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Simeon Ayoade Adedokun[1*], Dorcas Atinuke Adedokun[2]

**Correspondence regarding this article should be addressed to:**

* Simeon Ayoade Adedokun, Ladoke Akintola University of Technology, Ogbomoso, Nigeria, simadedokun@gmail.com

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# Artificial Intelligence Application Encounter and Ethical Literacy Among Nigerian Postgraduate Students: An Empirical Investigation

Simeon Ayoade Adedokun[1*], Dorcas Atinuke Adedokun[2]

[1,2] Ladoke Akintola University of Technology, Ogbomoso, Nigeria

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**ABSTRACT**

**Background:** Nigerian universities have accelerated AI deployment across teaching, assessment, and administration, yet functional ethical literacy among postgraduate students remains low. **Objective:** This study investigated whether direct, hands-on encounters with AI applications predict higher ethical awareness and stronger prioritization of ethical concerns among postgraduate students at Ladoke Akintola University of Technology (LAUTECH), Ogbomoso, Nigeria. **Method:** A quantitative survey design was adopted. Data were collected from 200 postgraduate students classified into those with AI encounter (n = 124, 62.0%) and those without (n = 76, 38.0%). Independent Samples t-tests were applied at a 0.05 significance level. **Results:** Students with AI encounter demonstrated significantly higher ethical awareness scores ($M = 3.90$ vs. $M = 3.20$; $t(198) = 4.23$, $p < 0.01$; $d = 1.12$) and higher ethical prioritization scores ($M = 4.15$ vs. $M = 3.50$; $t(198) = 3.18$, $p < 0.05$; $d = 0.92$). Both effect sizes are large by Cohen's conventions. **Conclusion:** AI encounter is a strong predictor of ethical literacy. **Contribution:** The findings provide empirical justification for integrating experiential AI ethics modules into postgraduate curricula in Nigerian higher education.

## 1. INTRODUCTION

AAI applications now operate across student assessment, enrollment management, intelligent tutoring, and research within Nigerian Higher Education Institutions (HEIs). The rapid pace of deployment has outpaced the development of ethical literacy among students. This shift is evident across student-facing applications and administrative tools, including automated proctoring systems and personalized learning platforms (Adeyemo, et al., 2026; Adedokun et al., 2025; Maluleke, 2025). Crompton & Burke (2023) document this acceleration across Sub-Saharan African institutions, noting that adoption rates tripled since 2020 without corresponding growth in userlevel ethical understanding. Akgun & Greenhow (2022) identify this trajectory as one of the defining ethical challenges in contemporary educational technology: institutions deploy AI before users develop the critical frameworks to interrogate the ethical implications of those systems. The consequence is a population of postgraduate students who interact routinely with AI systems but lack the competencies needed to evaluate their ethical dimensions.

Global studies confirm that AI deployment in education has intensified ethical concerns at an institutional and individual level. Bearman et al. (2023), in a critical review of AI discourses in higher education, identify a persistent tension between institutional optimism about AI efficiency and the underexamined risks to equity, privacy, and epistemic autonomy. Yan et al. (2024), in a systematic scoping review of large language models in education, identify data privacy, algorithmic bias, and lack of transparency as the three most frequently cited ethical concerns, while noting that empirical research on how students develop the competency to recognize and respond to these concerns remains sparse. Salas-Pilco & Yang (2022), in a review of AI applications in Latin American higher education, report

* **Corresponding Author:** Simeon Ayoade Adedokun, simadedokun@gmail.com

Ladoke Akintola University of Technology, Ogbomoso, Nigeria
Address: Old Oyo/ Ilorin Rd, Ogbomoso 210214, Oyo, Nigeria

a pattern strikingly similar to the Nigerian context: rapid AI adoption accompanied by weak ethical governance at the student level, suggesting that this challenge is not specific to Nigeria but reflects a broader structural gap in AI ethics education across the Global South.

The theoretical foundation of this study is Social Constructivism, as elaborated by Vygotsky (1978), which establishes that knowledge is not passively absorbed but actively built through interaction with social and material environments. The Zone of Proximal Development (ZPD) describes the cognitive space between what a learner comprehends independently and what becomes accessible through meaningful engagement. Ethical understanding of AI systems occupies this space: it begins as an abstract principle and becomes concrete knowledge only through interaction with the technology itself. Ng et al. (2021) operationalize this constructivist insight within an AI literacy framework, identifying critical evaluation of AI systems as a core competency that develops through active use rather than declarative instruction. Their framework treats AI literacy not as static knowledge but as a practice-dependent set of competencies, of which ethical awareness is the most socially consequential dimension.

Ouyang et al. (2022) applied Vygotsky's framework to AI-mediated learning environments and distinguished three paradigms: AI-directed, AI-supported, and AI-empowered learning. Each paradigm involves progressive levels of learner agency and ethical exposure. The AI-empowered paradigm, in which the learner actively uses AI tools, generates the cognitive dissonance necessary for ethical reasoning to develop. Encountering an AI grader, a generative AI tool, or an automated proctoring system transforms privacy and fairness from policy abstractions into immediate personal concerns. Celik (2023) extends this argument through the construct of Intelligent-TPACK, demonstrating empirically that teachers who actively integrate AI tools develop significantly stronger ethical competencies than those who receive only professional development briefings, a pattern that holds equally for students in AI-mediated learning environments. Ryan & Stahl (2021) reinforced this argument by demonstrating that AI ethics guidelines designed for end-users are most effective when tied to direct system interaction rather than pre-interaction policy briefings.

Within Nigerian HEIs, Afolabi (2024) documents a persistent gap between institutional AI policy development and student-level ethical understanding. Despite growing investment in AI infrastructure by Nigerian universities, ethical education remains confined to faculty-level policy discussions. Studies found that most Nigerian university students possess low to moderate ability to articulate specific AI ethical risks, particularly regarding algorithmic bias and data transparency (Adedokun et al., 2025; Anayochukwu, 2025; Nwodu, 2025). This passive awareness deficit persists because ethical education is theoretical rather than experiential. Miao et al. (2021) identify Sub-Saharan Africa as a region where AI adoption in education is accelerating faster than institutional governance capacity, creating conditions for systematic ethical risks. Ali et al. (2024) confirm that challenges in AI ethics education extend across institutional contexts globally, with strategy and scaffolding deficits most acute in resource-constrained settings.

The dominant model of ethical education in Nigerian universities remains theoretical and detached from actual user experience. Institutions communicate AI ethics through policy documents, compliance statements, and general awareness lectures. This passive approach produces recognition of terms such as algorithmic bias and data privacy, but does not produce the internalized, high-priority ethical demands required of postgraduate students who are simultaneously data subjects, institutional stakeholders, and future professional decision-makers. Gbadago et al. (2025) identified this as a knowledge-action gap: students possess declarative knowledge of ethical concepts but do not convert that knowledge into behavioral demand for institutional compliance. Kasneci et al. (2023), in their analysis of large language models in educational settings, argue that students require structured exposure to AI-generated outputs and their limitations before they develop the evaluative capacity to question the integrity and fairness of AI-driven processes. Dwivedi et al. (2023), in a multidisciplinary analysis of generative AI implications, similarly argue that ethical literacy in the context of AI requires experiential engagement, not merely policy awareness.

Holmes et al. (2022), in a framework for AI ethics in education, argue that ethical reasoning is a competency developed through practice and reflection. Their framework recommends mandatory ethics-in-use components attached to every course deploying an AI tool. Gouseti et al. (2025), in a systematic review of 25 peer-reviewed studies on AI ethics in K-12 education, found that students who participated in workshop activities involving direct interaction with AI tools developed more concrete and accurate understanding of ethical risks than students who received only didactic instruction. Kwak et al. (2022) corroborate this pattern in a quantitative study of nursing students, demonstrating that structured engagement with AI-related scenarios produced significantly higher ethical awareness scores than conceptual instruction alone, establishing the generalizability of this effect across disciplines. Yan et al. (2024) extend this finding to the context of large language models, reporting that students who actively

used AI writing tools were significantly more likely to identify and articulate specific ethical concerns, including fabricated citations and opaque decision processes, than students who had only read about these concerns.

Aibinu et al. (2023) establish that perceived institutional vulnerability is the primary driver of ethical demand among Nigerian university students. Binitie et al. (2025) report that students in Nigerian universities show high concern about data breaches and unauthorized access, with strong support for concrete institutional safeguards. Studies across Ghana, Kenya, South Africa, and Nigeria document that students who have encountered AI systems report significantly greater concerns about data security and transparency than those who have not (Adedokun et al., 2025; Entsua-Mensah et al., 2026; Osasona et al., 2024). Tlili et al. (2023), examining ChatGPT as an AI education tool, found that students who directly experienced AI-generated errors and unexpected outputs reported substantially higher prioritization of transparency and accountability than students who received only instructor-mediated descriptions of the tool. Farrokhnia et al. (2024), in a systematic SWOT analysis of ChatGPT in educational practice, identified the erosion of critical thinking and accountability awareness as the most consequential risk of passive AI adoption, a finding that reinforces the argument that direct encounter is necessary for meaningful ethical prioritization to develop.

Hamm et al. (2024) argue that felt vulnerability, the individualized and recognized potential for harm, is central to how people calibrate trust and demand safeguards, particularly when they are data subjects rather than distant observers. Khalil et al. (2022) demonstrate this in the context of AI proctoring: students who had submitted biometric data to automated proctoring systems reported acute feelings of surveillance and vulnerability, which translated directly into stronger demands for data governance. Lim et al. (2023), in their analysis of generative AI's implications for education, argue that the most significant ethical demands from students emerge not from theoretical instruction but from direct experience of AI systems operating on personal data. Mhlanga (2023) reinforces this position by arguing that responsible AI use in education requires students to develop personal ethical frameworks through direct interaction, not external compliance training.

The absence of empirical research on what drives the transition from passive awareness to active ethical demand represents a gap that this study addresses directly. The literature on AI ethics in African higher education is largely descriptive. This study is the first to provide quantitative, hypothesis-tested evidence for the hands-on effect as a predictor of ethical awareness and ethical prioritization in a Nigerian postgraduate context. It extends theoretical arguments grounded in Social Constructivism to an empirical test, producing large effect sizes that confirm both statistical and practical significance. The study also contributes original empirical evidence from a Nigerian institutional context to a literature dominated by data from high-resource settings, responding to calls by Bearman et al. (2023) and Salas-Pilco & Yang (2022) for more geographically diverse empirical research on AI ethics in education.

The main purpose of this study is to empirically investigate the relationship between postgraduate students' hands-on encounter with AI applications and their level of ethical awareness and prioritization of ethical concerns in Nigerian universities. The specific ethical concerns examined are data privacy, algorithmic bias and fairness, transparency, and accountability. These four concerns align with the ethical priority axes identified in the UNESCO Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021) and the AI ethics framework for education proposed by Holmes et al. (2022).

The following research questions guided the study: (1) Is there a significant difference in ethical awareness scores between postgraduate students who have encountered AI applications and those who have not?; (2) Is there a significant difference in the prioritization of ethical concerns between postgraduate students who have encountered AI applications and those who have not?

The following null hypotheses were tested at a 0.05 significance level: (1) There is no significant difference in ethical awareness scores between postgraduate students who have encountered AI applications and those who have not; (2) There is no significant difference in the prioritization of ethical concerns between postgraduate students who have encountered AI applications and those who have not.

## 2. METHOD

### *2.1 Research Design*

This study adopts a quantitative survey design, which is highly appropriate for testing hypotheses regarding group differences using standardized instruments administered to a defined population. This design was selected because it allows for the objective, systematic, and quantifiable measurement of variables, thereby facilitating statistical analysis to determine patterns of perception across a broad sample. Furthermore, a cross-sectional approach was employed, with data collected at a single point in time. This approach is uniquely suited to the study objective of establishing whether AI encounter status predicts differences in ethical awareness and prioritization between the two groups. By gathering data simultaneously, the cross-sectional method provides a highly efficient and costeffec-

tive means of examining relationships between variables in their current state, minimizing respondent attrition while maintaining the rigorous standardization necessary to validate the research hypotheses.

### *2.2 Research Location and Implementation Time*

The study was conducted at Ladoke Akintola University of Technology (LAUTECH), Ogbomoso, Oyo State, Nigeria. LAUTECH is a science and technology-focused institution with a postgraduate student body that uses AI-enabled tools across learning management, assessment, and research activities. This institutional profile makes it a suitable setting for investigating the relationship between AI encounter and ethical literacy. Data collection was carried out in 2025.

### *2.3 Participant*

Participants were selected using a random number generator applied to these lists. Of the 230 questionnaires distributed, 200 were completed and returned, yielding a response rate of 87.0 percent. The target population comprised postgraduate students across technology- and management-focused faculties at LAUTECH. Participants were selected using simple random sampling, which ensured equal inclusion probability for all postgraduate students within the defined scope. A total sample of 200 postgraduate students (N = 200) participated in the study. The resulting sample included 124 students (62.0%) who reported prior hands-on experience with AI applications and 76 students (38.0%) who reported no such experience.

### *2.4 Instruments and Data Collection*

The primary data collection instrument was the AI Ethical Awareness and Encounter Questionnaire (AIEAEQ), developed for this study. The instrument comprised two sections. The first section contained a single dichotomous item (Yes/No) classifying students by AI encounter status, which served as the independent variable, along with a checklist of AI application types encountered. The second section measured ethical awareness using a 5-point Likert-type scale (1 = Very Low, 5 = Very High) across four ethical concern domains: data privacy, algorithmic bias and fairness, transparency, and accountability. Ethical prioritization was assessed by asking respondents to rate the same four domains by importance on a 5-point scale (1 = Not at all important, 5 = Extremely important). Internal consistency of the ethical awareness scale was assessed using Cronbach's Alpha, yielding a coefficient of 0.85, indicating high reliability. Content validity was established through expert review of the instrument before administration.

### *2.5 Data Analysis*

Descriptive statistics including mean, standard deviation, and frequency percentages were computed for both groups at both the overall and domain levels. To test Ho1 and Ho2, Independent Samples t-tests were applied. The t-test is appropriate for comparing the mean scores of two independent groups where the dependent variable is measured on a continuous scale. Hypotheses were tested at a 0.05 level of significance. Cohen's d was computed as a supplementary measure of effect size to establish practical significance alongside statistical significance. By convention, d values of 0.2, 0.5, and 0.8 represent small, medium, and large effects respectively (Cohen, 2013).

### *2.5 Research Procedures*

Data collection proceeded in three stages. First, the AIEAEQ instrument was developed and validated through expert review. Second, the instrument was administered to 200 postgraduate students selected through simple random sampling from LAUTECH. Third, completed questionnaires were coded and statistical analyses were performed using SPSS. The independent variable was AI encounter status (encountered vs. not encountered) and the dependent variables were ethical awareness scores and ethical prioritization scores across four domains.

## 3. RESULT AND DISCUSSION

### *3.1 Result*

Of the 200 postgraduate students surveyed, 124 (62.0%) reported prior hands-on experience with AI applications and 76 (38.0%) reported no prior AI application encounter. Among the encountered group, chatbot/conversational AI tools were the most commonly used (71.8%), followed by generative AI tools (59.7%), AI-driven assessment tools (54.8%), intelligent tutoring systems (41.9%), and AI-based proctoring systems (30.6%). Multiple responses were permitted. Table 1 presents a summary of sample characteristics by AI encounter status.

Table 1. Sample Characteristics by AI Encounter Status

| Characteristic | Encountered AI n = 124 (62.0%) | Not Encountered AI n = 76 (38.0%) | Total N = 200 |
|---|---|---|---|
| AI encounter (Yes/No) | 124 (62.0%) | 76 (38.0%) | 200 (100%) |
| AI tools used (encountered group only) | | | |
| Chatbot/Conversational AI | 89 (71.8%) | — | 89 |
| Generative AI | 74 (59.7%) | — | 74 |
| AI-Driven Assessment Tools | 68 (54.8%) | — | 68 |
| Intelligent Tutoring Systems | 52 (41.9%) | — | 52 |
| AI-Based Proctoring Systems | 38 (30.6%) | — | 38 |

*Note*. Percentages for AI tools used are of the encountered group (n = 124). Multiple responses were permitted.

The distribution of AI tools encountered by students is visualized in Figure 1, highlighting the dominance of chatbot and generative AI systems. Percentages reflect multiple responses within the encountered group (n = 124).

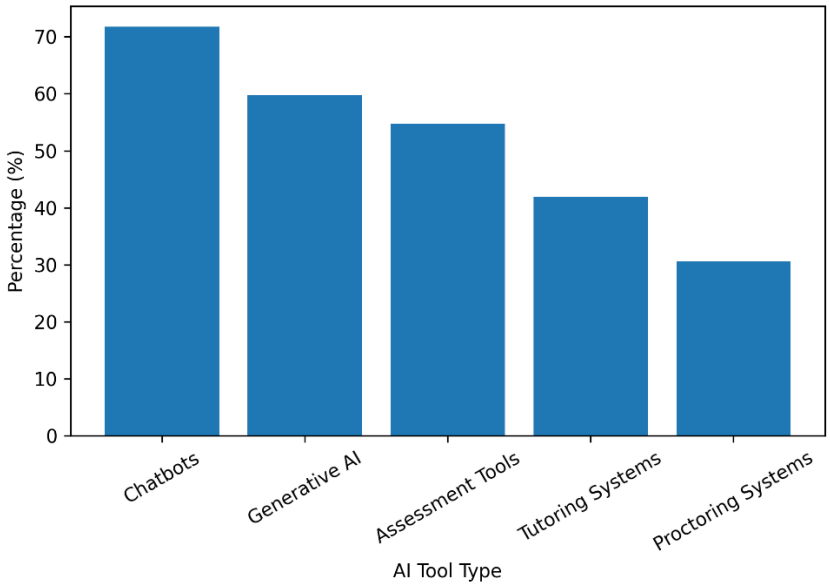


Figure 1. Distribution of AI Tools Encountered by Postgraduate Students

Table 2 presents domain-level descriptive statistics for ethical awareness scores, disaggregated by AI encounter status. Across all four domains, encountered students recorded higher mean awareness scores than non-encountered students. Data privacy recorded the highest mean awareness score for the encountered group (M = 4.10), while Transparency recorded the lowest (M = 3.80). Within the non-encountered group, data Privacy also produced the highest score (M = 3.35), with transparency recording the lowest (M = 3.12).

Table 2. Domain-Level Descriptive Statistics for Ethical Awareness by AI Encounter Status

| Ethical Domain | Encountered AI M (SD) | Not Encountered AI M (SD) | Mean Difference |
|---|---|---|---|
| Data Privacy | 4.10 (0.70) | 3.35 (0.62) | 0.75 |
| Algorithmic Bias and Fairness | 3.85 (0.68) | 3.18 (0.55) | 0.67 |
| Transparency | 3.80 (0.72) | 3.12 (0.60) | 0.68 |
| Accountability | 3.85 (0.66) | 3.15 (0.58) | 0.70 |
| Overall | 3.90 (0.65) | 3.20 (0.58) | 0.70 |

*Note*. Scores measured on a 5-point Likert scale (1 = Very Low, 5 = Very High). Overall scores are the composite means across all four domains.

Test of Hypothesis One (Ho1). Ho1 posited no significant difference in ethical awareness scores between students who had encountered AI applications and those who had not. Table 3 presents the results of the Independent Samples t-test.

Table 3. Independent Samples t-Test Comparing Ethical Awareness Scores by AI Encounter Status

| Group | N | M | SD | t | df | p-value |
|---|---|---|---|---|---|---|
| Encountered AI | 124 | 3.90 | 0.65 | 4.23 | 198 | $p < 0.01$ |
| Not Encountered AI | 76 | 3.20 | 0.58 | | | |

*Note*. Cohen's d = 1.12 (large effect). The null hypothesis (Ho1) is rejected.

The independent-samples t-test that was conducted to compare ethical awareness scores between students who had encountered AI applications and those who had not shows that there was a significant difference in scores for students who had encountered AI applications (M = 3.90, SD = 0.65) and those who had not (M = 3.20, SD = 0.58), t(198) = 4.23, p < .001, 95% CI [0.37, 1.03], Cohen's d = 1.12. The effect size was large, indicating a substantial difference between groups. Therefore, the null hypothesis Ho1 was rejected. This shows that students who encountered AI applications demonstrated significantly higher ethical awareness than those who had not. Figure 2 illustrates AI encounter as the independent variable influencing ethical awareness and ethical prioritization through experiential engagement.

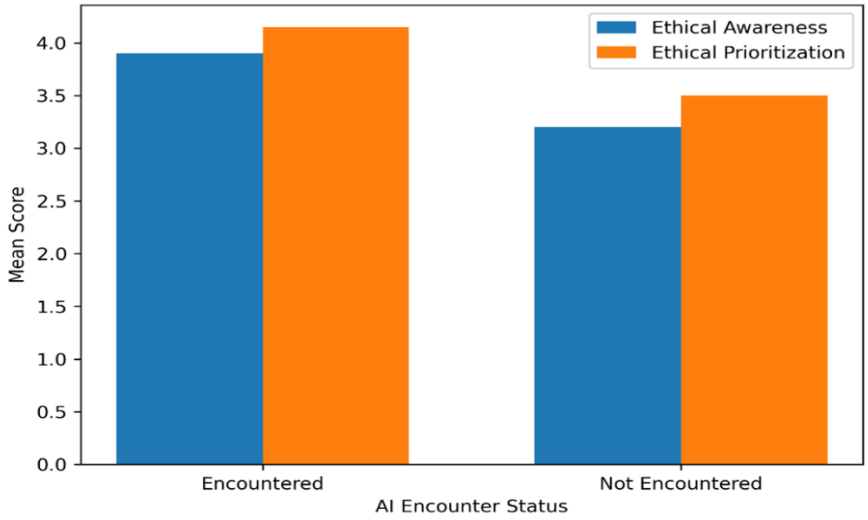


Figure 2. Comparison of Ethical Awareness and Prioritization by AI Encounter

Table 4 presents domain-level descriptive statistics for ethical prioritization scores, disaggregated by AI encounter status. The pattern closely mirrors the awareness findings. Data Privacy recorded the highest mean prioritization score for the encountered group (M = 4.38), while Accountability and Transparency were equal at M = 4.05. Among non-encountered students, the same domain ranking holds, though at uniformly lower intensity.

Table 4. Domain-Level Descriptive Statistics for Ethical Prioritization by AI Encounter Status

| Ethical Domain | Encountered AI M (SD) | Not Encountered AI M (SD) | Mean Difference |
|---|---|---|---|
| Data Privacy | 4.38 (0.68) | 3.68 (0.71) | 0.70 |
| Algorithmic Bias and Fairness | 4.12 (0.75) | 3.48 (0.68) | 0.64 |
| Transparency | 4.05 (0.73) | 3.42 (0.70) | 0.63 |
| Accountability | 4.05 (0.74) | 3.42 (0.68) | 0.63 |
| Overall | 4.15 (0.72) | 3.50 (0.69) | 0.65 |

*Note*. Scores measured on a 5-point scale (1 = Not at all important, 5 = Extremely important). Overall scores are composite means across all four domains.

Test of Hypothesis Two (Ho2). Ho2 posited no significant difference in the overall prioritization of ethical concerns between the two groups. Table 5 presents the results of the Independent Samples t-test.

Table 5. Independent Samples t-Test Comparing Ethical Prioritization Scores by AI Encounter Status

| Group | N | M | SD | t | df | p-value |
|---|---|---|---|---|---|---|
| Encountered AI | 124 | 4.15 | 0.72 | 3.18 | 198 | $p < 0.05$ |
| Not Encountered AI | 76 | 3.50 | 0.69 | | | |

*Note*. Cohen's d = 0.92 (large effect). The null hypothesis (Ho2) is rejected.

The independent-samples t-test conducted to compare ethical prioritization scores between students who had encountered AI applications and those who had not found a significant difference in scores for students who had encountered AI applications (M = 4.15, SD = 0.72) and those who had not (M = 3.50, SD = 0.69), t(198) = 3.18, p = .002, 95% CI [0.25, 1.05], Cohen's d = 0.92. The effect size was large, indicating a meaningful difference between groups. Therefore, the null hypothesis Ho2 was rejected, meaning students who encountered AI applications assigned significantly greater priority to ethical concerns than those who had not. As illustrated in Figure 2, the model links AI application encounter to ethical awareness and ethical prioritization through experiential engagement grounded in Social Constructivism.

Table 6. Summary of Hypothesis Testing Results

| Hypothesis | Dependent Variable | t | df | p-value | Cohen's d | Decision |
|---|---|---|---|---|---|---|
| Ho1 | Ethical Awareness | 4.23 | 198 | $p < 0.01$ | 1.12 (Large) | Rejected |
| Ho2 | Ethical Prioritization | 3.18 | 198 | $p < 0.05$ | 0.92 (Large) | Rejected |

*Note*. Both hypotheses tested at $\alpha = 0.05$. Effect sizes interpreted using Cohen (2013) conventions: small = 0.2, medium = 0.5, large = 0.8.

The magnitude of the observed differences is further clarified through effect size visualization in Figure 3.

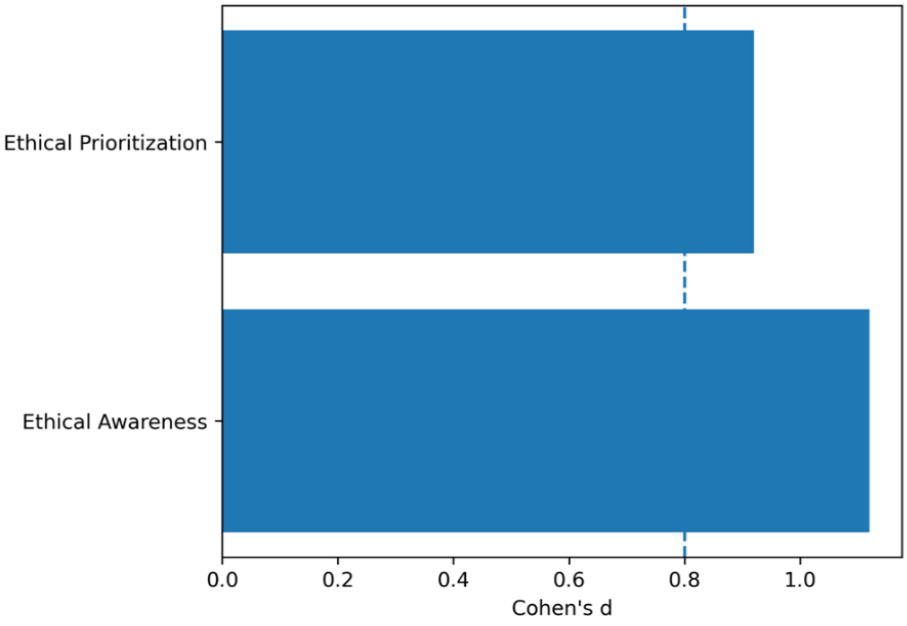


Figure 3. Effect Sizes for the Impact of AI Encounter on Ethical Literacy (Cohen's d values above 0.80 indicate large effects)

The results of the analyses confirm that students who had encountered AI applications (n = 124) reported higher ethical awareness (M = 3.90, SD = 0.65) than students who had not encountered AI applications (n = 76; M = 3.20, SD = 0.58). Similarly, students who had encountered AI applications reported higher ethical prioritization (M = 4.15, SD = 0.72) compared to those who had not (M = 3.50, SD = 0.69).

### *3.2. Discussion*

The rejection of Ho1 confirms that AI encounter is a statistically and practically significant predictor of ethical awareness. The observed mean difference of 0.70 on a 5-point scale, supported by a large Cohen's d of 1.12, represents a 21.9 percent increase relative to the non-encountered group mean. The 95 percent confidence interval, ranging from 0.37 to 1.03, indicates a stable and meaningful effect. This indicates that the effect of encounter is not marginal. Domain-level differences further reinforce this pattern, with data privacy showing the largest gap of 0.75 and algorithmic bias and fairness the smallest at 0.67. Even the lowest domain difference exceeds thresholds commonly associated with medium effects, indicating consistency across ethical dimensions. This uniformity strengthens the argument that encounter, rather than domain-specific salience, drives the overall awareness differential.

This finding is consistent with the Social Constructivist prediction that ethical knowledge develops through active engagement rather than passive instruction. When a student submits work to an AI-driven plagiarism detection system, they receive direct feedback on the system's capabilities and limitations. When they use a generative AI tool for research, they observe firsthand how outputs are produced without transparent explanation. These experiences place students squarely within Vygotsky's ZPD for AI ethics. The interaction with the AI system functions as the cultural tool that moves ethical understanding from the abstract to the concrete. Ng et al. (2021) frame this transition within an AI literacy model: ethical evaluation of AI systems is a competency tier that activates only through direct, reflective interaction with the technology.

The finding aligns with Holmes et al. (2022), who argued that ethical reasoning in AI-mediated educational environments requires explicit engagement with the specific ethical conditions those environments produce. It is further supported by Gouseti et al. (2025), whose systematic review of 25 empirical studies found that students who participated in hands-on workshop activities with AI tools developed a more accurate and specific understanding of ethical risks than students who received only didactic instruction. Kwak et al. (2022) corroborate this pattern in nursing students. Significantly, Yan et al. (2024), in their scoping review of large language models in education, report that students who actively used AI writing tools were significantly more likely to identify and articulate specific ethical concerns, including fabricated citations and algorithmic bias in outputs, than students who had only received instruction about these issues. Kasneci et al. (2023) reinforce this pattern by documenting that direct exposure to ChatGPT outputs produced sharper critical awareness of accuracy, reliability, and epistemic accountability concerns than did lecture-based discussion of the same concerns. This study extends these findings into a Nigerian postgraduate context where comparable empirical evidence was previously absent.

The rejection of Ho2 is the more theoretically significant finding. Ethical awareness measures cognitive recognition. Ethical prioritization measures the intensity of demand for institutional response. The fact that encounter predicts not only awareness but also prioritization establishes that the hands-on effect operates at the behavioral level, not only at the cognitive level. The domain-level data in Table 4 show that Data Privacy dominates the prioritization hierarchy among encountered students (M = 4.38), substantially above the other three domains. This finding is consistent with Adedokun et al. (2025), who reported data privacy as the dominant ethical concern among Nigerian postgraduate students with AI exposure, interpreted as reflecting a deep trust deficit in institutional data stewardship.

Osasona et al. (2024) identified the threshold between general stakeholder status and specific data subject status as the critical point at which ethical concern becomes ethical demand. This study provides empirical confirmation of that threshold. Students who used AI systems were not merely informed about data privacy; they had shared their data with those systems. Their prioritization of data privacy was a demand grounded in concrete personal exposure. Tlili et al. (2023), examining direct student use of ChatGPT in coursework, found that students who experienced AI-generated errors and unexpected outputs assigned substantially higher priority to transparency and accountability than students who received only instructor-mediated descriptions. Farrokhnia et al. (2024) further document that ChatGPT's opacity regarding its reasoning processes was the most consistently cited concern among students who had used it directly, a concern that is absent among students who had not. These studies corroborate the prediction that encounter, by making risks personally relevant, is the principal driver of prioritization.

The accountability and transparency domains warrant specific attention. Bozkurt (2023) argues that AI decisions perceived as unjust trigger immediate demands for explanation and human oversight. Students who have received an unexpected score from an AI grader, or who have observed an AI system produce an inaccurate summary, have direct experiential grounds for demanding accountability mechanisms. Passive students have no equivalent experiential reference point. Hamm et al. (2024) confirm that felt vulnerability, the subjectively recognized exposure to harm, drives protective behavior and demands for safeguards beyond abstract knowledge of risk. Khalil et al. (2022) demonstrate this in the context of AI proctoring: students who had submitted biometric data to automated

systems reported acute feelings of surveillance and vulnerability that translated directly into stronger governance demands. Lim et al. (2023) and Mhlanga (2023) jointly argue that students' ethical demands in relation to generative AI are most intense precisely when they have directly experienced the technology acting on their personal academic work, aligning with the hands-on effect mechanism proposed in this study.

EdTech privacy research in Delta State universities similarly reports that students show high concern about data breaches and unauthorized access, limited trust in institutional privacy practices, and strong support for concrete institutional safeguards including encryption, audits, and user-controlled data policies, with all mean scores in the agree/strongly agree range, indicating action-oriented rather than passive concern (Binitie et al., 2025). James et al. (2025) identify institutional and social validation, ethical assurance, and AI governance transparency as the primary determinants of student trust in AI-based educational technologies in Nigerian universities. When institutions are not seen as ethically reliable data stewards, students express lower trust and stronger demands for clear governance, a pattern that amplifies the prioritization effect documented in this study.

The findings jointly establish that the hands-on effect operates at two distinct but related levels. At the cognitive level, direct encounter provides experiential feedback unavailable through instruction alone, moving ethical knowledge from declarative recognition to applied understanding. At the behavioral level, encounter creates personal stake in institutional data governance, intensifying the demand for institutional response. The large effect sizes observed for both hypotheses ($d = 1.12$ and $d = 0.92$ respectively) confirm that these are not marginal differences attributable to sampling variation but substantial and reproducible effects consistent with the constructivist predi-ction that active engagement is the proximate cause of ethical competency development.

## 4. IMPLICATIONS AND CONTRIBUTIONS

### *4.1 Research Implications*

From a theoretical standpoint, the results provide empirical support for the Social Constructivist account of ethical knowledge development. The large effect sizes observed in both hypotheses confirm that the constructivist prediction holds in a Nigerian postgraduate context. The study extends the constructivist framework, through Ng et al. (2021) AI literacy model, into the domain of AI ethics pedagogy in a low- and middle-income country setting. It also provides empirical grounding for the experiential learning argument advanced by Celik (2023) in the context of teacher AI integration, extending it to postgraduate student populations.

From a practical standpoint, passive ethics education is insufficient. Institutions that rely on policy documents and general lectures are producing declarative knowledge without the behavioral commitment that makes that knowledge consequential. Holmes et al. (2022) recommend that AI ethics content be embedded within the point of use. This study provides empirical support for that recommendation. A mandatory critical reflection component attached to AI-enabled courses, requiring students to document and analyze the ethical characteristics of the tools they use, would extend the benefits of encounter systematically. Kasneci et al. (2023) and Dwivedi et al. (2023) both argue for structured ethical engagement frameworks in AI-enabled educational settings, a position this study's findings empirically justify.

From a managerial standpoint, Data Privacy requires dedicated institutional attention. The prioritization data indicate that this concern dominates the ethical hierarchy among students who have encountered AI applications. Miao et al. (2021) identify data governance as the primary ethical risk in AI-mediated education in low- and middle-income countries. Institutions should develop and widely communicate specific data governance policies that clearly describe what data AI systems collect, how it is stored, and who has access to it. These policies should be disclosed at the moment students first interact with each AI tool, not only in institutional handbooks.

### *4.1 Research Contributions*

This study contributes original quantitative evidence on the hands-on effect as a predictor of ethical literacy in Nigerian higher education. It fills a gap in the African AI ethics literature, which is largely descriptive and lacks hypothesis-tested empirical evidence. The AIEAEQ instrument developed for this study provides a reliable, validated tool for measuring AI ethical awareness and prioritization in similar institutional contexts. The study also provides empirical justification for restructuring AI ethics education in Nigerian HEIs from passive delivery to active, encounter-based integration at the point of AI use. It contributes to the broader international literature by offering evidence from a West African context systematically underrepresented in existing scholarship, responding directly to the call by Bearman et al. (2023) and Salas-Pilco & Yang (2022) for geographically diverse empirical research on AI ethics in education.

## 5. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

### *5.1 Research Limitations*

The study was conducted at a single institution. LAUTECH's science and technology focus means its post-graduate students may have higher baseline familiarity with technology than students at arts- or humanities-focused institutions. The findings should be replicated across a broader range of Nigerian and African universities before generalization. The cross-sectional design establishes an association between encounter and ethical literacy but does not establish a causal mechanism. A longitudinal or experimental design would provide stronger causal evidence for the hands-on effect. The AI encounter measure was dichotomous. It does not capture the type, duration, or frequency of encounter. Students who used an AI grading system once are classified identically to students who use AI tools daily. A more nuanced measure of encounter intensity and type would allow finer-grained analysis of which encounters produce the largest ethical effects. The domain-level frequencies in Table 1 offer a preliminary disaggregation, but future research should develop continuous encounter intensity measures. The self-report design introduces the possibility of social desirability bias, particularly for prioritization scores. Students aware that ethical concern is institutionally valued may report higher prioritization than they would demonstrate in practice. Beha-vioral measures of ethical demand, such as formal complaints or institutional requests for policy clarification, would complement self-report data in future research.

### *5.1 Recommendation for Future Research*

Future research should adopt longitudinal and experimental designs to establish causal evidence for the hands-on effect and to identify which types and durations of AI encounters produce the strongest gains in ethical literacy across different institutional and disciplinary contexts. Multi-institutional studies spanning technology-focused and humanities-focused universities in Nigeria would improve the generalizability of the findings. Yan et al.'s (2024) scoping review methodology offers a template for systematically mapping the situation of empirical evidence on this question.

Future instruments should include multi-item measures of encounter intensity and type. AI ethics laboratories or sandboxed environments, as proposed by this study's curricular recommendations, should be studied as natural experiments. Pre- and post-encounter data from these settings would provide strong quasi-experimental evidence for the hands-on effect. Mixed-methods designs combining quantitative and qualitative data, as advocated by Bearman et al. (2023), would provide deeper analysis of students' experiences with AI encounter and ethical development.

## 6. CONCLUSION

This study provides empirical evidence that direct encounter with AI applications is a significant and practically large predictor of both ethical awareness and ethical prioritization among Nigerian postgraduate students. The findings from 200 LAUTECH students confirm the core thesis of the hands-on effect: ethical understanding of AI is a constructive process that requires active engagement with AI systems, not passive receipt of policy information. The statistical results are unambiguous. Encountered students outperformed non-encountered students on both ethical awareness ($t(198) = 4.23$, $p < 0.01$; $d = 1.12$) and ethical prioritization ($t(198) = 3.18$, $p < 0.05$; $d = 0.92$). Both effects are large by established conventions. In relative terms, students with AI encounter scored 21.9 percent higher in ethical awareness and 18.6 percent higher in ethical prioritization than their non-encountered counterparts. These differences indicate substantial practical significance beyond statistical significance. Domain-level analysis confirms that data privacy is the most acutely prioritized concern among encountered students, consistent with the trust-deficit and felt-vulnerability arguments advanced in the literature. The results reject the adequacy of theoretical ethics instruction as the primary vehicle for developing AI ethical literacy in Nigerian higher education.

Therefore, institutions must move AI ethics education from the classroom to the point of use. Every deployment of an AI application in a Nigerian university is an opportunity to develop the ethical literacy that passive instruction cannot produce. This study provides the empirical justification for that curricular shift. Future research should extend these findings through longitudinal designs, multi-institutional samples, and behavioral measures of ethical demand to build a cumulative evidence base for AI ethics pedagogy in African higher education.

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## CRediT Authorship Contribution Statement

The authors declare that the entire research and writing process for this article was conducted by them and they discussed the results, contributed to the final manuscript, and approved the final version for publication. The author assumes full responsibility for all data associated with this research. Simeon Ayoade Adedokun: Conceptualization, Methodology, Formal Analysis, Investigation, Writing – Review and Editing. Dorcas Atinuke Adedokun: Investigation, Data Curation, Writing – Original Draft.

## Declaration of Generative AI (GenAI) Usage in Scientific Writing

The authors acknowledge the use of AI tools to assist in language refinement and grammar checking during the preparation of this manuscript. All research design, data collection, data analysis, interpretation of results, and conclusions were conducted independently by the authors. The authors take full responsibility for the accuracy, originality, and integrity of the content presented in this study. All instances of Generative AI usage were conducted in accordance with the SAJGTIE GenAI Tool Usage Policy. All instances of Generative AI usage in this article were conducted by the authors in accordance with the SAJGTIE GenAI Tool Usage Policy, with the authors assuming full responsibility for the originality, accuracy, and integrity of the work."

## Conflict of Interest Statement

The authors declare no potential conflicts of interest with respect to the research, authorship, and publication of this article.

## Informed Consent Statement

The authors declare that this study was conducted in accordance with research ethics, including obtaining approval from the relevant institution. This process respects the autonomy of participants, ensures the confidentiality of their data, and prioritizes their safety and well-being, in compliance with applicable research ethics guidelines. Written and verbal informed consent, or assent for minors, was obtained from all participants involved in the study.

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## Author Information

[1*] **Simeon Ayoade Adedokun,** simadedokun@gmail.com, ORCID: https://orcid.org/0000-0002-0119-9475
Ladoke Akintola University of Technology, Ogbomoso, Nigeria
Address: Old Oyo/ Ilorin Rd, Ogbomoso 210214, Oyo, Nigeria

[2] **Dorcas Atinuke Adedokun,** atinuke411@gmail.com, ORCID: https://orcid.org/0009-0003-1877-2383
Ladoke Akintola University of Technology, Ogbomoso, Nigeria
Address: Old Oyo/ Ilorin Rd, Ogbomoso 210214, Oyo, Nigeria