The Effect of Academic Burnout on AI Dependence: The Mediating Role of Self-Efficacy

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Abstract

AI tools have become part of ordinary university study. Students use them to locate material, clarify difficult ideas, prepare drafts, and work through assignments. This convenience is useful, but it also makes it easier to hand over parts of the learning process to a system. Drawing on 548 valid questionnaires, the present study examined the association between academic burnout and dependence on AI, with general self-efficacy considered as a possible mediator. Burnout was positively related to AI dependence and negatively related to self-efficacy, whereas self-efficacy was inversely related to AI dependence. The regression results showed that burnout remained a significant predictor of AI dependence after demographic variables and self-efficacy were controlled. Bootstrap analysis further identified a significant indirect effect through self-efficacy; this pathway accounted for 14.52% of the total effect, so the mediation was partial rather than complete. The findings suggest that problematic AI reliance cannot be addressed only through rules about technology use. Support for students who are exhausted by study, together with opportunities to regain confidence through successful independent work, may be equally important.

Keywords

Academic Burnout; AI Dependence; Self-Efficacy; Mediating Effect; College Students.

1. Introduction

Generative AI is no longer an occasional novelty in higher education. For many students, it is already one of the tools opened during routine study: a question is entered, an explanation is requested, or a draft is checked before submission. Large language models can improve access to explanations, feedback, and learning support, but they also raise concerns about inaccurate output, overreliance, misuse, and the erosion of critical engagement [1]. These apparently conflicting outcomes point to a distinction that is easy to miss. AI can assist a learner who has already attempted a problem, yet it can also take over the reasoning that the task was designed to develop. The educational issue is therefore not use versus non-use, but the extent to which students retain responsibility for understanding, judging, and producing their work.

Students do not approach this choice under identical psychological conditions. Academic burnout, which develops under sustained study demands, is typically reflected in exhaustion, detachment from learning, and a reduced sense of accomplishment [2]. When students are already depleted, the effort needed to read closely, compare evidence, or revise an unsatisfactory answer may feel unusually costly. A system that can produce a coherent response in seconds then offers more than convenience; it offers relief. Repeatedly choosing that relief may gradually turn assistance into dependence.

Self-efficacy may help explain why this shift occurs for some students but not for others. Bandura defined self-efficacy as a person's belief in the capability to organize and execute the actions required to attain a given performance [3]. In university learning, stronger academic

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self-efficacy is associated with better performance and with motivational processes such as effort regulation and goal orientation [4]. Recent evidence on problematic AI use suggests that lower academic self-efficacy may increase reliance on AI indirectly by heightening academic stress [5]. A student who still expects to make progress independently may consult AI selectively; a student who doubts that possibility may treat the same output as a necessary substitute. On this basis, the study tests whether burnout is associated with AI dependence directly and also indirectly through lower self-efficacy.

2. Literature Review and Research Hypotheses

2.1. Academic Burnout and AI Dependence

Academic burnout is more than temporary tiredness before an examination. It describes a relatively persistent response to academic demands, marked by depleted energy, psychological distance from study, and a weakening sense of competence [2]. These conditions matter for behavior. Faced with a demanding assignment, a burned-out student may postpone the work, reduce the effort invested, or search for a way to finish without engaging fully with the task. Generative AI makes the last option readily available.

Frequent AI use is not necessarily dependence. The term is used here for a multidimensional pattern involving emotional, functional, and cognitive reliance on AI, together with loss of control over its use [6]. When AI substitutes for the learner's own cognitive work, dependence may be accompanied by cognitive fatigue and weaker critical thinking [7]. Burnout is likely to increase the appeal of that replacement. For an exhausted student, a complete AI response lowers the immediate cost of a difficult task. If this strategy is repeated, the short-term reduction in effort may be reinforced even though independent engagement continues to decline. This reasoning leads to the first hypothesis:

H1: Academic burnout positively predicts AI dependence.

2.2. Academic Burnout and Self-Efficacy

Within social cognitive theory, self-efficacy concerns perceived capability rather than objective skill alone [3]. Students who believe they can deal with a task are generally more willing to set demanding goals, invest effort, and persist after setbacks. A systematic review of university research found academic self-efficacy to be positively associated with academic performance and related motivational processes [4]. These effects are relevant to AI use because the decision to seek a complete external answer is partly a judgment about whether one's own effort is likely to succeed.

Burnout can alter that judgment. Exhaustion reduces the resources available for sustained work, while repeated disengagement or disappointing outcomes provide discouraging feedback about personal competence. Students may begin to read these experiences as evidence that they are unable to learn effectively, even when the difficulty is partly a consequence of excessive demands. Research with university students has reported a clear inverse association between academic self-efficacy and burnout [8]. The direction may be reciprocal over time, but the present model concentrates on the path from burnout to efficacy beliefs. Thus:

H2: Academic burnout negatively predicts self-efficacy.

2.3. Self-Efficacy and AI Dependence

Confidence in personal capability also affects the way an external aid is used. A student with strong self-efficacy may ask AI for a second explanation, compare two solution methods, or use feedback to revise an initial draft. Control of the task remains with the learner. When self-efficacy is weak, however, AI output may be accepted as a replacement for one's own reasoning

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or judgment. Research on problematic AI use indicates that academic self-efficacy is connected to AI dependence through academic stress and performance expectations [5]. The contrast becomes particularly important when tasks are complex and an apparently finished answer is available immediately.

The expected association is therefore negative. As students become more confident that they can begin and complete academic work themselves, they should have less reason to transfer the whole task to AI. Low confidence, in contrast, can make external assistance appear necessary rather than optional, increasing the likelihood of repeated delegation. Since prior evidence suggests that this relationship may be indirect rather than uniformly direct [5], the present study tests the relationship in a new sample. Accordingly:

H3: Self-efficacy negatively predicts AI dependence.

2.4. The Mediating Role of Self-Efficacy

The four proposed relationships form a coherent, but not exclusive, process. Burnout may increase reliance on AI because it encourages immediate relief from effortful work. At the same time, exhaustion, detachment, and a weak sense of accomplishment may reduce students' confidence in independent performance. Once that confidence has fallen, AI-generated answers can seem indispensable. Self-efficacy should therefore account for part of the association between burnout and AI dependence, while other routes may remain. The final hypothesis is:

H4: Self-efficacy mediates the relationship between academic burnout and AI dependence.

3. Method

3.1. Participants

Students were recruited by cluster sampling at an institute of technology in Y City, China. Six hundred questionnaires were distributed. Responses were removed when they contained repetitive answer patterns, implausible completion times, or substantial missing information, leaving 548 usable cases and a valid-response rate of 91.33%. The final sample comprised 268 men (48.9%) and 280 women (51.1%), aged 18 to 22 years. Analyses were conducted with the valid observations available for the variables in each model; the descriptive statistics and correlations in Table 1 use all 548 retained questionnaires.

3.2. Measures

3.2.1. General Self-Efficacy Scale

General self-efficacy was measured with the Chinese version of the General Self-Efficacy Scale validated by Wang et al. [9]. The instrument contains 10 positively worded items and represents a single dimension. Respondents indicate how well each statement describes their ability to deal with problems, pressure, and goal-directed tasks, using a four-point response format from 1 (completely incorrect) to 4 (completely correct). Item scores are summed, with larger totals indicating stronger self-efficacy. Cronbach's alpha in the present sample was 0.933.

3.2.2. Academic Burnout Scale

Academic burnout was assessed with the 16-item Adolescent Student Burnout Inventory developed by Wu et al. [10]. The scale covers emotional exhaustion, academic alienation, and low achievement. Each item is rated from 1 (strongly inconsistent) to 5 (strongly consistent). Positively phrased items are reverse scored before the total is calculated. A higher total score represents a more pronounced level of burnout.

3.2.3. AI Dependence Scale

AI dependence was assessed with the AIDep-22 scale developed for Chinese undergraduates [6]. Its 22 items cover emotional, functional, and cognitive dependence, together with loss of

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control. Responses range from 1 (strongly disagree) to 5 (strongly agree), yielding total scores between 22 and 110; larger values indicate greater reliance on AI in academic work. In this sample, Cronbach's alpha was 0.870 for emotional dependence, 0.912 for functional dependence, 0.922 for cognitive dependence, and 0.922 for loss of control.

3.3. Statistical Analysis

SPSS 27.0 was used for data screening and analysis. Means, standard deviations, and Pearson correlations were calculated first. Harman's single-factor procedure was then applied as a diagnostic check for common-method variance. The mediation model was estimated with the PROCESS macro, with academic burnout specified as X, self-efficacy as M, and AI dependence as Y. Gender, age, and registered residence were entered as covariates. The indirect effect was estimated from 5,000 bootstrap resamples following the resampling approach recommended for mediation analysis [11]. It was treated as significant when its 95% confidence interval did not contain zero.

4. Results

4.1. Common Method Bias Test

Several steps were taken to limit common-method bias. Questionnaires were completed anonymously, and participants were informed that there were no correct or incorrect responses. As a statistical check, all items from the focal variables were entered into an unrotated exploratory factor analysis. More than one factor had an eigenvalue greater than 1, and the first factor accounted for 28.81% of the variance. This value was below the 40% criterion commonly used with Harman's single-factor diagnostic in Chinese behavioral research [12]. The result does not eliminate common-method variance, but it provides no indication that a single factor dominated the data.

4.2. Descriptive Statistics and Correlation Analysis

The descriptive results are reported in Table 1. Academic burnout had a small negative correlation with self-efficacy (r = -0.101, p < 0.05) and a positive correlation with AI dependence (r = 0.386, p < 0.001). Self-efficacy was more strongly and negatively related to AI dependence (r = -0.550, p < 0.001). In substantive terms, students who reported more burnout also tended to report greater reliance on AI, whereas those who felt more capable reported less reliance. The correlations were consistent with the proposed directions and warranted testing the mediation model.

Table 1. Descriptive statistics and correlations among variables (N = 548)

Variable	M	SD	1	2	3	4	5	6
1. Academic burnout	48.68	6.41	1					
2. Self-efficacy	29.28	9.40	-0.101*	1				
3. AI dependence	66.18	22.69	0.386**	-0.550**	1			
4. Gender	1.51	0.50	-0.108*	-0.046	-0.060	1		
5. Age	19.69	1.21	-0.025	-0.022	0.019	-0.035	1	
6. Registered residence	2.07	0.89	-0.019	-0.007	0.056	0.068	-0.052	1

Note: Gender was coded as a dummy variable (male = 1, female = 2); registered residence was treated as an ordinal control variable. *p < 0.05, **p < 0.01 (two-tailed).

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4.3. Mediation Model Test

4.3.1. Regression Analysis of the Mediating Role of Self-Efficacy

For the mediation analysis, academic burnout was entered as the predictor, self-efficacy as the mediator, and AI dependence as the outcome. Gender, age, and registered residence were controlled in each equation. Table 2 presents the unstandardized regression coefficients.

Table 2. Regression analysis for the mediating effect of self-efficacy

Variable	Model 1: Self-efficacy (M) *B*	*t*	Model 2: AI dependence (Y, direct effect) *B*	*t*	Model 3: AI dependence (Y, total effect) *B*	*t*
Academic burnout (X)	-0.158	-2.209*	1.166	8.727***	1.364	8.519***
Gender	-1.087	-1.184	-2.320	-1.361	-0.960	-0.468
Age	-0.192	-0.543	0.305	0.464	0.546	0.689
Registered residence	-0.082	-0.155	1.635	1.664	1.738	1.467
Self-efficacy (M)	—	—	-1.251	-13.820***	—	—
R^2	0.014		0.419		0.154	
F	1.504		60.366***		19.082***	

Note: Model 1 regressed the mediator, self-efficacy, on academic burnout and control variables. Model 2 estimated the direct effect of academic burnout on AI dependence after controlling for self-efficacy. Model 3 estimated the total effect of academic burnout on AI dependence. *B* = unstandardized regression coefficient. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ (two-tailed).

In Model 1, academic burnout was associated with lower self-efficacy (B = -0.158, t = -2.209, $p < 0.05$). The total-effect model showed that burnout positively predicted AI dependence (B = 1.364, t = 8.519, $p < 0.001$). After self-efficacy was added, the burnout coefficient declined to 1.166 but remained significant (t = 8.727, $p < 0.001$). Self-efficacy also made an independent negative contribution (B = -1.251, t = -13.820, $p < 0.001$). The pattern is compatible with partial mediation: the mediator explains some of the association, but not the larger direct component. Fig. 1 summarizes the estimated model. Each of the three focal paths was statistically significant.

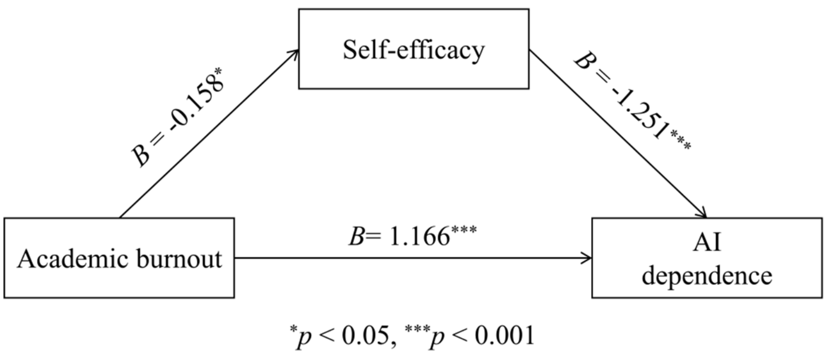

Figure 1. Mediation model of self-efficacy in the relationship between academic burnout and AI dependence

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Note: Values are unstandardized regression coefficients. $^{*}p < 0.05$, $^{***}p < 0.001$. Gender, age, and registered residence were controlled.

4.3.2. Bootstrap Test of the Mediating Effect of Self-Efficacy

The indirect, direct, and total effects were then separated by bootstrap estimation. Table 3 reports the point estimates, bootstrap standard errors, and bias-corrected confidence intervals.

Table 3. Decomposition of total, direct, and indirect effects

Effect type	Effect value	Boot *SE*	Boot 95% *CI* Lower	Boot 95% *CI* Upper	Relative effect
Indirect effect	0.20	0.11	0.02	0.47	14.52%
Direct effect	1.17	0.16	0.81	1.44	85.48%
Total effect	1.36	0.14	1.08	1.63	100.00%

Note: Boot *SE* and Boot 95% *CI* refer to the standard error and 95% confidence interval estimated using the bias-corrected percentile bootstrap method. Values are rounded to two decimal places.

The indirect effect through self-efficacy was 0.20 (Boot *SE* = 0.11), and its 95% bootstrap confidence interval ranged from 0.02 to 0.47. Because the interval did not cross zero, the indirect pathway was significant. The direct effect was 1.17 (Boot *SE* = 0.16, 95% *CI* [0.81, 1.44]), while the total effect was 1.36 (Boot *SE* = 0.14, 95% *CI* [1.08, 1.63]); both intervals also excluded zero. Self-efficacy accounted for 14.52% of the total effect, leaving 85.48% as the direct component. These proportions support a partial-mediation interpretation.

5. Discussion

5.1. The Effect of Academic Burnout on AI Dependence

The results place academic burnout among the psychological conditions associated with AI dependence. This is important because the availability of AI alone cannot explain why some students use it as an aid while others allow it to replace substantial parts of their work. Burnout involves low energy, detachment, and a diminished sense of achievement. Under these conditions, reading, reasoning, and revision may seem disproportionately demanding, whereas an AI-generated response offers immediate reduction of effort. The positive regression coefficient is consistent with the view that students under pressure can move from using AI to support learning toward using it to avoid learning. This interpretation is compatible with evidence that cognitive fatigue can help explain the association between AI dependence and weaker critical thinking [7].

Use frequency should therefore be interpreted cautiously. Two students may open the same system every day but retain very different levels of intellectual control: one tests and verifies the output, while the other delegates the central reasoning to the system. The latter pattern is the more relevant risk. Universities should pay attention to the motive for use and to the stage of work being transferred. For students with marked burnout, workload review, academic advising, counseling, and course-level support may reduce the need to seek AI primarily as an escape from difficult study experiences.

5.2. The Effect of Self-Efficacy on AI Dependence

Self-efficacy showed a clear inverse association with AI dependence. Students who trust their ability to understand material, develop an answer, and recover from mistakes have less reason to surrender control of a task. They can still use AI frequently, but are more likely to use it for

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comparison, feedback, or extension after making an initial attempt. Students with weak efficacy beliefs may approach the system from a different starting point: they expect their own answer to be inadequate and may therefore accept generated content with less scrutiny. Although prior research did not find a significant direct effect after mediators were entered, it showed that lower academic self-efficacy can contribute to AI dependence through higher academic stress [5].

The practical implication is not simply that students should be told to rely on themselves. Confidence is more likely to change when learners accumulate evidence that their own effort can succeed. Tasks with graduated difficulty, timely formative feedback, and opportunities to correct errors can provide such evidence. One workable classroom sequence is to require an independent first attempt, permit documented AI consultation afterward, and ask students to explain which suggestions they accepted, rejected, or revised.

5.3. The Mediating Role of Self-Efficacy

The mediation analysis provides a more specific account of the relationship. Burnout was linked to weaker self-efficacy, and weaker self-efficacy was in turn linked to greater AI dependence. A plausible sequence is that recurring exhaustion and limited feelings of accomplishment gradually change students' assessment of their own competence. Once confidence has fallen, an AI response may be experienced not merely as convenient but as necessary. The significant indirect effect supports this pathway. Nevertheless, its share of the total effect was modest, and the direct path remained substantial.

Self-efficacy should therefore be viewed as one mechanism rather than the whole explanation. Burnout may also influence motivation, perceived time pressure, self-control, attitudes toward AI, and sensitivity to peer practices. Some students may delegate work simply to obtain short-term relief even when they still believe they could complete it independently. Future studies could test these alternatives in the same model and examine whether the dominant pathway differs by discipline, assignment type, or level of AI literacy.

5.4. Educational Implications

The findings suggest three priorities for university practice. First, AI literacy should include judgment about when and how to use a system, not only instruction in prompts or functions. Students need concrete criteria for identifying stages that require their own reasoning, checking factual and logical accuracy, and recognizing when assistance has become substitution. Assessment instructions can also require a brief process record that identifies the student's initial work, the purpose of AI consultation, and the verification undertaken afterward.

Second, burnout prevention belongs within responsible-AI policy. Academic support, accessible counseling, realistic goal setting, and time-management assistance may reduce the avoidance-oriented use that arises under sustained pressure. Third, teaching should deliberately strengthen self-efficacy through attainable challenges, specific feedback, visible progress, peer examples, and repeated mastery experiences. These measures are most useful when combined with clear institutional rules and assessment designs that protect academic integrity while defining permissible uses of generative AI [13].

5.5. Research Limitations and Prospects

Several limitations qualify the interpretation of these results. The cross-sectional design identifies associations but cannot establish the order of change. Longitudinal data are needed to determine whether burnout precedes reductions in self-efficacy and subsequent AI reliance, and experimental work could test responses to changes in workload or efficacy support. The participants also came from a single institute of technology in one city, which limits generalization to other regions, disciplines, and types of university. Finally, the main variables were self-reported. Future research should combine questionnaires with AI-use logs, assignment histories, interviews, think-aloud protocols, or classroom observation to distinguish perceived dependence from actual delegation behavior.

6. Conclusion

In this sample of college students, greater academic burnout was associated with stronger dependence on AI and with lower self-efficacy. Self-efficacy, in turn, was associated with less dependence. The bootstrap analysis showed that reduced self-efficacy carried a statistically significant, but relatively small, part of the burnout-AI dependence relationship; most of the effect remained direct. Problematic reliance should therefore be understood as both a technology-use issue and a response to students' learning conditions. Rules about acceptable AI use are necessary, but they are unlikely to be sufficient without parallel efforts to reduce burnout, restore confidence in independent performance, and keep students cognitively engaged when AI is available.

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