



University Students' Perceptions of Artificial Intelligence Usage and Its Perceived Impact on Critical Thinking Skills: Evidence from Somali Higher Education

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Abstract

Artificial intelligence (AI) tools have rapidly penetrated higher education globally, yet their impact on students' critical thinking skills remains a contested empirical question. This study presents findings from a quantitative cross-sectional survey examining university students' perceptions of AI tool usage and its perceived effects on critical thinking skills in Somali higher education. Grounded in Cognitive Load Theory (Sweller, 1988), the Technology Acceptance Model (Davis, 1989), and Bloom's revised taxonomy (Anderson & Krathwohl, 2001), a 67-item structured questionnaire was administered to 105 undergraduate students at Hormuud University, Mogadishu, during Academic Year 2025–2026. Descriptive statistics, Pearson correlations, independent-samples t-tests, one-way ANOVA, and multiple regression were employed. Results reveal that 87.4% of students use ChatGPT, with 61.0% reporting daily or near-daily AI engagement. Critical thinking composite scores were moderate ($M = 3.42$, $SD = 0.36$ on a 5-point scale). Self-regulation emerged as the strongest predictor of perceived critical thinking development ($r = 0.609$, $p < .001$), substantially outweighing AI usage frequency ($r = 0.222$, $p = .025$). The multiple regression model ($R^2 = .458$, $Adj. R^2 = .441$) indicates that self-regulation, AI literacy, and usage frequency together explain 45.8% of variance in critical thinking perceptions. In alignment with Liu and Wang (2024), Wu and Yu (2024), and Brazão and Tinoca (2025), findings suggest that the quality of AI engagement is more influential than usage frequency for perceived cognitive outcomes. No significant gender or disciplinary differences were observed. Contextual findings highlight a moderate English-language barrier ($M = 3.19$) and inadequate institutional AI guidance ($M = 2.76$). This study makes a unique empirical contribution as one of the first studies to investigate AI and critical thinking in Somali higher education — a post-conflict, resource-constrained, and culturally distinctive context entirely absent from existing literature.

Keywords: Artificial intelligence in education, Critical thinking, Cognitive offloading, Bloom's taxonomy, Somali higher education, Self-regulated learning, Global South, AI literacy

1. Introduction

1.1 Background and Rationale

The integration of artificial intelligence tools into university learning environments constitutes one of the most significant pedagogical developments of the twenty-first century. Generative AI platforms — most notably ChatGPT, Google Gemini, Microsoft Copilot, and Anthropic’s Claude — have transitioned from specialist novelties to near-ubiquitous academic instruments. The Digital Education Council’s (2024) Global AI Student Survey reported that 86% of university students use AI tools on a weekly basis. This velocity of adoption has outpaced institutional readiness worldwide, and the knowledge base required to govern it responsibly remains fragmented, geographically skewed, and theoretically incomplete.

Critical thinking — broadly understood as purposeful, self-regulated judgement involving interpretation, analysis, evaluation, and metacognitive self-examination (Facione, 1990) — is widely recognised as the foundational competency higher education exists to cultivate. The cognitive offloading enabled by AI tools may directly undermine the effortful practice through which higher-order thinking skills are consolidated (Gerlich, 2025; Sweller, 1988). The empirical evidence, however, remains contested. Gonsalves (2024) found that AI most improves lower-order cognitive tasks. Zhao et al. (2025) and Liu and Wang (2024) demonstrated that when students engage deliberately with AI using self-regulation strategies, critical thinking benefits accrue. Wu and Yu’s (2024) meta-analysis of 41 studies reported consistently positive effects on learning performance ($SMD = 1.028$). A systematic review (Khoza & van der Walt, 2025) identified the Horn of Africa as having the most acute research deficits. The present study directly addresses this gap.

1.2 Research Objectives

The study pursues four objectives: (1) to document AI tool usage patterns at Hormuud University; (2) to assess students’ perceptions of AI’s influence on critical thinking across Bloom’s dimensions; (3) to identify individual-level moderators including self-regulation and AI literacy; and (4) to explore Somalia-specific infrastructure and contextual barriers. These four objectives correspond to research questions RQ1–RQ4.

1.3 Research Questions and Hypotheses

Two directional hypotheses are tested: H_1 — frequent AI use is negatively associated with higher-order critical thinking (Gerlich, 2025); H_2 — self-regulated AI use is positively associated with critical thinking (Zhao et al., 2025). An exploratory research question (RQ4) further examines whether infrastructure and contextual constraints shape perceived cognitive impact (Khoza & van der Walt, 2025), addressed descriptively in Section 4.5.

2. Literature Review

2.1 Theoretical Framework

2.1.1 Cognitive Load Theory

Cognitive Load Theory (Sweller, 1988; Sweller, van Merriënboer, & Paas, 1998) posits that learning requires investment of cognitive effort within the constraints of limited working memory. AI tools present a double-edged consequence: they may reduce extraneous load, freeing resources for deeper engagement; or they may reduce germane load by offloading the effort that drives skill development. Gerlich (2025) argues that habitual AI-enabled cognitive offloading progressively weakens the pathways associated with independent analytical reasoning.

2.1.2 Technology Acceptance Model

The Technology Acceptance Model (Davis, 1989) posits that technology adoption is determined by perceived usefulness and ease of use. Falebita and Kok (2024) adapted TAM for the Global South, demonstrating that structural barriers substantially shape adoption patterns. Malik et al. (2025), applying the Theory of Planned Behaviour in Sub-Saharan Africa, found that infrastructure access was a stronger predictor of AI adoption than attitudinal factors.

2.1.3 Bloom's Revised Taxonomy

Anderson and Krathwohl's (2001) revised taxonomy distinguishes lower-order thinking skills (LOTS: remembering, understanding, applying) from higher-order thinking skills (HOTS: analysing, evaluating, creating). Gonsalves (2024) found that AI most reliably improves LOTS while producing ambiguous effects on HOTS, directly informing the design of the Section D instrument.

2.2 AI and Critical Thinking: Global Evidence

Gerlich (2025), in a 666-respondent multi-country study, found significant negative associations between AI frequency and critical thinking. Gonsalves (2024) documented the LOTS/HOTS differential. Contesting this pessimistic reading, Zhao et al. (2025) and Abbas, Jam, and Khan (2024) demonstrated that self-regulation quality moderates the AI-CT relationship. Liu and Wang (2024) provided experimental corroboration: an eight-week intervention with 90 EFL learners showed significant critical thinking gains in the active AI engagement group versus passive controls. Wu and Yu (2024), in a meta-analysis of 41 studies, reported positive overall effects on learning performance ($SMD = 1.028$), self-efficacy ($SMD = 1.206$), and motivation ($SMD = 1.020$). Brazão and Tinoca (2025) documented progressive critical questioning development through AI-student dialogue. Collectively, these studies support the conditional thesis: AI is associated with critical thinking gains when students engage actively and reflectively.

2.3 AI in the Global South

A systematic review (Khoza & van der Walt, 2025) identified 47 eligible studies, none from the Horn of Africa. One identified Somali study (Isak & Isak, 2025) found performance improvements at Somali National University but did not examine critical thinking; it is currently available as a preprint pending peer review. Oxford Insights (2024) ranks Somalia among the least AI-ready nations; Datareportal (2024) estimates 34% internet penetration. English-only AI platforms and the Islamic *ijtihad* tradition of independent reasoning add distinctive dimensions absent from existing research.

2.4 Infrastructure, Language, and Cultural Context

The assumption of reliable digital infrastructure is one of the most significant unexamined premises in the AI-education literature. Somalia ranks among the ten least AI-ready countries globally (Oxford Insights, 2024), with internet penetration estimated at 34% (Datareportal, 2024). All major AI platforms operate primarily in English, creating a meaningful language barrier for students whose academic communication occurs predominantly in Somali and Arabic. Overlaid upon these structural conditions is the Islamic scholarly tradition of *ijtihad* — the expectation of independent critical reasoning — which represents a normative framework for intellectual engagement that prior research has not examined in relation to AI tool use.

3. Data and Method

3.1 Research Design

This study employs a quantitative cross-sectional survey design within a post-positivist paradigm. A descriptive-correlational approach combines frequency analysis with inferential analysis of hypothesised relationships. The cross-sectional design precludes causal inference — a limitation discussed in Section 5.

3.2 Sample

A convenience sample of 105 undergraduate students at Hormuud University's Faculty of Information Technology and Data Science participated ($N = 105$) during Academic Year 2025–2026. As illustrated in Figure 1, the sample comprised 69 males (67.6%) and 33 females (32.4%). Departments included Computer Science (35.3%), IT (28.4%), Software Engineering (23.5%), and Data Science (12.7%). The majority were in their 2nd Year (47.1%), followed by 4th Year (24.5%), 3rd Year (23.5%), and 1st Year (4.9%). Table 1 presents the full demographic profile.

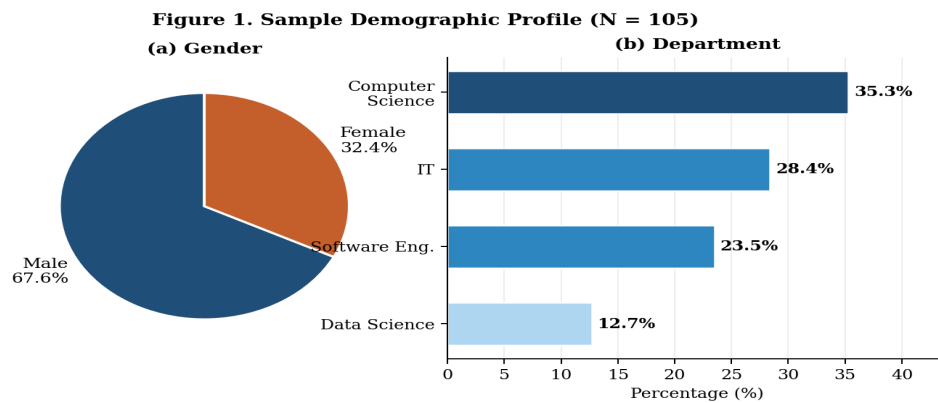


Figure 1. Sample demographic profile showing gender distribution (a) and department distribution (b) ($N = 105$).

Table 1. Demographic Profile of Respondents ($N = 105$)

Variable	Category	<i>n</i>	%
Gender	Male	69	67.6
	Female	33	32.4
Age Group	18–21	57	55.9
	22–25	41	40.2
	26+	4	3.9
Department	Computer Science	36	35.3
	IT	29	28.4
	Software Engineering	24	23.5
	Data Science	13	12.7
Year	1st Year	5	4.9
	2nd Year	48	47.1

	3rd Year	24	23.5
	4th Year	25	24.5
Internet	Mobile data (mostly stable)	50	49.0
	Fibre optic cable	39	38.2
	Mobile data (often unstable)	9	8.8
	Broadband	4	3.9

3.3 Instrument

Data were collected via a structured questionnaire. Section C (6 items, Falebita & Kok, 2024) measured AI literacy on a 5-point Likert scale. Section D (20 items, Gonsalves, 2024; Gerlich, 2025) assessed critical thinking across five Bloom’s sub-scales. Section E (8 items, Zhao et al., 2025) assessed self-regulated AI engagement. Section F (8 items, original) captured Somalia-specific contextual barriers. Negatively worded items were reverse-scored. The questionnaire was administered via Google Forms, with the survey link distributed through WhatsApp and email. Construct validity is supported by the adaptation of items from previously validated instruments (AI literacy: Falebita & Kok, 2024; critical thinking: Gonsalves, 2024, and Gerlich, 2025; self-regulation: Zhao et al., 2025).

3.4 Data Analysis

IBM SPSS (v29) was used for: descriptive statistics; Pearson correlations; independent-samples t-tests (Cohen’s *d*); one-way ANOVA (η^2); and OLS multiple regression (standardised β , R^2) following American Psychological Association (2020) effect size guidelines. Due to missing responses on individual items, valid case counts varied slightly across analyses (AI tool usage: $n = 103$; academic purposes: $n = 102$).

4. Results and Discussion

4.1 AI Tool Usage Patterns (RQ1)

As shown in Figure 2, 61.0% of students use AI daily or near-daily, with only 1.0% reporting no usage. ChatGPT dominated at 87.4%, followed by Google Gemini (68.0%) and Claude (64.1%), reflecting multi-tool engagement. Figure 3 illustrates academic purposes: coding (65.7%) and problem-solving (49.0%) were the most common, while language translation (30.4%) was the least frequent. The high Claude uptake likely reflects the platform’s technical coding utility, consistent with the sample’s technology orientation. These patterns align with the Digital Education Council’s (2024) global benchmark of 86% weekly AI use.

Figure 2. AI Tool Usage Patterns

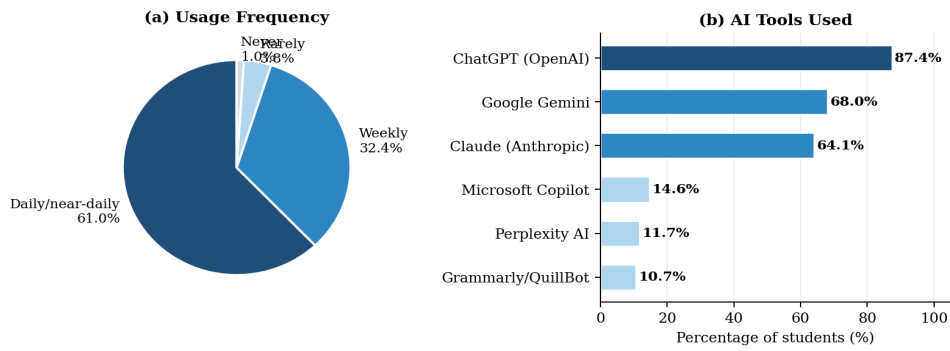


Figure 2. AI usage frequency (a) and AI tools used by students (b) (n = 103).

Figure 3. Academic Purposes for Which Students Use AI Tools (n = 102)

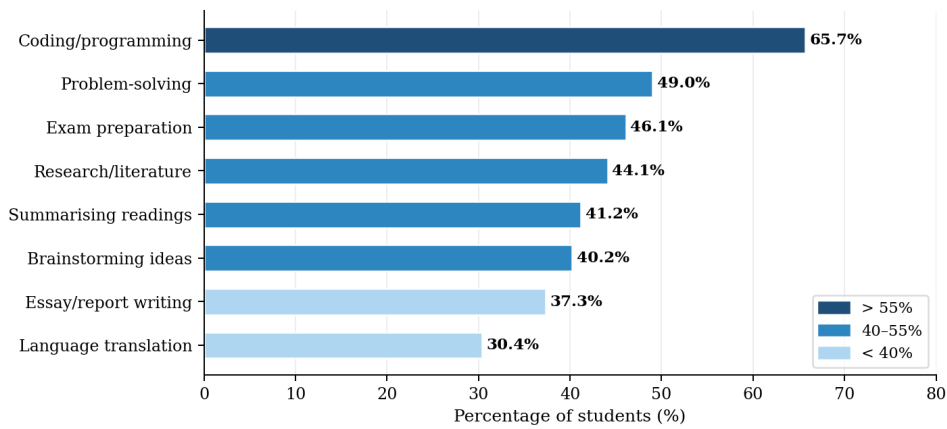


Figure 3. Percentage of students using AI for each academic purpose (n = 102). Darker shading indicates higher uptake.

4.2 Descriptive Findings: Critical Thinking and Self-Regulation (RQ2)

Figure 4 displays CT sub-scale means with standard deviation error bars. The composite score was moderate ($M = 3.42$, $SD = 0.36$), with sub-scales ranging from 3.30 (problem-solving) to 3.55 (HOT vs LOT awareness). Figure 5 shows the distribution of CT composite scores, indicating approximate normality around the mean with the majority of students scoring between 3.0 and 4.0. AI literacy was comparatively higher ($M = 3.85$), with hallucination awareness ($M = 4.08$) and responsible use knowledge ($M = 4.13$) as the strongest items, suggesting students recognise AI limitations without consistently acting on this awareness.

Figure 6 displays self-regulation item scores. Reflective post-AI practice ($M = 3.94$) and conscious use as a learning tool ($M = 3.86$) were highest, while the three dependency indicators — anxiety without AI ($M = 2.82$), motivation loss ($M = 2.85$), and AI dependency concern ($M = 2.89$) — were below neutral, indicating that dependency symptoms exist but are not dominant for most students. The gap between reflective intention (high) and systematic verification ($M = 3.48$, moderate) represents a key intervention target. Descriptive statistics for all sub-scales are presented in Table 2.

Table 2. Descriptive Statistics for All Sub-Scales ($N = 105$)

Sub-Scale / Item	<i>M</i>	<i>SD</i>	Interpretation
AI Literacy (Section C)	3.85	0.64	Moderate-High
Awareness of AI hallucinations	4.08	0.95	High
Responsible use knowledge	4.13	0.93	High
Critical evaluation confidence	3.78	1.07	Moderate-High
Critical Thinking — Total (Section D)	3.42	0.36	Moderate
Analysis sub-scale	3.45	0.54	Moderate
Evaluation sub-scale	3.31	0.48	Moderate
Synthesis sub-scale	3.47	0.60	Moderate
Problem-solving sub-scale	3.30	0.42	Moderate
HOT vs LOT sub-scale	3.55	0.53	Moderate-High
Self-Regulation — Total (Section E)	3.38	0.49	Moderate
Reflective post-AI practice	3.94	0.93	Moderate-High
Conscious use as learning tool	3.86	0.98	Moderate-High
AI-challenge strategy	3.59	0.98	Moderate-High
Boundary-setting	3.52	1.00	Moderate
Contextual Barriers (Section F)			
Language barrier (English vs Somali)	3.19	1.31	Moderate
Western AI design mismatch	3.24	1.08	Moderate
Institutional AI guidance adequacy	2.76	1.26	Low-Moderate
Mobile data cost barrier	2.63	1.17	Low-Moderate

Figure 4. Critical Thinking Sub-scale Mean Scores ($N = 105$)

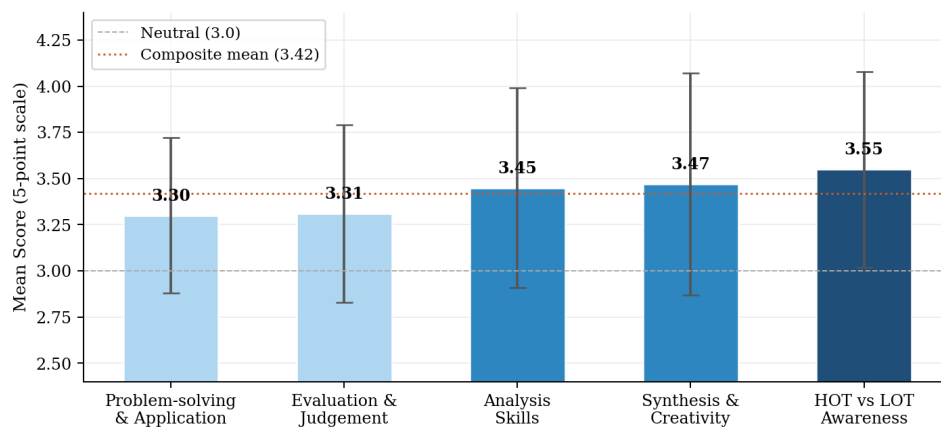


Figure 4. Critical thinking sub-scale mean scores with standard deviation error bars. Dashed lines indicate the neutral midpoint (3.0) and composite mean (3.42).

Figure 7. Distribution of Critical Thinking Composite Scores (N = 101)

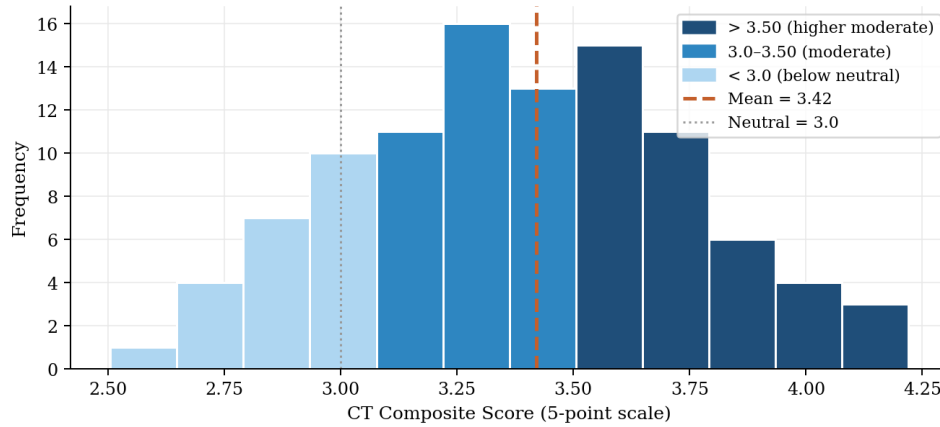


Figure 5. Distribution of CT composite scores (N = 101). The histogram indicates approximate normality, with the majority of scores in the moderate range (3.0–4.0).

Figure 8. Self-Regulation Item Mean Scores (Section E, N = 105)

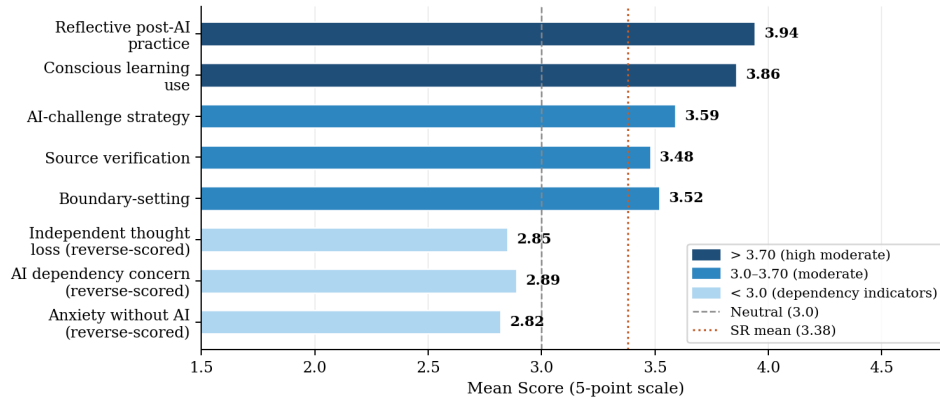


Figure 6. Self-regulation item mean scores (Section E). Items below 3.0 are dependency indicators (reverse-scored); items above 3.0 reflect positive regulatory behaviours.

4.3 Inferential Results (RQ3, H₁–H₂)

Figure 7 displays the three Pearson correlation coefficients, visually illustrating the dominance of self-regulation. Table 3 presents full inferential results. H₁ was not supported: AI frequency showed a small but statistically significant positive correlation with CT ($r = 0.222$, $p = .025$), not negative as predicted. This aligns with Liu and Wang (2024), who found significant CT gains among active AI users, and Wu and Yu's (2024) meta-analytic evidence of positive learning performance effects. H₂ was supported: self-regulation showed a large positive correlation ($r = 0.609$, $p < .001$), consistent with Zhao et al. (2025), Abbas, Jam, and Khan (2024), and Brazão and Tinoca (2025). AI literacy showed a medium effect ($r = .309$, $p = .002$). No significant gender ($t = 0.831$, $p = .408$), departmental ($F = 0.035$, $p = .991$), or year of study differences ($F = 1.498$, $p = .220$) were found.

Figure 5. Pearson Correlation Coefficients: Predictors vs Critical Thinking

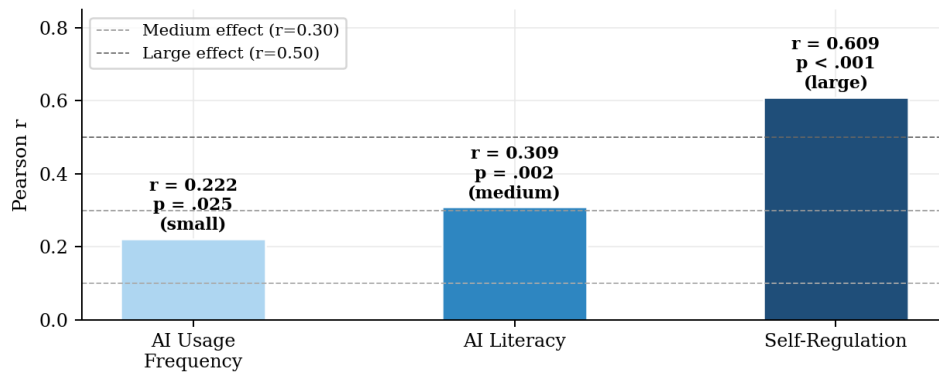


Figure 7. Pearson correlation coefficients for three predictors of perceived critical thinking development. Reference lines indicate small ($r = .10$), medium ($r = .30$), and large ($r = .50$) effect size thresholds.

Table 3. Summary of Inferential Statistical Analyses

Analysis	Statistic	p-value	Effect Size	Decision
AI Frequency → CT (r)	$r = .222$	.025	Small	Significant
Self-Regulation → CT (r)	$r = .609$	< .001	Large	Significant
AI Literacy → CT (r)	$r = .309$	.002	Medium	Significant
Gender (t-test)	$t = 0.831$	.408	$d = 0.18$	Not significant
Department (ANOVA)	$F = 0.035$	.991	$\eta^2 = 0.001$	Not significant
Year of Study (ANOVA)	$F = 1.498$	.220	$\eta^2 = 0.044$	Not significant
Multiple Regression (SR + Freq + Lit)	$R^2 = .458$	< .001	Adj. $R^2 = .441$	Significant

4.4 Multiple Regression Analysis

Multiple regression with AI frequency, self-regulation, and AI literacy explained 45.8% of variance in CT perceptions ($R^2 = .458$, Adj. $R^2 = .441$, $p < .001$). Self-regulation was the dominant predictor ($\beta = .440$), followed by frequency ($\beta = .116$) and literacy ($\beta = .086$). Consistent with Wu and Yu (2024) and Liu and Wang (2024), the model indicates that engagement quality is more strongly associated with perceived critical thinking than usage frequency. Brazão and Tinoca (2025) report at the qualitative level that dialogic reflective AI engagement develops higher-order questioning skills. Interventions targeting self-regulatory capacity will therefore generate substantially greater returns than frequency restriction policies. Multicollinearity was within accepted thresholds and inspection of residual plots indicated no major violations of normality or homoscedasticity.

4.5 Contextual and Infrastructure Findings (RQ4)

Figure 8 displays the contextual barrier mean scores with error bars. The English language barrier ($M = 3.19$) and perceived Western design mismatch ($M = 3.24$) were the most prominent barriers, both above the neutral midpoint. Institutional AI guidance adequacy was rated low ($M = 2.76$), indicating the absence of formal AI policy at the participating institutions. Mobile data cost ($M = 2.63$) was the lowest-rated barrier, suggesting affordability is less of a constraint

than language and policy. Cultural and religious values moderately influenced AI decisions ($M = 2.78$), consistent with qualitative awareness of the *ijtihad*-AI tension.

Figure 6. Mean Scores for Contextual and Infrastructure Barriers (Section F)

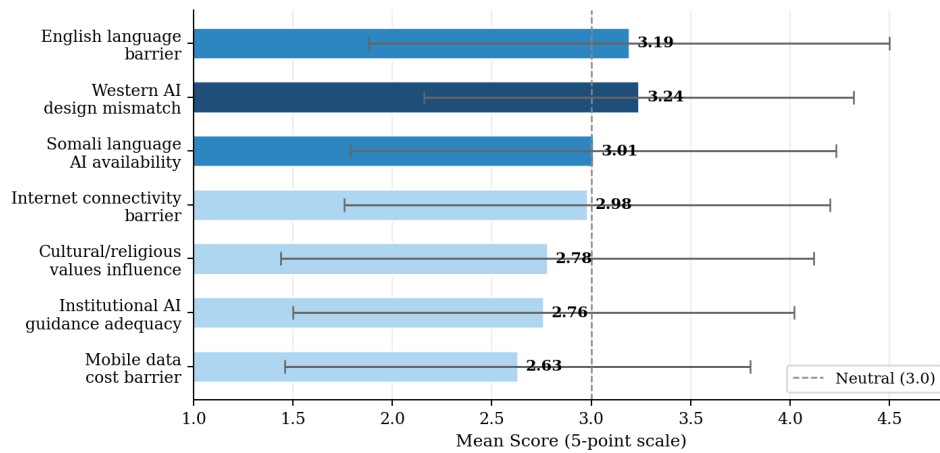


Figure 8. Mean scores for contextual and infrastructure barriers (Section F) with standard deviation error bars. The dashed line indicates the neutral midpoint (3.0).

5. Conclusion

This study examined university students' perceptions of AI tool usage and its impact on critical thinking in Somali higher education. Findings from 105 students at Hormuud University reveal a high-frequency, multi-tool AI adoption landscape, as shown in Figures 2 and 3. Critical thinking composite perceptions are moderate ($M = 3.42$; Figure 4), with self-regulation emerging as the overwhelmingly dominant predictor ($r = 0.609$; Figure 7), explaining 45.8% of variance alongside AI literacy and frequency. In alignment with Liu and Wang (2024), Wu and Yu (2024), and Brazão and Tinoca (2025), the evidence suggests that the quality of engagement is more influential than usage frequency. The contextual barrier profile (Figure 8) reveals English-language constraints and institutional policy absence as the most urgent addressable challenges.

Three principal contributions are made: (1) one of the first empirical studies examining AI and critical thinking in Somali higher education; (2) validation of the self-regulation–critical thinking nexus in a resource-constrained, mobile-first, multilingual environment; and (3) identification of Somalia-specific barriers previously absent from the literature. Institutions should urgently develop formal AI use policies, embed self-regulated learning strategies, and support English-language AI proficiency. Limitations include the cross-sectional design, which precludes causal inference; the single-faculty, all-technology convenience sample, which limits generalisability; the reliance on self-reported perceptions of critical thinking rather than objectively assessed ability; and potential common-method bias arising from single-source, single-time-point self-report data. Future research should employ longitudinal designs, diverse disciplines, standardised critical thinking assessments, and qualitative exploration of the *ijtihad*-AI tension.

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Ethical Approval

This study was approved by the Institutional Review Board of Hormuud University. Written informed consent was obtained from all participants.

Conflict of Interest

The author declares no conflict of interest.

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