



Artificial Intelligence in Higher Education: Examining Its Impact on Student Learning Outcomes and Critical Thinking

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Abstract. The rapid proliferation of artificial intelligence (AI) tools in academic environments has generated substantial debate regarding their influence on higher-order cognitive processes. This study examines the relationship between AI tool usage frequency and students' cognitive learning strategies, specifically elaborative reasoning, critical thinking, and metacognitive self-regulation, as operationalized by an adapted version of the Motivated Strategies for Learning Questionnaire (MSLQ). A quantitative descriptive design was employed with 337 purposively sampled higher education students from Bengaluru, India. Pearson correlation, multiple linear regression and one-way ANOVA were conducted. AI use was significantly correlated with elaboration ($r = .655$), critical thinking ($r = .558$), and metacognition ($r = .546$). However, regression analysis revealed that AI use did not independently predict critical thinking ($\beta = .062$, $p = .168$) when elaboration ($\beta = .456$, $p < .001$) and metacognitive self-regulation ($\beta = .362$, $p < .001$) were control factors. Critical thinking outcomes are driven by underlying cognitive tendencies rather than the frequency of AI use. To optimize the educational potential of AI tools, pedagogical frameworks must place a high priority on intentional cognitive engagement and metacognitive scaffolding.

Keywords: Artificial Intelligence in Education, Higher education, Elaborative reasoning, AI literacy.

1 Introduction

Rapid integration of AI tools ranging from large language models to intelligent tutoring assistants, which help students with on demand content generation and personalised feedback (Crompton & Burlee, 2023). This may, however, affect the learning capacity of students and offload the cognitive labour onto the AI system, which can hamper deep and enduring learning (Kasneci et al., 2023).

Existing studies mostly do not have a scientific consensus. On the one hand, researchers discuss about the positive effect of AI including enhanced efficiency and comprehension (Zawacki- Richler et al., 2019), whereas becoming passive users of such tools can negatively affect an individual's reasoning capacity and their drive towards daily "productive cognitive struggle" (Baidoo-Anu & Ansah, 2023; Mollick & Mollick, 2023). Moreover, prior research in this area has both methodological and theoretical limitations. There is a considerable lack of credible evidence as most studies are either qualitative or small studies and concentrate only academic motivation rather than independent thinking and cognitive load.

In this regard, the current study employs the MQLP which is a psychometric instrument validated in the study setting to generate empirical data on the relationship between usage AI software's and cognitive strategies among both undergraduate and post graduate students in Bangalore, India. Thus, study tries to combine well established learning theories with statistical techniques; thereby provide a robust explanatory account, which can impact both teaching-learning and pedagogy in future technology oriented educational environments.

2 Research Objectives

- To examine the frequency of usage of AI tools by students in higher education institutions
- To assess the perception of students regarding the impact of AI tools on their understanding of academic concepts, elaborate reasoning and overall academic performance

- To ascertain the impact of AI tool usage on critical thinking skill and problem-solving ability of students
- To understand students' concerns regarding AI overdue and its effect on their deep academic engagement and analytical thinking.

3 Literature Review

3.1 Scope of AI in Higher Education: An Overview

In the realm of tertiary education, AI tools offer a deeply personalised and immediate experience when it comes to learning. A comprehensive systematic review by Zawacki-Richter et al., (2019), ascertained that artificial intelligence tools in higher education serve three board functions, “profiling and prediction systems, assessment tools and intelligent instructional systems”. The impact of such scaffolds on the cognitive processes and growth of students is a matter of serious debate.

Nevertheless, most research in this area, has not given due importance to the cognitive effects of such AI systems, but rather looked at its impact in other such as administration and assessment according to a systematic review by Crompton and Burke (2023). This clearly points towards the need for research into the meta-cognitive and learning impact of AI system rather than just concentrating on the surface level engagement metrics.

More importantly, AI tools can create an illusion of competence among the learners, where they overly rely on readymade answers and omit the necessary cognitive struggle that leads to deep learning and understanding (Baidoo-Anu and Ansah, 2023). Thus, the corner stone of this study is the cognitive illusion that robs student of a necessary learning hoops such as “retrieval practice, inter-learning, elaborative questioning”, as proposed by Bjork and Bjork (2011) in their desirable difficulties theory.

3.2 Dependency is a byproduct of frequent AI use

Post pandemic, generative AI tools have become a major part of the academic life in higher education students for a, myriad of functions including writing essays, literature

reviews and mathematical analysis which can lead to “cognitive offloading”. An after effect of this can be the loss of confidence in one’s own academic and intellectual abilities that calls into question the larger intellectual capacity building in the future (Baidoo-Anu and Ansah, 2023).

This can be further explained by a combination of both Bandura’s self-efficacy theory and the idea of cognitive load (Sweller, 1988). The self-efficacy theory throws light on the gradual reduction in the ability of students to create knowledge on their own after getting accurate responses from AI platforms without any kind of deep engagement. Adding to this, the cognitive load viewpoint stresses on the lack of both internal and external load or demand which may not call for any kind of intellectual struggle from the learner leading theoretical gaps warrant an empirical inquiry into the kind of effect regular AI usage would have on self-reported cognitive function of the learners.

3.3 Critical thinking in the age of AI

Another important area which can be affected by frequent use of AI tools is critical thinking. It is a complex and cognitively rigorous process, which involves assessing, analysing and applying information obtained through various means such as observation experience, reflection, reasoning and communication (Paul & Elder, 2006). Even though unregulated use of AI may seem to have negative effects on critical thinking capacity of learners, Mollick and Mollick (2023), mention that AI can promote deep information analysis with conscious and intentional use. The converse might be true with AI use without any metacognitive intentional involvement and the ability to cognitive uncertainty may be reduced. This is because learning in the sphere of higher education also involves the growth of an individual’s independent scholarly judgement.

3.4 Metacognitive Self-Regulation and Learning Strategies

Most people agree that the most powerful individual-level predictor of academic success is metacognitive self-regulation, or the ability to organise, track, and assess one’s own cognitive processes (Pintrich, 2004; Zimmerman, 2002). The MSLQ metacognition subscale captures students’ awareness of their own understanding, their use of self-

testing strategies and their adaptive adjustment of learning tactics in response to comprehension failures. In the context of AI-integrated learning, metacognition becomes even more important: students who possess strong metacognitive skills are better able to assess AI outputs critically, identify AI-generated errors or oversimplifications made by AI as a guide for more in-depth research rather than an instant fix.

A key component of meaningful learning is the creation of conceptual links between new material and pre-existing knowledge structures, which is reflected by the MSLQ elaboration subscale (Biggs, 1987). It is still an empirical topic to what degree the usage of AI promotes or hinders elaborative processing. Even when students' performance metrics seem satisfactory, the depth of their learning may be impaired if they use AI to obtain synthesised responses without engaging in the connective thinking required for elaboration.

4 Methodology

4.1 Research Design and Paradigm

This study adopted a quantitative analytical research design to examine students' perceptions of the role of AI in shaping learning outcomes and critical thinking skills in higher education. Given the study's goals of systematic measuring of constructs, discovery of statistical correlations and generalization of findings across a defined population, quantitative methodologies were judged to be most appropriate. (Creswell & Creswell, 2018).

Subscribing to the positivist research paradigm the study aimed to both describe the characteristics of the population and find statistically significant relationships between the various subscales of the study instrument (Bryman, 2016). This is in tandem with the approaches used in empirical educational psychology.

4.2 Participants and Sampling

The study was conducted in Bangalore due to its importance as not just a technological hub, but also one of the foremost academic centers in the country with a large number of higher education institutions with exposure to academic systems which are AI integrated (Nair & Rajan, 2022). A total of 337 students were selected from various tertiary institutions to the city using a purposive sampling technique, using certain inclusion criteria. A major inclusion criterion was that only these students in higher education institutions who had a hands-on experience with AI educational tools would be selected. This was done to ensure that the sampling was property reprentative and would do justice to the research instrument (Patton, 2002). Table 1 represents a demographic breakdown of the sample collected.

Table 1. Demographic Characteristics of Participants (N=337).

Variable	Category	N(%)
Gender	Female	251 (74.5%)
	Male	86 (25.5%)
Level of Study	Undergraduate	318 (94.4%)
	Postgraduate	19 (5.6%)
AI Use Frequency	Daily	162 (48.1%)
	Weekly	98 (29.1%)
	Occasionally	70 (20.8%)
	Rarely	7 (2.1%)
Mean Age (SD)	-	19.62 (1.95)

4.3 Instrument

The study employed a modified session of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1991). The tool has six subscales which are theoretically grounded viz. “the frequency and context of AI use, elaborative learning strategies, critical thinking engagement, metacognitive self-regulation perceived AI impact on learning and worries about AI dependency”. Even though the original sub-scale structure of the instrument was maintained, certain items were modified to suit the current time as the tool was created before the widespread use of AI tools in education. The tool follows a five-point Likert scale scoring format (1= strongly disagree to 5=strongly agree).

The adaptation of the tool was done in two stages. The first stage consisted of content validation by a panel of three subject-matter experts in educational technology and psychology. The assessment criteria include the degree to which the intended construct is measured and the relevance and clarity of each item. This was then pilot tested using a sample of 30 students (not part of the main analysis). Then, minor item refinements and reliability analysis was conducted to avoid any changes to psychometric properties of the original scale. The final data collection was done over a period of six weeks using the refined instrument.

4.4 Statistical Analysis

Data analysis for the study was conducted using SPSS software. The first line of the analysis was descriptive statistics including mean, standard deviation, frequencies and percentages to identify the trends and response patterns across all the subscales of the instrument. Cronbach's alpha co-efficient was used as a means of internal consistency and an alpha value of $\geq .70$ was accepted or valid (Nunnally, 1978).

Secondly correlation analysis was conducted using the Pearson product- moment method to measure the relationship between AI usage frequency and other learning related variables. This is statistically accurate, since all the variables were measured at interval level using 5-point Likert scale (Field, 2018). This was followed by various multiple linear regression analyses to identify the predictor of critical-thinking using the sub-scales.

Finally, a one-way between groups ANOVA test was done for all subscales with IA use frequency as the grouping variable (with the groups being daily, weekly, occasionally, rarely). For all inferential analyses, a p value of $< .05$ was taken as the significance threshold (Creswell & Creswell, 2018). Moreover, all the conditions including normality, linearity, homogeneity of variance and absence of multicollinearity were satisfied before all statistical analyses.

5 Results and Analysis

5.1 Descriptive Statistics and Reliability

Table 2 depicts the descriptive statistics and reliability scores of the all MSLQ subscales. The mean scores for all the subscales are high, starting from $M=3.55$ (AI impact on learning) to $M=3.97$ (Critical thinking). This shows that the overall perception of students regarding both their cognitive involvement and the role that AI plays in their learning. The Cronbach's alpha co-efficients were also significantly above the minimum threshold of 0.70 ($\alpha = .806$ to $\alpha = .899$), which shows strong internal consistency across the adapted revisions of all the sub-scales (Nunnally, 1978).

Table 2. Descriptive Statistics and Reliability Coefficients (N = 337)

Subscale	M	SD	Min	Max	α
AI Use	3.96	0.87	1.00	5.00	.869
Elaboration	3.82	0.78	1.00	5.00	.894
Critical Thinking	3.97	0.81	1.00	5.00	.887
Metacognitive Self-Regulation	3.86	0.85	1.00	5.00	.899
AI Impact on Learning	3.55	0.74	1.00	5.00	.806

M = Mean; SD = Standard Deviation; α = Cronbach's Alpha.

5.2 Pearson Correlation Analysis

Correlation analysis was conducted among all the cognitive engagement subscales and the results showed positive correlations between all the variables (with a p value $< .001$). The variable pairs elaboration and Critical thinking ($r = .755$), Elaboration and Metacognition ($r = .714$) and Critical thinking and Metacognition ($r = .721$) exhibited strong correlation. This confirmed the theoretical independence of these three dimensions within the MSLQ framework.

AI use on the other hand, demonstrated moderate positive correlation with cognitive variable viz Elaboration ($r = .655$), AI Impact ($r = .622$), Critical Thinking ($r = .558$) and Metacognition ($r = .546$). the finding of positive association between the AI impact construct and all the other sub-scale points towards aware and reflective AI users who are meta cognitively active. This indicates that strong users of AI tools are more aware of its cognitive after effects, the same is represented in Table 3.

Table 3 Pearson Correlation Matrix for MSLQ Subscales and AI Measures (N = 337)

Subscale	AI Use	Elaboration	Critical Thinking	Metacognition	AI Impact
1. AI Use	—				
2. Elaboration	.655**	—			
3. Critical Thinking	.558**	.755**	—		
4. Metacognition	.546**	.714**	.721**	—	
5. AI Impact	.622**	.477**	.430**	.393**	—

Note: ** $p < .01$ (two-tailed)

5.3 Multiple Regression, Predictors of Critical Thinking

The simultaneous multiple linear regression model, where the effects of Metacognitive self-regulation, AI use and Elaboration as independent variables on Critical thinking as the lone dependent variable was statistically significant with an $F(3, 333) = 197.12$, $p < .001$. It amounted to a significant 64% variance in critical thinking scores ($R^2 = .640$, $\text{Adj. } R^2 = .637$). This indicated that the model has strong explanatory power to ascertain the independent predictors of Critical thinking.

It is worth to note that individual cognitive habits are stronger prediction of critical thinking and also mediate the bivariate relationship between AI engagement and critical thinking. Elaboration ($\beta = .456$, $p < .001$) and Metacognition self-regulation ($\beta = .362$, $p < .001$) were found to be the strongest independent predictors of critical thinking. Moreover, AI usage's ability to predict Critical thinking was not statistically significant ($\beta = .062$, $p = .168$).

Table 4 Multiple Regression Analysis Predicting Critical Thinking (N = 337)

Predictor	B	β	t	p
Intercept	0.591	—	—	—
AI Use	0.058	.062	1.38	.168
Elaboration	0.475	.456	9.87	< .001
Metacognition	0.347	.362	7.96	< .001

DV = Critical Thinking; β = standardized regression coefficient

5.4 One-way ANOVA: AI use Frequency and Critical Thinking

A one-way ANOVA (between subjects) conducted among the four AI groups based on AI frequency (Daily, Weekly, Occasionally, Rarely) revealed that was no statistically significant difference between these groups when it comes critical thinking. The Levene's test (for homogeneity of variance was non-significant ($p > .05$); therefore, the equal variance assumptions were met. The test score and significance value ($F(3, 333) = 0.76$, $p = .519$) both clearly point towards the lack of significant difference the groups. The mean scores also across the four groups did not show much difference and the range was from $M=3.89$ (rarely) to $M=4.04$ (Daily). This is in tandems with the findings from the regression analysis that AI use is not a major predictor of critical thinking.

Table 5. One-Way ANOVA: Critical Thinking Scores by AI Use Frequency (N = 337)

AI Frequency	Use	N	M	SD	F (p)
Daily		162	4.04	0.86	0.76 (.519)
Weekly		98	3.90	0.70	
Occasionally		70	3.92	0.87	
Rarely		7	3.89	0.64	

Note: $F(3, 333) = 0.757$, $p = .519$.

6 Discussion

Unmonitored use of AI among students in higher education is on the rise and its effects on their cognitive strategies is something that is of permanent interest. In this regard this study tried to ascertain the relationship between the AI use of undergraduate and post graduate students in Bengaluru and their critical thinking abilities. It employed the MSLQ among 337 selected higher education students who have experience with various AI tools. The results paint a nuanced picture which includes both significant challenges and the potential gains that AI can bring to the higher education landscape.

The positives from the study are the strong bivariate correlation between AI use and variables pertaining to deep learning such as Elaboration, Metacognition and critical thinking. Self-reported measures of critical thinking, metacognition and elaboration were higher among students who utilised AI tools more. This can be backed up by the proposition by Kasneci et al.'s (2023) that of students can have a critical view of the results provided by AI tool rather than passively consuming them, AI is something that can enhance cognitive abilities. This is further solidified by the results from the AI impact subscale, where it is evident that although students appreciate the efficiency such tools bring, they also are cautious about the risks it can pose to their critical thinking capabilities. Therefore, students showed strong affinity towards independently verifying answers presented by AI tools, which suggest a considerable amount of metacognitive awareness among them.

Nevertheless, the results from the regression analysis significantly affect their optimistic view point. When Elaboration and Metacognitive Self-Regulation were simultaneously entered as predictors, AI Use ceased to significantly predict Critical Thinking ($\beta = .062, p = .168$). This result suggests that the apparent bivariate relationship between the use of AI and critical thinking is statistically incorrect due to the shared variance caused by the fact that students who are cognitively active are also more likely to use AI tools intentionally and to think critically. Higher-order learning outcomes are determined by students' underlying cognitive disposition and metacognitive capacity, not by AI use as such. This interpretation is consistent with both Baidoo-Anu and Ansah's

(2023) warning that the use of AI without metacognitive scaffolding may result in superficial rather than deep understanding and Pintrich's (2004) fundamental claim that metacognitive self-regulation is the primary proximal determinant of higher-order learning outcomes. The non-significant ANOVA result reinforces this conclusion. Students who use AI on a daily basis do not report much better critical thinking than those who use it rarely or occasionally. ($F = 3, 333 = 0.76, p = .519$). This finding makes it clear that the frequency of engagement with AI tools cannot be a substitute for quality which actually enhances cognitive abilities and critical thinking. Therefore, it is evident that institutions and education should avoid the trap of using quantitative AI use metrics as benchmark of learning and instead should focus on increasing the intentional use of such platforms to enhance metacognition of students while using them.

6.1 Implications for practice

The findings of this study carry considerable practical implications for teaching-learning, policy and curriculum design in the field of higher education. This is particularly relevant when rampant use of AI tools by students in higher education is calling into question their critical thinking and higher order reasoning abilities.

First and foremost, students should be given AI integrated assignments, which must mandatorily require them to critically evaluate, reflect and elaborate upon the content generated by AI instead of just reproducing it. This deliberate inclusion of AI should aim to foster cognitive engagement of higher order rather than bypassing it. Secondly, faculty members should also be trained in incorporating evidence-based AI frameworks into their pedagogical methods in order to ensure cognitive challenge, while still reaping all the efficiency benefits of AI. Thirdly, structured AI literary programmes should be provided by educational institutions to students, which give them the metacognitive skills to critically evaluate AI generated content and its limitations. Even in a future scenario with AI assisted workflows, students should be able to preserve their intellectual autonomy and recognize bias and errors in AI content.

Finally, educational institutions can embed MSLQ type cognitive strategy assessments to identify students who may need assistance with developing their metacognitive skills to make the future world where AI would be an integral part of the teaching learning process. The benefit of such an approach bring tailor made programmes to help students based on their need for metacognitive development instead of their AI engagement.

6.2 Limitations and Future Research Direction

Even though the findings of the present study on AI usage and its effect on cognitive strategies is significant, it is paramount to recognise its limitations. These can be addressed in future studies to further build upon the insights received here.

Firstly, since the study has a cross-sectional design, it is difficult to draw causal inferences. This can be overcome by commissioning longitudinal studies to find out whether AI usage can causally influence students' development of causal strategy. Secondly, generalisability, might be at risk since most of the respondents were female (74.5%) and were undergraduate (94.4%), that too from only one Metropolitan content. This can curtail student's ability to make broader national and international claims.

Another potential limitation can be the social desirability bias stemming from self-reported measures even though it is psychometrically valid. To overcome this bias, future studies can include methods which can objectively measure learning outcomes such as using both self-reported measures and log-file analysis of student AI intersection or checking how students perform on transfer task. Experimental and quasi-experimental designs comparing AI-assisted and non-AI conditions, longitudinal panel studies tracking cognitive development across academic years and multi-institutional cross-disciplinary samples represent the most productive avenues for future empirical investigation in this domain.

7 Conclusion

This study provides strong quantitative proof that the use of AI tools in higher education is strongly correlated with cognitive learning strategies as assessed by the modified MSLQ. However, when students' elaborative reasoning and metacognitive self-regulation are taken into consideration, AI tool use does not independently predict critical thinking. Across a sample of 337 higher education students in Bengaluru, India, the strongest unique predictors of critical thinking were Elaboration and Metacognitive Self-Regulation.

The findings of the study point towards the importance of being able to promote and measure cognitive engagement over mere AI software engagement metrics as measurement if actual learning in the higher education setting. A more nuanced understanding of the same would be that AI use would add value in an educational setting only when it brings help. Students develop meta cognition and provide students with a elaborate orientation. This balanced approach towards AI in higher education can bridge the gap between the pessimism and the over enthusiasm around using AI tools in the educational setting.

Although a cross sectional study, the implications of the thought process presented in this study can go beyond the individual level to the institutions and even impact educational policy. The larger aim is to recommend that, at both these levels, leaders and policy makers should not just promote and reward AI usage and adoption, but rather faster meaningful use of such tools which can help develop the spirit of critical thinking in students. Teaching-learning approached and curriculum frameworks that incentivise critical evaluation and metacognitive awareness of AI tools will be the key to unlock the real potential of AI compared to ones that only look for mechanical engagement numbers.

In conclusion, technology on its own is not the panacea to faster critical evaluation skills in undergraduates and postgraduates. It is the metacognitive abilities, willingness to learn and institutional support for these that determines it. In this regard, future stud-

ies should focus on conducting methodologically diverse studies including experimental, multi-institutional and longitudinal studies.

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