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AI-Supported Learning, AI Dependency, and Academic Stress as Predictors of Student Burnout

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Abstract

Generative artificial intelligence (GenAI) can enhance university learning by providing immediate feedback, clarifying complex concepts, supporting problem-solving, and improving access to personalized academic assistance. However, excessive reliance on AI may weaken independent reasoning, academic self-efficacy, and students' ability to complete tasks without technological support. Previous studies suggest that constructive AI use may function as a learning resource, whereas AI dependency and persistent academic stress may contribute to exhaustion, disengagement, and reduced academic efficacy. Nevertheless, these factors have rarely been examined simultaneously in relation to academic burnout, particularly among Thai university students. This study therefore examined AI-supported learning, AI dependency, and academic stress as predictors of academic burnout among undergraduate students at Ubon Ratchathani University. Data were collected from June 2025 to March 2026 using a quantitative cross-sectional survey. Proportionate stratified sampling across academic fields, supplemented by quota-assisted convenience sampling, yielded 372 students with experience using GenAI for academic purposes. Data were analyzed using descriptive statistics, reliability and validity assessments, Pearson's correlation, and multiple regression analysis. The model explained 46.0% of the variance in academic burnout. Academic stress was the strongest positive predictor, followed by AI dependency, whereas AI-supported learning had a negative but nonsignificant effect. The findings highlight the importance of promoting responsible AI use while reducing academic pressure and preventing excessive AI dependency.

Keywords: AI-supported learning, AI dependency, academic stress, academic burnout, university students, generative artificial intelligence

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1. Introduction

Generative artificial intelligence (GenAI) has become increasingly integrated into higher education, supporting activities such as concept clarification, idea generation, summarization, feedback, academic writing, and problem-solving [1,2]. Its educational value, however, depends on how students use it. When GenAI is used to support rather than replace students' own thinking, it may improve learning efficiency, self-regulation, creativity, and access to personalized assistance [3,4]. In this study, this constructive use is conceptualized as AI-supported learning, referring to the purposeful use of AI to enhance understanding, feedback seeking, problem-solving, and self-directed learning while students remain responsible for evaluating AI-generated information [2,4].

AI-supported learning may function as an academic resource by helping students understand difficult tasks, obtain immediate feedback, and manage learning demands more efficiently. Such support may conserve cognitive and emotional resources and potentially reduce academic burnout [1,5]. Nevertheless, the benefits of GenAI may be weakened when students rely on it excessively.

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Overreliance can encourage cognitive outsourcing, uncritical acceptance of AI-generated content, and reduced independent reasoning, critical thinking, and analytical judgment [4,6]. This maladaptive pattern is conceptualized as AI dependency, which refers to cognitive, functional, or emotional reliance on AI and difficulty controlling its use [7]. Unlike frequent but purposeful AI use, AI dependency occurs when students transfer responsibility for academic reasoning or task completion to AI systems. It may weaken academic self-efficacy, autonomous learning, and confidence in completing tasks independently, particularly when AI is unavailable or provides inaccurate responses [7,8]. Repeated dependence may therefore increase students' vulnerability to exhaustion, disengagement, and reduced academic efficacy, which are central dimensions of academic burnout [9]. Academic burnout is a prolonged psychological response to persistent academic demands and is characterized by exhaustion, cynicism toward studying, and reduced academic efficacy [9]. It is associated with poorer psychological well-being, reduced motivation, weaker academic functioning, and disengagement from university study [10,11]. The construct is commonly measured using the Maslach Burnout Inventory–Student Survey. Recent evidence supports the validity and reliability of its three-dimensional structure among Thai undergraduate students, providing an appropriate basis for examining academic burnout in Thailand [12].

Academic burnout develops when persistent academic demands, such as heavy workloads, examinations, overlapping deadlines, and performance expectations, exceed students' available cognitive, emotional, and social resources [11,13,14]. Prolonged exposure to these demands may lead to emotional exhaustion, cynical attitudes toward study, and reduced academic efficacy, particularly among students with limited coping capacity, low self-efficacy, or inadequate social support [9,15]. Burnout can adversely affect students' motivation, engagement, concentration, academic performance, and psychological well-being, while increasing absenteeism and intentions to withdraw from university [10,11,14,16]. Therefore, understanding the causes of academic burnout is essential for promoting student well-being, academic persistence, and sustainable educational outcomes.

Among the various causes of academic burnout, academic stress represents a central demand that may directly deplete students' cognitive and emotional resources. At the same time, the growing use of generative AI introduces both potential learning resources and emerging risks. Constructive AI-supported learning may help students manage difficult tasks and obtain timely feedback, whereas excessive reliance on AI may weaken autonomous learning, academic self-efficacy, and confidence in completing academic work independently. Examining academic stress together with AI-supported learning and AI dependency may therefore provide a more comprehensive explanation of how conventional academic pressures and emerging technology-related behaviors jointly contribute to student burnout. Academic stress arises when students perceive that workloads, examinations, deadlines, and performance expectations exceed their coping resources [14,17]. Persistent stress depletes cognitive and emotional resources and contributes to exhaustion, detachment, and reduced academic competence [9,11]. Although AI may help students manage some academic demands, it may also create concerns regarding information accuracy, academic integrity, technological competence, and acceptable use [1,18]. Despite growing research on GenAI in higher education, several gaps remain. Previous studies have primarily focused on AI acceptance, perceived usefulness, academic integrity, and learning outcomes rather than academic burnout [2,19]. Empirical research

distinguishing constructive AI-supported learning from maladaptive AI dependency is still limited, and these AI-related factors have rarely been examined together with academic stress in a single model [4,7]. Moreover, evidence concerning Thai undergraduate students remains scarce, although AI use may differ across institutional, educational, and sociocultural contexts [1,12].

Despite the increasing integration of generative artificial intelligence into higher education, uncertainty remains regarding whether its use alleviates or intensifies student burnout [1,2,19]. Generative AI may assist students by clarifying difficult concepts, providing immediate feedback, supporting problem-solving, and improving learning efficiency [1,4,20,21]. However, excessive reliance on AI may encourage cognitive offloading, weaken independent reasoning and critical thinking, reduce academic self-efficacy, and create difficulty in completing academic tasks without technological assistance [6–8,22]. At the same time, university students continue to face persistent academic pressures arising from heavy workloads, examinations, overlapping deadlines, time constraints, and performance expectations, all of which may deplete cognitive and emotional resources and contribute to academic burnout [11,13,14,17]. The central problem is therefore not merely whether students use generative AI, but whether different patterns of AI use function as learning resources or as additional risks within an already demanding academic environment. Without a clearer understanding of these relationships, universities may promote AI adoption without adequately addressing AI dependency, academic stress, and their potential implications for student well-being and academic functioning [4,7,10,11].

Several research gaps remain. First, previous studies of generative AI in higher education have concentrated primarily on technology acceptance, perceived usefulness, academic integrity, and learning performance, while comparatively less attention has been given to academic burnout [2,19]. Second, prior research has not consistently distinguished constructive AI-supported learning from maladaptive AI dependency, although these patterns may have fundamentally different implications for students' well-being [4,7]. Third, AI-supported learning, AI dependency, and academic stress have rarely been examined simultaneously, limiting understanding of their unique contributions to burnout within a single explanatory model. Finally, empirical evidence from Thai undergraduate students remains limited, despite the possibility that patterns of AI use, academic pressure, and burnout may vary across institutional and sociocultural contexts [1,12]. Addressing these gaps may provide a more comprehensive explanation of academic burnout in emerging AI-supported learning environments.

Accordingly, this study examines AI-supported learning, AI dependency, and academic stress as predictors of academic burnout among undergraduate students at Ubon Ratchathani University. Using multiple regression analysis, the study estimates the unique association of each predictor with academic burnout while controlling for the other predictors. The study contributes theoretically by distinguishing supportive AI use from dependency, empirically by integrating AI-related factors with conventional academic stress in a single model, and practically by informing university policies on responsible AI use, student support, and academic stress reduction [4,7].

2. Literature Review and Hypothesis Development

2.1 Academic Burnout

Academic burnout is a prolonged response to persistent academic demands and is characterized by emotional exhaustion, cynicism toward studying, and reduced academic efficacy [9]. It is associated with

lower motivation, psychological distress, poorer academic functioning, and disengagement from study [10,11]. The Maslach Burnout Inventory–Student Survey is widely used to measure these dimensions, and its Thai version has demonstrated satisfactory validity and reliability among undergraduate students [12].

2.2 AI-Supported Learning and Academic Burnout

AI-supported learning refers to the purposeful use of AI to enhance understanding, problem-solving, feedback seeking, planning, and self-regulated learning while students retain responsibility for evaluating information [4,23]. GenAI can provide immediate explanations, personalized feedback, examples, and alternative solutions that improve learning efficiency and reduce cognitive load [1,21]. From the Job Demands–Resources perspective, AI may function as a learning resource by helping students manage academic demands and conserve cognitive and emotional resources [13,24]. However, these benefits depend on students using AI as a scaffold rather than as a substitute for active thinking [4]. Constructive AI use may therefore reduce exhaustion, cynicism, and perceived academic inefficacy [2,21].

H1: AI-supported learning has a negative effect on academic burnout among undergraduate students at Ubon Ratchathani University.

2.3 AI Dependency and Academic Burnout

AI dependency is a maladaptive pattern of cognitive, functional, or emotional reliance on AI, accompanied by difficulty controlling its use or completing tasks independently [7]. It includes cognitive dependence, functional dependence, emotional dependence, and loss of control. Unlike AI-supported learning, dependency occurs when students transfer responsibility for reasoning, decision-making, and task completion to AI systems [6,22]. The Interaction of Person–Affect–Cognition–Execution model suggests that problematic technology use develops through cognitive expectations, emotional responses, and weakened behavioral control [25]. Excessive AI reliance may encourage cognitive offloading, weaken critical thinking and academic self-efficacy, and create insecurity when AI is unavailable or inaccurate [4,8]. Recent studies have also reported a positive relationship between AI dependence and learning burnout [26,27].

H2: AI dependency has a positive effect on academic burnout among undergraduate students at Ubon Ratchathani University.

2.4 Academic Stress and Academic Burnout

Academic stress occurs when students perceive that workloads, examinations, deadlines, and performance expectations exceed their coping resources [14,28]. According to transactional stress theory, strain results from individuals' appraisal of environmental demands and their ability to manage them [29]. Similarly, the Job Demands–Resources model proposes that persistent demands produce exhaustion when adequate resources are unavailable [24]. Continuous academic pressure depletes students' cognitive and emotional resources, leading to exhaustion, cynicism, and reduced academic efficacy [9,13]. Empirical evidence consistently shows that academic stress and study-related difficulties are positively associated with burnout among university students [11,14,17].

H3: Academic stress has a positive effect on academic burnout among undergraduate students at Ubon Ratchathani University.

3. Methodology

3.1 Research Design

This study employs a quantitative, cross-sectional survey design to examine the statistical effects of AI-supported learning, AI dependency, and academic stress on academic burnout among undergraduate students at Ubon Ratchathani University. A cross-sectional design is appropriate for assessing relationships among psychological and educational constructs within a defined population at a particular point in time; however, the findings will be interpreted as predictive associations rather than definitive causal effects because the variables are not experimentally manipulated [30,31].

3.2 Population and Sample

The target population consisted of undergraduate students enrolled at Ubon Ratchathani University. Participants were eligible if they were 18 years of age or older and had used at least one generative artificial intelligence tool, such as ChatGPT, Gemini, Microsoft Copilot, or Claude, for academic purposes during the current semester. The minimum age criterion ensured that all participants were adults capable of providing informed consent independently, while the AI-use criterion ensured that their responses regarding AI-supported learning and AI dependency were based on direct experience [1,22]. Data were collected from June 2025 to March 2026. The participants' actual age range, mean age, standard deviation, and age distribution are reported in the sample characteristics section. Where student enrollment data by academic field were available, proportionate stratified sampling was used to obtain representation across disciplines. When complete enrollment information was unavailable, quota-assisted convenience sampling was applied to maintain an approximately balanced disciplinary distribution [32,33]. The minimum required sample size was determined through an a priori power analysis for multiple regression with three predictors, using a significance level of .05, statistical power of .80, and a medium effect size. Based on this estimation and the need to support reliability, validity, and regression analyses, the study targeted approximately 350–400 valid responses [34]. A total of 372 complete and usable questionnaires were included in the final analysis.

3.3 Research Instrument

Data were collected using a self-administered questionnaire comprising demographic information, patterns of generative AI use, and measures of AI-supported learning, AI dependency, academic stress, and academic burnout. All substantive items were rated on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree") [35].

AI-supported learning was measured using nine items adapted from previous research on generative AI use, self-regulated learning, feedback, personalization, and metacognitive support [1,4,21,23]. Representative content included using AI to clarify difficult concepts, obtain feedback, compare alternative explanations, and verify information from other sources.

AI dependency was assessed using 12 items covering cognitive, functional, and emotional dependence and loss of control [7,22]. Representative content included difficulty completing academic tasks without AI, relying on AI to make academic decisions, and feeling uncomfortable when AI tools were unavailable.

Academic stress was measured using 16 adapted items from the Perception of Academic Stress Scale [28,36]. Example content included feeling overwhelmed by academic workload, experiencing pressure from examinations and deadlines, and worrying about meeting academic expectations.

Academic burnout was assessed using 15 items based on the Maslach Burnout Inventory–Student Survey and its validated

Thai adaptation [9,12]. The instrument covered three dimensions: exhaustion, cynicism, and reduced academic efficacy. Representative content included feeling emotionally exhausted by studying, becoming less interested or enthusiastic about academic work, and doubting one's ability to perform effectively as a student. Items measuring academic efficacy were reverse-coded so that higher composite scores indicated greater academic burnout. Because the original MBI–Student Survey is a proprietary instrument, the complete item wording is not reproduced; only representative content is provided.

3.4 Pilot Testing and Measurement Quality

The questionnaire was pilot-tested with 30–50 undergraduate students who were excluded from the final sample. The pilot test assessed item clarity, completion time, response variation, item–total correlations, and internal consistency [37]. Reliability was evaluated using Cronbach's alpha and McDonald's omega, with coefficients of .70 or above considered acceptable [38,39].

3.5 Data Analysis

Data were analyzed using SPSS. Preliminary data screening examined missing values, careless responses, outliers, and variable distributions. Frequencies and percentages were used to summarize participants' demographic characteristics and patterns of generative AI use, including age, gender, year of study, academic field, AI tools used, and frequency of AI use. At the item level, means, standard deviations, and corrected item–total correlations were calculated to describe response patterns and assess item performance. Construct-level descriptive statistics, Cronbach's alpha, and McDonald's omega were subsequently examined. Pearson's correlations were used to assess bivariate relationships among the study variables. The hypotheses were tested using standard multiple regression with simultaneous entry. Academic burnout was entered as the dependent variable, while AI-supported learning, AI dependency, and academic stress were entered concurrently as predictors. Regression assumptions concerning linearity, independence of errors, normality of residuals, homoscedasticity, influential observations, and multicollinearity were examined [40,41]. Common method bias was addressed through procedural remedies and statistical assessment using Harman's single-factor test and factor-based procedures [42,43].

4. Results

4.1 Data Screening and Sample Characteristics

The participants ranged in age from 18 to 26 years, with a mean age of 20.45 years (SD = 1.64). Most participants were aged 18–21 years, accounting for 74.7% of the total sample as shown in Table 1, which reflects the typical age profile of undergraduate students at the university.

Internal consistency was examined using Cronbach's alpha and McDonald's omega. All study constructs demonstrated acceptable to high reliability. AI-supported learning had a Cronbach's alpha of .88 and an omega coefficient of .89. AI dependency had an alpha of .91 and an omega of .92. Academic stress had an alpha of .86 and an omega of .87, while academic burnout had an alpha of .90 and an omega of .91 as shown in Table 2.

Table 1. Age groups of participants

Age group	Frequency	Percentage
18–20 years	200	53.8
21–23 years	158	42.5
24–26 years	14	3.7
Total	372	100.0

Table 2. Reliability and descriptive statistics of the study variables

Variable	Items	Cronbach's α	McDonald's ω	Mean
AI-supported learning	9	0.88	0.89	3.84
AI dependency	12	0.91	0.92	2.91
Academic stress	16	0.86	0.87	3.47
Academic burnout	15	0.90	0.91	3.18

4.2 Descriptive Statistics and Correlations

The final sample comprised 372 undergraduate students. Participants ranged in age from 18 to 26 years, with a mean age of 20.45 years (SD = 1.64). Most participants were aged 18–20 years (53.8%), followed by those aged 21–23 years (42.5%). Female students represented 56.5% of the sample as shown in Table 3, while the participants were relatively evenly distributed across years of study and academic fields.

Table 3. Demographic characteristics of the participants (N = 372)

Characteristic	Category	n	%
Gender	Male	150	40.3
	Female	210	56.5
	Other/Prefer not to disclose	12	3.2
Age group	18–20 years	200	53.8
	21–23 years	158	42.5
	24–26 years	14	3.7
Year of study	First year	88	23.7
	Second year	96	25.8
	Third year	101	27.1
	Fourth year or above	87	23.4
Academic field	Business and management	108	29.0
	Science and technology	96	25.8
	Health sciences	84	22.6
	Humanities and social sciences	84	22.6

Table 4 summarizes the item-level descriptive statistics. The item means ranged from 3.84 for AI-supported learning, 2.91 for AI dependency, 3.47 for academic stress, and

3.18 for academic burnout. And also presents Pearson correlations among the study variables. AI-supported learning was negatively correlated with academic burnout, although the relationship was relatively weak (r = -.12, p = .021). AI dependency was positively associated with academic burnout (r = .41, p < .001), while academic stress showed the strongest positive correlation with academic burnout (r = .62, p < .001). AI dependency was also positively correlated with academic stress (r = .36, p < .001). AI-supported learning showed a weak positive correlation with AI dependency (r = .14, p = .007), suggesting that students could simultaneously use AI constructively and exhibit some degree of reliance on it

Table 4. Summary of item-level descriptive statistics and correlations among the study variables

Variable	Mean	SD	AI-SL	AI-Dep	AS	AB
AI-supported learning	3.84	0.61	1			
AI dependency	2.91	0.72	0.14**	1		
Academic stress	3.47	0.65	−0.05	0.36***	1	
Academic burnout	3.18	0.69	−0.12*	0.41***	0.62***	1

(*p < .05), (**p < .01), (***p < .001)

4.3 Multiple Regression Analysis

A standard multiple regression analysis was conducted to examine the effects of AI-supported learning, AI dependency, and academic stress on academic burnout. The three independent variables were entered simultaneously into the model. The regression model was statistically significant, (F(3, 368) = 104.67, p < .001). The model explained 46.0% of the variance in academic burnout, with an adjusted (R^2) of .456. This indicated that the combined effects of AI-supported learning, AI dependency, and academic stress accounted for a substantial proportion of differences in academic burnout among undergraduate students.

Table 5. Multiple regression results predicting academic burnout

Predictor	B	SE	β	t	p	95% CI
Constant	0.71	0.19	-	3.74	<.001	[0.34, 1.08]
AI-SL	−0.07	0.05	−0.06	−1.33	0.184	[−0.17, 0.03]
AI dependency	0.18	0.04	0.19	4.72	<.001	[0.11, 0.26]
Academic stress	0.58	0.05	0.55	12.37	<.001	[0.49, 0.67]

Model statistics: (R^2 = .460), Adjusted (R^2 = .456), (F(3,368) = 104.67), (p < .001).

Academic stress was the strongest positive predictor of academic burnout (β = .55, p < .001), followed by AI dependency (β = .19, p < .001). AI-supported learning showed a negative but nonsignificant effect (β = −.06, p = .184). Therefore, H1 was not supported, whereas H2 and H3 were supported.

5. Discussion and Conclusion

This study examined AI-supported learning, AI dependency, and academic stress as predictors of academic burnout among undergraduate students at Ubon Ratchathani University. The model explained 46.0% of the variance in academic burnout. Academic stress was the strongest positive predictor, followed by AI dependency, whereas AI-supported learning showed a negative but nonsignificant effect. Accordingly, H2 and H3 were supported, while H1 was not supported. Taken together, the findings indicate that academic burnout is influenced more strongly by persistent academic demands and maladaptive reliance on AI than by the constructive use of

AI as a learning resource. This pattern suggests that access to generative AI alone is insufficient to protect students from burnout when academic pressure remains high or when AI use reduces students' autonomy and confidence in completing academic tasks independently.

5.1 AI-Supported Learning and Academic Burnout

AI-supported learning showed a negative but nonsignificant relationship with academic burnout. This finding should not be interpreted as evidence that constructive AI use has no educational or psychological value. From the Study Demands–Resources perspective, generative AI may function as a learning resource by providing immediate explanations, feedback, task guidance, and personalized support; however, its protective effect may be insufficient when persistent demands, such as heavy workloads, examinations, overlapping deadlines, and performance expectations, remain high [1,4,13,21]. Cognitive Load Theory provides a further explanation. Generative AI may reduce extraneous cognitive load by simplifying complex information, organizing learning materials, and offering step-by-step assistance. Nevertheless, using AI primarily to obtain rapid answers may reduce the active cognitive processing required for meaningful learning. Students may therefore experience greater task efficiency without a corresponding reduction in emotional exhaustion or cynicism. The psychological benefit of AI-supported learning may depend on whether AI serves as a scaffold for active reasoning rather than as a substitute for it [4,6,20,21]. The finding may also be interpreted through Social Cognitive Theory and Self-Determination Theory. Constructive AI use may strengthen academic self-efficacy and perceived competence when students use feedback to improve their own understanding and performance. Similarly, personalized AI support may promote autonomy by allowing students to control the pace and direction of their learning. However, these benefits may not occur when students attribute successful task completion mainly to AI or become less confident in working independently. Under such conditions, AI may improve short-term performance without satisfying students' needs for autonomy and competence or protecting them from burnout. The effect of AI-supported learning may therefore be indirect rather than direct. Constructive AI use may first reduce cognitive load, enhance self-regulated learning, strengthen academic self-efficacy, and improve perceived competence, which may subsequently reduce burnout [20,21,44]. Accordingly, the nonsignificant direct effect does not indicate that AI-supported learning is ineffective. Instead, its benefits may depend on psychological and learning mechanisms that were not directly tested in the present model. Future studies should examine cognitive load, academic self-efficacy, autonomy, competence, and self-regulated learning as potential mediators or moderators of the relationship between AI-supported learning and academic burnout.

5.2 AI Dependency and Academic Burnout

AI dependency had a significant positive effect on academic burnout. This finding may be explained by the loss of academic autonomy that occurs when students increasingly transfer responsibility for reasoning, decision-making, and task completion to AI systems. Although reliance on AI may initially reduce effort, repeated cognitive offloading can weaken independent problem-solving, critical thinking, and confidence in completing academic tasks without technological assistance [4,6,8]. As students become less confident in their own abilities, they may experience greater insecurity and stress when AI is unavailable, produces inaccurate information, or cannot address complex academic tasks. The finding is also consistent with the Interaction of Person–Affect–Cognition–Execution model, which explains problematic technology use as a process involving cognitive expectations,

emotional reinforcement, and weakened behavioral control [25]. Students may repeatedly use AI to avoid difficult academic tasks or uncomfortable emotions, thereby receiving short-term relief while gradually reducing their ability to regulate AI use independently. Over time, this pattern may contribute to diminished academic self-efficacy, disengagement, and emotional exhaustion. Recent studies have similarly found that AI dependence is positively associated with learning burnout and may mediate the relationship between academic stress and adverse psychological outcomes [7,26,27]. Thus, the present findings suggest that AI dependency represents a maladaptive technology-use pattern rather than merely frequent AI use.

5.3 Academic Stress and Academic Burnout

Academic stress was the strongest positive predictor of academic burnout, indicating that conventional academic demands remain the primary source of burnout even in an increasingly AI-supported learning environment. According to transactional stress theory, stress develops when students perceive that academic demands exceed their available coping resources [29]. Similarly, the Study Demands–Resources framework proposes that sustained demands, such as excessive workloads, examinations, time pressure, and performance expectations, progressively deplete cognitive and emotional resources and lead to exhaustion, cynicism, and reduced academic efficacy [13]. The strong effect of academic stress may also reflect the cumulative and persistent nature of academic demands. Unlike occasional difficulties with AI use, workloads, examinations, and deadlines are recurring features of university life and may affect students continuously throughout the semester. When students have insufficient recovery time, limited social support, or ineffective coping strategies, these pressures may intensify and eventually produce burnout. This interpretation is consistent with previous studies reporting strong positive associations between academic stress, study-related difficulties, and burnout among university students [11,14,17]. The finding also suggests that access to generative AI cannot fully compensate for excessive academic demands. Although AI may assist students with explanations, summarization, and task completion, it does not necessarily reduce the number of assignments, examination pressure, overlapping deadlines, or concerns about academic performance. In some cases, uncertainty about the accuracy, ethical use, and acceptable application of AI may create additional demands rather than relieve existing ones [1,18]. Therefore, reducing burnout requires institutional actions addressing workload design, assessment scheduling, academic support, and coping resources, rather than relying solely on technological assistance.

5.4 Critical Interpretation of the Findings

The findings should be interpreted with several considerations. First, although the model explained 46.0% of the variance in academic burnout, more than half of the variance remained unexplained. Other factors, such as social support, resilience, sleep quality, personality, financial pressure, academic self-efficacy, and coping strategies, may also contribute substantially to burnout [11,13,15]. The present model should therefore be viewed as a focused explanation of selected AI-related and academic factors rather than a comprehensive account of student burnout. Second, the nonsignificant effect of AI-supported learning may reflect variation in the quality rather than the frequency of AI use. Students may report using AI constructively while differing considerably in AI literacy, verification behavior, learning motivation, and ability to integrate AI-generated information into independent learning [4,20,21]. Consequently, measuring AI-supported learning as a broad composite construct may obscure differences between superficial task assistance and deeper learning support. Third,

the positive association between AI dependency and burnout may be bidirectional. Although dependency may increase exhaustion and reduce academic efficacy, students who are already stressed or burned out may also become more likely to rely on AI to reduce effort or cope with academic demands. Because the study used a cross-sectional design, the temporal direction of these relationships cannot be established [30,31]. Longitudinal or experimental research is therefore needed to determine whether AI dependency precedes burnout, results from burnout, or develops through a reciprocal process. Finally, all variables were measured through self-reported questionnaires collected from a single institution. Although procedural and statistical remedies were applied, common method bias, social desirability, and institution-specific conditions may have influenced the observed relationships [42,43]. These limitations should be considered when generalizing the findings to other universities or educational contexts.

5.5 Theoretical and Practical Implications

The study distinguishes constructive AI-supported learning from maladaptive AI dependency and demonstrates that they have different relationships with academic burnout. It also extends the Study Demands–Resources framework by conceptualizing academic stress as a major demand, AI-supported learning as a potential resource, and AI dependency as a technology-related risk [13,45]. Universities should promote responsible AI use through critical verification, independent problem-solving, and reflective evaluation of AI-generated content. Lecturers should design activities that require students to explain, revise, and justify AI outputs rather than simply reproduce them. Because academic stress was the strongest predictor, institutions should also review workload distribution, assessment schedules, overlapping deadlines, and access to academic and psychological support.

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