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The Impact of Generative AI on Critical Thinking and Academic Integrity in Higher Education: A Mixed-Methods Study

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ABSTRACT

Accessibility and integration of generative artificial intelligence (GenAI) tools like ChatGPT, Claude, and Gemini into higher education present both unprecedented opportunities and significant challenges. This study addresses the growing concern that overreliance on GenAI may compromise students' independent reasoning and the authenticity of academic work. Through an explanatory sequential mixed-methods design, this research examines the impact of GenAI on critical thinking and academic integrity. The quantitative phase surveyed 450 undergraduate students across three Nigerian institutions and three disciplines, using the California Critical Thinking Skills Test (CCTST) and the SAMR model to assess integration levels. The qualitative phase utilized semi-structured interviews and focus groups to explain the statistical results. Key findings reveal a stark dichotomy: students integrating AI at the 'Modification/Redefinition' level demonstrated significant gains in critical thinking, effectively using AI as a Vygotskian "More Knowledgeable Other." Conversely, those at the 'Substitution' level exhibited stagnation in reasoning skills and higher rates of plagiarism flags, utilizing AI merely as a "Cognitive Shortcut." The study further identifies an "Ethical Gray Zone" caused by institutional policy lags and instructor ambivalence. Ultimately, this paper argues that GenAI is not inherently detrimental; rather, its impact relies on the pedagogical framework—specifically, shifting from shortcut-seeking behaviors to partnership-oriented workflows.

Keywords: *Generative AI, Academic Integrity, Higher Education, AI Integration*

I. INTRODUCTION

The rapid evolution of Generative Artificial Intelligence (GenAI), demonstrated by tools such as ChatGPT, Google Bard, and Microsoft Copilot, is fundamentally transforming higher education (Hughes et al., 2025; Michel-Villarreal et al., 2023). These technologies, designed to generate human-like text and support complex cognitive tasks, are increasingly being adopted in academic environments for research, writing assistance, and tailored learning (Kaushika et al., 2025; Saúde et al., 2024). While this integration has opened new instructive possibilities, it has also raised pressing questions about its impact on core academic values, particularly critical thinking and academic integrity (Bittle & ElGayar, 2025; Yusuf et al., 2024).

As higher education institutions grapple with how to incorporate GenAI tools, two interconnected challenges emerge. There is growing concern that overreliance on GenAI may compromise students' ability to engage in deep, independent reasoning (Gonsalves, 2024). Simultaneously, the authenticity of academic work is under threat, as conventional plagiarism detection systems struggle to identify AI-generated content, thereby complicating the enforcement of academic honesty (Wiredu et al., 2024; Fischer et al., 2024).

Recent scholarship underscores these dualities and complexities. Kaushika et al. (2025) emphasize both the pedagogical potential and ethical predicaments associated with GenAI, calling for human-centered integration and comprehensive policy reform. Similarly, Bittle and ElGayar (2025) highlight systemic gaps in current detection tools and raise critical concerns about student misuse of AI technologies. From a multicultural perspective, Yusuf et al. (2024) urge institutions to consider cultural diversity when assessing GenAI's ethical implications, arguing that context-specific approaches are essential for effective implementation. These studies collectively emphasize the urgent need for a balanced, evidence-based framework to harness the benefits of GenAI while safeguarding fundamental academic standards (Sertel et al., 2025; Li & Akula, 2024).

In response to these tensions and the evolving landscape of AI in education, this study adopts a mixed-methods approach to examine how GenAI integration shapes critical thinking and academic integrity. The key ideas driven by this research center on the distinction between AI as a 'Cognitive Partner' versus a 'Cognitive Shortcut.' We posit that when AI is used to scaffold learning (aligned with Vygotsky's Zone of Proximal Development) and integrated at high levels of the SAMR model, it enhances critical thinking. However, without clear institutional guidance, students fall into an 'Ethical Gray Zone,'

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leading to surface-level usage that threatens academic integrity. By combining qualitative insights with quantitative data, the research provides a comprehensive roadmap for transforming AI from a threat into a pedagogical asset.

II. LITERATURE REVIEW

Recent literature reveals a complex landscape where transformative opportunities intersect with significant ethical and pedagogical challenges, creating an imperative for comprehensive research that addresses both the promise and perils of AI-mediated learning environments.

Contemporary scholarship consistently identifies the dualistic nature of GenAI integration in academic settings. Kaushika et al. (2025) present a nuanced examination of GenAI's multifaceted impact, highlighting both pedagogical potential and ethical predicaments through their thematic analysis of educator perspectives. This duality is further emphasized by Yusuf et al. (2024), who investigate GenAI as simultaneously a threat to academic integrity and a catalyst for educational reformation, particularly through multicultural lenses that reveal how cultural dimensions shape perceptions and usage patterns across diverse educational contexts. Hughes et al. (2025) extend this understanding by mapping the complex challenges facing higher education institutions in GenAI adoption, utilizing mixed-methods frameworks to reveal interdependent risk factors affecting pedagogical integrity, assessment design, and institutional policy.

The impact of GenAI on academic integrity emerges as a recurring theme across multiple studies, revealing both systemic vulnerabilities and the inadequacy of current detection mechanisms. Bittle and ElGayar (2025) provide a comprehensive systematic review of 41 peer-reviewed articles, documenting how ghostwritten assignments evade traditional plagiarism detection tools and highlighting widespread concerns about student overreliance and diminished originality. Wiredu et al. (2024) corroborate these concerns through their 3.0
case study in Ghana's Upper East Region, demonstrating that while GenAI tools like ChatGPT and Bard can enhance student learning, maintaining academic integrity and fostering independent thinking remain critical challenges.

Gonsalves (2024) offers a particularly compelling reexamination of Bloom's Taxonomy, arguing that traditional hierarchical models fail to capture the fluid, recursive nature of cognitive engagement in AI-enhanced environments. Through 3.1
longitudinal diary studies, Gonsalves identifies emergent competencies such as melioration, ethical reasoning, and metacognitive refinement that extend beyond traditional cognitive frameworks, positioning AI as a dynamic collaborator rather than merely a threat to critical thinking. Akbar (2025) advances this conversation by shifting focus from reactive detection strategies to proactive assessment design, proposing an innovative framework that integrates Bloom's Taxonomy with advanced AI tools to assess cognitive complexity and "AI-solvability" of academic tasks.
Yusuf et al. (2024) specifically address gaps in understanding how cultural dimensions shape AI perceptions and usage patterns, arguing for culturally contextualized approaches to policy development. Saúde et al. (2024) further emphasize the importance of stakeholder engagement, demonstrating that GenAI's educational potential can only be fully realized when institutions, educators, and learners engage critically and ethically with these technologies. A significant theme across the literature is the identification of substantial gaps between institutional policies and practical implementation needs. Li and Akula (2024) surface critical misalignments between institutional, national, and international policies and the ethical realities experienced by users, while Michel-Villarreal et al. (2023) contribute to this policy discourse through their innovative "thing ethnography" methodology, emphasizing the need for institutional AI policies grounded in transparency, ethical design, and pedagogical alignment.

The convergence of these scholarly perspectives reveals why comprehensive research on GenAI's impact on critical thinking and academic integrity is essential at this historical moment. Current research reveals significant methodological limitations, including small sample sizes, disciplinary focus, convenience-based sampling, and limited cultural diversity across studies. These limitations, coupled with the rapid pace of technological advancement, create an urgent need for robust, mixed-methods research that can provide a nuanced understanding of GenAI's multifaceted impact on higher education. The intersection of these studies reveals that successful GenAI integration requires not merely technological adoption but fundamental reconceptualization of pedagogical practice, assessment design, and institutional governance, making a comprehensive investigation of GenAI's impact on critical thinking and academic integrity both timely and essential for the future of higher education.

III. THEORETICAL FRAMEWORK

This study is built on a multi-faceted theoretical framework, which is used to synthesize principles involved in learning science, technology adoption models, cognitive psychology, and ethics to provide a comprehensive view for analysis. The framework is designed to navigate from the broad socio-cognitive context of learning down to the specific cognitive actions performed with AI, monitored by a normative ethical perspective.

A. Sociocultural Learning Theory: Generative AI as a Digital ‘More Knowledgeable’ Other

Two concepts – the Zone of Proximal Development (ZPD) and the More Knowledgeable Other (MKO), both from Vygotsky's sociocultural theory of learning, were used as the epistemological foundation of this research work (Vygotsky, 1978; Wertsch, 1985). The ZPD defines the cognitive gap between a learner's unassisted capabilities and their potential achievement with expert guidance, while MKO is any entity possessing greater knowledge or skill that provides this scaffolding (Wood et al., 1976). In this work, generative AI was conceptualized and used as a potential digital MKO. As such, AI plays the role of an interactive tutor, a dialogue partner, or a feedback mechanism, which enables students to tackle complex problems that lie within their ZPD.

This arrangement, however, introduces a vital theoretical tension that studies investigate the role performed by AI-as-MKO in either scaffolding or supplanting cognitive effort (Jonassen, 1999). To achieve this feat, the study uses this dichotomy to interpret whether observed AI integration patterns correlate with cognitive enhancement or cognitive offloading.

B. SAMR Model: A Taxonomy for AI Integration in Pedagogy

Puentedura's SAMR (Substitution, Augmentation, Modification, Redefinition) model was employed in this study to operationalize and classify the various ways AI is integrated into learning tasks (Puentedura, 2006, 2012). The SAMR model provides an analytical rubric for evaluating the level of technological integration, from direct tool replacement with no functional change (Substitution) to the creation of novel tasks previously inconceivable (Romrell et al., 2014; Hamilton et al., 2016). While the engagement at the Modification/Redefinition, known as transformation, is more likely to be associated with gains in critical thinking, Substitution/Augmentation, called Enhancement, may correlate with stagnation or even a decline in higher-order cognitive skills.

C. Digital Bloom's Taxonomy: Mapping AI Use to Cognitive Processes

Digital Bloom's Taxonomy, an adaptation of the classical Bloom taxonomy framework designed by Churches (2008), was deployed to disaggregate the broad construct of "critical thinking" for the contemporary digital environment. In this digital taxonomy, a hierarchical structure for classifying cognitive skills, from Lower-Order Thinking Skills (LOTS) such as Remembering and Understanding, to Higher-Order Thinking Skills (HOTS) such as Analyzing, Evaluating, and Creating, is emphasized (Anderson & Krathwohl, 2001; Heick, 2020). This framework serves to:

i. Inform the design of our critical thinking assessments and survey instruments, and

ii. Provide a coding framework for analyzing qualitative data on student workflows.

D. An Ethical Framework for Responsible AI Integration

As the first three theories are within a normative ethical framework grounded in principles of responsible innovation, digital citizenship, and academic integrity (Ribble, 2015; UNESCO, 2021), another framework focuses on addressing the ethical valences of AI use, thus moving the analysis beyond a purely cognitive approach (Floridi et al., 2018; Jobin et al., 2019).

In this work, a framework that raises negotiation between academic authorship and intellectual ownership was considered to guide our inquiry into how students, instructors, and institutions navigate the shift in boundaries between permissible assistance and academic misconduct where AI is used as a tool or as an author. It further explains how policies can foster a culture of transparency and intellectual honesty.

IV. RESEARCH DESIGN AND METHODOLOGY

A mixed–methods explanatory sequential design (QUAN) delineated by Creswell and Plano Clark was employed. This two-phase approach (quantitative and qualitative) is suited to the research objectives. The quantitative phase is dominant as it establishes statistical patterns and relationships between AI use and the primary variables of interest. The qualitative, on the other hand, explains, contextualizes and provides a nuanced understanding of the quantitative findings. The study emphasizes the practical application of research to address real-world problems – a pragmatic research paradigm.

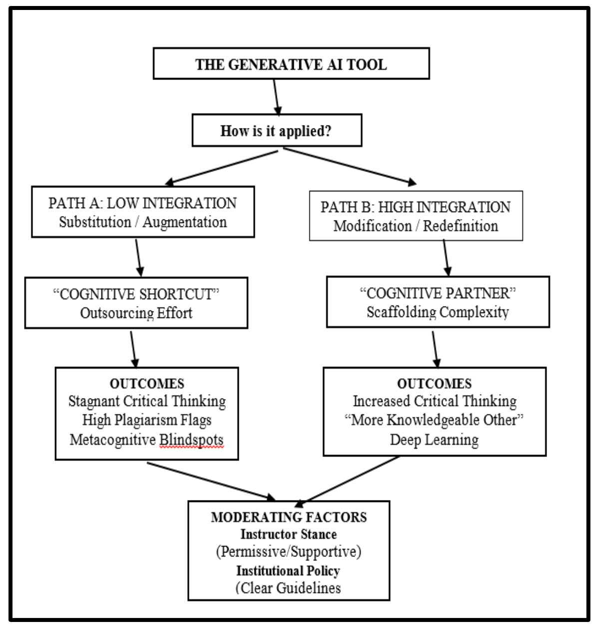

Figure 1:The Impact of GenAI Usage Patterns on Student Outcomes

A. *Phase 1: Quantitative Investigation*

A stratified purposive sample of approximately N = 450 undergraduate students will be recruited from three higher education institutions: a large public university - University of Ibadan, Ibadan (UI), a private university - McPherson University (McU), and Tai Solarin University of Education (TASUED), Ijebu – Ode, all in Nigeria. From different institutions, students in three different areas: Science, Technology, Engineering, and Mathematics (STEM), Humanities, and Social Sciences were considered for this research work in this number. The stratification by institution type and academic division is intended to enhance the external validity of the findings and allow for subgroup comparisons. The objective of this phase is to quantitatively assess the impact of generative AI integration on students' critical thinking skills, academic performance, and patterns of academic integrity.

Instruments for this phase include:

1. The validated California Critical Thinking Skills Test (CCTST) is being administered as both a pre-test and post-test to measure changes in core reasoning skills.

2. AI integration survey – a custom survey instrument with items informed by the SAMR model and Digital Blooms' Taxonomy will be administered. This gathers data on the frequency, type, and purpose of AI tool usage, as well as student attitudes towards AI and self-perceived ethical boundaries.

With appropriate permission, anonymized archival data will be collected from the institutions. These include: Learning Management System (LMS) engagement metrics, course grades, and grades on specific high-stakes assignments. In addition, aggregated, anonymized reports from academic integrity offices and plagiarism detection software are used as a correlational indicator.

Data in this phase will be analyzed using IBM SPSS Statistics with paired – sample t-tests to compare pre- and post-test CCTST scores, Analysis of Variance (ANOVA) to examine differences in score changes across institutions, disciplines, and levels of AI use, Pearson correlation coefficients to assess relationships between AI usage patterns and CCTST scores and multiple linear regression to model the predictors of academic performance and integrity flags.

B. Phase 2: Qualitative Exploration

Phase 2 is set to further describe and explain the statistical findings from Phase 1 by looking into the lived experiences, perceptions, and decision-making processes of both the students and the faculty members.

This is achieved through purposive, criterion-based sampling. In this work, participants from the Phase 1 sample with distinct analytical cohorts based on their statistical profiles, such as significant CCTST gains, high AI use at the "Redefinition" level, and students whose work was flagged for integrity concerns, were invited for follow-up. Additionally, a sample of 15 – 20 instructors and 3 – 5 academic integrity officers across the participating institutions is recruited to provide institutional context.

The data for this stage was obtained through the following method:

i. Student focus groups of 4 – 6 participants each were formed from the selected students to uncover shared norms, peer culture, and collective sense-making regarding the use of AI in academic work.
ii. A semi-structured, in-depth, one-on-one interview was conducted with students, faculty members, and academic integrity officers to explore individual perspectives, pedagogical strategies, and institutional challenges.

To analyse these qualitative data, inductive thematic analysis is employed on (i) 100% and (ii) 20% transcribed audio recordings. The six-phase process of inductive thematic analysis will be managed using NVivo 14 software. These two cases will be coded in the software to establish inter-rater reliability.

C. Mixed-Methods Integration

The integration of both datasets (quantitative and qualitative) will take place at the interpretation and reporting stages. An explanatory depth for the quantitative results is provided using the qualitative theme in a process of narrative weaving. A rich, contextualized narrative is derived from the transformation of statistical findings resulting from this integration.

D. Ethical Considerations

The research directorate of all participating institutions was sought for the research protocol approval. All participants were fully briefed on the purpose and procedures of the study, potential risks, and their right to withdraw at any time without penalty, after which they were asked to present a well-written consent. Also, participant names will be replaced with pseudonyms and institutional identity or personal details removed from transcripts as well as datasets. The sensitivity of academic integrity data would be handled with extreme care, reporting only in aggregate, and stored on a secure, encrypted server accessible only to the primary research team.

V. RESULTS AND FINDINGS

Based on the explanatory sequential design deployed in this work, the results are presented in two main parts: i) Phase 1, which details the quantitative results derived from the pre- and post-semester critical thinking assessments, student surveys, and institutional academic analytics. These results describe the statistical relationships between AI usage, student outcomes, and contextual variables. ii) Phase 2 outlines the key themes that emerged from the thematic analysis of qualitative focus groups and interviews with students, instructors, and academic integrity officers. These themes provide a rich, explanatory context for the quantitative findings. Lastly, a mixed-methods integration section synthesizes both data sources, demonstrating how the qualitative data clarifies and gives meaning to the statistical patterns observed.

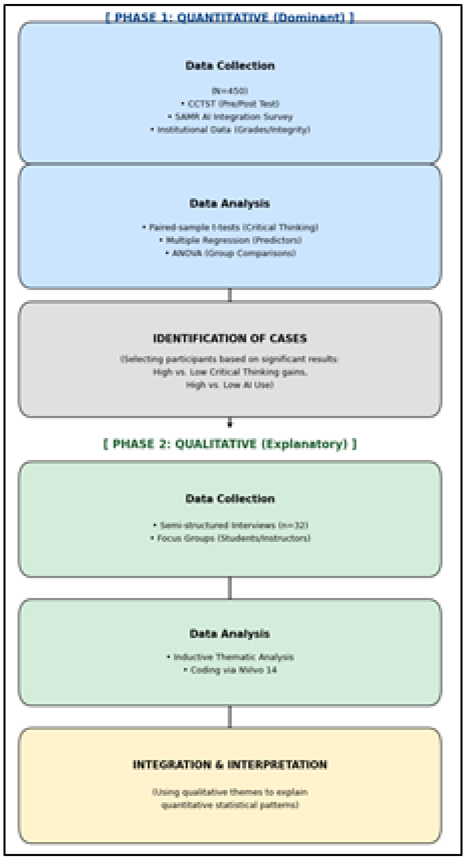

Figure 2: Explanatory Sequential Mixed Method Design

A. Phase 1: Quantitative Findings

A total of N=450 undergraduate students from three distinct institutions completed the pre- and post-semester instruments. The sample was distributed across UI (STEM – 100, Humanities - 80 and Social Science – 75), McU (STEM – 40, Humanities – 20 and Social Science – 22) and TASUED (STEM – 40, Humanities – 35 and Social Science – 38) providing a diverse cross-section of the higher education landscape. The quantitative analysis focused on changes in critical thinking skills, predictors of this change, and academic integrity metrics.

1. Critical Thinking Performance

In assessing the impact of AI integration on critical thinking, paired-samples t-tests were conducted on the CCTST scores, comparing pre-test and post-test means for three distinct student groups based on their self-reported level of AI usage. The result is shown in Table 1.

From Table 1, a stark contrast between the groups was recorded. A negligible and non-significant increase in CCTST scores was recorded in students in the Low / No AI Use group, a slight but non-significant decrease in the Substitution/Augmentation group, while a large and statistically significant increase was noted in the critical thinking scores of the Modification / Redefinition group.

TABLE 1: PRE &POST-CRITICAL THINKING SCORES (CCTST) BY LEVEL OF AI INTEGRATION

Level of AI Integration (Self-Reported, based on SAMR)	N	Pre-Test Mean (SD)	Post-Test Mean (SD)	Mean Difference [95%, CI]	t-statistic	*p*-value
Low/No AI Use	102	17.4 (4.1)	17.8 (4.2)	+0.4 [-0.1, 0.9]	1.54	.126
Substitution/Augmentation	215	18.1 (3.9)	17.9 (4.0)	-0.2 [-0.8, 0.4]	-0.67	.504
Modification/Redefinition	133	18.5 (4.3)	20.9 (4.5)	+2.4 [1.9, 2.9]	9.82	<.001

Where CI = Confidence Interval Value of CCTST scores range between 0 and 34.

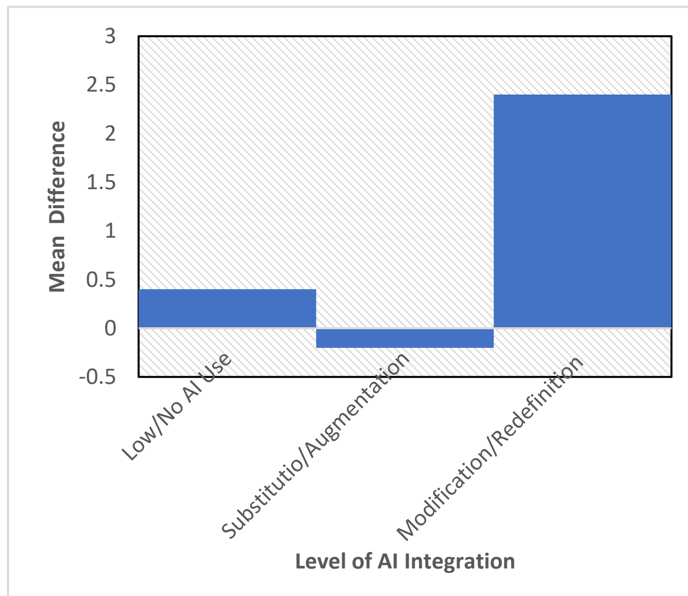

Figure 3: A bar chart showing the mean difference in CCTST Score for each AI usage group

2. Predictors of Critical Thinking Gains

After the critical thinking performance had been done, a multiple regression analysis was carried out to further investigate the factors contributing to changes in critical thinking. The level of AI usage, institution type, academic division, and students' perception of their instructor's stance on AI were used as predictor variables, while the change in CCTST score in Pre-Test and Post-Test is the dependent variable. The result of the analysis shows that the overall model was statistically significant and accounted for 19% of the variance in CCTST score change ($R^2 = .19$, $F(7, 442) = 14.8$, $p < .001$).

TABLE 2: MULTIPLE REGRESSION ANALYSIS PREDICTING CHANGE IN CCTST SCORE

Predictor Variable	*B*	*SE*	*β*	*p*-value
(Constant)	1.15	0.45		
AI Usage Level (Ref: Low/No Use)				
Substitution / Augmentation	- 0.62	0.28	- 0.11	.029*
Modification / Redefinition	2.01	0.31	0.34	<.001*
Institution Type (Ref: UI)				
Humanities	0.45	0.29	0.08	.121
Social Sciences	- 0.21	0.30	- 0.04	.485
Academic Division (Ref: Humanities)				
STEM	-0.15	0.27	-0.03	.580
Social Sciences	0.19	0.28	0.04	.499
Instructor's Stance on AI	0.55	0.19	0.14	.004

With Dependent Variable = Post-Test CCTST Score – Pre-Test CCTST Score
B = Unstandardized Beta, SE = Standard Error, β = Standardized Beta.

The regression analysis confirmed that the level of AI usage was the strongest predictor of change in critical thinking. Compared to groups, using AI for Modification/Redefinition was associated with a 2.01-point increase in CCTST score change, while using AI for Substitution /Augmentation was associated with a small but statistically significant 0.62-point decrease in score change. The instructor's stance on AI stood out as the second significant predictor. This shows a more permissive and encouraging stance, which is positively associated with gains in critical thinking, independent of the level of AI the student used.

3. Academic Integrity Metrics

In providing a preliminary insight into the academic integrity issues, descriptive data on course grades and AI detection flags from Turnitin (a plagiarism check software) were analyzed. Table 3 reveals that final course grades were relatively consistent across the three groups, with a slight increase for the Modification / Redefinition group. However, a dramatic difference was experienced in the AI detection data, with the Substitution/Augmentation group having 18.4% of its assignments flagged for having over 20% AI-generated content, a rate substantially higher than the other two groups.

TABLE 3: ACADEMIC INTEGRITY METRICS BY PRIMARY AI USAGE LEVEL

Level of AI Integration	Mean Course Grade (SD)	% of Assignments Flagged by Turnitin AI Detector (>20% score)
Low / No AI Use	85.1 (7.2)	2.1%
Substitution/Augmentation	84.8 (8.1)	18.4%
Modification/Redefinition	87.5 (6.9)	9.3%

B. Phase 2: Qualitative Themes

In addressing the reasons behind the quantitative results, thematic analysis was conducted on 32 semi-structured interviews comprising18 students, 10 instructors, 4 integrity officers, and 6 student focus groups. This analysis produced three primary overarching themes that explain the complex dynamics of AI integration into students' academic lives.

TABLE 4: MAJOR THEMES FROM QUALITATIVE ANALYSIS

Main Theme	Sub-Themes
1. AI as a Cognitive Partner VS a Cognitive Shortcut	• Scaffolding Complexity: AI as a Socratic partner for brainstorming and outlining. • Outsourcing Effort: Using AI to bypass difficult tasks like synthesis and analysis. • Metacognitive Blindspot: Students' inability to evaluate the quality or accuracy of AI outputs.
2. Navigating the "Ethical Gray Zone"	• Policy Vacuum leading to a lack of clear, actionable institutional and course-level policies. • Instructor Ambivalence reflecting conflicting messages from instructors, from outright prohibition to tacit encouragement. • Peer-Driven Norms show student behavior heavily influenced by what they perceive their peers are doing.
3. Institutional and Pedagogical Lag	• Assessment Inertia based on continuous reliance on traditional essays, which can be easily automated by AI. • Faculty Apprehension & Workload resulting in instructors lacking time, training, and confidence to redesign curriculum. • Equity and Access Gaps: Disparity between students who can afford premium AI tools and those using free, less capable versions.

1. Theme 1: AI as a Cognitive Partner vs. a Cognitive Shortcut

A central theme was the dual nature of AI as either a tool foiiir intellectual enhancement or a means of intellectual evasion. AI was seen as a i) cognitive partner and ii) cognitive shortcut. As a cognitive partner, AI is used to scaffold complex thinking, while as a cognitive shortcut majorly outsource effort on tasks they find tedious or difficult. The difference between the two is accompanied by a metacognitive blindspot, where students, particularly those using AI as a shortcut, admitted they often accepted AI-generated text uncritically, unable to discern subtle inaccuracies or logical flaws.

2. Theme 2: Navigating the "Ethical Gray Zone

The decision on how and when to use AI by students was made within a confusing and ambiguous ethical landscape. Policy vacuum was the most common sentiment, where institutional guidelines were perceived as either non-existent or too broad to be useful for specific assignments. This was compounded by instructor ambivalence, with students receiving mixed messages that range from strict prohibition in one class to active encouragement in another. In the absence of clear directives, peer-driven norms became a powerful influence. The belief of many students that "everyone else is doing it" creates a social pressure to use AI to keep up, often leading to a risk-assessment calculus where the primary goal is avoiding detection rather than upholding academic integrity.

3. Theme 3: Institutional and Pedagogical Lag

The systemic challenges preventing effective AI integration were considered here. Instructors and administrators pointed to assessment inertia – a condition where continuous reliance on traditional assignments is particularly vulnerable to automation by generative AI. Many faculty members expressed deep apprehension about AI while citing a lack of adequate time, formal training, and institutional support required to redesign students, courses, and assessments. In another quarter, concerns were also raised on equity and access gaps, as students and instructors noted a growing disparity among students based on their subscription.

C. Mixed-Methods Integration

The explanatory power of this study emerges from the deliberate integration of the quantitative and qualitative data streams. Table 5 summarizes the integrated insights that support the creation of the qualitative themes that provide a narrative framework that explains the statistical patterns observed in Phase 1, connecting the "what" with the "why".

The qualitative data essentially reveals that the stagnant critical thinking scores and high rates of AI detection in the Substitution/Augmentation group are not merely a result of using technology, but a consequence of using it as a cognitive shortcut to bypass learning – a behavior fostered by the "ethical gray zone" where students feel such use is a low-risk necessity. Conversely, the significant gains in the Modification/Redefinition group are explained by their conceptualization of AI as a cognitive partner. Students in this group engaged the technology in a dialogic process that pushed their thinking, mirroring the pedagogical concept of scaffolding within a student's Zone of Proximal Development.

In addition, the statistical significance of an instructor's permissive stance is explained by its power to mitigate the negative effects of the "ethical gray zone". Open dialogue and clear, supportive guidance from an instructor appear to shift students away from secretive, shortcut-seeking behavior and towards more productive, partnership-oriented use.

TABLE 5: INTEGRATION OF QUANTITATIVE AND QUALITATIVE FINDINGS

Quantitative Finding (QUAN)	Connecting Qualitative Theme (QUAL)	Integrated Insight
Students in the Substitution/Augmentation group showed a slight, non-significant *decrease* in CCTST scores (Table 1) and had the highest rates of AI detection flags (Table 3).	AI as a Cognitive Shortcut and Navigating the "Ethical Gray Zone"	Surface-level AI use for tasks like paraphrasing encourages cognitive offloading of foundational skills and is perceived by students as a low-risk, borderline-acceptable behavior due to unclear policies, leading to higher misconduct flags.
Students in the Modification/Redefinition group showed a large, statistically significant *increase* in CCTST scores (Tables 1 & 2).	AI as a Cognitive Partner	When students are taught or discover how to use AI for higher-order tasks, the tool acts as a Vygotskian MKO, scaffolding their development within their ZPD and fostering measurable gains in critical thinking.
A permissive instructor stance was a significant positive predictor of CCTST score change, independent of AI usage level (Table 2).	Institutional and Pedagogical Lag and Navigating the "Ethical Gray Zone"	Instructors who openly discuss and model thoughtful AI use create a classroom environment that reduces student anxiety and secrecy. This encourages more purposeful, less illicit use of AI, thereby

		facilitating its potential as a learning tool rather than a cheating device.
There was no significant difference in CCTST change across academic divisions (STEM, Humanities, etc.) in the regression model (Table 2).	AI as a Cognitive Partner vs. a Cognitive Shortcut	The *way* AI is used is a more powerful determinant of its impact on critical thinking than the subject matter itself. The core tension between scaffolding and offloading appears to be a universal phenomenon across disciplines.

Lastly, the lack of difference across academic divisions suggests that the central tension between using AI as a partner versus a shortcut is a fundamental, discipline-agnostic phenomenon. The cognitive function that AI serves in a student's workflow to either enhance or replace human thought is an important factor that warrants more study than the specific subject matter being studied.

Despite the promising results, we acknowledge the following as limitations of this work:

a. Reliance on student declarations for SAMR categorization may introduce social desirability bias and limit precision.
b. The sample of three institutions and three academic divisions may not represent broader higher education contexts or international settings.
c. The explanatory sequential design establishes associations but does not confirm causal pathways between AI integration levels, instructor stance, and critical thinking gains.

VI. CONCLUSION

This study provides empirical evidence resolving the debate on whether Generative AI is a threat or a tool for higher education. The central conclusion of this work is that the impact of GenAI is not determined by the technology itself, but by the depth of its integration (SAMR level) and the pedagogical environment.

Key insights from this research include:

1. The Dichotomy of Usage: Quantitative data confirmed that only students engaging AI at the 'Modification/Redefinition' level achieved significant critical thinking gains. In this context, AI functions as a Cognitive Partner and a Vygotskian "More Knowledgeable Other," scaffolding complex reasoning.
2. The Risks of Substitution: Conversely, utilizing AI at the 'Substitution' level acts as a Cognitive Shortcut, resulting in stagnant reasoning skills and high academic integrity flags. This confirms that cognitive offloading without metacognitive engagement is detrimental to learning.
3. The Role of Context: The "Ethical Gray Zone"—characterized by policy vacuums and instructor ambivalence—encourages the "Shortcut" pathway. Regression analysis proved that a supportive instructor stance is a critical predictor in shifting students toward the "Partner" pathway.

Recommendations:
To safeguard academic integrity while enhancing critical thinking, institutions must move beyond detection and prohibition. We recommend:

i. Pedagogical Pivot: Educators must design assessments that require 'Redefinition'—tasks where AI is used to iterate and critique, rather than generate and submit.
ii. Policy Clarity: Institutions must eliminate the "Ethical Gray Zone" by establishing clear guidelines that define responsible AI partnership.

By viewing AI through the lens of cognitive partnership rather than automated cheating, higher education can evolve to meet the demands of the digital age.

References

Akbar, M. S. (2025). *Beyond detection: Designing AI-resilient assessments with an automated feedback tool to foster critical thinking*. http://arxiv.org/abs/2503.23622

Anderson, L. W., & Krathwohl, D. R. (Eds.). (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives. Longman.*

Bittle, K., & El-Gayar, O. (2025). Generative AI and academic integrity in higher education: A systematic review and research agenda. *Information*, *16*(296). https://doi.org/10.3390/info16040296

Churches, A. (2008). *Bloom's digital taxonomy*. *Educational Origami*. https://edorigami.wikispaces.com/Bloom%27s+Digital+Taxonomy

Fischer, I., Sweeney, S., Lucas, M., & Gupta, N. (2024). Making sense of generative AI for assessments: Contrasting student claims and assessor evaluations. *International Journal of Management Education*, *22*(3). https://doi.org/10.1016/j.ijme.2024.101081

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., &Vayena, E. (2018). AI4People—an ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*(4), 689-707. https://doi.org/10.1007/s11023-018-9482-5

Gonsalves, C. (2024). Generative AI's impact on critical thinking: Revisiting Bloom's taxonomy. *Journal of Marketing Education*. https://doi.org/10.1177/02734753241305980

Hamilton, E. R., Rosenberg, J. M., &Akcaoglu, M. (2016). The substitution augmentation modification redefinition (SAMR) model: A critical review and suggestions for its use. *TechTrends*, *60*(5), 433-441. https://doi.org/10.1007/s11528-016-0091-y

Heick, T. (2020). *Bloom's taxonomy: The complete guide*. TeachThought. https://www.teachthought.com/learning/what-is-blooms-taxonomy-a-definition-for-teachers/

Hughes, L., Malik, T., Dettmer, S., AlBusaidi, A. S., &Dwivedi, Y. K. (2025). Reimagining higher education: Navigating the challenges of generative AI adoption. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-025-10582-6

Jobin, A., Ienca, M., &Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389-399. https://doi.org/10.1038/s42256-019-0088-2

Jonassen, D. H. (1999). Designing constructivist learning environments. In C. M. Reigeluth (Ed.), *Instructional-design theories and models: A new paradigm of instructional theory* , Vol. 2, pp. 215-239

Kaushika, A., Yadav, S., Browne, A., Lillis, D., Williams, D., McDonnell, J., Grant, P., Connolly Kernan, S., Sharma, S., & Arora, M. (2025). *Exploring the impact of generative artificial intelligence in education: A thematic analysis*. Preprint submitted to Elsevier.

Kernan, S., Sharma, S., and Arora, M. (2025). *Exploring the Impact of Generative Artificial Intelligence in Education: A Thematic Analysis*. Preprint submitted to Elsevier.

Li, Z., & Akula, J. L. (2024). *Generative AI in higher education academic assignments: Policy implications from a systematic review of student and teacher perceptions*.

Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., &Gerardou, F. S. (2023). Challenges and opportunities of generative AI for higher education, as explained by ChatGPT. *Education Sciences*, *13*(9). https://doi.org/10.3390/educsci13090856

Puentedura, R. R. (2006). *Transformation, technology, and education*. http://hippasus.com/resources/tte/

Ribble, M. (2015). *Digital citizenship in action: Empowering students to engage in online communities*. International Society for Technology in Education.

Romrell, D., Kidder, L. C., & Wood, E. (2014). The SAMR model is a framework for evaluating mLearning. *Journal of Asynchronous Learning Networks*, *18*(2), 1-15. https://doi.org/10.24059/olj.v18i2.435

Saúde, S., Barros, J. P., & Almeida, I. (2024). Impacts of generative artificial intelligence in higher education: Research trends and students' perceptions. *Social Sciences*, *13*(8), Article 410. https://doi.org/10.3390/socsci13080410

Sertel, G., Karadag, E., &Ciftci, S. K. (2025). Educational researchers' perceptions of editorial ethics and attitudes in Turkish academic journals: A mixed-methods study. *International Journal for Educational Integrity*, *21*(19). https://doi.org/10.1007/s40979-025-00194-7

UNESCO. (2021). *AI and education: Guidance for policy-makers*. UNESCO Publishing. https://unesdoc.unesco.org/ark:/48223/pf0000376709

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds.). Harvard University Press.

Wertsch, J. V. (1985). *Vygotsky and the social formation of mind*. Harvard University Press.

Wiredu, J. K., Abuba, N. S., &Zakaria, H. (2024). Impact of generative AI in academic integrity and learning outcomes: A case study in the Upper East region. *Asian Journal of Research in Computer Science*, *17*(7), 214-232. https://doi.org/10.9734/ajrcos/2024/v17i7491

Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry*, *17*(2), 89-100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x

Yusuf, A., Pervin, N., &Román-González, M. (2024). Generative AI and the future of higher education: A threat to academic integrity or reformation, evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education*, *21*(21). https://doi.org/10.1186/s41239-024-00453-6