

The Moderating Role of AI Literacy in the Relationships Between Generative AI Reliance, Academic Self-Efficacy, and Cognitive Engagement Among Adolescents

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E d i t o r	R e v i e w e r s
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1. Round 1

1.1. Reviewer 1

Reviewer:

In the paragraph beginning “One of the most consequential constructs in this emerging area is generative AI reliance,” the sentence “Reliance differs conceptually from ordinary use because it reflects the degree to which learners come to depend on AI systems to initiate, sustain, complete, or validate academic work” is central to the article and should be developed more rigorously. The authors should specify whether reliance is conceptualized as a behavioral tendency, a cognitive dependency, a motivational orientation, or a multidimensional construct combining these elements. This matters because the measurement section appears to combine behavioral dependence, psychological necessity, and verification habits within one scale. A stronger construct definition would improve content validity and interpretation of the findings.

In the Introduction paragraph on academic self-efficacy, the sentence “Repeated dependence on AI may also undermine students’ confidence in their own competence if successful performance becomes increasingly attributed to technological assistance rather than personal capability” provides a plausible mechanism, but this is currently presented as an inference rather than as a fully elaborated process. I recommend explicitly discussing mastery experiences and attributional processes as

possible explanatory mechanisms. The authors should also acknowledge the alternative possibility that students with low academic self-efficacy may be more likely to become dependent on generative AI, thereby highlighting potential bidirectionality before presenting the study hypotheses.

In the Data Analysis section, the sentence “Generative AI reliance and AI literacy scores were mean-centered to reduce nonessential multicollinearity and facilitate interpretation of the regression coefficients” is appropriate, but the moderation analysis would be more transparent if the authors explicitly identified the PROCESS model used, presumably Model 1, and specified the bootstrap settings if bootstrapped confidence intervals were estimated. The manuscript should report the number of bootstrap samples, confidence level, coding of categorical covariates, handling of the nonbinary gender category, and whether heteroskedasticity-consistent standard errors were considered.

In the Findings section, Table 1 reports both Cronbach’s alpha and composite reliability, but the analytical framework appears to rely on observed scale scores rather than a latent-variable model. The authors should explain how composite reliability was calculated and why it is reported alongside alpha. If CR was derived from a confirmatory factor analysis, then the CFA procedure and factor loadings should be described in the Methods and relevant fit indices should be reported. If no CFA was conducted, reporting CR may be methodologically inconsistent and should either be justified or omitted.

The assumption-check paragraph following Table 1 states that “variance inflation factor values ranged from 1.08 to 1.47” and that residual diagnostics showed no influential observations. These are useful checks, but the manuscript should provide greater methodological precision regarding normality and heteroscedasticity. In moderation models involving interaction terms, the normality of raw variables is less important than the behavior of residuals and the robustness of standard errors. The authors should consider reporting residual plots, heteroskedasticity tests, and, ideally, heteroskedasticity-consistent confidence intervals to strengthen the inferential credibility of the models.

In Table 2, the correlation between academic self-efficacy and cognitive engagement is reported as $r = .57, p < .001$. This is theoretically plausible and supports related but distinct constructs, yet the manuscript should explicitly note whether discriminant validity was examined, especially because both outcomes include elements of persistence and regulation. If validated multi-item scales were used, reporting factor correlations or HTMT values from a measurement model would help demonstrate that academic self-efficacy and cognitive engagement are empirically distinguishable.

Authors uploaded the revised manuscript.

1.2. Reviewer 2

Reviewer:

In the paragraph on cognitive engagement, the sentence “When learners rely on AI-generated answers without evaluating, reconstructing, or extending them, the same technology may reduce the need for sustained cognitive effort” is persuasive, but the manuscript should more clearly distinguish cognitive engagement from related constructs such as behavioral engagement, motivation, and self-regulated learning. Since the instrument reportedly covers deep processing, elaboration, metacognitive regulation, persistence, and critical evaluation, the authors should provide a concise construct boundary statement in the Introduction to clarify that the outcome is specifically cognitive rather than general engagement.

In the paragraph beginning “Within this framework, AI literacy emerges as a particularly important moderating factor,” the sentence “AI literacy extends beyond technical proficiency and includes knowledge of how AI systems operate, awareness of their limitations, the capacity to evaluate generated content critically, the ability to formulate effective prompts, and understanding of ethical issues” is appropriately multidimensional. However, the moderation hypothesis would be stronger if the authors explained precisely why AI literacy should weaken rather than strengthen the negative association between reliance and outcomes. The current argument implies a buffering effect, but the mechanism should be stated explicitly: AI-literate students may rely on AI strategically while retaining epistemic control, independent verification, and task ownership, whereas low-literacy students may be more prone to passive acceptance and cognitive substitution.

In the final paragraph of the Introduction, the aim sentence states that the study seeks “to determine whether AI literacy moderates the relationships between generative AI reliance and both academic self-efficacy and cognitive engagement.” This

is clear, but the manuscript would benefit substantially from explicit hypotheses immediately before the aim or directly following the theoretical rationale. At minimum, the authors should formulate hypotheses predicting negative direct associations of reliance with self-efficacy and engagement, positive associations of AI literacy with both outcomes, and positive interaction effects indicating attenuation of the negative reliance slopes at higher levels of AI literacy.

In the Methods section under “Study Design and Participants,” the sentence “A total of 612 adolescents participated in the study” provides the sample size but does not explain how this number was determined. A manuscript using moderation analysis should report an a priori power analysis or, if data were already collected, a sensitivity analysis. The authors should specify the assumed effect size for the interaction term, alpha level, statistical power, number of predictors, and required minimum sample size. Because moderation effects are often small, demonstrating adequate statistical power is particularly important for supporting the validity of the interaction findings.

In the participant description, the sentence “Students were recruited from public secondary schools located in Ontario, British Columbia, Alberta, and Quebec” suggests geographic heterogeneity, but the sampling procedure remains somewhat underspecified. The authors state that a multistage procedure was used, yet they do not report how many schools, school boards, or classrooms participated, whether schools were randomly selected, or whether recruitment depended on administrative willingness. These details are necessary for evaluating selection bias and external validity. The manuscript should also explain whether the questionnaire was administered only in English and, if so, how this may have affected participation in Quebec.

In the Methods paragraph on eligibility, the sentence “self-reported use of a generative AI system such as ChatGPT, Gemini, Microsoft Copilot, Claude, or a comparable platform for at least one school-related activity during the preceding three months” establishes an exposure criterion, but it may introduce range restriction by excluding nonusers. The authors should justify why the research question requires prior AI use and acknowledge that the resulting sample represents AI-exposed adolescents rather than the broader secondary-school population. This is especially important when interpreting mean AI reliance scores and generalizing the moderation findings.

In the Data Collection Tools section, the sentence “Generative AI reliance was assessed using a multi-item Generative AI Reliance Scale adapted for the educational context” is insufficiently specific for reproducibility. The manuscript should identify the original source of the scale, the number of items retained, the adaptation process, sample items, response format, scoring method, and evidence of construct validity. If the measure was newly developed for this study, the authors should state this explicitly and provide item-generation procedures, expert-review methods, pilot testing, exploratory or confirmatory factor analysis, and reliability estimates rather than describing it as merely “adapted.”

The same issue applies to the statement “AI literacy was assessed as the proposed moderating variable” and the subsequent description of four dimensions. The authors should clarify whether these four dimensions derive from an established validated AI literacy instrument or from a study-specific measure. Because AI literacy is the central moderator, measurement validity is especially consequential. The manuscript should report the number of items per dimension, whether a total score was empirically justified, factor structure, internal consistency for each subdimension where applicable, and evidence that the instrument functions appropriately in an adolescent rather than university population.

In the Methods paragraph on academic self-efficacy, the sentence “The academic self-efficacy measure included items assessing confidence in understanding difficult academic material, successfully completing challenging assignments, learning complex concepts, solving academic problems, maintaining performance when coursework became demanding, organizing learning activities, and achieving satisfactory academic outcomes through personal effort” describes content but does not identify the instrument. A peer-reviewed manuscript should provide the name and original developers of the scale, publication year, number of items, original psychometric evidence, any adaptation for Canadian adolescents, and reliability in the current sample. The same requirement applies to the cognitive engagement measure.

Authors uploaded the revised manuscript.

2. Revised

Editor’s decision after revisions: Accepted.

Editor in Chief's decision: Accepted.