testing

The standardized path coefficients with their t-values, p-values, and bootstrapped 95% confidence intervals are shown in Table 3 for the structural model. There was a significant positive association between generative AI literacy and critical thinking disposition (supporting H1), as well as a significant negative association between generative AI literacy and cognitive offloading (supporting H2), and a significant negative association between cognitive offloading and critical thinking disposition (supporting H3). The model accounted for 41% of the variance in cognitive offloading ($R^2 = .41$) and 47% of the variance in critical thinking disposition ($R^2 = .47$).

Table:3

Structural Model Results and Hypothesis Testing

Path	β	t-value	p-value	95% CI	Decision
GenAI Literacy → Critical Thinking (H1)	.33	6.12	<.001	[.23, .43]	Supported

Path	β	t-value	p-value	95% CI	Decision
GenAI Literacy → Cognitive Offloading (H2)	-.45	8.04	<.001	[-.55, -.34]	Supported
Cognitive Offloading → Critical Thinking (H3)	-.29	5.47	<.001	[-.39, -.19]	Supported

Mediation Analysis

The bootstrapped indirect-effect test for H4 is shown in Table 4. The indirect effect of GenAI literacy on critical thinking disposition via cognitive offloading is positive and significant (β = .13, 95% CI [.08, .19]), and because the direct effect (β = .33) remains significant even with the indirect effect of the same sign, the findings are consistent with complementary (partial) mediation, with approximately 28% of the total effect transmitted through cognitive offloading, meaning that cognitive offloading explained a significant but not overwhelming proportion of the total effect of GenAI literacy on critical thinking disposition.

Table:4

Mediation Analysis

Effect	β	SE	95% Bootstrapped CI	VAF	Mediation Type
Direct: GenAI Literacy → Critical Thinking	.33	.054	[.23, .43]	—	—
Indirect: via Cognitive Offloading	.13	.028	[.08, .19]	28%	Partial (complementary)
Total Effect	.46	.051	[.36, .56]	—	—

Full-collinearity VIF analysis results were also consistent with common method bias not being a significant problem, with all VIF values falling below the conservative threshold of 3.3 across the constructs, while Harman's single-factor test revealed no single factor representing a majority of the variance.

Discussion

The tested model aims to fill a gap identified in Section 2 and examines whether generative AI literacy has a direct effect on critical thinking, an indirect effect via cognitive offloading, or a combined effect. The pattern of findings emerging during the present study (described numerically in Section 5) is consistent with a re-framing of the findings reviewed in Section 2.2. In contrast to the view of cognitive offloading as a threat to CT that much of the panicked literature portrays (Gerlich, 2025), the model presented in this paper posits that a more cognitively literate generation of AI students is characterized by reduced reliance on cognitive offloading and increased critical thinking disposition. However, the negative relationship between offloading and critical thinking seen at the population level in previous studies (Gerlich, 2025) may be partially attributed to differences in AI literacy; students who showed higher literacy had higher levels of critical thinking disposition and lower levels of cognitive offloading, while students who showed lower literacy had higher levels of cognitive offloading and lower levels of critical thinking disposition.

It is consistent and builds upon the qualitative results of Roy (2025), who found that participants had mixed emotions about their reduced effort, which can be formalized in the present model as a combination of a positive direct pathway (H1) and a large indirect pathway (H2) involving cognitive offloading. Also, it extends the applicability of cognitive load theory (CLT; Sweller, 1988) to this area: literate students may be better able to distinguish between extraneous load that can be offloaded (e.g., source location) and germane load that cannot be offloaded (e.g., evaluating argument validity), which was not measured in the current study but is worth being investigated in future studies. This model is supported by the context of higher education evidence presented in Section 2.5 from Pakistan. The results obtained in the present study are in line with the results obtained by Alghazo et al. (2025), who found that generative AI literacy is significantly related to cognitive offloading and critical thinking disposition, while simultaneously perceiving ChatGPT as beneficial and being worried about over-reliance and accuracy. The cross-sectional design, however, does not allow for causal inferences regarding whether these patterns are a result of differences in AI literacy.

Implications

The model extends the concept of the metacognitive appraisal process, which underlies offloading decisions, to the qualitatively different domain of generative/synthesis-capable AI systems, adding to the cognitive offloading theory (Risko & Gilbert, 2016), which has been developed primarily for physical and simple digital offloading behaviours. It also adds to the AI literacy literature (Ng et al., 2021, 2024) by showing a concrete downstream behavioural and cognitive pathway (offloading behaviour) whereby AI literacy is statistically associated with critical thinking disposition, moving beyond descriptive competency mapping to a testable nomological network.

Pedagogical and institutional implications

The results indicate that a structured approach to instruction on AI literacy (how the LLM creates text, its tendency to hallucinate and/or bias, and how to verify information) may be more useful than restricting or banning GenAI tools, particularly in an AI-saturated learning environment, as was suggested in the reviewed systematic reviews (Roy, 2025). Rethinking how AI is used in the curriculum by asking students to reflect on, verify, or critically evaluate AI-generated content could encourage more critical interaction with the AI tool and limit excessive dependence on it.

Policy Implications

The findings also provide justification for considering AI-literacy competencies in general education or academic-skills courses at the institutional and national policy level, in line with recent recommendations for AI-literacy standards in the Pakistani higher education sector (ProPakistani, 2025, summarising UNESCO guidance) and international competency frameworks (Ng et al., 2021). Assessment policy may also require review and adjustment to make explicit the value of the values of the verified, critically integrated use of GenAI rather than its full prohibition or its unregulated use.

Limitations and directions for future research

Some caveats need to be taken into account when reading the results. First, the cross-sectional design does not allow for causal inference; indeed, it is possible that reduced critical thinking disposition would lead to higher levels of cognitive offloading, or that higher levels of cognitive offloading would lead to reduced critical thinking disposition as well. Longitudinal or experimental designs such as randomly assigning students to AI-literacy training or a control condition and measuring offloading and critical thinking scores after a semester of training would significantly enhance the causal inferences made, as suggested by recent calls for longitudinal studies in this literature (Roy, 2025). Second, all measures were self-reported and, while the measures had various process and statistical safeguards outlined in Section 4.5, it is not possible to completely eliminate the threat of social desirability bias, especially for the items related to critical thinking disposition. Future research could also examine the use of performance-based critical thinking assessments, such as standardised critical thinking skills tests, and behaviour/Log measures of actual GenAI usage patterns as supplements to self-report. Third, the general cognitive offloading measure used in the present study does not, on its own, differentiate between reflective and unreflective offloading, which should be formally validated and added to the model as a moderator or second mediator in subsequent model development. Lastly, the sample is limited to a purposively selected sample within a single national higher-education context, necessitating cross-national replication to validate generalisability of the observed mediation pathway across contexts of higher education in countries with different levels of institutional AI governance and digital infrastructure.

Conclusion

This paper has reviewed existing, reliable, indexed literature on generative AI literacy, cognitive offloading, and critical thinking, and tested a mediation model whereby generative AI literacy is directly and indirectly related to students' critical thinking disposition through their cognitive offloading behavior in the university context. The results do not highlight the view of support the generative AI is posing to critical thinking in general but rather the hypothesis that higher generative AI literacy was linked to an increase in critical thinking disposition and a decrease in cognitive offloading, and that cognitive offloading was linked to a decrease in critical thinking disposition. The significant indirect the effect also suggests that the generative AI literacy and critical thinking disposition was mediated in part by cognitive offloading. The relationships were examined in the framework of a quantitative design, multi-item measures with acceptable evidence of reliability and validity in the current sample, and PLS-SEM. Due to the cross-sectional design and purposive sampling employed in this study, however, the results should be viewed as associations instead of causal relationships and cannot be extrapolated to other similar higher education settings without additional evidence. The results offer a framework for educators, curriculum designers, and policymakers to reflect on the need for and approach to AI-literacy development in the context of responsible GenAI integration in higher education, especially in developing-country settings like Pakistan, where formal AI-literacy curricula are still in their early stages.

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