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IMPLICATIONS OF GENERATIVE AI ON ACADEMIC INTEGRITY, RESEARCH QUALITY, AND PEDAGOGY IN NORTH-WEST NIGERIAN UNIVERSITIES

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The rapid integration of generative artificial intelligence (AI) tools has transformed higher education, offered efficiency gains while challenged academic integrity, research authenticity, and pedagogical practices. This Institutional-Based Research (IBR)-funded study examines the implications of AI-generated content for academic integrity, research quality, and pedagogy in universities across North-West Nigeria. Employing a convergent mixed-methods design, quantitative data were collected via structured questionnaires from 368 participants (students 63%, lecturers 25%, administrators 12%; 92% response rate) across 6 Universities, supplemented by 20 semi-structured interviews. Descriptive statistics revealed widespread adoption (65% active users overall; 70% among students), with 58% of student users primarily employing AI for writing assignments. Inferential analyses showed a moderate positive correlation between AI literacy and ethical usage ($r = .46$, $p < .001$), a negative correlation between AI dependency and perceived integrity ($r = -.41$, $p < .001$), and a multiple regression model where literacy and ethical awareness explained 53% of variance in integrity outcomes ($R^2 = .53$, $f^2 = 1.13$, large effect). Thematic analysis of qualitative data highlighted utility–integrity tensions, literacy as empowerment, institutional silence, and needs for pedagogical adaptation. Grounded in TAM, UTAUT2, TPACK, and Academic Integrity Theory, findings reject prohibition in favor of governance, mandatory literacy integration, assessment redesign, faculty development, and infrastructure investment to address digital divides. Limitations include the cross-sectional design and self-reported biases; future research should pursue longitudinal and intervention studies. These region-specific insights contribute to global discourse on equitable AI governance in Sub-Saharan African higher education.

Keywords: generative AI, academic integrity, AI literacy, pedagogy, Nigeria

1. Introduction

The advent of generative artificial intelligence (AI)—most visibly embodied in large language models (LLMs) such as ChatGPT—has initiated a far-reaching transformation in how knowledge is produced, accessed, and engaged within

academic settings (Dwivedi et al., 2023; Wang, 2024). These systems demonstrate a remarkable capacity to produce coherent, contextually appropriate academic text, enabling users to undertake a broad spectrum of scholarly

tasks, from drafting and summarization to idea generation, conceptual mapping, and referencing support. In doing so, they have meaningfully lowered barriers to academic participation and introduced new efficiencies into teaching and learning environments.

Nevertheless, this technological momentum carries within it an inherent tension. On one hand, generative AI holds genuine promise as a pedagogical instrument—one capable of tailoring

learning experiences, amplifying research output, and compensating for resource disparities in underfunded educational settings. On the other hand, its unchecked adoption raises substantive concerns regarding the erosion of academic integrity, including risks of covert plagiarism, diminished intellectual originality, uncritical overreliance, and the gradual atrophying of students' independent reasoning capacities (Cotton et al., 2023; Kasneci et al., 2023; Kofinas, 2025; Lee, 2024; UNESCO, 2023).

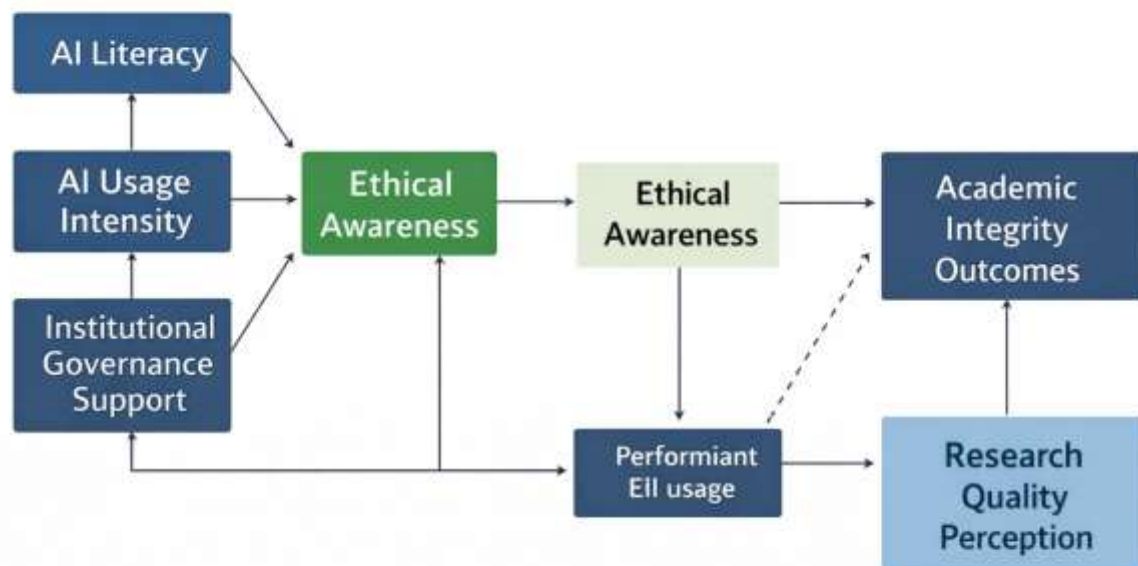


Figure 1. Conceptual Framework Linking AI Literacy, Usage, and Academic Integrity

Note: The dotted line represents an indirect or moderating relationship, indicating that institutional governance influences ethical awareness through mediating variables such as policy clarity and training.

Institutions in technologically advanced economies have begun confronting these tensions through revised academic policies, ethical frameworks, and reimagined assessment strategies. By

contrast, higher education systems across the developing world—including Nigeria—have been considerably slower to mount coherent institutional responses. Governance structures for AI use remain embryonic or inconsistently applied,

compounded further by infrastructural deficits, entrenched digital inequalities, and heterogeneous levels of AI literacy among academic communities (Ebiringa, 2025; Essien, 2024; Yusuf et al., 2024). Evidence emerging from Sub-Saharan Africa paints a picture of accelerating student uptake set against a backdrop of unresolved integrity concerns, absent regulatory clarity, and uneven technological access. Despite this, granular, context-sensitive empirical inquiry—particularly from geographically and institutionally specific settings such as North-West Nigeria—remains conspicuously underdeveloped in the existing literature (Apata, 2025; Guadu, 2025; Oyelere, 2025).

Despite the rapid adoption of generative AI tools in higher education, there remains limited empirical evidence on how such technologies affect academic integrity, research quality, and pedagogical practices within the Nigerian context. Existing studies are largely global and fail to capture region-specific dynamics such as infrastructural limitations, policy gaps, and uneven AI literacy. This creates a critical gap in understanding how AI can be responsibly integrated into teaching and learning without compromising academic standards. This study aims to:

1. Examine the extent of generative AI adoption among students, lecturers, and administrators.
2. Assess the relationship between AI literacy, ethical awareness, and academic integrity.

3. Evaluate the impact of AI usage on research quality and pedagogical practices.
4. Identify institutional challenges and propose policy recommendations for responsible AI integration.

Organization of the Paper

The remainder of this paper is organized as follows: Section 2 reviews relevant literature and theoretical frameworks. Section 3 presents the research methodology. Section 4 discusses the results. Section 5 provides analysis and discussion. Section 6 outlines policy implications. Section 7 presents limitations and future research directions, while Section 8 concludes the study.

2. Literature Review and Theoretical Framework

2.1 Generative AI in Higher Education

Generative AI systems, underpinned by transformer-based neural architectures and developed through exposure to extraordinarily large textual datasets, have demonstrated a sophisticated command of language that makes them increasingly attractive for a range of academic applications—among them, essay composition, literature synthesis, citation assistance, and programming support (Bobula, 2024; Dwivedi et al., 2023). A growing body of empirical scholarship confirms that students across diverse institutional contexts are embracing these tools with considerable enthusiasm and frequency (Kasneci et al.,

2023; Oyelere, 2025; Zawacki-Richter et al., 2019).

This widespread uptake is not without consequence, however. Mounting concerns suggest that habitual dependence on AI-generated outputs may cultivate superficial approaches to learning and impede the cultivation of robust higher-order cognitive capacities (Sharma, 2025; Zawacki-Richter et al., 2019). Within Sub-Saharan African contexts, including Nigeria, the trajectory of AI adoption is further mediated by a constellation of socio-cultural factors, infrastructural inadequacies, disparate digital connectivity, and fluid ethical norms—conditions that risk deepening pre-existing inequities in educational access and participation (Ebiringa, 2025; Essien, 2024).

2.2 Academic Integrity in the AI Era

At its foundation, academic integrity is anchored in principles of honesty, trust, fairness, respect, and individual responsibility (International Center for Academic Integrity [ICAI], 2021). The ascendance of generative AI has unsettled conventional understandings of plagiarism: AI-produced text can convincingly simulate original scholarly authorship while concealing the absence of genuine student intellectual engagement (Bittle, 2025; Cotton et al., 2023; Lund et al., 2025). Compounding this challenge, research has demonstrated that AI-generated content routinely evades standard plagiarism detection mechanisms, thereby undermining the reliability of institutional assessment processes (Perkins, 2023; Tan, 2024).

These developments have contributed to a measurable uptick in academic misconduct, with documented evidence that significant proportions of students engage in ethically questionable AI-assisted practices (Peterson, 2025; Tan, 2024). In the Nigerian higher education environment, analogous patterns are discernible, further aggravated by underdeveloped institutional policy infrastructure, constrained detection capacity, and resource limitations that hinder proactive and anticipatory governance (Ebiringa, 2025).

2.3 AI and Research Quality

From a constructive standpoint, generative AI offers tangible advantages in enhancing the coherence, organisation, and communicative accessibility of scholarly writing and research outputs (Dwivedi et al., 2023; Francis, 2025). However, uncritical or excessive dependence on these tools carries the potential to hollow out methodological rigour, diminish the depth of critical analysis, and dilute the originality of scholarly contribution (Kasneci et al., 2023; Sharma, 2025). Across African higher education institutions, although generative AI presents considerable opportunity for bolstering research productivity in resource-constrained environments, its transformative potential continues to be circumscribed by persistent competency gaps, unresolved ethical ambiguities, and inadequate technological infrastructure (Oyelere, 2025; Wiredu, 2024).

2.4 Theoretical Framework

To furnish a comprehensive interpretive lens for understanding AI adoption patterns and their associated ethical implications within North-West Nigerian universities, this study draws on four mutually reinforcing theoretical frameworks.

1.

The **Technology Acceptance Model (TAM)** posits that an individual's intention to adopt a given technology is primarily governed by their perceptions of its usefulness and ease of use (Davis, 1989). This model speaks directly to the Nigerian student context, where AI tools are frequently embraced as practical mechanisms for managing academic workload and meeting performance expectations under resource-constrained conditions (Ebiringa, 2025; Pasupuleti, 2025).

2.

The **Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)** extends its predecessor by incorporating consumer-relevant constructs such as hedonic motivation, perceived value, habitual use, and facilitating conditions, moderated by demographic variables including age, gender, and prior experience (Venkatesh et al., 2012; Shrivastava, 2025). Within educational and AI adoption contexts, this framework draws attention to the influence of peer

dynamics and the presence or absence of institutional support in shaping how technology is integrated into academic practice (Essien, 2024; Kashif, 2025).

3.

Technological Pedagogical Content Knowledge (TPACK) advances the argument that meaningful technology integration in education demands the purposeful alignment of technological competence, pedagogical strategy, and disciplinary expertise (Mishra & Koehler, 2006; Kashif, 2025). This framework reorients institutional attention away from blanket restriction toward the deliberate and contextually appropriate embedding of AI within learning environments.

4.

Academic Integrity Theory conceptualises ethical conduct as a product of institutional culture, awareness of normative expectations, and the consistency with which those expectations are upheld and enforced (Bittle, 2025; ICAI, 2021). Ethical awareness, within this framework, functions as a pivotal determinant of responsible behaviour—a proposition directly interrogated through this study's regression analysis linking AI literacy and ethical awareness to measurable academic integrity outcomes.

Collectively, these four frameworks constitute a multi-dimensional analytical architecture capable of unpacking the

interplay among adoption drivers, ethical tensions, and pedagogical possibilities within North-West Nigerian higher education (Fainholc, 2026; Wang, 2024). Their synthesis enables a nuanced reading

3. Methodology

3.1 Research Design

This study adopted a convergent parallel mixed-methods design, in which quantitative and qualitative data are collected concurrently, analyzed separately, and integrated during

of the study's empirical findings—one that holds global theoretical models in productive dialogue with locally situated realities.

interpretation to yield comprehensive insights (Creswell & Creswell, 2018). This approach was selected to combine the statistical generalizability of survey data with the contextual depth of participant narratives, thereby strengthening triangulation, construct validity, and interpretive richness.

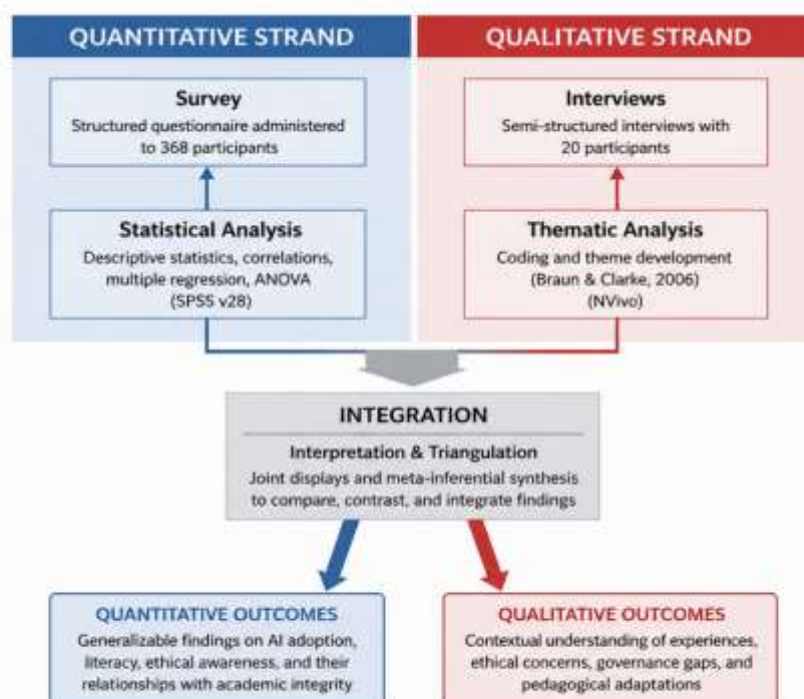


Figure 2. Convergent Mixed-Methods Research Design Diagram Showing Parallel Quantitative and Qualitative Strands and Point of Integration

Figure 2 shows how the quantitative strand used a cross-sectional survey to assess AI adoption rates, literacy levels, and associations with academic integrity perceptions. The qualitative strand employed semi-structured interviews to explore ethical concerns, governance gaps, and pedagogical adaptations. Integration occurred through joint displays and meta-inferential synthesis, highlighting convergence, complementarity, and any divergences between strands.

3.2 Population and Sample

The target population included undergraduate and postgraduate

students, academic staff, and administrators from federal and state universities in North-West Nigeria. Due to the absence of a unified sampling frame

across these institutions, sample size was estimated using Cochran's (1977) formula for large/unknown populations:

$$n_0 = \frac{Z^2 p(1-p)}{e^2}$$

Here, $Z = 1.96$ (95% confidence level), $p = 0.50$ (maximum variability), and $e = 0.05$ (margin of error).

$n_0 = 384.16 \approx 384$

To accommodate potential non-response (~4%), the target was adjusted upward:

$$n = \frac{n_0}{1-r}$$

□ n = adjusted sample size

□ n_0 = initial sample size from Cochran's formula

□ r = anticipated non-response rate

$$n = \frac{384}{1-0.04} \approx 400$$

A multi-stage proportionate stratified random sampling procedure was applied:

- (1) stratification by university type (federal/state)
- (2) random selection of departments within strata
- (3) proportionate random selection of participants within departments, ensuring representation across stakeholder groups.

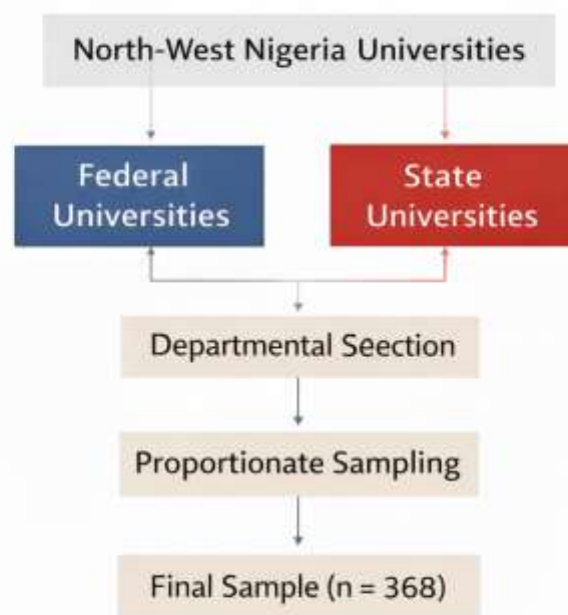


Figure 3. Multi-Stage Sampling Procedure Across Federal and State Universities in North-West Nigeria

Of 400 distributed questionnaires, 368 valid responses were obtained (92% response rate). A purposive subsample of 20 participants (10 students, 7 lecturers, 3

administrators) was selected for interviews to maximize diversity in AI experience and perspectives. Although the sample size ($n = 368$) meets Cochran's recommended threshold for large

populations, the study acknowledges its regional focus. The choice of North-West Nigeria was deliberate to provide in-depth, context-specific insights. Future studies should expand to other geopolitical zones for broader generalizability.

3.3 Instruments

Quantitative data were collected via a structured self-administered questionnaire with four sections:

- (1) demographics (e.g., role, gender, institution)
- (2) AI usage patterns (frequency and primary purposes)
- (3) an 8-item AI literacy scale (Likert-rated self-assessment of knowledge and competence)
- (4) a 10-item scale on academic integrity perceptions (ethical attitudes and AI dependency impacts).

Scales were adapted from established sources (e.g., ICAI, 2021; Kasneci et al., 2023) and pilot-tested for cultural appropriateness. Reliability was strong: Cronbach's $\alpha = .86$ (AI literacy) and $\alpha = .84$ (integrity perceptions), exceeding the .70 threshold (Field, 2018).

Qualitative data were gathered through semi-structured interviews using a protocol organized into four thematic clusters: AI adoption experiences, ethical perceptions, pedagogical impacts, and institutional recommendations. Interviews

(30–45 minutes) were audio-recorded with consent and designed to elicit in-depth, reflective responses.

3.4 Ethical Considerations

Ethical clearance was obtained from the relevant Institutional Review Board prior to data collection. Participants received detailed information sheets outlining study aims, procedures, risks, and benefits. Informed consent was secured in writing, with emphasis on voluntary participation and the right to withdraw at any time without penalty. Anonymity and confidentiality were maintained through coded identifiers, secure data storage, and restricted access during analysis and reporting.

3.5 Data Analysis

Quantitative analysis used IBM SPSS Statistics Version 28. Descriptive statistics summarized demographics, usage patterns, and variable distributions. Inferential tests included Pearson correlations (for relationships among variables), multiple linear regression (to predict integrity outcomes from AI literacy and ethical awareness), and one-way ANOVA (for group differences by role), all at $p < .05$. Practical significance was assessed via Cohen's f^2 :

$$f^2 = \frac{R^2}{1 - R^2}$$

This value indicates a large effect (Cohen, 1988), reflecting substantial explanatory power.

Qualitative data underwent reflexive thematic analysis following Braun and Clarke's (2006) six-phase process: familiarization, coding, theme generation,

review, definition, and reporting. NVivo supported coding and organization. Integration involved joint displays to compare and synthesize findings across strands, ensuring holistic interpretation.

4. Results

4.1 Descriptive Statistics

4.1.1 Demographic Characteristics

Of the 400 questionnaires administered across participating institutions, 368 were returned in a condition suitable for analysis, representing a response rate of 92%. The demographic composition of the analytical sample is presented in Table 1.

Figure 4. Distribution of Respondents by Institutional Type (Federal vs. State Universities)

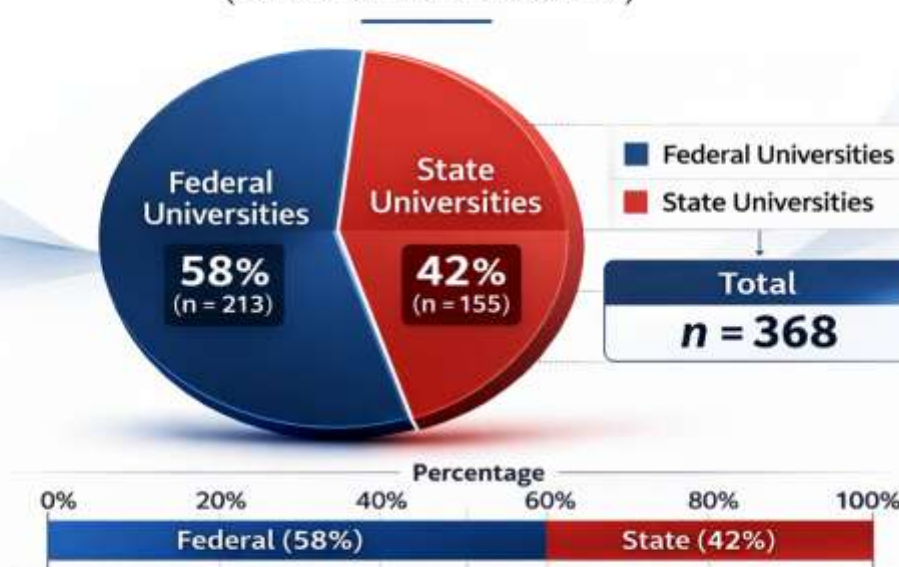


Figure 4. Distribution of Respondents by Institutional Type (Federal vs. State Universities)

Table 1 presents the demographic characteristics of respondents, indicating a balanced representation across

institutional roles and disciplines. This diversity strengthens the reliability of the findings.

Variable	Category	n	%
Role	Students	232	63.0
	Lecturers	92	25.0
	Administrators	44	12.0

Variable	Category	n	%
Gender	Male	221	60.1
	Female	147	39.9
Discipline	Humanities	118	32.1
	Social Sciences	106	28.8
	Natural Sciences	81	22.0
	Professional Fields	63	17.1

Note: n = frequency (number of respondents); SD = standard deviation.

From Table1 Students constituted the largest stakeholder cohort at 63.0%, followed by lecturers (25.0%) and administrators (12.0%). Male respondents accounted for 60.1% of the sample, with female participants comprising the remaining 39.9%. Disciplinary representation was broadest within the Humanities (32.1%) and Social Sciences (28.8%), with Natural Sciences (22.0%)

and Professional Fields (17.1%) contributing smaller but meaningful proportions. Institutional experience varied considerably across roles, as detailed in Table 2, with administrators recording the highest mean tenure ($M = 11.4$ years, $SD = 6.1$), compared to lecturers ($M = 8.7$, $SD = 5.3$) and students ($M = 3.2$, $SD = 1.4$).

Table 2 summarizes years of institutional experience across roles, highlighting differences in professional exposure that may influence perceptions of AI usage.

Role	Mean (M)	SD
Students	3.2	1.4
Lecturers	8.7	5.3
Administrators	11.4	6.1

4.1.2 Generative AI Adoption and Usage Patterns

Across the full sample, 240 respondents (65.2%) indicated that they actively engage with generative AI tools in their

academic or professional activities. Disaggregation by institutional role, presented in Table 3, reveals pronounced variation in adoption rates, with students recording the highest uptake at 70.3%, followed by lecturers at 58.7% and administrators at 45.5%.

Table 3 *Generative AI Adoption Rates by Institutional Role*

Role	Users (n)	% within Role
Students	163	70.3
Lecturers	54	58.7
Administrators	20	45.5

A chi-square test of independence confirmed that role-based differences in adoption were statistically significant, $\chi^2(2, N = 368) = 14.82, p < .001$, with Cramér's $V = .20$ indicating a small-to-medium practical effect.

dominant application among students (58.3%), while lecturers most frequently deployed AI for literature searching (35.2%), and administrators concentrated their use on report generation (45.0%) and communication tasks (35.0%).

Patterns of functional AI use differed markedly across roles, as summarised in Table 4. Writing assistance was the

Table 4 *Primary AI Applications by Institutional Role*

Application	Students (%)	Lecturers (%)	Administrators (%)
Writing Assistance	58.3	24.1	10.0
Literature Search	18.4	35.2	10.0
Coding / Data Analysis	23.3	11.1	5.0
Report Generation	5.0	10.0	45.0
Communication	4.0	8.0	35.0

With respect to usage frequency, weekly use was most prevalent (41.7%, $n = 100$),

followed by daily use (32.1%, $n = 77$) and occasional use (26.3%, $n = 63$), as detailed in Table 5.

Table 5 *Generative AI Usage Frequency Among Active Users*

Frequency	n	%
Daily	77	32.1

Weekly	100	41.7
Occasional	63	26.3

4.2 Correlational Analysis

Pearson product–moment correlations among the four primary study variables are presented in Table 6. AI literacy demonstrated a moderate, statistically significant positive association with ethical usage ($r = .46, p < .001$), indicating that participants with stronger AI literacy tended to report more ethically oriented patterns of tool engagement. Academic

integrity perceptions were positively and substantially associated with both AI literacy ($r = .58, p < .001$) and ethical usage ($r = .52, p < .001$). Conversely, AI dependency exhibited significant negative correlations with both ethical usage ($r = -.33, p < .001$) and academic integrity ($r = -.41, p < .001$), suggesting that heightened reliance on AI tools was accompanied by diminished integrity perceptions and less responsible usage.

Table 6 *Pearson Correlation Matrix for Primary Study Variables*

Variable	1	2	3	4
1. AI Literacy	—			
2. Ethical Usage	.46	—		
3. AI Dependency	-.29	-.33	—	
4. Academic Integrity	.58	.52	-.41	—

Note. $p < .001$.

4.3 Multiple Regression Analysis

To determine the extent to which AI literacy and ethical awareness predicted academic integrity perceptions, a multiple linear regression model was estimated with these two variables as predictors. Results, presented in Table 7, indicate that both predictors contributed uniquely and significantly to the outcome. AI literacy emerged as the stronger predictor

($\beta = .40, t = 8.94, p < .001, sr^2 = .12$), followed by ethical awareness ($\beta = .35, t = 7.82, p < .001, sr^2 = .09$). The overall model accounted for 53.0% of the variance in academic integrity perceptions ($R^2 = .530$, Adjusted $R^2 = .528$), and was statistically robust, $F(2, 365) = 205.84, p < .001$. Cohen's $f^2 = 1.13$ substantially exceeded the threshold of 0.35 conventiona

lly associated with large effects, attesting to the exceptional explanatory power of the fitted model.

Table 7 *Multiple Regression Analysis Predicting Academic Integrity Perceptions*

Predictor	<i>B</i>	<i>SE B</i>	β	<i>t</i>	<i>p</i>	<i>sr</i> ²
Constant	1.24	.18	—	6.89	<.001	—
AI Literacy	.38	.04	.40	8.94	<.001	.12
Ethical Awareness	.32	.04	.35	7.82	<.001	.09

Note. $R^2 = .530$; Adjusted $R^2 = .528$; $F(2, 365) = 205.84$, $p < .001$; Cohen's $f^2 = 1.13$.

4.4 Analysis of Variance

One-way ANOVA was conducted to determine whether ethical concern scores differed significantly across the three institutional role groups. The omnibus test yielded a statistically significant result, $F(2, 365) = 4.92$, $p = .008$, $\eta^2 = .026$, indicating a small but meaningful proportion of variance in ethical concern attributable to role membership (Table 8).

Table 8 *One-Way ANOVA: Ethical Concern Scores by Institutional Role*

Source	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>p</i>	η^2
Between Groups	4.87	2	2.44	4.92	.008	.026
Within Groups	181.05	365	0.50			
Total	185.92	367				

Post-hoc comparisons using the Tukey

HSD procedure, reported in Table 9, identified a statistically significant difference exclusively between students and administrators (Mean Difference = 0.43, 95% CI [0.13, 0.73], $p = .003$). Differences between students and

lecturers ($p = .210$) and between lecturers and administrators ($p = .072$) did not attain statistical significance, suggesting that the group-level effect was principally driven by the student–administrator contrast.

Table 9 Post-Hoc Tukey HSD Pairwise Comparisons

Comparison	Mean Difference	95% CI	p
Students – Administrators	0.43	[0.13, 0.73]	.003
Students – Lecturers	0.15	[−0.05, 0.35]	.210
Lecturers – Administrators	0.28	[−0.02, 0.58]	.072

4.5 Qualitative Findings

Thematic analysis of the 20 semi-structured interviews produced four overarching themes, each capturing a distinct dimension of participants' experiences with and orientations toward generative AI in academic life, as summarised in Table 10.

Table 10 Summary of Emergent Qualitative Themes

Theme	Core Meaning	Interpretive Significance
Utility–Integrity Tension	Efficiency versus authenticity	Heavy AI use generates persistent ethical ambivalence
Literacy Empowerment	as Knowledge enables critical engagement	Higher literacy predicts more responsible, reflective use
Institutional Silence	Normative and policy ambiguity	Absence of clear governance heightens behavioural risk
Pedagogical Adaptation	Assessment and instructional redesign	Institutions are reactively recalibrating teaching practice

The first theme—the *Utility–Integrity Tension*—captured participants' awareness of a fundamental conflict between AI's efficiency gains and its implications for authentic intellectual authorship. The second theme, *Literacy as*

Empowerment, reflected consistent accounts of how deeper AI knowledge equipped users to engage critically and responsibly rather than uncritically. The third theme, *Institutional Silence*, described widespread normative uncertainty arising from the absence of

coherent institutional governance and policy frameworks. The fourth theme, *Pedagogical Adaptation*, revealed emergent but largely reactive institutional efforts to redesign assessments and instructional approaches in response to AI proliferation.

5. Analysis and Discussion

The quantitative findings underscore generative AI's pervasive integration into academic workflows, especially among students, where adoption reaches 70% and primary usage centers on writing assignments (58%). This pattern raises profound concerns, as writing tasks are fundamentally intended to evaluate students' abilities in synthesis, critical reasoning, and original scholarship. By outsourcing these processes to AI, there is a risk of eroding core competencies essential to research and intellectual development. Qualitative insights reinforce this, with lecturers expressing uncertainty in assessments: "We've designed our assessments for a pre-AI world. Now I read a beautifully crafted essay and I honestly don't know if it's the student's voice or the machines." Such tensions, amplified by themes of utility-integrity conflict and institutional silence, highlight how unchecked AI reliance could compromise the authenticity of educational outcomes.

Nevertheless, the inferential results illuminate viable mitigation strategies. The moderate positive correlation between AI literacy and ethical usage ($r = .46$) empirically endorses a proactive, education-focused response rather than outright bans. This association implies

that equipping users with knowledge of AI mechanics, limitations, and ethical boundaries fosters responsible application, aligning with qualitative narratives of "literacy as empowerment." For instance, participants described how demystifying AI transformed it from a crutch to a collaborative tool: "Once I understood that ChatGPT doesn't actually 'know' anything—it's just predicting the next word—I stopped treating it as an authority." The regression model's substantial explanatory power ($R^2 = .53$, $f^2 = 1.13$) further emphasizes that AI literacy and ethical awareness are dominant predictors of integrity, validating Academic Integrity Theory's emphasis on awareness and institutional culture in shaping behavior.

Conversely, the negative correlation between AI dependency and perceived integrity ($r = -.41$) corroborates concerns about diminished ownership and superficial engagement, as echoed in qualitative accounts of overreliance fostering ethical dilemmas. The ANOVA results, despite a small effect size ($\eta^2 = .026$), reveal nuanced role-based differences: students' higher ethical concerns ($M = 3.45$) likely stem from their direct immersion in AI-driven tasks, contrasting with administrators' lower scores ($M = 3.02$) and potential detachment from frontline challenges. This perceptual divide, supported by themes of pedagogical adaptation and resistance, suggests that interventions must address varying stakeholder experiences to build cohesive governance. Through the lens of the multi-theoretical framework, these patterns cohere seamlessly. TAM and UTAUT2 account for

high adoption, driven by perceived usefulness in resource-limited settings and facilitating conditions like peer influence. Yet, ethical outcomes hinge on moderating factors such as ethical awareness (Academic Integrity Theory) and technological-pedagogical integration (TPACK). The predictive role of literacy highlights TPACK's call for educators to weave AI knowledge into curricula, shifting from reactive policing to proactive redesign—e.g., process-oriented assessments that emphasize human-AI collaboration over product alone.

Relative to global patterns, North-West Nigeria's context parallels adoption and integrity issues in developed regions (Cotton et al., 2023; Lund et al., 2025), but infrastructural constraints and policy vacuums exacerbate vulnerabilities (Ebiringa, 2025; Essien, 2024). This "perfect storm" of rapid uptake amid limited guidance amplifies risks, as qualitative themes of institutional silence illustrate: "The university has no policy... Silence is interpreted as consent." Consequently, the findings advocate for contextually tailored strategies that leverage literacy to harness AI's benefits while safeguarding academic values, setting the stage for evidence-based policy reforms.

6. Policy Implications

The empirical findings—particularly the strong predictive role of AI literacy and ethical awareness ($R^2 = .53$), the positive literacy–ethical usage correlation ($r = .46$), and qualitative themes of institutional silence and utility–integrity tension—underscore the need for proactive, multifaceted policy responses in North-

West Nigerian universities and comparable Sub-Saharan African contexts. Rather than prohibition, which risks driving clandestine use and widening digital divides, the evidence supports structured governance, capacity building, and pedagogical innovation.

1.

Establish Comprehensive Institutional AI Governance Frameworks:

Universities should urgently develop and disseminate clear, enforceable policies that delineate acceptable generative AI applications in teaching, learning, research, and assessment. These frameworks should move beyond blanket restrictions to specify permitted uses (e.g., brainstorming, editing, literature synthesis) while prohibiting full substitution of original work. Grounded in Academic Integrity Theory and UNESCO (2023) guidance, such policies would reduce ambiguity identified in qualitative data ("Silence is interpreted as consent") and align with regional calls for context-sensitive regulation (Bittle, 2025; Ebiringa, 2025).

2.

Require Transparent AI Disclosure and Reflective Statements:

Assessment policies should mandate disclosure of AI use in all submitted work, accompanied by a brief reflective statement explaining how the tool was employed and what human contributions were made. This practice fosters metacognition,

reinforces ownership, and shifts emphasis from punitive detection to responsible integration—directly addressing the dependency–integrity link ($r = -.41$) and empowering students as ethical users (Peterson, 2025).

3.

Embed AI Literacy as a Core Curriculum Component: AI literacy must be integrated systematically across general education and discipline-specific courses, covering technical mechanics, algorithmic biases, epistemic limitations, and ethical decision-making. Given literacy's robust predictive power for ethical behavior, mandatory modules would operationalize TPACK principles and equip stakeholders to navigate AI responsibly rather than reactively (Kashif, 2025; Pasupuleti, 2025). In resource-constrained settings, low-cost, open-access resources and peer-led training can facilitate scalable implementation.

4.

Redesign Assessments for Authenticity and AI Resilience: Traditional product-focused assessments (e.g., take-home essays) are vulnerable to AI substitution. Institutions should prioritize process-oriented, human-centered methods: in-class timed writing, oral examinations, viva voce defenses of drafts, annotated research logs, and portfolios documenting iterative development. These approaches

safeguard the measurement of synthesis and critical thinking while accommodating AI as a supportive tool (Kofinas, 2025; Sharma, 2025), directly mitigating concerns raised by lecturers in qualitative interviews.

5.

E

Prioritize Faculty Professional Development: Ongoing training programs are essential to build faculty capacity in AI-integrated pedagogy. Workshops should emphasize TPACK-informed strategies—blending technological, pedagogical, and content knowledge—to redesign courses and assessments effectively. Training must be culturally responsive and address regional realities, including limited infrastructure and varying digital fluency (Essien, 2024; Oyelere, 2025). Faculty development would also reduce resistance and promote adaptive practices observed in qualitative data.

6.

Invest in Equitable Infrastructure and Access: Without addressing digital divides, policy interventions risk exacerbating inequalities. Governments, universities, and partners should prioritize reliable broadband, device provision, subsidized AI tool access, and electricity stability—particularly in rural and under-resourced North-West campuses. Equitable access is foundational to realizing AI's pedagogical potential while preventing literacy gaps from

widening existing disparities (Ebiringa, 2025; Yusuf et al., 2024).

These recommendations are interdependent: governance provides structure, literacy builds competence, assessment redesign ensures authenticity, faculty development enables implementation, and infrastructure guarantees feasibility. Implemented collectively, they offer a balanced, evidence-informed pathway to harness generative AI's benefits while preserving academic integrity in resource-constrained higher education systems.

7: Limitations and Future Research:

This section transparently acknowledges several limitations of the study while outlining directions for future work:

Key Limitations:

- (1) The cross-sectional design limits causal inferences and long-term insights into how AI adoption and its effects evolve over time.
- (2) Reliance on self-reported data (surveys and interviews) introduces risks of social desirability bias, recall errors, or underreporting of unethical behavior.
- (3) The sample is regionally focused (North-West Nigeria, $n = 368$), restricting generalizability to other Nigerian zones, broader Sub-Saharan Africa, or global contexts.
- (4) The purposive qualitative subsample ($n = 20$) provides depth but may miss perspectives from underrepresented groups (e.g., rural campuses, non-users).

- (5) Unmeasured variables (e.g., socio-economic or cultural factors) may explain remaining variance in integrity outcomes beyond the 53% accounted for by the regression model.
- (6) Methodological trade-offs (e.g., no ethnographic observation or objective AI usage logs) constrain detection of unarticulated practices.

Future Research Directions:

- (1) Longitudinal studies to track AI's evolving impact on learning outcomes, skill development, and equity.
- (2) Intervention trials evaluating proposed policies (e.g., literacy programs, assessment redesigns) using experimental or quasi-experimental designs.
- (3) Comparative research across African regions or Global South settings to examine how infrastructure, culture, and policy differences shape AI effects.
- (4) Inclusion of underrepresented voices and investigation of emerging AI technologies (e.g., multimodal models) to anticipate future challenges.

Overall, the section positions these constraints as opportunities for refinement, reinforcing the study's solid foundation and calling for continued, contextually sensitive scholarship to support equitable AI integration in higher education.

8. Conclusion

This Institutional-Based Research (IBR)-funded study demonstrates that generative artificial intelligence is firmly embedded in the academic ecosystems of North-West Nigerian universities, with 65% overall adoption and 70% among students, predominantly for writing assignments (58%). While these tools offer substantial gains in efficiency, accessibility, and productivity, their prevalent substitutional use poses an immediate and substantial risk to academic integrity, authentic skill development, and the cultivation of independent critical thinking.

The empirical evidence—particularly the moderate positive correlation between AI literacy and ethical usage ($r = .46$), the negative association between dependency and perceived integrity ($r = -.41$), and the large explanatory power of literacy and ethical awareness in predicting integrity outcomes ($R^2 = .53$, $f^2 = 1.13$)—rejects prohibition as a viable or sustainable response. Instead, the findings strongly advocate for a proactive, multi-pronged strategy: institutional governance frameworks to reduce ambiguity, mandatory AI literacy integration across curricula to build discerning users, and pedagogical redesign to prioritize process-oriented, AI-resilient assessments. Qualitative themes of utility–integrity tension, literacy as empowerment, institutional silence, and adaptive resistance further reinforce those ethical outcomes depend not merely on tool availability, but on structured support, awareness, and contextual adaptation.

In the Sub-Saharan African context, where infrastructural constraints and policy gaps amplify vulnerabilities, these recommendations offer a regionally grounded pathway to harness generative AI's transformative potential while safeguarding core academic values. By prioritizing education over restriction, universities can foster responsible innovation rather than reactive enforcement, as elaborated in the policy implications and limitations sections.

Authors' Contributions

1.

Suleiman Ibrahim:

Conceptualization, Methodology, writing – Original Draft, Writing – Review & Editing, Funding Acquisition, and Project Administration.

2.

Uhammad Hamza Adam:

Formal Analysis, Investigation, Data Curation, Visualization, Writing – Original Draft, and Writing – Review & Editing.

3.

Alim Ahmad: Validation, Software, Formal Analysis, Supervision, and Writing – Review & Editing.

All authors have read and approved the final version of the manuscript and agree to its submission for publication.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this paper. The research

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