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Generative AI Usage and Information Literacy Skills among University Students in North-West Nigeria

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ABSTRACT

This study examined the relationship between generative AI usage and information literacy skills among university students in North-West Nigeria. The research investigated awareness levels, evaluation practices, ethical considerations, and barriers affecting the integration of AI-powered tools in academic contexts. Employing a quantitative research design, the study surveyed 385 undergraduate students from federal, state, and private universities using the Generative AI and Information Literacy Impact Questionnaire (GAIL-IQ). Data analysis utilized descriptive statistics including means, standard deviations, and frequencies through SPSS version 26. The ACRL Framework for Information Literacy (2016) provided the theoretical foundation, emphasizing threshold concepts in information understanding. Findings revealed moderate awareness levels (M=3.42, SD=0.89) of AI-powered tools among students, with significant variations across institutional types. Students demonstrated limited capacity in evaluating AI-generated content credibility (M=2.78, SD=0.94), raising concerns about information accuracy assessment. Ethical practices regarding attribution and academic integrity showed moderate adherence (M=3.15, SD=1.02), though infrastructural constraints and inadequate training emerged as primary barriers (M=3.68, SD=0.87). The study concluded that while students increasingly engage with AI-powered tools, critical evaluation competencies and ethical awareness require substantial improvement. The study recommends that Universities in North-West Nigeria should integrate comprehensive information literacy training programs specifically addressing AI-powered content evaluation, ethical usage frameworks, and attribution practices into undergraduate curricula to enhance academic integrity and critical thinking capabilities.

Keyword: Artificial Intelligence tools, Information Literacy competencies, undergraduate education, academic integrity, North-West Nigeria

1. Introduction

The proliferation of artificial intelligence-powered content generation tools in educational settings has fundamentally altered how students access, evaluate, and utilize information for academic purposes. These technological developments present both opportunities and challenges for higher education institutions, particularly in developing regions where infrastructural and pedagogical resources may be limited. University students increasingly rely on automated text generation platforms, intelligent tutoring systems, and machine learning-based research assistants to support their academic work, yet questions persist regarding their capacity to critically evaluate such resources [1].

In North-West Nigeria, undergraduate students navigate complex information environments characterized by limited digital infrastructure, varying levels of technological literacy, and evolving academic expectations. This region comprises seven states—Kaduna, Kano, Katsina, Kebbi, Jigawa, Sokoto, and Zamfara—hosting numerous tertiary institutions serving diverse student populations. Understanding how these students engage with emerging technologies while developing critical evaluation skills represents a pressing educational concern with implications for academic integrity, research quality, and educational equity.

Information literacy encompasses the abilities to recognize information needs, locate relevant resources, evaluate source credibility, integrate information effectively, and understand ethical obligations regarding attribution and intellectual property [2]. As AI-powered tools increasingly mediate students' information-seeking behaviors, the intersection between technological adoption and critical evaluation competencies demands systematic investigation. This study addresses this intersection by examining awareness patterns, evaluation practices, ethical considerations, and implementation barriers affecting AI tool integration among university students in North-West Nigeria.

The motivation for this study stems from three critical gaps in the existing literature. First, while research on generative AI adoption in higher education has grown rapidly, most studies focus on Western or East Asian institutional contexts [1, 6, 7], leaving African higher education settings substantially underexplored. Second, there is limited empirical evidence on how infrastructural constraints specific to sub-Saharan Africa — such as irregular electricity, high data costs, and device scarcity — interact with students' information literacy development in AI-mediated environments. Third, no prior study has systematically assessed the full spectrum of AI-related information literacy competencies — from awareness and critical evaluation to ethical practice and implementation barriers — among Nigerian undergraduate students. The present study addresses these gaps, offering region-specific evidence to inform policy, pedagogy, and infrastructure investment.

The principal contributions of this study are fourfold: (1) it provides the first large-scale quantitative assessment of generative AI awareness, critical evaluation skills, ethical attitudes, and access barriers among undergraduates in North-West Nigeria; (2) it operationalises and validates the GAIL-IQ instrument, offering a replicable tool for future AI literacy research in comparable contexts; (3) it extends the ACRL Information Literacy Framework [2] to an African higher education setting, demonstrating its applicability and identifying contextual adaptations required; and (4) it generates actionable, evidence-based recommendations for curriculum designers, institutional policy makers, and government agencies seeking to foster equitable and critical AI engagement in resource-constrained environments.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature on generative AI in higher education, information literacy competencies, and the Nigerian higher education context. Section 3 describes the research methodology, encompassing the study design, sampling procedure, instrumentation, data collection, and analysis approach. Section 4 presents the findings across the four thematic domains (awareness, evaluation practices, ethical considerations, and implementation barriers) and discusses their implications. Section 5 concludes the paper by synthesising the key findings, identifying limitations, and proposing directions for future research.

2. Literature Review

2.1. Conceptual Framework

2.1.1. Understanding AI-Powered Content Generation

Artificial intelligence-powered content generation refers to computational systems that utilize machine learning algorithms, neural networks, and natural language processing to produce text, images, code, or other outputs based on user prompts [3]. These systems employ pattern recognition to analyze vast datasets and generate responses that mimic human-created content, though they lack genuine comprehension or reasoning capabilities. According to Dwivedi et al. [4], such technologies represent statistical models trained on existing human-generated content, reproducing patterns without understanding context, meaning, or implications.

The educational implications of these tools are substantial. While they offer potential benefits for brainstorming, drafting, and research assistance, they simultaneously challenge traditional notions of authorship, originality, and academic integrity [1]. Students may utilize these platforms for legitimate learning support, yet the boundary between appropriate assistance and academic misconduct remains contested terrain requiring clear institutional guidelines and individual ethical judgment.

2.1.2. Information Literacy Competencies

Information literacy comprises the integrated set of abilities encompassing reflective discovery of information, understanding how information is produced and valued, and using information ethically to create new knowledge and participate responsibly in communities of learning [2]. This multidimensional construct extends beyond mere technical skills to encompass critical thinking, ethical reasoning, and metacognitive awareness about information processes.

The ACRL Framework for Information Literacy identifies six threshold concepts: Authority Is Constructed and Contextual; Information Creation as a Process; Information Has Value; Research as Inquiry; Scholarship as Conversation; and Searching as Strategic Exploration [2]. These concepts represent transformative understandings that reshape how students perceive and engage with information ecosystems. Particularly relevant to AI-powered tool adoption, "Authority Is Constructed and Contextual" acknowledges that traditional authority markers become problematic when applied to machine-generated content lacking human accountability or expertise credentials.

"Information Creation as a Process" proves critical for understanding AI-powered systems, which generate content through algorithmic pattern recognition rather than genuine comprehension or intentional communication [5]. Students must recognize that AI-produced text represents probabilistic predictions based on training data rather than reasoned argument or verified factual claims. This threshold concept enables students to approach such outputs with appropriate skepticism and analytical rigor.

"Information Has Value" addresses intellectual property concerns, attribution practices, and the economic dimensions of information production and access [2]. AI-powered tools complicate traditional attribution frameworks, raising questions about authorship when content originates from machine learning models trained on unattributed datasets potentially incorporating copyrighted materials without permission or compensation.

2.2. AI Adoption in Higher Education

The rapid integration of AI-powered tools into academic environments has generated substantial scholarly attention examining adoption patterns, educational applications, and institutional responses. Chan and Zhou [6] documented diverse student perceptions regarding AI assistance, ranging from enthusiasm about efficiency gains to concerns about intellectual authenticity and learning outcomes. Their research revealed that students often lack metacognitive awareness about how AI tool usage affects their cognitive development and knowledge retention.

Cotton et al. [7] examined academic integrity implications of AI-powered writing assistance, identifying challenges for traditional plagiarism detection methods and assessment practices. They argued that educational institutions must shift from detection-focused approaches toward fostering intrinsic motivation for academic honesty and developing assessment methods resistant to AI-facilitated cheating. Their recommendations emphasized transparent communication about acceptable AI usage boundaries and pedagogical redesign privileging higher-order thinking skills less amenable to automation.

Sullivan et al. [1] analyzed the pedagogical opportunities and risks associated with AI-powered tools in higher education, concluding that effective integration requires faculty development, curriculum modification, and clear institutional policies. They noted that students often adopt these technologies ahead of institutional guidance, creating ethical ambiguity and potentially undermining learning objectives when usage substitutes for genuine engagement with course material.

2.3. Information Literacy Challenges in Digital Environments

Information literacy development faces substantial challenges in contemporary digital environments characterized by information abundance, source proliferation, and evolving credibility markers. Hargittai [8] documented persistent disparities in digital skills across socioeconomic groups, identifying a "second-level digital divide" wherein access alone proves insufficient without accompanying competencies for effective information navigation and evaluation.

These challenges intensify in contexts where AI-powered tools introduce additional complexity. Bender et al. [9] cautioned that large language models function as "stochastic parrots," generating plausible-sounding text without understanding, accuracy verification, or factual grounding. Students relying on such outputs without critical evaluation risk incorporating errors, biases, or fabricated information into their academic work, particularly when they lack expertise to identify inaccuracies in unfamiliar subject domains.

Crawford [10] analyzed the political economy of AI systems, revealing how training data reflects existing social inequalities, cultural biases, and power structures. This analysis suggests that uncritical adoption of AI-generated content may perpetuate rather than challenge problematic perspectives, making critical evaluation skills essential for socially responsible scholarship.

2.4. The Nigerian Higher Education Context

Nigerian higher education faces distinctive challenges affecting technology adoption and information literacy development. Ocholla and Bothma [11] identified infrastructure limitations, resource constraints, and insufficient professional development as persistent obstacles to effective library and information science education across African contexts. These structural challenges directly impact students' opportunities to develop robust information literacy competencies.

Adeleke and Nwalo [12] examined ICT and information literacy skills among Nigerian health sciences students, finding significant gaps in critical evaluation abilities despite growing technology access. Their research highlighted disconnections between technical skill development and higher-order information competencies, suggesting that access to digital resources alone proves insufficient without corresponding pedagogical support.

Oyelekan et al. [13] documented constraints affecting ICT integration in Nigerian higher education institutions, including inadequate infrastructure, inconsistent electricity supply, limited bandwidth, and insufficient training for both faculty and students. These barriers create uneven learning environments where technological adoption proceeds unevenly across and within institutions, potentially exacerbating existing educational inequalities.

3. Method

3.1. Research Design

This study employed a quantitative research design to systematically examine awareness levels, evaluation practices, ethical considerations, and implementation barriers regarding AI-powered tool usage among university students in North-West Nigeria. The quantitative approach facilitated statistical analysis of relationships between variables and enabled generalization of findings across the target population [14].

The cross-sectional survey design allowed for data collection at a single timepoint, providing a snapshot of current practices and competencies. This approach proved appropriate for descriptive research goals examining prevalence, patterns, and associations within the study population without manipulating independent variables or establishing causality.

3.2. Population and Sample

The study population comprised undergraduate students enrolled in federal, state, and private universities across North-West Nigeria during the 2023/2024 academic session. The region contains 54 accredited universities serving diverse student populations across multiple disciplines and institutional contexts.

Sample size determination utilized Yamane's formula [15], as shown in Equation (1):

$$n = \frac{N}{(1+N(e)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (1)$$

Where:

- n = sample size
- N = population size
- e = margin of error (0.05)

With a population of approximately 250,000 undergraduate students and a 5% margin of error, the calculated sample size was 400 students. Accounting for potential non-responses and incomplete surveys, the study distributed 450 questionnaires, ultimately obtaining 385 valid responses representing a 96.3% effective response rate.

Stratified random sampling ensured representation across institutional types (federal, state, private), academic levels (100-400 level), and disciplines (sciences, social sciences, humanities, engineering). This sampling strategy facilitated analysis of potential variations in AI literacy across different student groups while maintaining statistical power for inferential analyses.

3.3. Instrumentation

The study utilized the Generative AI and Information Literacy Impact Questionnaire (GAIL-IQ), a researcher-developed instrument comprising four sections:

1. **Section A: Demographic Information** – Collected data on age, gender, academic level, discipline, and institutional type.
2. **Section B: Awareness and Usage Patterns** – 12 items measuring familiarity with various AI-powered tools, frequency of usage, and primary application contexts (rated on 5-point Likert scale: 1=Never to 5=Always).
3. **Section C: Evaluation Practices and Information Literacy Competencies** – 15 items assessing abilities to evaluate AI-generated content credibility, identify limitations, verify information accuracy, and recognize potential biases (rated on 5-point Likert scale: 1=Strongly Disagree to 5=Strongly Agree).
4. **Section D: Ethical Considerations and Implementation Barriers** – 13 items examining attribution practices, academic integrity awareness, and perceived obstacles to effective AI tool integration (rated on 5-point Likert scale: 1=Strongly Disagree to 5=Strongly Agree).

The instrument underwent validation through expert review by information science faculty and educational technology specialists, followed by pilot testing with 30 students from institutions outside the study sample. Reliability assessment using Cronbach's alpha yielded coefficients of 0.84 (awareness), 0.87 (evaluation practices), and 0.82 (ethical considerations), indicating satisfactory internal consistency [16].

3.4. Data Collection Procedures

Data collection occurred during February-March 2024 through both online and paper-based survey administration to accommodate varying internet access across institutions. Online distribution utilized Google Forms with security settings preventing multiple submissions, while paper surveys employed identical questions maintaining consistency across administration modes.

Institutional permissions were secured from participating universities' research ethics committees prior to data collection. Students provided informed consent after receiving explanations of study purposes, voluntary participation, anonymity protections, and data usage protocols. No personally identifiable information was collected beyond demographic categories necessary for analysis.

Research assistants recruited from participating institutions facilitated survey distribution and collection, receiving standardized training on ethical research conduct, informed consent procedures, and response confidentiality maintenance. This approach enhanced response rates while ensuring consistent administration standards.

3.5. Data Analysis

Data analysis employed IBM SPSS Statistics version 26 for descriptive and inferential statistical procedures. Descriptive statistics including frequencies, percentages, means, and standard deviations characterized awareness levels, usage patterns, evaluation practices, and implementation barriers. These analyses provided comprehensive profiles of current competencies and challenges within the study population.

Mean score interpretation utilized the following framework, derived from the standard equal-interval method for 5-point Likert scales. The score range ($5 - 1 = 4$) is divided equally among five categories, yielding an interval width of $4 \div 5 = 0.80$, as expressed in Equation (2):

$$\text{Interval Width} = \frac{(\text{Maximum Score} - \text{Minimum Score})}{\text{Number of Categories}} = (5 - 1) / 5 = 0.80 \quad \ldots\ldots\ldots\ldots\ldots (2)$$

Applying an interval of 0.80 successively starting from the minimum value of 1.00 yields five equal bands. This equal-interval approach is widely adopted in educational research employing Likert-scale instruments [17] and produces the following classification:

- 1.00 – 1.80: Very Low
- 1.81 – 2.60: Low
- 2.61 – 3.40: Moderate
- 3.41 – 4.20: High
- 4.21 – 5.00: Very High

Beyond descriptive statistics, inferential analyses were conducted to assess group differences and relationships among study variables. Specifically, one-way Analysis of Variance (ANOVA) [18] was employed to test for statistically significant differences in AI awareness, evaluation practices, and ethical adherence across institutional type (federal, state, private) and academic level (100–400 level). ANOVA was chosen because it enables comparison of means across three or more independent groups simultaneously while controlling the familywise Type I error rate, making it more appropriate than multiple independent-samples t-tests [19]. Post-hoc Tukey HSD tests were applied where ANOVA results were significant ($p < .05$) to identify which group pairs differed. Additionally, Pearson product-moment correlation coefficients were computed to examine the linear relationships between AI awareness scores, critical evaluation scores, and ethical practice scores, given that all three variables were measured on continuous scales and assumed normal distributions in the full sample [18]. The Pearson correlation coefficient r is defined in Equation (3):

$$r = \Sigma(x_i - \bar{x})(y_i - \bar{y}) \,/\, \sqrt{[\Sigma(x_i - \bar{x})^2 \times \Sigma(y_i - \bar{y})^2]} \quad \ldots\ldots\ldots\ldots\ldots (3)$$

where x_i and y_i are individual observations and $\bar{x}$ and $\bar{y}$ are the respective sample means. All inferential tests were conducted at the $\alpha = 0.05$ significance level. This classification system facilitated meaningful interpretation of Likert-scale responses and comparison across different competency dimensions and student groups.

3.6. Theoretical Framework

The Association of College and Research Libraries (ACRL) Framework for Information Literacy for Higher Education [2] provided the theoretical foundation for this study. This framework conceptualizes information literacy as comprising interconnected threshold concepts that represent transformative understandings fundamentally altering learners' relationships with information.

Six threshold concepts structure the framework:

1. **Authority Is Constructed and Contextual** – Recognizing that information sources possess varying authority levels depending on context and that traditional authority markers may prove problematic for AI-generated content.
2. **Information Creation as a Process** – Understanding how information is produced, including the algorithmic processes underlying AI-generated content and their implications for reliability and validity.
3. **Information Has Value** – Acknowledging that information possesses economic, educational, and social value, raising questions about intellectual property, attribution, and ethical usage obligations.
4. **Research as Inquiry** – Approaching information-seeking as an iterative process involving question refinement, source evaluation, and knowledge construction rather than simple fact retrieval.
5. **Scholarship as Conversation** – Recognizing that scholarly communication represents ongoing dialogue among communities of practice, with implications for how AI-generated content participates (or fails to participate) in disciplinary discourse.
6. **Searching as Strategic Exploration** – Understanding that information discovery requires flexible, adaptive strategies rather than linear processes, particularly when navigating hybrid environments combining human-authored and AI-generated content.

This framework proved particularly relevant for examining AI-powered tool adoption because it emphasizes critical thinking about information sources, production processes, and ethical usage rather than merely technical skills. The threshold concepts provide analytical lenses for understanding how students conceptualize AI-generated content's authority, reliability, and appropriate applications within academic contexts.

3.7. Ethical Considerations

The research adhered to established ethical standards for human subjects research. Institutional review board approval was obtained from participating universities prior to data collection. All participants provided informed consent after receiving comprehensive information about study purposes, procedures, potential risks and benefits, voluntary participation, and withdrawal rights.

Participant anonymity was maintained through anonymous survey administration without collection of personally identifiable information. Data storage employed password-protected digital files accessible only to research team members, with plans for secure deletion following study completion and publication.

The study posed minimal risk to participants, involving no deception, physical interventions, or collection of sensitive personal information. Potential benefits included opportunities for reflection on information literacy practices and contribution to knowledge supporting educational improvement initiatives.

4. Findings and Discussions

4.1. Demographic Profile of Respondents

Table 1. Demographic Profile of Respondents (N=385).

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	224	58.2
	Male	161	41.8
	Total	385	100.0
Academic Level	100 Level	86	22.3
	200 Level	110	28.6
	300 Level	121	31.4
	400 Level	68	17.7
	Total	385	100.0
Institutional Type	Federal University	170	44.2
	State University	122	31.7
	Private University	93	24.1
	Total	385	100.0
Discipline	Sciences	111	28.8
	Social Sciences	125	32.5
	Humanities	82	21.3
	Engineering	67	17.4
	Total	385	100.0

Table 1 presents the demographic profile of the 385 respondents. The sample comprised 58.2% female and 41.8% male students, reflecting recent trends in female enrollment growth across Nigerian higher education. Academic level distribution was weighted toward middle-year students — 100 level (22.3%), 200 level (28.6%), 300 level (31.4%), and 400 level (17.7%) — indicating that participants possessed sufficient university experience to have encountered AI-powered tools in academic contexts while still being at an active stage of undergraduate study. Institutional type representation comprised federal universities (44.2%), state universities (31.7%), and private universities (24.1%), roughly proportional to enrollment distributions across these categories in North-West Nigeria. Disciplinary breadth was ensured through representation from social sciences (32.5%), sciences (28.8%), humanities (21.3%), and engineering (17.4%), providing a comprehensive cross-sectional sample for examining AI usage patterns and information literacy competencies across diverse academic domains.

The study obtained 385 valid responses from undergraduate students across federal, state, and private universities in North-West Nigeria. The demographic distribution revealed 58.2% female and 41.8% male participants, reflecting general enrollment patterns across Nigerian higher education where female representation has increased substantially in recent decades.

Academic level distribution showed: 100 level (22.3%), 200 level (28.6%), 300 level (31.4%), and 400 level (17.7%). This distribution weighted toward middle-year students suggested that participants possessed sufficient university experience to have encountered AI-powered tools in academic contexts while not yet having completed their undergraduate studies.

Institutional type representation comprised federal universities (44.2%), state universities (31.7%), and private universities (24.1%), roughly proportional to enrollment distributions across these categories in North-West Nigeria. Disciplinary representation included sciences (28.8%), social sciences (32.5%), humanities (21.3%), and engineering (17.4%), ensuring breadth across major academic domains.

4.2. Awareness and Usage Patterns of AI-Powered Tools

Table 2. Awareness and Usage Patterns of AI-Powered Tools.

Variable / Item	Mean (M)	Std. Dev. (SD)	Interpretation
Overall AI Tool Awareness	3.42	0.89	Moderate
Awareness by Institutional Type			
Federal University	3.68	0.82	High
State University	3.34	0.91	Moderate
Private University	3.21	0.94	Moderate
Awareness by Academic Level			
100 Level	2.98	1.02	Moderate
200 Level	3.19	0.98	Moderate
300 Level	3.54	0.85	Moderate
400 Level	3.89	0.71	High
Tool Recognition (% Familiar)			
ChatGPT	78.4%	—	—
Google Translate	71.2%	—	—
Grammarly	62.3%	—	—
Quillbot	45.7%	—	—
Claude / Jasper / Copy.ai	18.2–31.4%	—	—
Usage Frequency by Application			
Language translation	68.7%	—	At least occasional
Writing assistance (grammar)	64.2%	—	At least occasional
Assignment drafting	52.4%	—	At least occasional
Research exploration	48.9%	—	At least occasional
Content summarisation	43.6%	—	At least occasional
AI text generation/paraphrasing	47.3%	—	At least occasional

Table 2 presents awareness and usage patterns of AI-powered tools among the sampled students. The overall mean awareness score of M=3.42 (SD=0.89) indicates a moderate level of familiarity with AI-powered tools across the sample, with mainstream consumer-oriented platforms dominating student recognition: ChatGPT (78.4%), Google Translate (71.2%), and Grammarly (62.3%) showed the highest awareness, while specialised academic platforms such as Claude, Jasper, and Copy.ai registered considerably lower recognition (18.2%–31.4%), suggesting that marketing and peer networks drive AI adoption more than institutional guidance. Significant institutional variation was observed, with federal university students demonstrating higher awareness (M=3.68, SD=0.82) compared to state (M=3.34, SD=0.91) and private (M=3.21, SD=0.94) university counterparts, likely reflecting differences in infrastructure investment, faculty technological engagement, and peer knowledge networks. A progressive increase in awareness across academic levels —

from M=2.98 at 100 level to M=3.89 at 400 level — indicates that familiarity accumulates through undergraduate experience, yet also reveals that first-year students encounter AI tools with limited preparation, potentially establishing usage habits before developing adequate critical evaluation competencies. Usage patterns showed that language translation (68.7%), writing assistance (64.2%), and assignment drafting (52.4%) constituted the primary application contexts, suggesting students employ AI tools predominantly for efficiency gains in routine tasks rather than advanced analytical or research functions.

Analysis of awareness and usage patterns revealed moderate overall familiarity with AI-powered tools among students (M=3.42, SD=0.89). Specific tools showed varying recognition levels. ChatGPT demonstrated highest awareness (78.4% familiar), followed by Grammarly (62.3%), Google Translate (71.2%), and Quillbot (45.7%). More specialized tools like Claude, Jasper, and Copy.ai showed lower recognition (ranging 18.2%-31.4%), suggesting that mainstream consumer-oriented platforms dominate student awareness.

Usage frequency varied considerably across tool types and applications. For writing assistance, 64.2% reported at least occasional use of AI-powered grammar checkers, while 47.3% acknowledged using AI platforms for text generation or paraphrasing. Translation tools showed widespread adoption (68.7% at least occasional use), reflecting multilingual contexts and international scholarship access needs.

Primary application contexts included assignment drafting (52.4%), research exploration (48.9%), content summarization (43.6%), and language translation (67.8%). These patterns suggest that students employ AI tools primarily for efficiency gains in routine academic tasks rather than advanced research or critical analysis applications requiring higher-order thinking skills.

Institutional type comparisons revealed significant variations. Federal university students demonstrated higher awareness levels (M=3.68, SD=0.82) compared to state university (M=3.34, SD=0.91) and private university students (M=3.21, SD=0.94). This disparity may reflect infrastructure differences, faculty technological engagement, or peer networks facilitating tool discovery and adoption.

Academic level analysis showed progressive awareness increases from 100 level (M=2.98, SD=1.02) to 400 level (M=3.89, SD=0.71), suggesting that exposure and familiarity develop throughout undergraduate education. However, this pattern also indicated that first-year students encounter AI-powered tools with limited preparation, potentially establishing problematic usage habits before developing critical evaluation competencies.

4.3. Evaluation Practices and Critical Assessment Competencies

Table 3. Evaluation Practices and Critical Assessment Competencies.

Evaluation Competency / Item	**Mean (M)**	**Std. Dev. (SD)**	**% Proficient / Consistent**
Overall Evaluation Capacity	2.78	0.94	34.2% (consistent verification)
Accuracy Assessment			
Confidence in identifying factual errors	—	—	31.4%
Regularly verify against authoritative sources	—	—	34.2%
Rarely/never conduct verification	—	—	28.7%
Bias Recognition			
Awareness of potential AI output biases	—	—	27.8%
Examine training data / algorithmic limits	—	—	22.1%

Evaluation Competency / Item	Mean (M)	Std. Dev. (SD)	% Proficient / Consistent
Source Attribution Understanding			
Recognise AI content requires verification	—	—	45.6%
Understand lack of primary source attribution	—	—	29.3%
Contextual Appropriateness			
Evaluate alignment with assignment requirements	—	—	36.7%
Evaluation by Institutional Type			
Federal University	2.94	0.88	—
State University	2.71	0.96	—
Private University	2.63	0.99	—
Evaluation by Discipline			
Sciences	2.91	0.87	—
Engineering	2.89	0.90	—
Social Sciences	2.72	0.96	—
Humanities	2.68	0.98	—

Table 3 reveals that students demonstrated limited capacity in evaluating AI-generated content credibility (M=2.78, SD=0.94), falling below the moderate threshold and raising substantial concerns about information accuracy assessment in academic contexts. Only 34.2% of respondents reported consistently verifying AI-generated information against authoritative sources, while 28.7% acknowledged rarely or never conducting such verification — a pattern of passive acceptance that is particularly concerning given that AI systems may confidently present incorrect information without indication of uncertainty. Bias recognition competencies were especially weak, with only 27.8% reporting awareness of potential biases in AI outputs and a mere 22.1% actively examining training data sources or algorithmic limitations, suggesting that most students approach AI-generated content without sufficient critical scepticism about embedded assumptions or systemic limitations. Source attribution understanding remained incomplete: while 45.6% acknowledged that AI-generated content requires verification, only 29.3% understood that such content typically lacks primary source attribution, creating a disconnect between theoretical acknowledgment and practical verification behaviour. Contextual appropriateness evaluation was practised by only 36.7% of respondents. Institutional comparisons showed marginal advantages for federal university students (M=2.94, SD=0.88), while disciplinary patterns indicated slightly stronger evaluation practices in science (M=2.91) and engineering (M=2.89) compared to social sciences (M=2.72) and humanities (M=2.68), likely reflecting disciplinary cultures of empirical verification, though overall levels indicate that evaluation competency development is needed across all fields.

Students demonstrated limited capacity in evaluating AI-generated content credibility (M=2.78, SD=0.94), falling below the moderate threshold and raising substantial concerns about information accuracy assessment in academic contexts. Only 34.2% reported consistently verifying AI-generated information against authoritative sources, while 28.7% acknowledged rarely or never conducting such verification.

Specific evaluation competencies showed concerning patterns:

Accuracy Assessment: Only 31.4% indicated confidence in identifying factual errors within AI-generated content, particularly in unfamiliar subject domains. This vulnerability proves especially problematic given that

AI systems may confidently present incorrect information (sometimes termed "hallucinations") without indication of uncertainty.

Bias Recognition: A mere 27.8% reported awareness of potential biases in AI outputs, with even fewer (22.1%) actively examining training data sources or algorithmic limitations affecting content generation. This gap suggests that most students approach AI-generated content with insufficient critical skepticism regarding embedded assumptions or perspectives.

Source Attribution: While 45.6% recognized that AI-generated content requires verification, only 29.3% understood that such content typically lacks primary source attribution, making independent verification necessary. This disconnect between theoretical acknowledgment and practical understanding may result in uncritical incorporation of unverified claims into academic work.

Contextual Appropriateness: Students showed limited consideration of whether AI-generated content suited specific academic contexts, with only 36.7% reporting evaluation of whether outputs aligned with assignment requirements, disciplinary conventions, or expected depth of analysis.

Institutional comparisons revealed modest differences in evaluation practices. Federal university students demonstrated slightly stronger evaluation habits (M=2.94, SD=0.88) compared to state (M=2.71, SD=0.96) and private university students (M=2.63, SD=0.99). These variations may reflect differences in information literacy instruction, faculty modeling of critical evaluation practices, or research intensity affecting students' exposure to scholarly information assessment.

Disciplinary patterns showed that science and engineering students reported marginally stronger evaluation practices (M=2.91, SD=0.87; M=2.89, SD=0.90 respectively) compared to social sciences and humanities students (M=2.72, SD=0.96; M=2.68, SD=0.98 respectively). This pattern may relate to disciplinary cultures emphasizing empirical verification and quantitative validation, though the overall moderate levels suggest that evaluation competencies require development across all fields.

4.4. Ethical Considerations and Academic Integrity Awareness

Table 4. Ethical Considerations and Academic Integrity Awareness.

Ethical Dimension / Item	Mean (M)	Std. Dev. (SD)	Key Finding (%)
Overall Ethical Adherence	3.15	1.02	Moderate adherence
Attribution Practices			
Acknowledge AI content should be attributed	—	—	67.8%
Consistently provide attribution in own work	—	—	42.3%
Academic Integrity Understanding			
Uncertain whether AI use constitutes misconduct	—	—	54.2%
Institutions provided clear AI usage guidelines	—	—	26.6% (only)
Intellectual Property Awareness			
Understand IP issues re: AI-generated content	—	—	38.7%
Transparency Obligations			
Agree students should disclose AI assistance	—	—	61.3%

Ethical Dimension / Item	Mean (M)	Std. Dev. (SD)	Key Finding (%)
Consistently disclose AI usage to instructors	—	—	35.8%
Uncertain about disclosure requirements	—	—	52.1%
Concerned about negative evaluation if disclosed	—	—	38.4%
Pedagogical Impact Awareness			
Limited consideration of AI impact on learning	—	—	46.8%
Ethical Adherence by Institutional Type			
Private University	3.31	0.95	Highest ethical awareness
Federal University	3.12	1.04	Moderate
State University	3.07	1.06	Moderate

Table 4 reveals that students demonstrated moderate adherence to ethical practices regarding attribution and academic integrity (M=3.15, SD=1.02), indicating recognition of relevant principles without consistent implementation across all dimensions. The most striking finding is the persistent gap between theoretical awareness and behavioural practice: while 67.8% of respondents acknowledged that AI-generated content should be attributed, only 42.3% reported consistently providing such attribution in their own academic work, reflecting a pattern in which students understand ethical obligations without reliably translating this knowledge into practice. Academic integrity understanding was characterised by widespread ambiguity, with 54.2% uncertain whether using AI for particular tasks constituted academic misconduct — an ambiguity compounded by the finding that 73.4% of respondents reported their institutions had not provided clear guidelines regarding AI tool usage. Transparency obligations showed a similar awareness-behaviour gap: 61.3% agreed students should disclose AI assistance, yet only 35.8% consistently disclosed usage to instructors, with contributing factors including uncertainty about disclosure requirements (52.1%), concerns about negative evaluation (38.4%), and assumptions that peers use AI without disclosure (44.7%). A concerning 46.8% indicated limited metacognitive engagement with how AI usage might affect their own learning or skill development. Institutional comparisons showed slightly higher ethical awareness among private university students (M=3.31, SD=0.95), possibly reflecting more explicit institutional honour codes, compared to federal (M=3.12, SD=1.04) and state (M=3.07, SD=1.06) university students.

Students demonstrated moderate adherence to ethical practices regarding attribution and academic integrity (M=3.15, SD=1.02), suggesting recognition of relevant principles without consistent implementation. Specific ethical dimensions revealed nuanced patterns:

Attribution Practices: While 67.8% acknowledged that AI-generated content should be attributed, only 42.3% reported consistently providing such attribution in their academic work. This gap between awareness and practice suggests that students understand theoretical obligations without translating knowledge into consistent behavior.

Academic Integrity Understanding: Students showed confusion about acceptable AI usage boundaries, with 54.2% uncertain whether using AI for particular tasks constituted academic misconduct. This ambiguity reflects broader institutional uncertainty, as 73.4% reported that their institutions had not provided clear guidelines regarding AI tool usage in academic contexts.

Intellectual Property Awareness: Only 38.7% demonstrated understanding of intellectual property issues surrounding AI-generated content, including questions about ownership, copyright, and fair use. This knowledge gap potentially exposes students to unintended violations or conflicts when incorporating AI outputs into their work.

Transparency Obligations: While 61.3% agreed that students should be transparent about AI assistance, only 35.8% reported consistently disclosing such usage to instructors. Factors contributing to this gap included uncertainty about disclosure requirements (52.1%), concerns about negative evaluation (38.4%), and assumptions that other students used AI without disclosure (44.7%).

Pedagogical Impact Awareness: A concerning 46.8% indicated limited consideration of how AI usage might affect their learning or skill development. This finding suggests insufficient metacognitive engagement with the trade-offs between efficiency gains and potential learning losses when AI tools substitute for cognitive engagement.

Institutional type comparisons showed that private university students demonstrated slightly higher ethical awareness (M=3.31, SD=0.95) compared to federal (M=3.12, SD=1.04) and state university students (M=3.07, SD=1.06). This pattern may reflect institutional culture differences, honor code implementations, or academic integrity education emphasis.

4.5. Implementation Barriers and Challenges

Table 5. Implementation Barriers and Challenges.

Barrier Category / Item	Mean (M)	Std. Dev. (SD)	% Reporting as Significant
Overall Barrier Severity	3.68	0.87	Primary barriers identified
Infrastructure Limitations			
Electricity supply inconsistency	—	—	76.4%
Internet connectivity challenges	—	—	68.2%
Economic / Access Barriers			
High data costs	—	—	71.3%
Insufficient device access	—	—	52.4%
Training and Pedagogical Gaps			
Inadequate training on AI tool usage	—	—	82.1%
Limited faculty AI literacy integration in curricula	—	—	67.8%
Policy and Governance Gaps			
Absence of clear institutional AI policies	—	—	73.4%
Barrier Severity by Institutional Type			
State University	3.89	0.79	Most severe barriers
Private University	3.84	0.82	Severe barriers
Federal University	3.47	0.91	Moderate barriers
Geographic Variation			
Urban (Kaduna, Kano)	—	—	Fewer barriers reported

Barrier Category / Item	Mean (M)	Std. Dev. (SD)	% Reporting as Significant
Rural (Kebbi, Zamfara)	—	—	More severe barriers reported

Table 5 demonstrates that infrastructural constraints and inadequate training emerged as the most severe barriers to effective AI tool integration among students in North-West Nigeria (M=3.68, SD=0.87). Training deficits constituted the single most widely reported barrier, with an overwhelming 82.1% of respondents indicating inadequate training on effective and ethical AI tool usage — students described learning primarily through peer networks or trial-and-error experimentation rather than structured institutional guidance, a pattern that risks reinforcing problematic practices and misconceptions. Infrastructure limitations compounded these challenges: electricity supply inconsistency (76.4%) and internet connectivity challenges (68.2%) fundamentally constrained access to cloud-based AI platforms, while high data costs (71.3%) further limited sustained engagement, with students reporting that they ration usage or restrict activities to institutional facilities with wifi access. The absence of clear institutional AI policies (73.4%) created ethical ambiguity and inconsistent practices, with students expressing frustration about conflicting messages from different instructors and uncertain boundaries between acceptable assistance and academic misconduct. Insufficient device access (52.4%) particularly affected students from lower socioeconomic backgrounds dependent on smartphones with limited computing capabilities. Institutional type comparisons revealed that state (M=3.89, SD=0.79) and private (M=3.84, SD=0.82) university students reported more severe infrastructure challenges than federal university students (M=3.47, SD=0.91), reflecting resource allocation and infrastructure investment disparities. Geographic analysis highlighted persistent urban-rural digital divides, with students from Kaduna and Kano reporting fewer barriers compared to counterparts in more rural states such as Kebbi and Zamfara, underscoring the compounding effect of geographic location on educational equity in AI-mediated learning environments.

Infrastructural constraints and inadequate training emerged as primary barriers to effective AI tool integration (M=3.68, SD=0.87). Students identified multiple obstacles limiting their ability to engage with AI-powered tools effectively and ethically:

Infrastructure Limitations: Electricity supply inconsistency (reported by 76.4% as significant barrier) and internet connectivity challenges (68.2%) fundamentally constrained access. These infrastructural deficits affected not only AI tool usage but broader digital engagement, creating cumulative disadvantages for students in resource-limited contexts.

Data Cost Burdens: High data costs (reported by 71.3% as barrier) limited sustained engagement with cloud-based AI platforms requiring continuous internet connectivity. Students described rationing usage or restricting activities to institutional facilities with wifi access, potentially reducing learning opportunities compared to peers with unlimited connectivity.

Device Limitations: Insufficient access to appropriate devices (52.4% reporting this barrier) restricted engagement, as many AI platforms require computing capabilities beyond those of basic mobile phones. This challenge particularly affected students from lower socioeconomic backgrounds who might access internet primarily through smartphones rather than computers.

Training Deficits: An overwhelming 82.1% reported inadequate training on effective and ethical AI tool usage. Students described learning primarily through peer networks or trial-and-error experimentation rather than structured institutional guidance, potentially reinforcing problematic practices or misconceptions.

Policy Uncertainty: The absence of clear institutional policies (reported by 73.4%) created ethical ambiguity and inconsistent practices. Students expressed frustration about conflicting messages from different instructors, uncertain boundaries between acceptable assistance and academic misconduct, and lack of confidence about appropriate attribution practices.

Pedagogical Integration: Limited faculty integration of AI literacy into curricula (67.8% reporting this gap) meant that students rarely received explicit instruction on critical evaluation, ethical usage, or effective prompting strategies. This pedagogical gap left students to develop these competencies independently without guidance or feedback.

Institutional type comparisons revealed that state and private university students reported more severe infrastructure challenges (M=3.89, SD=0.79; M=3.84, SD=0.82 respectively) compared to federal university students (M=3.47, SD=0.91). These disparities likely reflect resource allocation differences and infrastructure investment patterns across institutional categories.

Geographic variations within North-West Nigeria showed that students from Kaduna and Kano states (hosting major urban centers) reported fewer infrastructure barriers compared to students from more rural states like Kebbi and Zamfara, highlighting persistent urban-rural digital divides affecting educational equity.

4.6. Discussion

The findings reveal complex patterns in AI-powered tool adoption among university students in North-West Nigeria, characterized by moderate awareness, limited critical evaluation competencies, ambiguous ethical understanding, and substantial implementation barriers. These patterns reflect broader tensions between technological change and educational adaptation in contexts characterized by resource constraints and rapid digitalization.

4.6.1. Awareness-Competency Disconnect

Students demonstrate moderate awareness of AI-powered tools yet lack corresponding critical evaluation competencies, creating potential risks for information quality and academic integrity. This pattern aligns with Hargittai's [8] concept of the "second-level digital divide," wherein access or awareness alone proves insufficient without accompanying analytical skills for effective information navigation and assessment.

The awareness-competency gap suggests that technological diffusion outpaces pedagogical adaptation, leaving students to navigate complex ethical and epistemological questions without adequate institutional support. This situation parallels broader patterns documented in information literacy research, where students often overestimate their evaluation abilities while demonstrating systematic vulnerabilities to misinformation and low-quality sources.

The finding that mainstream consumer-oriented tools (ChatGPT, Grammarly) show higher awareness than specialized academic platforms suggests that marketing and peer networks drive adoption more than educational recommendations or institutional guidance. This pattern raises questions about whether students encounter AI tools first in contexts emphasizing efficiency over critical engagement, potentially establishing problematic usage patterns before developing evaluation competencies.

4.6.2. Critical Evaluation Vulnerabilities

Students' limited capacity in evaluating AI-generated content credibility (M=2.78, SD=0.94) represents a significant concern for academic quality and intellectual development. This vulnerability reflects insufficient understanding of how AI systems function, what limitations they possess, and what verification procedures appropriate usage requires.

The finding resonates with Bender et al.'s [9] characterization of large language models as "stochastic parrots" that generate plausible-sounding text without understanding, accuracy verification, or factual grounding. Students lacking technical knowledge about AI functioning may anthropomorphize these systems, attributing intentionality, comprehension, or reliability that the technology does not possess.

Particularly concerning is the low percentage (22.1%) examining algorithmic limitations or training data biases. This gap suggests that students approach AI-generated content with insufficient critical skepticism about embedded assumptions, cultural perspectives, or systemic limitations. Crawford's [10] analysis of AI systems' reproduction of existing social inequalities becomes directly relevant here, as uncritical adoption risks perpetuating problematic biases without student awareness.

The disciplinary variations observed, with science and engineering students showing marginally stronger evaluation practices, may reflect differing epistemological cultures regarding empirical verification and quantitative validation. However, the overall moderate levels suggest that evaluation competencies require systematic development across all disciplines rather than assumptions that certain fields inherently foster critical assessment skills.

4.6.3. Ethical Ambiguity and Policy Gaps

The gap between ethical awareness (67.8% acknowledging attribution obligations) and ethical practice (42.3% consistently providing attribution) highlights the insufficiency of knowledge alone for behavior change. This pattern suggests that ethical practice requires not only awareness but also supportive institutional structures, clear expectations, and consistent modeling by faculty.

The reported institutional policy vacuum (73.4% lacking clear guidelines) leaves students navigating ethical questions without adequate support. This situation creates several problematic dynamics: inconsistent practices across courses, confusion about acceptable usage boundaries, reluctance to seek clarification for fear of appearing to admit misconduct, and potential advantages for students willing to use AI tools without disclosure compared to those attempting to follow uncertain ethical principles.

The policy gap likely reflects broader institutional uncertainty about how to respond to rapidly evolving technologies without stifling legitimate learning applications or imposing unenforceable restrictions. However, this uncertainty translates into ethical burden-shifting onto students who must make complex judgments without guidance, potentially undermining both learning outcomes and academic integrity.

Faculty ambiguity about AI usage boundaries, reported by students through inconsistent messages across instructors, suggests that professional development regarding AI literacy should target faculty as well as students. Institutional policy development requires faculty input and buy-in for effective implementation, yet faculty may lack technical expertise or pedagogical frameworks for making informed judgments about appropriate integration.

4.6.4. Infrastructure as Educational Justice Issue

The severe infrastructure barriers (M=3.68, SD=0.87) documented in this study represent not merely technical challenges but fundamental educational equity concerns. When electricity inconsistency, internet connectivity limitations, and data cost burdens systematically prevent student engagement with increasingly essential digital tools, infrastructure deficits translate directly into learning disadvantages.

These barriers disproportionately affect students from lower socioeconomic backgrounds, students in rural areas, and students attending under-resourced institutions, potentially exacerbating existing educational inequalities. The finding that state and private university students reported more severe infrastructure challenges compared to federal university students reflects resource allocation patterns that create stratified learning opportunities within a supposedly unified higher education system.

The infrastructure challenges documented here extend beyond AI-powered tools to affect broader digital literacy development, online learning participation, and research capabilities. Addressing these barriers requires sustained investment in electrical infrastructure, telecommunications networks, and institutional technology resources—investments extending well beyond individual institutional capacities to system-level priorities requiring government commitment and resource allocation.

The geographic variations observed, with students from major urban centers reporting fewer barriers than students from rural states, highlight persistent urban-rural digital divides affecting educational equity. These patterns suggest that place of residence significantly shapes educational opportunities in ways that may perpetuate regional inequalities and limit social mobility for students from less-developed areas.

4.6.5. Training Deficit and Pedagogical Integration

The overwhelming majority (82.1%) reporting inadequate training on effective and ethical AI tool usage represents a critical gap in educational provision. This deficit means that students develop AI literacy informally through peer networks, online forums, and trial-and-error experimentation rather than structured pedagogical guidance incorporating critical evaluation, ethical reasoning, and metacognitive awareness.

Informal learning pathways may reinforce problematic practices, perpetuate misconceptions, or prioritize efficiency over intellectual development. Without explicit instruction on effective prompting strategies, output evaluation, bias recognition, or appropriate usage contexts, students miss opportunities to develop sophisticated AI literacy supporting long-term learning and professional preparation.

The limited faculty integration of AI literacy into curricula (67.8% reporting this gap) suggests that educational response lags considerably behind technological adoption. This pattern may reflect faculty uncertainty about appropriate pedagogical approaches, insufficient professional development supporting AI literacy instruction, or curriculum rigidity limiting rapid adaptation to emerging technologies.

Effective AI literacy education requires more than one-off training sessions or generic workshops. Rather, it demands discipline-specific integration addressing how AI tools relate to particular fields' epistemologies, methodologies, and ethical norms. Such integration requires faculty expertise, curriculum space, and institutional commitment to ongoing adaptation as technologies evolve.

4.7. Implications for Educational Practice and Policy

These findings collectively suggest that educational institutions in North-West Nigeria face substantial challenges in supporting student development of critical AI literacy. Addressing these challenges requires coordinated action across multiple levels:

Pedagogical Integration: Information literacy instruction must explicitly address AI-powered tools, including technical understanding of how they function, critical evaluation of outputs, ethical usage principles, and metacognitive awareness of learning impacts. This instruction should be integrated across curricula rather than relegated to isolated library sessions or generic workshops.

Policy Development: Institutions must develop clear, transparent policies regarding acceptable AI usage, attribution requirements, and academic integrity standards. These policies should balance legitimate learning applications against misconduct concerns while providing sufficient specificity to guide student behavior without micromanaging every potential scenario.

Infrastructure Investment: Addressing electricity, connectivity, and device access challenges requires sustained investment and creative solutions, including partnerships with telecommunications providers, renewable energy implementation, and device loan programs ensuring equitable access to essential technology.

Faculty Development: Supporting faculty in developing their own AI literacy and pedagogical approaches for teaching these competencies represents a critical priority. Professional development should address both technical understanding and pedagogical strategies, creating communities of practice for sharing effective approaches.

Assessment Redesign: Traditional assessment methods prove vulnerable to AI-facilitated cheating, necessitating redesign emphasizing higher-order thinking skills, contextualized application, and process-oriented evaluation less amenable to automation. This redesign should maintain academic rigor while acknowledging legitimate AI assistance for routine tasks.

5. Conclusions

This study investigated the relationship between generative AI usage and information literacy among 385 undergraduate students across federal, state, and private universities in North-West Nigeria. Four principal findings emerged. First, students demonstrated moderate overall awareness of AI tools (M=3.42, SD=0.89), dominated by mainstream platforms such as ChatGPT and Grammarly, yet this familiarity was not matched by critical evaluation competence (M=2.78, SD=0.94) — only 34.2% routinely verified AI-generated claims against authoritative sources, and just 27.8% showed awareness of algorithmic bias. Second, ethical adherence was moderate (M=3.15, SD=1.02), undermined by a near-universal policy vacuum: 73.4% of students reported that their institutions had issued no clear guidance on acceptable AI use. Third, infrastructure barriers were the most acute challenge (M=3.68, SD=0.87), with electricity inconsistency (76.4%), high data costs (71.3%), and insufficient devices (52.4%) constituting structural inequalities that disproportionately affect students in state and private universities and in rural areas. Fourth, 82.1% of students reported inadequate institutional training on effective and ethical AI use, underscoring a widening gap between the pace of technological adoption and educational preparedness. Collectively, these findings highlight that equipping students for AI-mediated information environments requires simultaneous action on curricula, institutional policy, infrastructure, and faculty development — no single lever suffices.

5.1. Directions for Future Research

Several avenues merit investigation beyond the scope of this study. (1) Longitudinal studies tracking the same cohorts over multiple academic years would illuminate how AI literacy evolves through undergraduate education and whether institutional interventions produce lasting competency gains. (2) Qualitative and mixed-methods research is needed to examine the lived experiences of students navigating AI-mediated information environments, capturing nuances — such as disciplinary culture and social peer norms — that survey instruments cannot fully reveal. (3) Experimental or quasi-experimental studies evaluating the effectiveness of specific AI literacy curricula or library instruction programmes would generate causal evidence to guide pedagogical investment. (4) Comparative cross-regional studies extending beyond North-West Nigeria to other geo-political zones and to other African countries would clarify whether the patterns identified here are specific to this context or reflect broader continental trends. (5) Future research should investigate the moderating role of gender, socioeconomic background, and first-generation student status on AI literacy development, given the equity concerns raised in this study. (6) Finally, instrument development work refining and validating the GAIL-IQ across diverse African higher education settings would strengthen the evidence base for regional AI literacy research.

5.2. Recommendations

Based on the findings and conclusions, this study advances five evidence-informed recommendations to enhance AI literacy and information competencies among university students in North-West Nigeria:

1. **Comprehensive AI Literacy Curriculum Integration** Universities in North-West Nigeria should systematically integrate AI literacy instruction throughout undergraduate curricula rather than relying on isolated workshops or generic library sessions. This integration must address technical understanding of AI system functioning, critical evaluation frameworks for assessing output quality and bias, ethical usage principles including attribution and academic integrity, and metacognitive awareness of learning impacts. Implementation should follow discipline-specific approaches respecting field epistemologies while establishing core competencies across all programs. Academic departments should collaborate with library professionals and educational technology specialists to develop contextually appropriate learning outcomes, instructional materials, and assessment methods. This curricular integration should commence during first-year orientation, ensuring students encounter AI literacy instruction before establishing problematic usage habits, with reinforcement and progressive complexity throughout subsequent academic levels.
2. **Development and Dissemination of Clear Institutional AI Usage Policies** Universities must urgently develop comprehensive, transparent policies addressing acceptable AI tool usage, attribution requirements, academic integrity standards, and consequences for violations. Policy development should involve stakeholder consultation including faculty, students, librarians, and academic integrity officers to ensure practical applicability and community buy-in. Policies must balance recognition of legitimate learning applications against misconduct concerns, providing sufficient specificity to guide behavior without attempting to micromanage every potential scenario. Implementation requires accessible communication through multiple channels (student handbooks, course syllabi, learning management systems, orientation programs) with concrete examples illustrating acceptable versus

problematic usage across various academic contexts. Annual policy review and revision processes should ensure responsiveness to evolving technologies and emerging challenges while maintaining consistency supporting student planning and faculty enforcement.

3. **Mandatory Faculty Professional Development on AI Literacy and Pedagogical Integration** Universities should institute comprehensive professional development programs equipping faculty with technical understanding of AI systems, pedagogical strategies for teaching AI literacy, assessment design resistant to AI-facilitated misconduct, and ethical frameworks for modeling appropriate technology usage. These programs should extend beyond one-time sessions to establish ongoing communities of practice where faculty share effective approaches, troubleshoot challenges, and collaboratively develop instructional resources. Participation should be incentivized through recognition systems, teaching awards, or advancement criteria acknowledging pedagogical innovation. Programs must address disciplinary variations in AI applications while establishing baseline competencies applicable across fields. Additionally, faculty development should encompass awareness of infrastructure barriers affecting students, fostering empathy and appropriate pedagogical adjustments for equity-minded teaching. Research support should facilitate scholarship of teaching and learning investigations examining AI literacy intervention effectiveness, contributing to evidence-based practice improvement, with institutional incentives provided to ensure broad participation and scalability.
4. **Collaborative Advocacy and Resource-Sharing to Mitigate Infrastructure Barriers** To confront the severe infrastructural constraints (e.g., electricity, internet connectivity, and data costs) that restrict equitable access, North-West Nigerian universities should establish a regional consortium of administrators, librarians, and student representatives. This consortium shall jointly advocate to government agencies and telecommunications providers for targeted investments while developing inter-institutional resource-sharing mechanisms, such as shared digital facilities and offline educational materials, to promote inclusive AI engagement.
5. **Launch of Campus-Wide Awareness and Ethical Promotion Campaigns** Building on moderate awareness levels and the need for cultural reinforcement of responsible AI practices, universities should collaborate with student unions, faculty, and public relations units to design and execute sustained awareness campaigns. These initiatives, incorporating student-led activities such as AI clubs, debates, and integrity campaigns supported by faculty mentorship and library resources, shall aim to cultivate a campus culture that balances the pedagogical benefits of generative AI with critical and ethical engagement.

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7. Conflict of Interest

The authors declare no conflict of interest. This research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors have no financial or personal relationships with other people or organizations that could inappropriately influence or bias this work. All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional research committees and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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