Advances in Educational Technology and Psychology (2026)
Clausius Scientific Press, Canada

DOI: 10.23977/aetp.2026.100409
ISSN 2371-9400 Vol. 10 Num. 4

Generative AI Dependence on Master's Students' Study Engagement: Serial Mediation by Academic Burnout and Procrastination

Zimo Yang

School of Psychology, Shaanxi Normal University, Xi'an, China
yzmpsy@126.com

Keywords: Generative AI Dependency; Academic Boredom; Academic Procrastination; Learning Engagement

Abstract: Generative artificial intelligence (GenAI) can provide master's students with immediate academic support, yet dependency on such tools may be associated with lower levels of sustained learning engagement. This study examined the association between GenAI dependency and learning engagement and tested the serial mediating roles of academic boredom and academic procrastination. Four-wave matched survey data from 646 master's students were analyzed. GenAI dependency was negatively associated with learning engagement (B=−0.397, p<0.001). Bootstrap analyses showed a significant negative indirect effect through academic procrastination (B=−0.424, 95% CI [−0.547, −0.300]) and a significant serial indirect effect through academic boredom and academic procrastination (B=−0.357, 95% CI [−0.462, −0.257]). The specific indirect effect through academic boredom alone was positive, indicating an inconsistent mediation pattern. These findings suggest that higher GenAI dependency is associated with lower learning engagement and that academic boredom may be linked to lower engagement partly through greater academic procrastination.

1. Introduction

For master's students, generative artificial intelligence (GenAI) is reshaping how academic work is organized over time. Students can quickly obtain conceptual explanations, writing suggestions, and assignment support, but immediate assistance does not necessarily translate into more active learning[1,2]. GenAI dependency differs from general frequency of use. It is characterized by persistent cognitive preoccupation with the tool, negative consequences associated with use, and discomfort when the tool is unavailable[3]. A recent study of Chinese university students found that perceived usefulness of GenAI for learning was associated with GenAI dependency, with metacognitive self-management and academic procrastination contributing to this statistical association[4]. Existing research has focused mainly on the development of dependency, while its association with learning engagement remains insufficiently examined.

Learning engagement refers to vigor, dedication, and absorption in learning[5]. When AI-supported learning environments promote autonomy and autonomous motivation, students may show higher

levels of engagement[6]. Dependency may produce a different pattern. Cognitive offloading can conserve limited cognitive resources, but when students routinely delegate planning, judgment, and verification to GenAI, they may have fewer opportunities to process learning materials themselves[7]. Accordingly, H1 predicted that higher GenAI dependency would be associated with lower subsequent learning engagement.

Academic boredom and academic procrastination may help explain the association between GenAI dependency and learning engagement. Control-value theory suggests that boredom is more likely when learners perceive low task value or insufficient control[8]. When GenAI repeatedly substitutes for students' own explanations and content generation, it may reduce the challenge and sense of agency involved in learning activities. Prior research has also linked boredom with mind wandering, reduced effort, and poorer academic outcomes[9]. Procrastination refers to a self-regulatory failure in which individuals delay intended tasks despite knowing that the delay may have negative consequences[10]. From a short-term mood-repair perspective, students may postpone tasks to temporarily avoid boredom or discomfort[11]. The immediate availability of GenAI may also reduce the perceived urgency of starting early, while procrastination compresses the time available for deeper processing and revision[12]. We therefore expected GenAI dependency to positively predict academic boredom and academic procrastination (H2 and H3), academic boredom to positively predict academic procrastination (H4), and both academic boredom and academic procrastination to negatively predict learning engagement (H5 and H6).

Few studies have examined GenAI dependency, academic boredom, academic procrastination, and learning engagement within a model that separates these variables across time. The present study measured the four variables sequentially and tested three indirect effects: the specific indirect effect through academic boredom (H7), the specific indirect effect through academic procrastination (H8), and the serial indirect effect through academic boredom followed by academic procrastination (H9). Separating variables across measurement waves can reduce ambiguity arising from same-wave measurement, but it cannot replace an experimental design or a longitudinal model that controls for baseline stability[13]. The hypothesized model is shown in Figure 1.

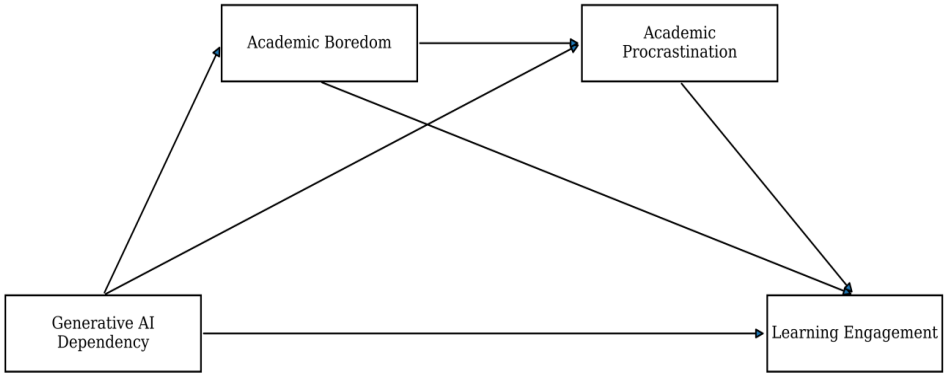


Figure 1: Hypothesized model.

2. Methods

2.1. Participants and Procedure

Participants were master's students from several universities in Shaanxi and Gansu Provinces, China. Data collection took place from October 2025 to April 2026. A total of 699 participants were initially recruited. After data cleaning, complete matched data from all four waves were retained for 646 participants, yielding a retention rate of 92.42%. Questionnaires with obvious straight-line

response patterns, internally inconsistent responses, or implausible completion times were excluded. Participants ranged in age from 18 to 29 years (M=22.34, SD=2.23), including 298 men (46.13%) and 348 women (53.87%). The sample included 364 first-year, 262 second-year, and 20 third-year master's students.

The study was approved by the Ethics Committee of the School of Psychology, Shaanxi Normal University (2026-06-02). Questionnaires were administered online via Wenjuanxing, and electronic informed consent was obtained before participation. All questionnaire items were set as required responses. Participants were informed that participation was voluntary, that the data would be used solely for academic research, and that they could withdraw at any time.

2.2. Measures

2.2.1. Generative AI Dependency

GenAI dependency was measured with the Generative AI Dependency Scale developed by Goh et al.[3]. Participants responded with reference to the GenAI tool they had used most frequently for learning during the previous month. The 11-item scale comprises cognitive preoccupation (3 items), negative consequences (4 items), and withdrawal reactions (4 items). Cognitive preoccupation assesses urges to use GenAI even when it is not clearly necessary; negative consequences assess reliance on GenAI to complete tasks and perceived adverse effects on personal capability; and withdrawal reactions assess uneasiness, concentration difficulties, or irritability when GenAI is unavailable. Items were rated from 1 (strongly disagree) to 5 (strongly agree). For the primary analysis, mean scores were first calculated for each dimension and then averaged so that the three dimensions contributed equally to the total score. Scores ranged from 1 to 5, with higher scores indicating stronger GenAI dependency. In the present study, Cronbach's α was 0.915

2.2.2. Academic Boredom

Academic boredom was assessed using the learning-related boredom subscale of the Achievement Emotions Questionnaire-Short[14]. Participants responded with reference to their typical experiences during coursework and related learning tasks. The subscale contains four items assessing boredom with learning content, mind wandering, and task avoidance. Items were rated from 1 (strongly disagree) to 5 (strongly agree), with no reverse-scored items. The mean of the four items was used as the academic boredom score, ranging from 1 to 5; higher scores indicated greater boredom. In the present study, Cronbach's α was 0.911 .

2.2.3. Academic Procrastination

Academic procrastination was measured using the Chinese Aitken Procrastination Inventory-Short Form[15]. The four items assess delayed task initiation, failure to finish work on time because of procrastination, rushing close to deadlines, and the ability to begin tasks promptly. Participants rated how well each item described their usual behavior when completing coursework, reviewing material, and writing papers, from 1 (does not describe me at all) to 5 (describes me very well). Item P4 is positively worded and was reverse-scored before the scale score was calculated. Scores ranged from 1 to 5, with higher scores indicating greater procrastination. In the present study, Cronbach's α was 0.934 .

2.2.4. Learning Engagement

Learning engagement was measured using the Utrecht Work Engagement Scale-Student-9

(UWES-S-9)[5]. The scale contains nine items, with three items each for vigor, dedication, and absorption. The items assess energy and persistence during learning, enthusiasm and pride in learning, and immersion in learning activities. Participants rated how often they experienced these states in daily learning from 0 (never) to 6 (always/every day). Psychometric evidence from Chinese undergraduate students supports the use of the nine items as an overall indicator of learning engagement[16]; therefore, the present study used the mean of all nine items. Scores ranged from 0 to 6, with higher scores indicating greater learning engagement. In the present study, Cronbach's α was 0.910 .

2.3. Data Analysis

Descriptive statistics, Pearson correlations, Cronbach's α, and McDonald's ω were first calculated. PROCESS Model 6 was then used to test the serial mediation model[17]. X, M1, M2, and Y represented T1 GenAI dependency, T2 academic boredom, T3 academic procrastination, and T4 learning engagement, respectively. Indirect effects were estimated using percentile 95% confidence intervals based on 5,000 bootstrap resamples. An indirect effect was considered statistically supported when its 95% confidence interval did not include zero.

3. Results

3.1. Descriptive Statistics and Correlations

As shown in Table 1, GenAI dependency was positively correlated with academic boredom and academic procrastination and negatively correlated with learning engagement. Academic boredom was positively correlated with academic procrastination, and both variables were negatively correlated with learning engagement. All correlations were significant at $p<0.001$.

Table 1: Reliability, descriptive statistics, and correlations.

Variable	α	ω	M	SD	1	2	3	4
1. GenAI dependency	0.915	0.916	2.899	0.864	1			
2. Academic boredom	0.911	0.911	3.002	0.872	0.783***	1		
3. Academic procrastination	0.934	0.934	3.002	1.004	0.615***	0.620***	1	
4. Learning engagement	0.910	0.910	3.038	1.277	−0.397***	−0.307***	−0.735***	1

Note: N=646. *** p<0.001.

3.2. Serial Mediation Analysis

The path coefficients are presented in Table 2. The total association between GenAI dependency and learning engagement was negative and statistically significant, supporting H1. GenAI dependency positively predicted academic boredom and academic procrastination, and academic boredom positively predicted academic procrastination, supporting H2-H4. Academic procrastination negatively predicted learning engagement, supporting H6. After the mediators were included, GenAI dependency retained a significant negative direct association with learning engagement. Contrary to H5, the conditional regression coefficient from academic boredom to learning engagement was positive. The R^2values for the three regression equations were 0.614, 0.428, and 0.581, respectively.

Table 2: Path coefficients for the serial mediation model.

Path	*B*	*SE*	β	*t*	*p*	95% CI
X → Y	−0.586	0.053	−0.397	−10.964	< 0.001	[−0.691, −0.481]
a_1: X → M_1	0.790	0.025	0.783	31.979	< 0.001	[0.741, 0.838]
a_2: X → M_2	0.388	0.056	0.334	6.958	< 0.001	[0.278, 0.497]
d_{21}: M_1 → M_2	0.413	0.055	0.358	7.469	< 0.001	[0.304, 0.521]
c′: X → Y	−0.174	0.063	−0.118	−2.758	0.006	[−0.297, −0.050]
b_1: M_1 → Y	0.467	0.063	0.319	7.448	< 0.001	[0.344, 0.590]
b_2: M_2 → Y	−1.095	0.043	−0.860	−25.488	< 0.001	[−1.179, −1.010]

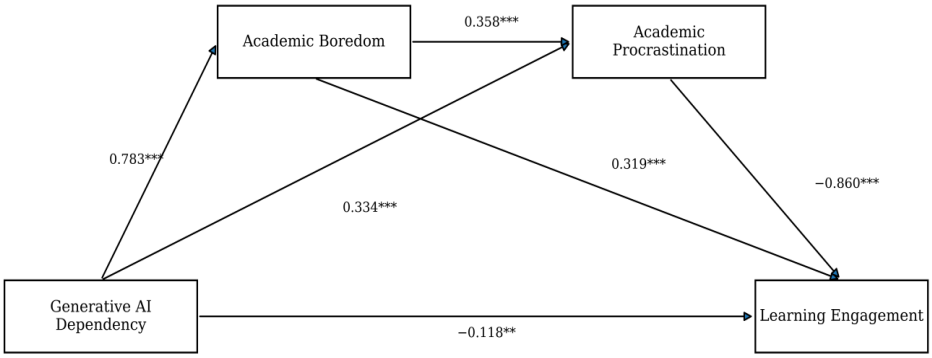
Note: X=GenAI dependency; M_1=academic boredom; M_2=academic procrastination; Y=learning engagement. B=unstandardized coefficient; β=standardized coefficient.

The indirect effects are shown in Table 3. The specific indirect effect of GenAI dependency on learning engagement through academic procrastination was negative, supporting H8. The serial indirect effect through academic boredom and then academic procrastination was also negative, supporting H9. In contrast, the specific indirect effect through academic boredom alone was positive, opposite to the direction predicted in H7. The total indirect effect was negative. The hypothesized model is shown in Figure 2.

Table 3: Bootstrap tests of specific indirect effects.

Path	*B*	Boot *SE*	Bootstrap 95% CI
X → M_1 → Y	0.369	0.051	[0.269, 0.468]
X → M_2 → Y	−0.424	0.063	[−0.547, −0.300]
X → M_1 → M_2 → Y	−0.357	0.052	[−0.462, −0.257]
Total indirect effect	−0.412	0.060	[−0.531, −0.292]

Note: Percentile 95% confidence intervals based on 5,000 case-resampling bootstrap samples.



Note: **:p<0.001;***:p<0.001.

Figure 2: Standardized path coefficients for the serial mediation model.

4. Discussion

The present study found that GenAI dependency was associated with lower learning engagement and supported a negative serial indirect effect through academic boredom and academic procrastination. This pattern suggests that dependency should be distinguished from ordinary AI-assisted learning. Previous research indicates that when AI supports autonomous choice and

autonomous motivation, students may maintain higher engagement[6]. The dependency measured here instead includes cognitive preoccupation, negative consequences, and discomfort when the tool is unavailable. These patterns of use therefore have different psychological implications. Because the UWES-S-9 operationalizes learning engagement as vigor, dedication, and absorption, the association with dependency may involve not only changes in study time but also students' energy, sense of involvement, and sustained concentration during learning.

The serial indirect effect further showed that greater GenAI dependency was associated with stronger academic boredom, which in turn was associated with more academic procrastination, and procrastination was subsequently associated with lower learning engagement. Control-value theory proposes that low task value or insufficient perceived control makes boredom more likely[8], whereas the short-term mood-repair perspective suggests that students may delay tasks to temporarily escape boredom or discomfort[11]. When GenAI can provide immediate support for a task, postponement may be easier to sustain. Academic procrastination may therefore represent an important behavioral process through which boredom is further associated with lower learning engagement.

Self-determination theory offers another possible interpretation. Sustained learning engagement depends partly on the satisfaction of autonomy, competence, and relatedness[18]. When GenAI is used to retrieve information, clarify concepts, or obtain feedback, it can support autonomous choice. However, when students routinely delegate planning, judgment, and content generation to the tool, GenAI use may shift from an assistive strategy toward external substitution, reducing opportunities to organize and evaluate learning materials independently. In this way, GenAI dependency may weaken students' sense of autonomy and competence during learning. Because these psychological needs were not directly measured in the present study, this interpretation remains theoretical and was not tested by the model.

The specific indirect effect through academic boredom alone was opposite in direction to the hypothesis. Academic boredom was negatively correlated with learning engagement at the zero-order level, but its conditional coefficient became positive after controlling for GenAI dependency and academic procrastination. This pattern is consistent with inconsistent mediation or local suppression[19] and may indicate that academic procrastination accounts for a substantial portion of the shared negative association between boredom and lower engagement. The positive conditional coefficient should not be interpreted as evidence that boredom improves engagement. This pathway requires replication in new samples, latent-variable models, and stronger temporal designs. Research on academic emotions also shows that emotional experiences vary across learning tasks and contexts[20,21]; future work should therefore distinguish among courses, task difficulty, and evaluation demands.

The study also has limitations. Although the variables were measured sequentially across four waves, each construct was assessed only once and baseline stability was not controlled. Reverse ordering and unmeasured common causes therefore cannot be ruled out. Future studies could manipulate task value and tool availability while directly measuring autonomy, competence, control, and learning strategies. Research on self-regulated learning identifies goal setting, time management, and self-monitoring as important processes related to academic procrastination[22,23]. Cross-lagged models or experimental manipulations could be used to test the temporal ordering of these variables more rigorously.

5. Conclusions

Higher GenAI dependency was associated with lower learning engagement, and academic boredom may be linked to lower engagement through greater academic procrastination. Self-determination theory and control-value theory suggest that educators should focus not only on

how often students use GenAI but also on whether students retain responsibility for task selection, process monitoring, and outcome verification. When integrating GenAI into instruction, universities can preserve students' self-regulatory involvement through staged assignments, independent first drafts, prompt records, and source verification while monitoring changes in learning engagement.

References

[1] Kasneci, E., Sessler, K., Küchemann, S., et al. (2023) ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education. Learning and Individual Differences, 103, 102274.

[2] Chan, C.K.Y. and Hu, W. (2023) Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. International Journal of Educational Technology in Higher Education, 20, 43.

[3] Goh, A.Y.H., Hartanto, A. and Majeed, N.M. (2025) Generative Artificial Intelligence Dependency: Scale Development, Validation, and Its Motivational, Behavioral, and Psychological Correlates. Computers in Human Behavior Reports, 20, 100845.

[4] Liu, Y. and Liu, Y. (2026) Association between Perceived Usefulness of Generative AI for Learning and Generative AI Dependency among University Students in Changde, China: A Cross-Sectional Study of Statistical Indirect Effects. Frontiers in Psychology, 17, 1859317.

[5] Schaufeli, W.B., Bakker, A.B. and Salanova, M. (2006) The Measurement of Work Engagement with a Short Questionnaire: A Cross-National Study. Educational and Psychological Measurement, 66(4), 701-716.

[6] Ahmed, A. and Sultan, A. (2026) Examining the Impact of Generative AI on Student Motivation and Engagement: The Mediating Role of Autonomy Support and Autonomous Motivation in Education. Frontiers in Psychology, 17, 1852265.

[7] Risko, E.F. and Gilbert, S.J. (2016) Cognitive Offloading. Trends in Cognitive Sciences, 20(9), 676-688.

[8] Pekrun, R. (2006) The Control-Value Theory of Achievement Emotions: Assumptions, Corollaries, and Implications for Educational Research and Practice. Educational Psychology Review, 18(4), 315-341.

[9] Tze, V.M.C., Daniels, L.M. and Klassen, R.M. (2016) Evaluating the Relationship between Boredom and Academic Outcomes: A Meta-Analysis. Educational Psychology Review, 28(1), 119-144.

[10] Steel, P. (2007) The Nature of Procrastination: A Meta-Analytic and Theoretical Review of Quintessential Self-Regulatory Failure. Psychological Bulletin, 133(1), 65-94.

[11] Sirois, F. and Pychyl, T. (2013) Procrastination and the Priority of Short-Term Mood Regulation: Consequences for Future Self. Social and Personality Psychology Compass, 7(2), 115-127.

[12] Kim, K.R. and Seo, E.H. (2015) The Relationship between Procrastination and Academic Performance: A Meta-Analysis. Personality and Individual Differences, 82, 26-33.

[13] Cole, D.A. and Maxwell, S.E. (2003) Testing Mediational Models with Longitudinal Data: Questions and Tips in the Use of Structural Equation Modeling. Journal of Abnormal Psychology, 112(4), 558-577.

[14] Bieleke, M., Gogol, K., Goetz, T., Daniels, L. and Pekrun, R. (2021) The AEQ-S: A Short Version of the Achievement Emotions Questionnaire. Contemporary Educational Psychology, 65, 101940.

[15] Zeng, L., Li, Y., Wang, T., et al. (2026) A Brief Measure of Academic Procrastination in University Students: Development and Validation of the Aitken Procrastination Inventory-Short Form. Frontiers in Psychology, 17, 1836609.

[16] Wei, Z., Yang, T., Gu, X., Dong, J. and Hassan, N.C. (2025) Psychometric Validation of Utrecht Work Engagement Scale-Student-9 in Chinese Undergraduate Students. Frontiers in Psychology, 16, 1486363.

[17] Hayes, A.F. (2022) Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. 3rd ed., Guilford Press, New York.

[18] Ryan, R.M. and Deci, E.L. (2000) Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. American Psychologist, 55(1), 68-78.

[19] MacKinnon, D.P., Krull, J.L. and Lockwood, C.M. (2000) Equivalence of the Mediation, Confounding and Suppression Effect. Prevention Science, 1, 173-181.

[20] Pekrun, R., Goetz, T., Frenzel, A.C., Barchfeld, P. and Perry, R.P. (2011) Measuring Emotions in Students' Learning and Performance: The Achievement Emotions Questionnaire (AEQ). Contemporary Educational Psychology, 36(1), 36-48.

[21] Pekrun, R., Goetz, T., Titz, W. and Perry, R.P. (2002) Academic Emotions in Students' Self-Regulated Learning and Achievement: A Program of Qualitative and Quantitative Research. Educational Psychologist, 37(2), 91-105.

[22] Wolters, C.A. (2003) Understanding Procrastination from a Self-Regulated Learning Perspective. Journal of Educational Psychology, 95(1), 179-187.

[23] Broadbent, J. and Poon, W.L. (2015) Self-Regulated Learning Strategies and Academic Achievement in Online Higher Education Learning Environments: A Systematic Review. The Internet and Higher Education, 27, 1-13.