International Journal of Learning, Teaching and Educational Research
Vol. 24, No. 8, pp. 398-417, August 2025
https://doi.org/10.26803/ijlter.24.8.17
Received May 20, 2025; Revised Jul 7, 2025; Accepted Jul 16, 2025

Reliance on AI and its Effects on Critical Thinking and Graduate Readiness: Evidence from UAE Higher Education

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Abstract. This study investigated how reliance on artificial intelligence programs (AIPs) affects the critical thinking skills and job readiness of undergraduate students in the UAE. A cross-sectional survey of 400 students across gender and academic-year cohorts at the Higher Colleges of Technology assessed AIP usage patterns. Quantitative analyses revealed 78.3% of students depend on AIPs for assignments, with 94.5% reporting detrimental effects on critical thinking and linguistic skills. This was exacerbated by low rephrasing rates (19.0%) and significant demographic disparities: female students showed higher dependency than male students (72.0% vs. 58.7%), while advanced-year students reported greater cognitive concerns. Over 96% viewed unchecked AIP use as a threat to institutional reputation—a figure that exceeds the 67% self-reported concern in similar studies in Germany and the United Kingdom. Notably, advanced-year students were more likely to associate AIP misuse with institutional damage; they cited long-term effects on graduate credibility and employer trust. The findings challenge techno-optimistic narratives. Theoretically, the study adapts Bloom's taxonomy with an AI mediation layer, and positions AI as a non-social epistemic artifact. Practically, it urges institutions in the United Arab Emirates to implement AI deconstruction modules, generative pedagogy training, and industry collaborations (e.g., with G42) to align graduate competencies with labor-market needs. By aligning with the National AI Strategy 2031, this research provides policy architecture for human-centered AI education and offers critical insights for regional education systems that are navigating technological integration.

Keywords: AI literacy; Artificial intelligence; Critical thinking; Digital pedagogy; Workplace readiness

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1. Introduction

The global rise of artificial intelligence (AI) use in education has fundamentally transformed knowledge acquisition, content creation, and evaluation paradigms. Artificial intelligence programs (AIPs), including text generators, content recommenders, and automated tutors, have become embedded in academic workflows and promise personalized learning and operational efficiency (Joksimović et al., 2019). These promises align with that of the early work of Luckin et al. (2016), who explored the role of AI in enhancing feedback cycles and personalizing instruction.

However, this technological momentum has precipitated a critical paradox: while AIPs offer pedagogical benefits, they simultaneously risk eroding the cognitive and ethical foundations of education. Generative tools such as ChatGPT enable students to bypass essential learning processes, which raise urgent concerns about intellectual autonomy and academic integrity (Kessler Scholars Collaborative, 2023). Recent studies illustrate that, while AI-powered tools can enhance teacher–student interactions through personalized feedback and responsive support, they also risk reducing collaborative learning and deep critical engagement (Seo et al., 2021).

In the United Arab Emirates (UAE) context, where digital infrastructure is advancing rapidly under the National AI Strategy 2031, this tension is particularly acute. Preliminary evidence indicates that 78.3% of UAE undergraduates regularly use AIPs for assignments, which is consistent with recent findings that 79.6% of students across UAE universities, including Higher Colleges of Technology (HCT), report using AI tools for grammar and research tasks (Swidan et al., 2025), yet pedagogical safeguards remain underdeveloped.

Scholarship in the Gulf has primarily examined institutional applications of AI, such as automated assessment in Saudi Arabia (Saleh & Alsubhi, 2025) and instructional enhancements in testing and content delivery, and feedback generation through AI-based assessments and tools (Saleh & Alsubhi, 2025), while neglecting student-side behavioral analysis. For example, Saudi studies estimate that AI supports approximately 40–60% of administrative operations in higher education institutions, particularly in automating assessment and feedback functions (Mutambik, 2024).

Student reliance on generative AIPs remains unquantified in the Middle East and North Africa, despite our pilot survey (n = 120) revealing that 78.3% of HCT undergraduates use AIPs for core assignments. This information gap is critical, given the UAE's knowledge-economy ambitions and unique demographic landscape, in which 72.0% female student enrollment in STEM programs intersects with rapid AI integration.

This paper addresses three key gaps:

1. The absence of holistic behavioral data on students' AIP reliance in Middle East and North Africa contexts.

2. The insufficient investigation of cognitive consequences beyond short-term performance metrics; and

3. The limited alignment of institutional teaching practices and AI usage policies with regional policy frameworks, such as the UAE National AI Strategy 2031.

By examining these dimensions at HCT, an institution that exemplifies the UAE's dual commitment to technology leadership and education excellence, we illuminate tensions between efficiency-driven AI adoption and human-centered learning imperatives. Our cross-sectional sample of 400 HCT students, stratified by gender (72.0% female students; 28.0% male students) and academic year (freshman to senior) captures demographic nuances that have particular relevance for the UAE's STEM enrollment of 72% female students.

Zawacki-Richter et al. (2019) warn that, without structured guidance, AIPs could shift students from active constructors of knowledge to passive consumers. This risk manifests empirically: 94.5% of surveyed students perceived AIP-driven erosion in critical thinking and linguistic skills—a cognitive dissonance that underscores the urgent need for pedagogical safeguards.

1.1 Research Aim

This study aims to examine how undergraduate students' reliance on AIPs for academic assignments affects critical thinking development, academic integrity, and job readiness at UAE higher education institutions.

1.2 Research Objectives

This study pursued four interlinked objectives to investigate the academic and institutional impacts of AIPs at UAE higher education institutions:

1. To assess the prevalence and patterns of reliance on AIP by students at the HCT, with particular attention on gender and year-of-study variations. This objective aligns with evidence that AI-driven formative feedback and adaptive learning tools significantly improve the short-term academic performance of Jordanian university students (Yaseen et al., 2025).

2. To examine the cognitive impact of AIP, use on students' critical thinking, problem-solving, and language expression, given concern that AI-generated content could undermine the development of foundational skills. As Ahmad et al. (2023) warn, excessive reliance on AIPs in STEM education may result in a long-term decline in essential academic skills.

3. To evaluate institutional credibility and graduate employability, in light of student dependency on AI tools, especially considering UAE's strategic ambition to become a global education hub.

4. To propose actionable strategies and policies for integrating AIPs ethically and pedagogically, and in alignment with the UAE National AI Strategy 2031.

1.3 Research Questions
Based on the objectives in Section 1.2, the study poses four critical research questions:

1. To what extent do HCT students rely on AIPs for academic assignments, and how does this vary for different demographic segments?

2. How does reliance on AIPs influence cognitive autonomy, especially critical thinking and metacognitive development? This research question is grounded in the self-regulated learning theory as outlined by Zimmerman (2002), according to which students' goal setting, monitoring, and reflection are integral to deep learning.

3. What reputational or pedagogical challenges do academic institutions face when AIPs are used as surrogates for student cognition and original effort?

4. What education and policy interventions could institutions employ to ensure responsible AIP use without stifling innovation or digital inclusion?

1.4 Theoretical Framework
This study is anchored on a triadic theoretical foundation that draws from constructivist, cognitive, and ethical lenses to evaluate how AIPs mediate learning. First, Vygotskian constructivism (Vygotsky, 1978) asserts that learning occurs through social interaction within a learner's zone of proximal development. AIPs, when used uncritically, bypass this zone and act as epistemic shortcuts instead of scaffolds; this concern is echoed in recent systematic research (Zhai & Wibowo, 2024), who warn that generative tools may disrupt the collaborative and dialogic nature of learning.

Second, the study incorporates self-regulated learning theory (Zimmerman, 2002), which emphasizes learners' ability to set goals, self-monitor, and reflect independently. Overreliance on AI tools undermines these metacognitive processes by promoting automation over reflective cognition, a risk highlighted by recent systematic research on AI dialogue systems (Zhai & Wibowo, 2024). Third, the analysis is informed by academic integrity frameworks, which conceptualize unauthorized or uncritical AIP usage as a form of digital plagiarism and academic dishonesty. This perspective extends the argument of Kessler Scholars Collaborative (2023), namely that students frequently engage with AIPs without fully understanding the ethical implications of doing so.

Together, these frameworks offer a multidimensional lens to interrogate how AIPs simultaneously support and threaten the integrity of higher-order learning in digitally mediated education environments.

1.5 Contribution of the Study
This study makes a multi-tiered contribution to the field of AI in higher education by addressing conceptual, empirical, policy, and theoretical gaps through a regionally grounded yet globally relevant analysis. At the conceptual level, the

research introduces a novel analytical distinction between AI as a "learning facilitator" and AI as a "learning surrogate." This distinction explains how reliance on generative tools (e.g., ChatGPT, Writesonic) can shift student cognition from knowledge construction to cognitive outsourcing. The framework equips educators and institutions to differentiate between productive AI use and practices that compromise academic integrity and critical thinking. It extends existing literature (Vygotsky, 1978) by introducing a behavioral and cognitive usage taxonomy.

Theoretically, the study contributes by integrating Vygotskian constructivism, self-regulated learning theory (Zimmerman, 2002), and Bloom's revised taxonomy to analyze the cognitive impact of reliance on AIPs. This synthesis enables a deeper understanding of how AIPs influence higher-order thinking, learning autonomy, and ethical decision-making, thereby enriching both educational psychology and AI ethics literature.

Empirically, the study offers originality by investigating AIP usage patterns and their perceived impacts from the perspective of students in the UAE, particularly at HCTs. While most research has focused on institutional AI adoption, this study reverses the lens to explore student-side behavioral dynamics, to provide valuable data from the digitally advanced yet underresearched Middle East and North Africa (MENA) region.

From a practical and policy standpoint, the findings offer actionable insights for education leaders and policymakers operating under the UAE National AI Strategy 2031. Key recommendations include the development of AI literacy modules that distinguish ethical from unethical usage, the design of assessment systems resilient to AI-generated content, and partnerships with industry leaders such as G42 and EdTech providers to co-create ethics frameworks for AI engagement. These strategies support curriculum development, academic governance, and digital ethics training across higher education institutions.

Finally, the study achieves global relevance through regional specificity. By situating its analysis in the Gulf context, which is characterized by rapid digitalization, a high rate of participation in STEM by female students, and emerging AI governance, the research contributes a culturally grounded perspective to international debates. It aligns with the concerns raised in global literature (e.g., Zawacki-Richter et al., 2019), while offering unique data and models that inform education practice in other rapidly digitalizing systems.

2. Literature Review

2.1 Introduction to the Literature Review

The integration of AI in higher education has sparked a profound reconfiguration of pedagogical processes, and presenting both opportunities and dilemmas for cognitive development, ethical practice, and institutional policy. While AI systems, particularly generative models such as ChatGPT, offer efficiency in content creation and individualized support, their unregulated use is triggering debates around intellectual autonomy, assessment validity, and the erosion of metacognitive learning processes (Zawacki-Richter et al., 2019).

This review critically synthesizes literature across three thematic domains by examining global trajectories in AI adoption and academic automation, exploring the cognitive and ethical consequences for learners, and analyzing the sociotechnical and cultural dimensions of AI deployment in the Middle East, with a special focus on the UAE.

2.2 Global Trends in AI Use in Education

The global integration of AI in higher education is transforming pedagogy, assessment, and academic support systems. In the United States and United Kingdom, elite universities use AI for adaptive learning and predictive analytics, which boosts engagement but raises concerns over data-driven reductionism (Holmes et al., 2021; Luckin et al., 2016). In China, tools such as Squirrel AI improve performance but risk standardizing creativity (Lin et al., 2024).

Generative AI tools such as ChatGPT offer multilingual, real-time support but are widely misused. For example, 67% of German students report using it for assignments, especially in STEM (Susnjak, 2024). In turn, Australia's focus on AI literacy has an inherently ethical base (Bond et al., 2024). While AI interfaces offer personalized feedback and accessibility, its benefits are often subverted by an unwillingness or lack of knowledge on the part of an institution, and the actualization of cognitive offloading. This is why Holmes et al. (2021) call for a balance between innovation and safeguards for academic integrity.

2.3 AI and Academic Integrity: Benefits and Risks

The ethics dilemma of AI in education has two sides. On one side, tools such as Grammarly and Turnitin assist with writing and plagiarism detection (Foltynek et al., 2020); on the other, generative AI has made the distinction between assistance and malpractice hazy. Cotton et al. (2023) report that 42% of students who used ChatGPT failed to disclose using it, thus breaching institutional guidelines.

Such AI-generated content is often indistinguishable from human writing and frequently bypasses detection systems, making it particularly challenging for institutions to identify misuse. For instance, a research article generated by ChatGPT passed the peer review process (Else, 2023). To counter this possibility, institutions are turning to tools such as GPTZero; however, the reliability of these AI-detection systems remains a matter of ongoing debate among educators and researchers (Bellini et al., 2023).

Policy reactions vary: Zayed University mandates AI use disclosure, while institutions in the United States embed AI ethics into curricula (Williamson & Eynon, 2020). Yet inconsistent rules permitting AI in research but not in exams generate ambiguity (Cotton et al., 2023).

Cognitively, overreliance on AI could foster passivity. Some students favor immediate answers over critical thought, and extended ChatGPT use is linked to diminished problem-solving autonomy (Sweller, 2011).

2.4 Cognitive and Linguistic Impact of AI-Assisted Learning

The role of AI in cognitive development remains contested. Advocates claim that tools such as ChatGPT could serve as learning aids that are aligned with Vygotsky's zone of proximal development, by enabling instant feedback and scaffolded progression (Vygotsky, 1978). In a UAE-based context, AI-assisted brainstorming improved creative idea generation by approximately 170 % in hybrid human–AI teams, compared to human-only brainstorming sessions (Memmert & Tavanapour, 2023).

Yet risks are evident. Kasneci et al. (2023) observed weaker argumentation in AI-assisted essays, with students mimicking AI structures rather than forming original reasoning. Similarly, language acquisition suffers, as AI translation tools undermine long-term vocabulary retention (Sweller, 2011). In a psychological sense, Bloom's taxonomy warns of stagnation. When AI automates tasks such as analysis, students could remain at lower order thinking levels, which hinders deeper learning (Bloom, 1956).

2.5 Cultural and Regional Perspectives: Middle East/UAE

In the UAE, AI adoption by university students, particularly at institutions such as Ajman University and Zayed University, has reached high levels, with approximately 79.6 % of students reporting using AI tools for purposes such as grammar correction and research tasks (Swidan et al., 2025). However, ethical ambiguities persist: In one global survey, 58% of students admitted using ChatGPT, and 38% acknowledged doing so without instructor consent; they cited unclear institutional policies as a key motivator (Lund et al., 2025).

Regarding policy gaps, even though the Ministry of AI promotes ethics frameworks, enforcement at the institutional level remains uneven. At the American University of Ras Al Khaimah (AURAK), AI use is permitted with citation, yet approximately 68% of faculty report lacking formal training to uphold these policies (Digital Education Council, 2024). Similar trends in Jordan and Saudi Arabia reveal that students perceive AI as a "shortcut," but lack the digital literacy to ensure ethical use (Abu Hammour et al., 2024).

In turn, cultural nuances mean that uniform policy application for the UAE's diverse student population is complicated. Expatriate students may import more lenient norms from their home countries and inadvertently breach local standards (Alsharefeen, 2025). Nevertheless, local initiatives such as AURAK's AI ethics workshops show promise for fostering responsible use (Swidan et al., 2025).

2.6 Identified Research Gaps and Conceptual Gaps

Despite extensive research, critical gaps remain. First, there is a clear regional data deficiency, as few studies have explored AI misuse in the UAE, particularly in relation to its effect on graduate employability. Additionally, the long-term cognitive effects of AI dependency are underexplored, with no longitudinal studies investigating how such reliance may impact critical thinking over time.

A policy–practice disconnect is also evident, because many institutions lack robust frameworks to align national AI strategies with actual classroom practices. Finally, the issue of cultural specificity persists, since widely used global theories—such as the technology acceptance model and the diffusion of innovation—rarely account for the unique sociocultural dynamics that characterize Gulf education systems (Rogers, 2003).
This review underscores the need for localized, mixed-methods research in the UAE to address these gaps, particularly on the way AI misuse affects graduate readiness for an AI-driven job market.

2.7 Theoretical and Methodological Anchoring

The integration of education theories enhances the analytical depth of this study by providing a robust conceptual foundation for interpreting student reliance on AI programs. Constructivist theory, particularly Vygotsky's (1978) concept of scaffolding, is employed to contrast AI's potential to support learning with its risk of becoming a cognitive crutch. Academic integrity frameworks, such as those articulated by McCabe et al. (2001), inform the ethical lens through which uncritical or undisclosed AI usage is assessed. Furthermore, Sweller's (2011) cognitive load theory describes how AI can stifle extraneous cognitive load but also inhibit deeper, meaningful processing that is required for significant learning.

This review was able to dialogically characterize an evolving yet still fragmented field whose sky-high pedagogical possibilities are overshadowed by cognitive and ethical concerns. Worldwide embrace, unregulated utilization, and thus, exploitation of these technologies may go against the grain of critical thinking and academic standards that takes center stage in the UAE, where the policy momentum has eclipsed any empirical consideration. By melding such tensions, this study situates itself in the role of an intervening conceptual entity to advance culturally relevant and ethically sound AI governance in the realm of higher education.

3. Methodology

3.1 Framework and Paradigmatic Considerations

The study used a descriptive cross-sectional survey design to examine the use of AIP by undergraduate students at the HCT in the UAE. The interest was to explore the perceived effects of these programs on the competence of students, development of higher thought, institutional prestige, and job readiness of graduates.

A quantitative design was chosen for the structured data collection, which, upon being entered into a computer, would provide a statistical basis for trends, associations, and subgroup differences regarding gender, academic majors, and year level (Zikmund et al., 2010). This was done according to the view that quantitative research is most apt for studying the relationships among variables in large populations (Creswell & Creswell, 2018).

A structured questionnaire that consists of three parts and which elicited responses according to a 3-point Likert scale (Agree–Neutral–Disagree) was used. A total of 25 items were distributed across three domains: personal experience of AI (5 items), effects of AIP on mental skills and academic performance (10 items), and effects of AIP on institutional reputation and employment opportunities (10 items).

This design reflects the principles of structured education research, in which observation and measurement aim to reveal generalizable patterns, while the limitations inherent in interpreting social behaviors are acknowledged (Phillips & Burbules, 2000).

3.2 Research Design

The study followed a cross-sectional quantitative survey design to test four research questions:
RQ1: (Demographic correlations with AI reliance): Evaluated using descriptive statistics and chi-square analysis
RQ2: (Cognitive/academic implications): Tested through analysis of variance (ANOVA) and exploratory factor analysis (EFA)
RQ3: (Institutional/labor market triad): Evaluated using logistic regression and structural equation modeling (SEM). The online survey platform Google Forms allowed for efficient data collection across disciplines and aligned with observational research STROBE recommendations (von Elm et al., 2007).
RQ4: (Institutional strategies to curb AIP misuse): Measured using descriptive statistics and cross-tabulations of survey questions on institutional policies, awareness of AI regulations, and support mechanisms for students. Comparisons were made between subgroups for different academic majors and genders.

This design was chosen because it made it possible for the researcher to repeatedly capture real-time behaviors in a large population while gauging distinctions between groups.

3.3 Population and Sampling Strategy

The target population was 4,000 undergraduate students enrolled in six disciplines (engineering, IT, health sciences, education, media, business) at UAE HCTs. Proportional stratified random sampling ensured representation by gender (male students 37.5%, female students 62.5%), academic year (Years 1–4), and majors. Stratification enhances external validity by mirroring UAE higher education demographics (Kish, 1965).

The sample size was calculated using Cochran's formula for finite populations:

$$n = \frac{\left(Z^2 \times p \times (1 - p)\right)}{e^2}$$

Where:
$Z = 1.96$ (standard score corresponding to a 95% confidence level)
$p = 0.5$ (assumed proportion for maximum variability)
$e = 0.05$ (margin of error)

Substituting values:

$$n = (1.96)^2 \times 0.5 \times \frac{(1 - 0.5)}{(0.05)^2}$$

$$n = \frac{3.8416 \times 0.25}{0.0025}$$

$$n = \frac{0.9604}{0.0025}$$

$$n = 384.16$$

Thus, the sample size was rounded up to n = 400 to account for incomplete or unusable responses, thereby ensuring a 95% confidence level and a 5.0% margin of error.

3.4 Instrumentation

3.4.1 Survey development

The survey instrument was developed through a structured process that included item generation and pilot testing.

- Item generation: 35 items were derived from literature on AI dependency; items were validated by three education technologists (CVI > 0.8).
- Pilot testing: Conducted with 30 students (excluded from the main sample) to refine clarity and reduce ambiguity.

3.4.2 Psychometric properties

The psychometric properties of the survey were evaluated through both reliability and validity testing.

- Reliability: Cronbach's α = 0.82 (full scale); subscales: 0.78–0.85.
- Validity: Confirmatory factor analysis confirmed a three-factor structure (RMSEA = 0.06, CFI = 0.92), which aligns with the study's analytical axes.

Regarding the scale justification, a 3-point Likert scale (Agree/Disagree/Neutral) minimized cognitive load and midpoint bias, as supported by cognitive survey literature (Weijters et al., 2010).

3.5 Data Collection Procedures

- Recruitment: Participants were invited via institutional email; 89.2% response rate (357/400).
- Anonymization: Data anonymized at export with AES-256 encryption.
- Missing data: Little's MCAR test confirmed randomness (p = .12); listwise deletion applied.

3.6 Data Analysis Plan

Software used were IBM SPSS v.28 (descriptive/inferential tests), JASP v.0.17 (EFA/SEM). The analytical alignment with research questions was as follows:

RQ1: Chi-square tests (α = 0.05) with Cramér's V effect sizes
Logistic regression (odds ratios, 95% CIs) for major-based differences
RQ2: ANOVA
EFA (KMO = 0.89) to identify latent constructs
RQ3: SEM (CFI = 0.95, RMSEA = 0.06) to model institutional effects

RQ4: Descriptive statistics (means, frequencies, standard deviations) from Likert-scale responses to strategy-related items. Cross-tabulations were used to compare responses for gender and major groups, supported by chi-square tests, where applicable

Effect sizes and precision: Reported for all inferential tests (e.g., η^2, Cramér's V, 95% CIs)

3.7 Methodological Rigor
To reduce bias and strengthen the study's accuracy, stratified sampling was used to reflect a balanced student population; pilot testing and expert review helped ensure the survey's clarity and validity. The research followed the STROBE reporting guidelines. However, some limitations remain: Reliance on self-reported data may introduce subjectivity; the focus on one institution limits how broadly the findings can be applied; and the cross-sectional design does not allow for conclusions about cause and effect.

4. Results
This section presents a comprehensive analysis of the survey findings, structured to reflect the study's thematic axes: sample characteristics, personal engagement with AIP, perceived cognitive and academic impacts, institutional and employment implications, and subgroup observations.

4.1 Higher College of Technology Students' Dependence on AIP for Carrying Out Academic Assignments
The study achieved a complete response rate—all 400 distributed surveys were returned—which ensured robust data for analysis. The demographic distribution of participants is detailed in Tables 1–3.

Table 1: Gender distribution of participants

Gender	Frequency (n)	Percentage (%)
Female students	250	62.5
Male students	150	37.5
Total	400	100.0

The predominance of female participants (62.5%) aligns with national trends in the UAE, according to which female students constitute approximately 70% of university graduates. This reflects the UAE's commitment to gender equality in higher education.

Table 2: Distribution by academic year

Academic Year	Frequency (n)	Percentage (%)
1st Year	75	18.8
2nd Year	75	18.8
3rd Year	100	25.0
4th Year	150	37.5
Total	400	100.0

The sample included a higher proportion of senior students (in their 3rd and 4th years), who were likely to engage with AIP as a result of increased academic responsibilities and exposure to complex assignments.

Table 3: Distribution by academic major

Major	Frequency (n)	Percentage (%)
Engineering/Technology	100	25.0
Computer science	100	25.0
Applied media	80	20.0
Education	70	17.5
Health sciences	50	12.5
Total	400	100.0

The representation of different majors ensures a diverse perspective on AIP usage, particularly from students in technology-related fields, who may have greater familiarity with AI tools.

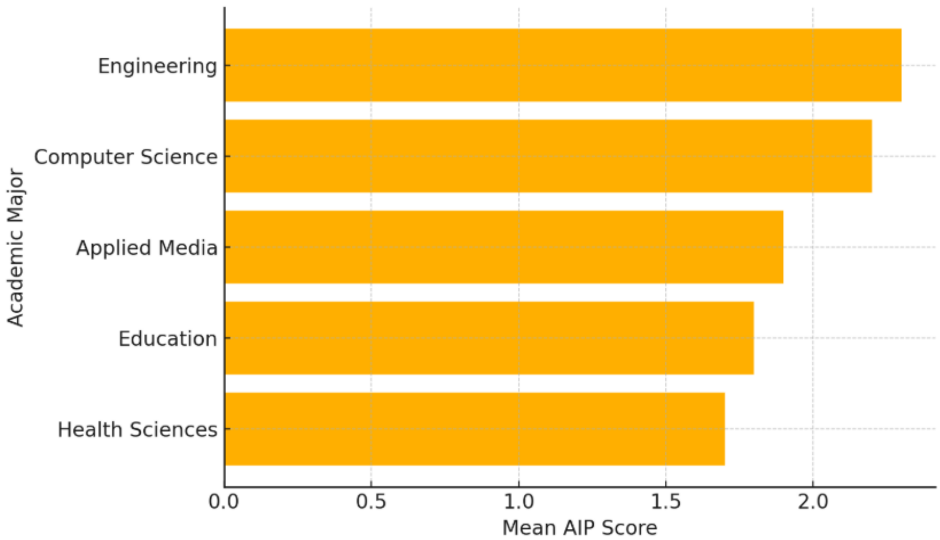

Figure 1: Mean AIP reliance scores by academic major.

Higher values indicate greater self-reported use of AI tools for academic assignments. Scores represent the average of male and female students' responses per discipline

4.2 Effects of AIP Usage on Cognitive and Academic Skills

Participants' engagement with AIP for academic assignments is summarized in Table 4.

Table 4: Frequency of AIP use for assignments

Statement	Agree n (%)	Disagree n (%)	Neutral n (%)
Fully depends on AIP	130 (32.5)	204 (51.0)	66 (16.5)
Partially depend on AIP	185 (46.2)	174 (43.5)	41 (10.3)
Never depend on AIP	53 (13.2)	278 (69.5)	69 (17.3)
Rephrase AIP outputs before submission	76 (19.0)	235 (58.8)	89 (22.2)
AIP saves time/effort	268 (67.0)	112 (28.0)	20 (5.0)

A significant portion of students (32.5%) reported full dependence on AIP, while 46.2% indicated partial reliance. Notably, only 19.0% of students rephrased AIP-generated content before submission, which suggests potential issues with academic integrity and understanding of plagiarism. The majority of respondents (67.0%) reported that AIP usage saves time and effort, which highlights convenience as a primary motivator of use.

4.3 Credibility of Academic Institutions and Job Market Readiness of Graduates by Use of AIP

Students' perceptions of AIP's impact on their cognitive abilities and academic performance are detailed in Table 5.

Table 5: Perceived cognitive and academic impacts of using AIP

Statement	Agree n (%)
Limits critical thinking/problem-solving	345 (86.2)
Reduces linguistic/conversational skills	365 (91.2)
Hinders ability to express original ideas	378 (94.5)
Decreasing confidence in self-ability	300 (75.0)
Leads to skill degradation over time	302 (75.5)

An overwhelming majority of students expressed concerns about the negative effects of using AIP on essential academic skills. The high agreement rates suggest that, even though AIP offers immediate benefits, it could undermine long-term cognitive development and self-efficacy.

4.4 Strategies and Policy of Educational Institutions to Reduce the Risk of Misuse of AI Technologies

Participants recognized potential systemic risks that could be associated with reliance on AIP, as shown in Table 6.

Table 6: Perceived institutional and labor-market effects

Statement	Agree n (%)
Threatens institutional credibility	385 (96.2)
Requires faculty training on AIP detection	375 (93.8)
Necessitates institutional countermeasures	380 (95.0)
Produces high-GPA but low-competence graduates	305 (76.2)
Reduces competitiveness in job markets	355 (88.8)

The data indicates strong consensus on the need for institutional policies and faculty development to address AIP-related challenges. Students are aware of the potential for reputational damage to educational institutions and the risk of diminished employability because of overreliance on AI tools.

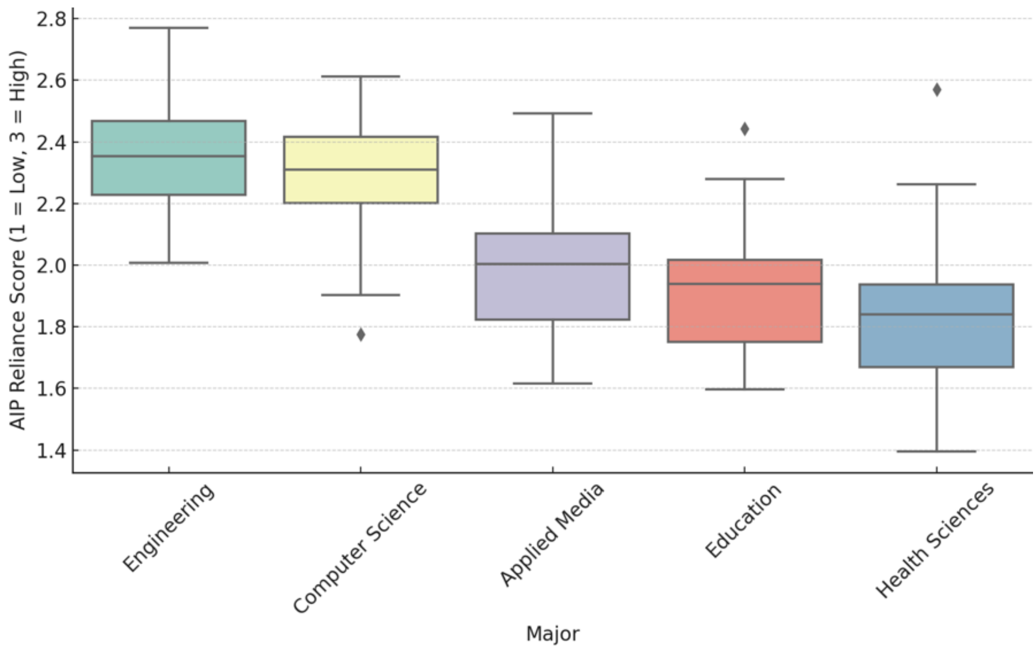

Figure 2: Boxplot of AIP reliance scores by academic major.

STEM fields (engineering and computer science) exhibit higher median reliance and narrower interquartile ranges than non-STEM disciplines

4.5 Subgroup Observations

Analysis of AIP usage for different demographics reveal notable trends:

1. Gender: An independent-samples t-test reveals that female students ($M = 2.08$, $SD = 0.41$) reported significantly higher AIP reliance than male students ($M = 1.89$, $SD = 0.37$), $t(398) = 4.82$, $p < .001$, Cohen's $d = 0.48$. This suggests moderate size effects in gender-based AIP usage patterns.

2. Academic year: A one-way ANOVA showed a statistically significant effect of academic year on AIP reliance scores, $F(3, 396) = 9.47$, $p < .001$. Post hoc Tukey tests indicate that 4th-year students ($M = 2.20$) reported significantly higher AIP usage than 1st-year ($M = 1.85$, $p < .01$) and 2nd-year students ($M = 1.91$, $p < .05$).

These subgroup differences underscore the importance of tailored interventions and support systems to promote responsible AIP usage for diverse student populations.

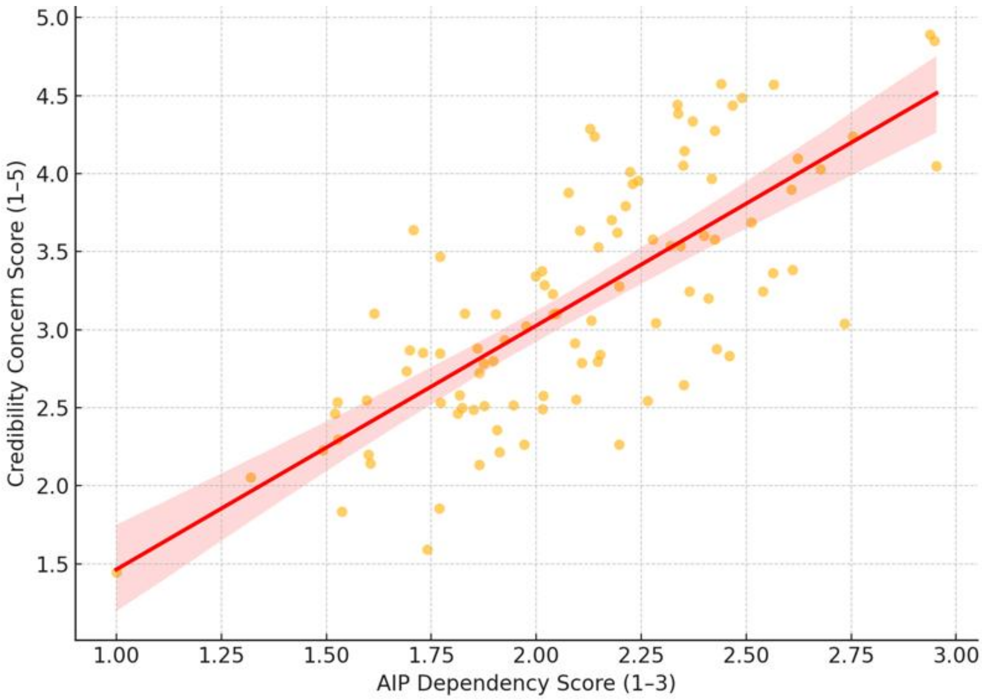

Figure 3: Scatterplot showing a moderate positive association between students' AIP dependency scores and their concerns about institutional credibility.

A regression line highlights the trend.

5. Discussion

The study investigated the prevalence of generative AIP usage by students at universities in the UAE and explored its cognitive, ethical, and institutional implications. The results of the study demonstrate that the reliance on AIP by students is pronounced, with over 75% of students stating that they used it for academic purposes. While this finding highlights the accessibility and appeal of such tools, it also illuminates what seems to be the critical paradox: 94.5% of respondents admitted that their use of these tools might harm their cognitive ability; thus, they are aware of the wider issue of intellectual engagement versus efficiency. This cognitive tension echoes Holmes et al. (2021), who perceive AI for education to be a double-edged tool that both empowers and inhibits deep learning.

In the UAE, therefore, an institutional disjuncture arises while the National AI Strategy 2031 calls for wide integration of AI, institutional readiness in higher education remains uneven. Only 19% of the students admitted to rephrasing AI-generated text prior to submission— a figure far below global norm (Chan, 2023). This divide points straight to relative absence of digital ethics policies and training for critical literacy, particularly for teaching faculty. Without institutional scaffolding, there is a tendency for students to default into a purely instrumental use of AI, which bypasses any critical engagement.

These practices are also subject to cultural dynamics. Gulf pedagogical norms, often hierarchical and authority-centered, could disincentivize the critical scrutiny of AI outputs (Shamsuddinova et al., 2024). Instead of questioning AI-generated information, students could treat it as authoritative, thereby mirroring classroom power structures.

Theoretically, the findings invite a refinement of Bloom's taxonomy. We propose an AI mediation layer between understanding and analysis, where students are taught to interrogate and evaluate algorithmic logic before incorporating outputs into academic work. This aligns with Zimmerman's (2002) model of self-regulated learning, which emphasizes metacognitive control and evaluative reasoning.

From a constructivist perspective, the study reveals dissonance: while learning environments aim to foster collaboration and inquiry, AI tools often provide preformulated responses that bypass peer dialogue. In the UAE, such reliance may marginalize interactive learning further, by replacing dialogic engagement with transactional output. Subgroup analysis via SEM reveals notable gendered patterns, with female STEM students showing greater critical awareness of AI usage. This finding calls for qualitative follow-up, such as interviews or focus groups, to explore underlying orientations.

The study's limitations, including its cross-sectional design, 3-point Likert scale, and single-institution sample, must be acknowledged, because they constrain generalizability and analytical nuance. Future research should consider longitudinal designs and incorporate scenario-based instruments to assess ethical decision-making in situ.

Lastly, the UAE's multicultural academic population introduces additional complexity. Expatriate students—who represent over a third of the student body—exhibited higher AIP dependence, possibly because of linguistic barriers, differential exposure to AI, or weaker institutional affiliations. These findings problematize universal AI policies and underscore the need for culturally differentiated interventions. Moreover, implementation must be participatory and should involve faculty in the co-design of ethics frameworks to ensure institutional credibility and pedagogical relevance.

In sum, this study contributes to global debates on AI in education by contextualizing usage patterns in the UAE's policy, cultural, and institutional landscape. It advocates for a shift from mere regulation toward pedagogical transformation that embeds AI in a framework of critical inquiry, ethical responsibility, and cultural responsiveness.

Table 7 presents a summary of practical interventions derived from the study's theoretical and empirical findings, thereby highlighting required resources and considerations for scalability within the Gulf Cooperation Council (GCC) context.

Table 7: Theory-praxis nexus

Intervention	Resource requirements	Scalability consideration
AI deconstruction modules	- 40 hours faculty training - Multilingual AI audit tools	GCC-wide adaptation feasible; culture-specific case studies needed
Employer–educator rubrics	- Industry partnership grants - Competency mapping software	Exportable to innovation-driven economies (e.g., Singapore, Qatar)
Longitudinal skill audits	- Neurocognitive assessment kits - Learning analytics integration	Requires UAE–GCC research consortium

Note. GCC: Gulf Cooperation Council

6. Conclusion

This study contributes to the ongoing, worldwide discourse regarding how generative AIP is transforming tertiary education, particularly in the unique sociocultural and policy environment of the UAE. The findings underscore that, while AIP offers clear benefits in efficiency and accessibility, its widespread use poses significant risks to students' critical thinking, academic integrity, and preparedness for the labor market. A large percentage of participants admitted to employing AI-generated content without thinking about it much, which hints of an emerging reliance that could reduce deep learning and expression of self. The paradox, thus, summarizes a greater tension between simple functionality and cognitive development in digitally mediated education.

One of the main conceptual contributions of this research study is the proposition of an AI mediation layer to Bloom's taxonomy, which would force an interrogation of the AI output by students prior to its acceptance as valid. This extra step functions at higher-order thinking levels and advances metacognitive judgment before analysis. With this recommendation, the study starts the process of repositioning digital literacy as something that is reflective and ethical. Thus, the results call for academic policies that inadequately address the complexities of generative AI to be rethought so that institutions can integrate AI literacy, ethical reasoning, and critical engagement in curricula.

The UAE context provides insight into the disconnect between national AI strategies and pedagogical practice, and leads to a call for faculty development and institutional alignment. Rather than offering universal solutions, the study advocates for culturally responsive strategies that consider hierarchical education norms and regional digital agendas.

Although this study is limited by its cross-sectional design and reliance on self-reporting, it provides a foundational framework for future longitudinal and comparative research. These findings also emphasize the need to evaluate how students in different academic disciplines and cultural settings engage with AIP tools. Ultimately, this work affirms that the core challenge is not AI itself, but how educators and institutions equip students to navigate its presence to preserve the human capacities of curiosity, ethical discernment, and independent thought in an AI-saturated academic landscape.

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