International Journal of Learning, Teaching and Educational Research
Vol. 24, No. 6, pp. 928-947, June 2025
https://doi.org/10.26803/ijlter.24.6.42
Received Apr 29, 2025; Revised Jun 3, 2025; Accepted Jun 16, 2025

Multifactorial Influences on Academic Performance among Medical Students: The Role of Study Habits, Artificial Intelligence, and Psychosocial Factors

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Abstract. Medical education is an academically demanding field influenced by various behavioral, technological, and psychosocial factors. This study investigated how study habits, artificial intelligence (AI) usage, stress levels, sleep patterns, English language proficiency, and social media engagement relate to academic performance among medical students at Hashemite University, Jordan. A cross-sectional survey was administered to 300 undergraduate students across all academic years. Respondents were categorized into high (GPA $\geq$ 3.0) and low (GPA < 3.0) academic achievers. Data were analyzed using chi-square and Mann–Whitney U tests and multivariable logistic regression ($a < 0.05$). Results indicate that students who studied alone, used structured learning resources, demonstrated strong English proficiency, lived with family, and maintained 6 to 7 hours of sleep before exams were significantly more likely to achieve a higher GPA. Although AI tools such as ChatGPT were widely used, no statistically significant association was found between AI usage frequency and GPA. In contrast, excessive social media use and elevated stress levels were negatively correlated with academic performance. Sole reliance on student handouts, especially outside exam periods, was also linked to lower GPA outcomes. These findings underscore the importance of promoting self-regulated learning strategies, cognitive load management, and responsible technology use in medical education. The study contributes a multifactorial perspective on academic success and calls for longitudinal research to further explore the nuanced role of AI and behavioral variables in academic achievement.

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Keywords: academic achievement; artificial intelligence; medical education; sleep patterns; study habits

1. Introduction

Medical education has always been one of the most intellectually demanding and emotionally taxing fields to venture into. Students will have to make an effort to understand a very large body of knowledge and simultaneously develop clinical as well as critical thinking skills. The complexity of the medical curriculum as well as intense assessments and the high expectations placed on future physicians will have positioned the bar so high as to have significant impacts on students' well-being and academic success (Klein & McCarthy, 2022). Although medical students may be the greatest achievers by the time they get selected, medicine then demands a whole new set of learning and time management skills and the adoption of a different way of studying (Abdulghani et al., 2014; Densen, 2011).

For educators and institutions keen on supporting student performance, understanding the factors contributing to academic success in medical school is vital. Of all these factors, learning habits are valued the most for influencing performance. Effective study behaviors such as structured time management, active learning techniques, and resource optimization have been positively associated with better academic performance, resilience in learning, and lowered rates of burnout (Bin Abdulrahman et al., 2021; Credé & Kuncel, 2008). Many students continue to rely on passive or ineffective study strategies, such as rote memorization or last-minute cramming, which can progressively exacerbate academic difficulties—even among otherwise capable and intelligent learners. Traditional study methods have been increasingly transformed by the integration of artificial intelligence (AI) technologies, which are reshaping the educational landscape through innovative, personalized, and data-driven learning approaches. AI tools such as ChatGPT, DeepSeek, and adaptive learning platforms have now found their way into students' academic lives to provide them either with new ways of adding value to the access of information, personalizing study plans, or streamlining high-efficiency learning plans. AI is indeed believed to produce better academic outcomes, according to preliminary research findings (Sun & Zhou, 2024). However, in medical education, such sources are unexplored regarding how AI usage aligns with traditional studying habits and performance indicators such as grade point average (GPA).

In addition, various psychosocial and surrounding issues are linked with study behavior in determining academic performance. Proficiency in English, especially in countries where medical education is imparted in English, has significantly been linked to comprehension, examination performance, and overall academic achievement, including in non-native English-speaking countries (Kaliyadan et al., 2015). Stress management, quality of sleep, and the role of social media can boost or impede academic success. For instance, high stress levels in students result in impaired cognitive functioning and lower academic achievement (Shadid et al., 2020), while sufficient sleep is essential for memory consolidation and cognitive flexibility (Taylor et al., 2013).

Although there have been a growing number of studies in the areas of study habits, stress, and technology use with respect to academic performance, research remains limited concerning their joint association in particular populations of medical students. This is particularly true for Jordan and other Middle Eastern countries, where the cultural, linguistic, and educational system differences might be modifiers of these effects. The current work attempted to address this void by studying the association between study habits, AI use, and academic performance among undergraduate medical students at Hashemite University in Jordan. Effective and harmful practices were explored, while taking into consideration factors such as English proficiency, stress levels, sleep patterns, and social media use.

Medical education requires not only an extensive acquisition of knowledge but also considerable self-regulating learning with cognitive, emotional, and technological constraints (Wu et al., 2020). Under these aspects, the present study was theoretically framed in two educational theories: self-regulated learning theory (Zimmerman, 2002) and cognitive load theory (Sweller, 1988). According to self-regulated learning theory, students who strategically plan, monitor, and adjust their study behaviors tend to achieve superior academic performance compared to their peers. According to cognitive load theory, minimizing extraneous mental loads such as stress, fatigue, and distraction is essential for maintaining optimal cognitive function, which is critical for effective learning. This study operated within a framework that examines how study habits—including patterns of AI use—interact with psychosocial stressors, sleep behaviors, and social media engagement to influence the academic performance of medical students.

Accordingly, this study sought to address the following research questions:

- RQ1. How do study habits and resource preferences influence academic performance among medical students?
- RQ2. What is the relationship between AI tool usage and students' GPA outcomes?
- RQ3. To what extent do psychosocial factors—such as stress, sleep duration, and social media usage—affect academic performance?
- RQ4. How does English language proficiency correlate with academic achievement in a non-native English-speaking context?

These questions were examined within the frameworks of self-regulated learning theory and cognitive load theory, which together provide a lens to interpret the dynamic interplay between individual learning behaviors, cognitive demands, and technological engagement in medical education.

2. Literature Review

2.1 Study Habits and Academic Performance

Numerous findings show that study habits are instrumental in determining academic outcomes across all levels of education. Study habits, skills, and attitudes are treated as the bedrock of collegiate success, alongside cognitive ability and academic self-efficacy (Credé & Kuncel, 2008). In medical education, where the cognitive load and demands on retention are most intense, efficient study habits become an even more central issue. Students who employ structured, active learning techniques, for example, paraphrasing information, spaced repetition, and self-testing, tend to outperform students who rely on passive techniques, such as rereading or cramming (Alzahrani et al., 2018; Bin Abdulrahman et al., 2021; D'antoni et al., 2010; Liew et al., 2015). It seems, therefore, that students who use study strategies compatible with the nature of the course content, for example, preparing concept maps for complex systems or utilizing question banks for factual retention, are likely to be more adaptive and resilient. However, some students are still relying on lecturer handouts or non-standardized summaries, inferring that this might enhance their development of superficial learning and limited integration of knowledge (Alzahrani et al., 2018). It thus becomes imperative to understand students' preferences and promote evidence-based study techniques as educational priorities (Rezaie Looyeh et al., 2017).

Self-regulated learning strategies are vital to effective academic performance and are characterized by the setting of goals, management of resources, and responsive adaptations to academic demands (Bin Abdulrahman et al., 2021; Credé & Kuncel, 2008). Self-regulated learning theory advances active, reflective, and strategic study methods (Zimmerman, 2002) to account for the superior performance of students when compared to passive-strategy use. In a parallel vein, in relation to the predicting variables of success propounded by cognitive load theory (Sweller, 1988), the theory posits that success arises through the reduction of unnecessary cognitive load. These predictors include high levels of stress, chronic sleep deprivation, and distractions through digital means, for example, excessive social media use. The newly introduced AI tools in education add a myriad of new variables into this equation that might, at this point, still not be well understood and influence cognitive load and self-regulation mechanisms.

2.2 Stress, Sleep Patterns, and Academic Achievement

Stress is one of the most significant issues for medical students, a state often determined by academic demands, clinical responsibilities, and uncertainties about the student's subsequent career prospects. High stress levels affect concentration and memory functions, ultimately resulting in lower academic achievement (Shadid et al., 2020). On the other hand, students facing excessive stress are at higher risk of burnout, depression, and leaving their academic path.

The quality of sleep is another cog in the wheel of academic success. That is, adequate sleep (6–7 hours per night) is needed for memory consolidation, executive function, and emotional regulation (Taylor et al., 2013). Evidence has shown that students who experience irregular sleep patterns or chronic sleep deprivation are at a disadvantage academically compared to their peers who are well rested (Nihayah et al., 2011). Interestingly, such findings imply that medical students tend to trade sleep time for study time, thus undermining their performance in academic endeavors.

2.3 English Language Proficiency as a Success Factor

Where English is the language of instruction, proficiency in English is a major academic performance predictor. Research from Saudi Arabia has shown a significant correlation between medical students' English language proficiency and their performance in both written and oral examinations (Kaliyadan et al., 2015). It can be safely asserted that students with limited English proficiency face compounded academic disadvantages as they struggle to comprehend difficult medical texts, articulate clinical reasoning, and perform well in oral examinations.

2.4 Artificial Intelligence in Enhancing Education

The expeditious incorporation of AI technologies into education has reshuffled the rigid traditional paradigms of learning. Generative AI tools such as ChatGPT furnish students with on-demand explanations, practice questions, and simulated patient scenarios. A meta-analysis conducted by Sun and Zhou (2024) found a positive correlation between academic enhancement due to AI integration in learning and teaching across various disciplines, showcasing its moderate effect size. Sugiarso et al. (2024) also found that the presence of AI tools enhances academic performance and promotes a higher degree of learning autonomy among high school students, casting the significance of these findings into the area of medical education.

The real impact of AI use among medical students is still unclear, however. Personalized learning is highly promising as an avenue provided by AI; however, many have warned that an overdependence on artificially generated and AI-assisted-generated content that has not been critically appraised could have a detrimental effect on the development of deep learning and therefore on clinical reasoning (Holmes et al., 2022; Zawacki-Richter et al., 2019). This research, therefore, contributes to the new discourse on the relationship between patterns of AI use and GPA outcomes among medical students.

2.5 Social Media Uses and Academic Distraction

Social media functions as a double-edged sword in the present day in regard to education. An array of educational content materials and peer collaboration opportunities abounds on YouTube, X (formerly Twitter), and Facebook; however, distractions of equal magnitude abound too. The problematic use of social media has been linked to declines in academic performance through time displacement, attenuated attention spans, and widespread procrastination (Takieddin et al., 2022). The relative impact of moderate or heavy AI use versus other study habits is an area still begging to be investigated.

3. Methodology

3.1 Study Design and Setting

A cross-sectional observational study was conducted at the Faculty of Medicine, Hashemite University, Zarqa, Jordan from March 2024 to May 2024 under the pre-graduate medical students of all academic years. Ethical clearance was obtained from the Institutional Review Board (IRB# No.13/7/2022/2023). All respondents provided informed consent electronically before completing the survey. Responses were kept fully anonymous and confidential and no identifying personal information was collected. Participation was fully voluntary, with no academic or financial benefits provided. The study aimed to investigate the relationship between study habits, AI utilization, psychosocial factors, and academic performance in a contemporary cohort of medical students.

3.2 Respondents and Sampling

The target population included undergraduate medical students from the first to the sixth year. Respondents were recruited voluntarily using a convenience sampling strategy. The online survey link was distributed through institutional email invitations, class announcements, student WhatsApp groups, and social media platforms affiliated with Hashemite University medical students. Participation was not randomized and was open to all students who met the inclusion criteria. While efforts were made to encourage wide participation across all academic years and gender groups, no stratification or randomization procedures were employed.

A total of 300 students completed the questionnaire. Inclusion criteria comprised being currently enrolled in the medical program and willing to participate. Exclusion criteria were incomplete surveys and students enrolled in non-medical programs. Although no a priori sample size calculation was conducted, a post-hoc sensitivity analysis indicated that a sample size of 300 provided approximately 80% statistical power to detect medium effect sizes (Cohen's $d \approx 0.3$) at a 5% significance level.

3.3 Development and Validation of the Study Instrument

The survey instrument was developed based on a comprehensive literature review of previous studies addressing study habits, AI usage, and factors influencing academic performance among medical students (Alzahrani et al., 2018; Bin Abdulrahman et al., 2021; Sun & Zhou, 2024). The questionnaire was divided into multiple domains, including demographic characteristics, academic background, study behaviors, technology usage, stress indicators, sleep patterns, and extracurricular involvement. The survey was developed to capture key constructs associated with self-regulated learning and cognitive load, assessing domains such as study planning behaviors, AI tool engagement, sleep patterns, stress experiences, and social media usage.

A form of content validation included was the review of the draft questionnaire by an expert panel consisting of three individuals with specialization in medical education and biostatistics. The reviewers provided feedback for the modification of items to meet the criteria of clarity, relevance, and comprehensiveness. A pilot study was conducted with 30 randomly selected medical students to evaluate the clarity, relevance, and reliability of the questionnaire. Based on respondent feedback, minor revisions were made to improve item clarity and response consistency. The data from the pilot study were excluded from the final analysis to ensure the integrity of the main dataset. Cronbach's alpha was used to evaluate internal consistency, yielding acceptable reliability (α = 0.82) in the self-constructed key scales.

3.4 Questionnaire Content

The final questionnaire covered the following domains:

- Demographic data: age, gender, place of residence (dormitory vs. family home), presence of chronic illnesses.
- Academic data: medical year, cumulative GPA, high school score, English language proficiency. High achievers were defined as GPA ≥ 3.0. Structured resources include lecture slides, textbooks, and validated multiple-choice question (MCQ) banks.
- Study behaviors: daily study hours, preferred study methods (individual, group, video-based learning, peer teaching), sources of study materials. Structured resources refer to officially provided materials such as lecture slides, textbooks, and verified MCQ banks, as opposed to informal notes or peer summaries.
- AI utilization: frequency of AI tool usage (daily, weekly, occasional), type of AI platforms used (ChatGPT, DeepSeek, Gemini, others), perceived impact of AI on study efficiency.
- Wellness indicators: sleep hours before exams, self-reported stress levels, use of stress-relief medications, regular exercise habits.
- Technology and social media use: daily hours spent on social media platforms for both academic and non-academic purposes.
- Extracurricular activities: involvement in research activities and educational programs outside the formal curriculum.

The survey assessed frequency and platform preference for AI use but did not specify the tasks performed (e.g., summarizing content, generating quizzes) or the depth of cognitive engagement, limiting the precision of AI-related interpretation. Stress was measured using a simplified self-report item adapted from the Perceived Stress Scale (PSS), and English proficiency was assessed through a single self-rated item rather than a standardized test. The complete questionnaire is available as supplementary material upon request.

3.5 Outcome Measures

The main outcome was academic performance as self-reported cumulative GPA. Academic achievement was operationalized using cumulative self-reported GPA. For the primary analysis, students were classified into high achievers (GPA ≥ 3.0) and low achievers (GPA < 3.0) based on institutional academic thresholds. However, exploratory sub-group analyses using finer GPA bands (e.g., 2.0–2.49, 2.5–2.99, 3.0–3.49, 3.5–4.0) were also conducted to investigate nuanced performance differences across the achievement spectrum.

3.6 Statistical Analysis

Stata version 17 (StataCorp LLC, College Station, TX, USA) was utilized to analyze all data. Descriptive statistics were computed for each variable. Continuous variables were assessed for their normality using a histogram, Q-Q plot, and Kolmogorov-Smirnov and Shapiro-Wilk tests. Normally distributed variables are presented as mean ± standard deviation (SD), while non-normally distributed variables are expressed as median with interquartile range (IQR). Categorical variables are also summarized using frequencies and percentiles.

The Mann-Whitney U Test was used to compare independent continuous variables, whereas the chi-square test was used to determine the association between categorical variables. The threshold for statistical significance was set up for two-tailed tests, less than 0.05. A multivariable logistic regression analysis was performed to determine the independent predictors of high academic achievement (GPA ≥ 3.0). The entry into the multivariate model was determined by clinical specificity and a very liberal cut-off of $p < 0.20$ from univariable analyses so as not to preclude the identification of any important predictors. Key confounding variables, such as year of medical study, English proficiency, hours of sleep, as well as social media usage, were controlled.

Variables such as year of study and English proficiency were controlled for in the multivariable regression. However, data on prior academic performance and learning disabilities were not collected and thus not included in the mode. Odds ratios (ORs) and 95% confidence intervals (CIs) were used to express the results. The model's goodness of fit was assessed using the Hosmer-Lemeshow goodness of fit test. Assessment of independent diversity variables for multicollinearity involved variance inflation factor (VIF) computation; any VIF > 5 was considered to have problematic collinearity. All statistical analyses were described according to the STROBE guidelines for observational studies reporting in epidemiology, cross-sectional study type.

4. Results

4.1 Respondent Characteristics

Data on the respondent characteristics are presented in Table 1. For the 300 medical students who returned their questionnaire forms, the age distribution was found to be 19 years at a minimum and 22 years at a maximum, with a median of about 20 years. Regarding gender, the female representation (57%) was larger compared to the male representation (43%). Most of the students (i.e., 92%) lived at home with their parents, whereas the remaining 8% lived in student hostels. Furthermore, 59.33% belonged to the basic sciences (first to third years), while 40.67% belonged to the clinical sciences (fourth to sixth years). The high-performing students (GPA ≥ 3.0) totaled 205 students or 68.33%. The remaining 95 students (31.67%) had a GPA of <3.0. Most of the students (>90%) were rated as having a high school grading of >90%, with their proficiency in the English language rated as good (63.67%) or excellent (28%). Only 7.7% of the respondents reported having a chronic illness.

Table 1: Demographic characteristics and factors associated with academic performance among participating medical students (N = 300)

Variable	Category	Frequency (%)
Age	Median (range)	20 (19–22)
Gender	Male	129 (43%)
	Female	171 (57%)
Place of residency	Family home	276 (92%)
	Dormitory	24 (8%)
Academic GPA	GPA ≥ 3.0	205 (68.33%)

	GPA < 3.0	95 (31.67%)
High school score	>90%	280 (93.33%)
	80%–90%	17 (5.67%)
	<80%	3 (1%)
English proficiency	Excellent	84 (28%)
	Good	191 (63.67%)
	Bad	25 (8.33%)
Chronic illness presence	Yes	23 (7.67%)
	No	277 (92.33%)

These findings suggest that students with stronger English proficiency and those residing with their family tend to perform better academically, supporting the role of both linguistic competence and a stable living environment in shaping GPA outcomes (RQ4).

The comparison between high and low GPA groups revealed that students who were dormitory residents were more likely to have a lower GPA than those living with family (12.63% vs. 5.85%, p = 0.04). Higher English proficiency was also associated with higher GPA performance (p = 0.022). A lower high school score (<80%) was significantly associated with a lower GPA (p = 0.011), although the presence of chronic illnesses showed no significant association with academic performance. These results are visually summarized in Figure 1, illustrating the distribution of key demographic and academic characteristics across GPA performance groups.

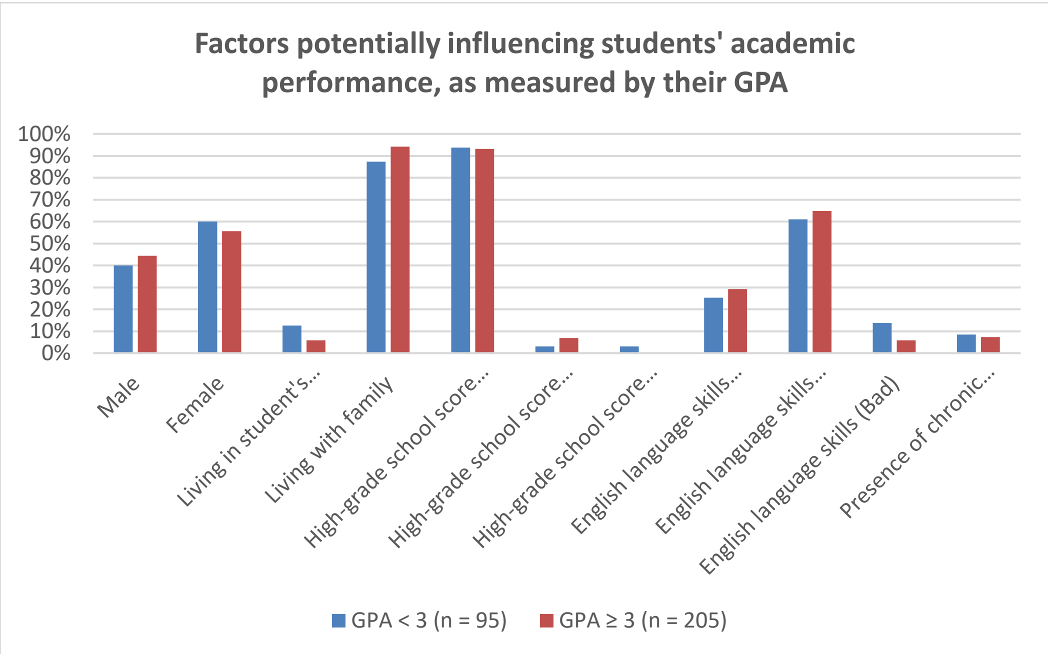

Figure 1: Factors influencing medical students' academic performance, including study habits, AI utilization, stress levels, and sleep patterns

4.2 Artificial Intelligence Usage

Among the respondents, 87.3% reported using AI tools for study purposes. Gender differences were noted, with 51.5% of male students and 35.8% of female students utilizing AI. Regarding usage frequency, 46.8% of the students reported daily use, 18.7% occasional use, 11.7% twice a week, and 15.7% four times a week. ChatGPT was the dominant AI tool used (86%), followed by smaller proportions using DeepSeek, Gemini, and other platforms. While 68.5% of respondents with a GPA ≥ 3.0 reported using AI, compared to only 18.7% among those with a lower GPA, the association between AI usage and GPA did not achieve statistical significance.

Although the majority of the respondents reported integrating AI tools into their study routines, the absence of a significant correlation with GPA indicates that the frequency of AI use alone does not predict academic success. This finding underscores the need to examine the quality and context of AI engagement rather than mere usage metrics (RQ2).

4.3 Study Habits

Table 2 displays data on the respondents' study habits.

Table 2: Study habits among participating medical students (N = 300)

Study habit	Category	Frequency (%)
Daily study hours	<1 hour	5.67%
	1–2 hours	14.33%
	3–4 hours	33.33%
	5–6 hours	29.00%
	>6 hours	17.67%
Preferred study method	Studying alone	57.33%
	Watching online videos	34.33%
	Group study	5.67%
	Teaching others	2.67%
Main study sources (non-exam period)	Lecture slides/notes	83.33%
	Videos	68%
	Student handouts	34%
	Reference textbooks	21.33%
	USMLE books	18.67%
	Internet resources	33.33%
	Question banks (Kaplan)	14%

Daily study hours varied among respondents, with 33.33% studying 3 to 4 hours, 29% studying 5 to 6 hours, and 17.67% studying more than 6 hours per day. There was no significant difference in daily study hours between high- and low-GPA groups. The preferred study method was solitary study (57.33%), followed by watching online medical videos (34.33%), group study (5.67%), and teaching others (2.67%). When exams were not imminent, the most common study resources were lecture slides with notes (83.33%) and online videos (68%), with lesser reliance on student handouts (34%) and textbooks (21.33%). However, when exams approached, reliance on lecture slides increased to 90.33%, while past exam questions (44%) and MCQ exam review books (38.67%) became significant supplementary resources. Furthermore, respondents with a higher GPA were significantly less likely to rely on student handouts when exams were not expected (p = 0.001) and more likely to use structured lecture materials when exams approached (p = 0.004). The use of previous exam questions, reference textbooks, and online self-assessment MCQs did not show statistically significant differences between groups.

These patterns indicate that the quality and structure of study strategies—particularly the preference for independent study and the use of curated academic resources—are more predictive of GPA outcomes than study duration alone. This supports the centrality of self-regulated and intentional learning habits in academic achievement (RQ1).

4.4 Stress, Sleep, and Social Media Usage

Table 3 displays data on factors associated with the respondents' academic performance.

Table 3: Factors associated with academic performance (GPA ≥ 3 vs. GPA < 3)

Variable	GPA < 3 (n = 95)	GPA ≥ 3 (n = 205)	*p*-value
Living with family	87.37%	94.15%	0.04
Poor English skills	13.68%	5.85%	0.022
High school score of <80%	3.16%	0%	0.011
Mild stress (before exams)	9.47%	20%	0.023
Extreme stress (before exams)	18.95%	11.2%	0.070
Sleep of <4 hours (before exams)	18.95%	9.76%	0.026
Sleep of 6–7 hours (before exams)	33.68%	50.24%	0.007
Social media use of >5h/day	33.68%	20.98%	0.018
Use of student handouts	47.37%	27.8%	0.001
Use of stress-relief medications	15.79%	8.29%	0.272

Stress levels varied significantly between the groups. Mild stress was more prevalent among high-achieving students (20% vs. 9.47%, p = 0.023), whereas extreme stress tended to be higher among those with a lower GPA, although not reaching statistical significance. Usage of medications for stress relief showed no significant association with GPA (p = 0.272). In terms of sleep, data show that respondents who slept for 6 to 7 hours the night before the exam attained a much higher GPA (p = 0.007) as compared to their counterparts who slept for less than

4 hours, who reported a significantly lower GPA (p = 0.026). Sleep duration thus appeared to play a critical role in academic outcomes. Social media usage was another important factor associated with academic performance. Respondents spending more than 5 hours daily on social media were significantly more likely to have a lower GPA (p = 0.018). However, no significant differences were observed for respondents spending 1 to 4 hours on social media daily.

Collectively, these findings highlight the detrimental effects of excessive stress, sleep deprivation, and prolonged social media use on academic performance. They affirm the significance of psychosocial and behavioral regulation in maintaining cognitive efficiency and sustaining academic outcomes (RQ3).

4.5 Multivariable Logistic Regression Analyses

Independent predictors of academic performance were identified by multivariable logistic regression (Table 4).

Table 4: Multivariable logistic regression for predictors of high academic achievement (GPA ≥ 3.0)

Predictor	Odds ratio (OR)	95% CI	p-value
Living with family	5.94	1.70–20.80	0.005
Self-assessment MCQ use	3.47	1.25–9.64	0.017
Extreme stress	0.15	0.04–0.56	0.005
High stress	0.22	0.07–0.71	0.011
Moderate stress	0.24	0.07–0.79	0.019
Use of student handouts (non-exam)	0.40	0.19–0.86	0.018

Family living increased the odds of a GPA ≥ 3.0 by 6 times (OR =5.94, p = 0.005). Generally, self-assessment MCQ tests from the Internet were positively related to better academic performance (OR = 3.47, p = 0.017). Extreme stress (OR = 0.15, p = 0.005) and high stress (OR = 0.22, p = 0.011), as forms of pre-examination psychological pressure, both emerged as significant negative predictors of GPA. Likewise, reliance on student handouts was negatively associated with academic success, suggesting limited effectiveness in supporting exam readiness (OR = 0.40, p = 0.018).

The multivariable analysis reinforces earlier findings. Structured study behaviors and familial support were strong positive predictors of GPA, while unmanaged stress and reliance on low-quality study materials posed significant risks to performance. Together, these results demonstrate the interdependence of cognitive, behavioral, and environmental factors in shaping academic achievement across all four research questions.

5. Discussion

This study examined the relationships between study habits, AI use, psychosocial factors, and academic performance among medical students at Hashemite University, Jordan. The results provide further insights into the multifactorial nature of achieving academic success in medical education and include the significance of traditional study methods, new-age technological tools, stress management, sleep hygiene, and social media behavior.

In relation to RQ1 (How do study habits and resource preferences influence academic performance among medical students?), the findings of this study align closely with established educational theories. Students who preferred solitary study and utilized structured resources such as lecture slides demonstrated higher academic performance, consistent with self-regulated learning theory, which emphasizes proactive, autonomous learning behaviors (Zimmerman, 2002). Conversely, students who reported excessive stress, shorter sleep durations before exams, or high daily social media use exhibited poorer academic outcomes, supporting the assertion of cognitive load theory that extraneous mental demands negatively impact learning efficacy (Sweller, 1988). The lack of significant correlation between AI usage frequency and GPA suggests that the quality and depth of AI engagement, rather than mere usage, may be critical, a nuance consistent with self-regulated learning principles that stress critical reflection and strategic tool use.

5.1 Study Habits and Academic Performance

The results confirmed that solitary study methods and reliance on structured resources such as lecture slides are associated with higher GPA outcomes. This aligns with previous studies that emphasized the effectiveness of independent study in promoting active engagement and deeper learning (Alzahrani et al., 2018; Bin Abdulrahman et al., 2021; Farkas et al., 2016). Although group study and teaching others are often promoted for collaborative learning, their lower prevalence in this sample may reflect a cultural or logistical preference for solitary study in this setting. Notably, an overreliance on student handouts without integrating broader textbook or evidence-based resources was negatively associated with academic success, supporting the need for a diversified and critical approach to studying.

5.2 The Emerging Role of Artificial Intelligence

In addressing RQ2 (What is the relationship between AI tool usage and students' GPA outcomes?), while a large proportion of the students reported utilizing AI tools, particularly ChatGPT, the correlation between AI usage and GPA was not statistically significant. This finding contrasts with emerging meta-analytic evidence suggesting positive effects of AI integration on student performance (Sun & Zhou, 2024). One possible explanation is that the mere use of AI tools does not guarantee effective learning; rather, the quality and critical engagement of AI-generated content and its integration into active study processes may be the determining factors. Additionally, differences in digital literacy and AI usage strategies could account for the lack of significant association observed. These findings highlight the need for future research into AI literacy and its role in optimizing educational outcomes.

5.3 Psychosocial Factors: Stress, Sleep, and Family Environment

In relation to RQ3 (To what extent do psychosocial factors—such as stress, sleep duration, and social media usage—affect academic performance?), it was found that psychosocial variables played a substantial role in academic performance. Consistent with prior studies (Shadid et al., 2020; Taylor et al., 2013), extreme and high stress levels were associated with significantly lower GPAs. Students who reported moderate or mild stress tended to perform better, suggesting that manageable levels of academic pressure might enhance performance through adaptive motivational mechanisms, while excessive stress impairs cognitive and emotional functioning.

Based on the integration of self-regulated learning theory and cognitive load theory, as well as the empirical findings of this study, we propose a multifactorial academic regulation (MAR) model for understanding the academic performance of medical students (Figure 2). This model conceptualizes student success as the result of an interplay between self-regulated study behaviors (e.g., structured solitary study, critical resource use), cognitive load management (e.g., stress reduction, sleep optimization, limited distraction), and technology engagement quality (e.g., strategic rather than passive AI use). The MAR model emphasizes that technological adoption alone is insufficient for improving academic outcomes unless it is embedded within self-regulatory strategies that minimize cognitive overload. Furthermore, it accounts for sociocultural factors, such as familial support, which may buffer cognitive stress in certain educational contexts. By framing academic performance as a dynamic, multi-domain regulatory process rather than a static outcome of isolated behaviors, the MAR model invites future longitudinal and interventional research to validate and refine its applicability across diverse medical education environments.

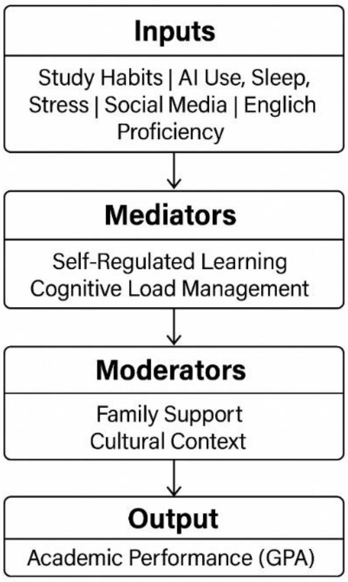

Figure 2: Multifactorial academic regulation (MAR) model integrating study behaviors, cognitive load, and technology use with sociocultural moderators influencing academic performance

Similarly, sleep duration emerged as a significant predictor of GPA. Students who maintained 6 to 7 hours of sleep before exams had better academic outcomes, consistent with the cognitive benefits of sleep in memory consolidation and problem-solving (Nihayah et al., 2011; Taylor et al., 2013). Moreover, this underlines the importance of including education on sleep in student counseling programs. Living arrangements were also found to influence academic outcomes, with GPAs being higher for students living with family compared to students staying in dormitories. This observation diverges from studies suggesting that on-campus living enhances academic engagement (Maddineshat et al., 2019), possibly reflecting cultural differences in family support systems and living conditions in Jordan.

5.4 English Proficiency and Academic Success
With regard to RQ4 (How does English language proficiency correlate with academic achievement in a non-native English-speaking context?), language proficiency emerged as a significant academic determinant, supporting prior findings showing that strong English skills correlate positively with exam performance (Kaliyadan et al., 2015). The main medium of curriculum instruction at Hashemite University is English, which does not bode well for students for whom English is not their first language. These students will end up suffering in terms of content comprehension and writing exams. Therefore, setting up programs for early English proficiency development among medical students is an imperative need in contexts where the English language is not a native one.

5.5 Social Media: A Double-Edged Sword
The negative impact of excessive social media usage (>5 hours/day) on GPA underscores concerns about time displacement and attentional fragmentation (Takieddin et al., 2022). While moderate use of educational platforms may support learning, excessive engagement likely disrupts study schedules and cognitive focus. However, the literature remains mixed in opinion, suggesting that context, type of usage, and self-regulation are key mediators of the academic impact of social media.

5.6 Critical Reflection
While the present study reinforces many established findings in the field, it also highlights emerging complexities that warrant further consideration. The divergence between our findings on AI usage and previous meta-analyses suggesting positive academic impacts (Sun & Zhou, 2024) may reflect critical differences in how AI tools are engaged by students. It is possible that superficial or passive use of AI platforms, without deeper cognitive integration or critical appraisal, may fail to translate into measurable academic benefits. Moreover, cultural, institutional, and curricular variations could influence the effectiveness of AI tools, suggesting that educational environments need to explicitly train students not just in using AI but in optimizing AI-supported learning.

While AI usage frequency was measured, the study did not capture how students used AI—such as for summarizing, generating questions, or explaining content—or whether usage was active or passive. This limitation may explain the lack of a significant correlation with GPA and suggests that task-specific and engagement-focused measures are needed in future research. Similarly, the unexpected advantage observed among students living with family, contrary to some prior literature (Maddineshat et al., 2019), could be explained by stronger familial support structures and reduced environmental distractions in the local context of Jordan. These nuances underscore the importance of considering sociocultural and behavioral moderators when interpreting academic performance data across different settings.

5.7 Strengths and Limitations

A major strength of this study is its comprehensive assessment of multiple variables, including traditional study habits, AI utilization, stress levels, sleep patterns, English proficiency, and social media usage, within a single analytic framework. The relatively large sample size enhances the generalizability of findings within the institution. However, there are certain limitations that require acknowledgment. The cross-sectional design rules out causal inference, while self-reporting holds room for issues related to recall and social desirability bias. AI usage was measured using a binary and frequency-based approach that did not qualitatively assess how AI was used or for what purpose; this might have further diluted any associations that were seen with GPA. Additionally, cultural factors specific to Jordanian medical education contexts may limit generalizability to other regions.

5.8 Practical Implications

The findings carry significant implications for the domains of medical education, governance, and student life. Institutions need to formulate intentional policies in relation to the promotion of structured study strategies; a critical approach to resource utilization, stress, and sleep management; and digital literacy, which entails the responsible use of AI and social media. In addition, tailored programs for English proficiency may serve to enhance the academic performance of at-risk students. Finally, researchers should implement longitudinal studies to investigate how changes in study habits and technological integration impact educational outcomes and professional competence over time (Dort et al., 2015).

6. Conclusion

Overall, in the case of medical students, success in academics is mediated by self-regulation of learning strategies and effective management of cognitive load. Therefore, any improvements in self-monitoring, critical engagement with digital learning aids, good patterns of sleep, and minimal extraneous stressors will contribute immensely to academic performance and outcomes. Embedding these theoretical considerations into curriculum design and student support would assist in achieving not only better academic performance but also better resilience and competency over time.

This study offers a comprehensive examination of how various academic, behavioral, technological, and psychosocial factors interplay to influence medical students' academic performance. In doing so, it makes a novel academic contribution by integrating traditional predictors of success (such as study habits and stress levels) with emerging factors such as AI utilization within a single analytic framework. Most prior studies addressed these dimensions separately; this research is among the first in a Middle Eastern medical education context to demonstrate how both classical and contemporary variables collectively shape academic achievement.

A key finding is that while AI tools such as ChatGPT are widely adopted by medical students, their mere use does not correlate significantly with academic success. This challenges the prevailing assumption that technological adoption inherently leads to better educational outcomes. Instead, the quality of AI engagement, critical thinking integration, and selective use aligned with curriculum demands may represent the true determinants of benefit – a nuanced perspective that adds a fresh dimension to AI-related education research. This lack of association may reflect either the ineffective or superficial use of AI tools by students, or it may indicate that AI integration into academic routines remains too recent or unstructured to generate measurable academic benefits.

Additionally, this study reinforces the traditional pillars of academic success, namely structured independent study habits, critical use of high-quality resources such as lecture slides and textbooks, moderate stress management, and adequate sleep, which continue to outperform newer interventions when applied consistently. Notably, environmental support factors, such as living with family and possessing higher English language proficiency, emerged as strong independent predictors of GPA. This finding underlines the ongoing importance of non-academic socio-environmental factors even amidst rapidly digitalizing learning environments.

As this is a cross-sectional study, causal inferences cannot be drawn, and longitudinal research is essential to establish directionality among variables. Importantly, the study advances the conceptualization of academic performance as a multifactorial construct rather than a function of isolated behaviors. It highlights the importance of holistic student support that addresses cognitive, emotional, technological, and environmental domains simultaneously. By providing a multifaceted model of student success, this research invites future educational policies and interventions to be similarly integrative rather than fragmented. The proposed MAR model offers one such integrative framework, combining cognitive, behavioral, technological, and environmental domains into a unified approach to optimizing academic performance.

In sum, the findings emphasize that while educational technologies such as AI offer exciting possibilities, foundational study behaviors, wellness practices, and personal support systems remain central to academic excellence. This integrated understanding offers new directions for research, program design, and institutional strategies aimed at optimizing performance among medical students in contemporary, high-stakes educational environments.

7. Recommendations

Drawing from the findings of this study, various recommendations are made in support of the academic success of medical students. First, it is recommended that medical schools introduce structured training on effective study techniques, critical resource evaluation, and time management during the early years of the curriculum (Miller, 2014). Institutions should offer workshops on AI use, provide counseling for stress and sleep hygiene, and discourage over-reliance on unstructured materials such as handouts. The adoption of active learning strategies, provided the focus is moved away from passive review methods, could potentially deepen understanding and establish academic resilience. Second, AI literacy programs should encompass sessions in which students are instructed about how to analyze AI tools critically, interpret AI outputs, and incorporate these resources meaningfully into their learning endeavors. Educators should foster a perception in students that AI should be used as a supplementary tool in conjunction with traditional study techniques. Third, stress management and wellness initiatives, including workshops on mindfulness, coping mechanisms, and sleep hygiene, should be incorporated into student services to reduce negative academic effects resulting from chronic stress and sleep deprivation. Fourth, customized English language programs must be offered specifically for non-native students to enhance their comprehension of medical material and their performance at examination. Finally, institutions should conduct campaigns on the responsible use of social media, focusing on how to balance academic work with online socializing. Such an integrated approach might improve student learning and wellness.

8. Future Directions

While this study provides important insights, several areas warrant further research. Future studies should adopt longitudinal cohort designs to track the evolution of study habits, AI utilization, stress management behaviors, and academic performance over time. Such designs would help establish causality and identify critical periods for intervention. Qualitative research exploring how students engage with AI tools, including their critical thinking processes, perceived benefits, and potential pitfalls, could provide a deeper understanding of the complex role AI plays in academic success. Future research should explore how students use AI—what tasks they apply it to and whether they engage with it actively or passively—to better evaluate its educational value.

Moreover, intervention studies are needed to test the efficacy of structured study skills programs, AI literacy workshops, and wellness initiatives in improving academic outcomes among medical students. Cross-institutional and cross-cultural comparisons would be beneficial in elucidating those differences in relation to cultural, linguistic, and educational systems with the relationship identified in the current study. Finally, future research should consider the impact of socio-economic factors such as family income, parental education, and technological resources on strategies for equitable education. Multifactorial student-centered approaches toward academic success would need consideration for future research.

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