



Research Article

From Awareness to Academic Use: Generative Artificial Intelligence Awareness as a Predictor of Utilisation for Learning Among Allied Health Undergraduates

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Abstract

Background: Generative artificial intelligence (GenAI) has moved quickly from novelty to an everyday learning resource in higher education. Yet frequent exposure does not necessarily mean that students understand how to use these systems critically, safely, and academically. This distinction is especially consequential in health-related education, where inaccurate outputs, privacy breaches, and uncritical reliance can shape learning habits with implications beyond the classroom. **Purpose:** This study examined GenAI awareness and learning-oriented utilisation among undergraduates in a specialised allied health sciences university in Nigeria and tested whether awareness statistically predicts academic use. **Sample:** The sample comprised 220 consenting first-year undergraduates drawn from 14 academic programmes. **Design and method:** An analytical cross-sectional survey was conducted from 6 to 10 September 2026. A study-specific questionnaire measured GenAI awareness with 10 items and utilisation for learning with 12 items, both on four-point scales. Internal consistency was high for awareness (Cronbach's $\alpha = .86$) and utilisation ($\alpha = .95$). Descriptive statistics, Pearson correlation, and simple linear regression were used, with HC3 robust standard errors and Spearman correlation as robustness checks. **Results:** GenAI exposure was widespread: 96.8% had heard of GenAI and 94.5% reported prior use. ChatGPT was the most frequently used tool (60.0%). Mean awareness was 3.48 (SD = .45), while mean utilisation was 3.44 (SD = .52). Awareness was moderately associated with utilisation ($r = .427$, 95% CI [.313, .530], $p < .001$) and significantly predicted utilisation ($B = .490$, HC3 SE = .073, $\beta = .427$, 95% CI [.346, .634], $p < .001$), explaining 18.3% of the variance. The pattern remained in a sensitivity analysis restricted to self-reported prior users. **Conclusions:** Awareness matters for academic GenAI use, but it is not sufficient. Students were more aware of GenAI capabilities than of privacy, bias, and academic-integrity risks, revealing a descriptive capability-criticality gap. Allied health institutions should therefore move beyond tool exposure towards structured AI literacy that combines practical use with verification, ethical judgement, confidentiality, and discipline-specific reasoning.

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Keywords

Generative Artificial Intelligence, AI Literacy, Awareness, Utilisation, Allied Health Education, Higher Education, Nigeria

1. Introduction

Generative artificial intelligence (GenAI; AI denotes artificial intelligence) has entered university learning at a speed that has outpaced most institutional responses. Students can now ask a conversational system to explain a difficult concept, generate an example, summarise a reading, critique a paragraph, construct practice questions, or suggest a route through an academic problem within seconds. In many universities, the central question is therefore no longer whether students encounter GenAI, but what kind of understanding guides the way they use it. This shift is educationally important because ease of use can create an illusion of competence: a student may be highly familiar with a tool while remaining poorly prepared to judge the reliability, bias, privacy implications, or academic legitimacy of its outputs [5, 8, 11].

The distinction between exposure and informed use is especially important in allied health education. Students in health-related programmes routinely learn with concepts, evidence, and professional norms that later inform clinical, managerial, technological, or patient-facing decisions. GenAI can support this learning by making explanations more accessible and by providing on-demand examples and feedback. The same systems, however, can produce plausible but incorrect information, obscure the provenance of claims, reproduce social or data biases, and invite users to disclose information that should remain confidential. These risks mean that an allied health student who knows how to obtain an answer from GenAI is not necessarily prepared to evaluate whether that answer should be trusted, used, cited, or discarded [4, 7, 13].

This study is situated within that tension. Rather than treating awareness as simple familiarity with the names of popular tools, it conceptualises GenAI awareness as knowledge of what these systems are able to do and of the conditions under which their outputs should be approached critically. It then asks whether that awareness is associated with the extent to which students use GenAI for concrete learning activities. Framing the problem this way shifts attention from technology adoption as a binary event to the relationship between what students know about GenAI and how frequently they bring it into their learning practices.

1.1. Generative AI and the Changing Ecology of Undergraduate Learning

The educational appeal of GenAI lies partly in its flexibility. Unlike earlier digital learning tools designed around a fixed task, contemporary large language model applications can respond to

a wide range of academic requests in natural language. Higher education students report using them to clarify concepts, generate ideas, summarise texts, improve writing, prepare for assessments, and support independent study [3, 5]. This breadth has helped position GenAI not as a single-purpose application but as a general academic companion whose functions can follow students across courses and study contexts.

The rapid normalisation of these tools has also complicated the meaning of 'use'. A student who opens ChatGPT once to test the interface and another who routinely relies on several GenAI platforms for explanation, revision, writing, and problem solving would both be counted as users in a simple yes/no measure. Such measures are useful for estimating reach, but they reveal little about the depth or educational character of engagement. Recent research has therefore begun to examine not only whether students have used GenAI, but how and why they use it, what they believe it can do, and how its use is shaped by usefulness, ease, social influence, institutional expectations, and access conditions [3, 17].

1.2. AI literacy: Moving from Familiarity to Critical Awareness

AI literacy offers a useful conceptual foundation for distinguishing superficial familiarity from more consequential awareness. Ng et al. [14] describe AI literacy as involving knowledge and understanding, use and application, evaluation, and ethical considerations. Applied to GenAI, this means that awareness should encompass more than recognising ChatGPT, Gemini, Claude, or Copilot. Students also need to understand that prompt formulation influences outputs; that fluent text can contain fabricated or misleading information; that outputs require verification; and that privacy, bias, authorship, and academic integrity are part of responsible use.

This broader conception is important because GenAI systems often reward users with immediate, confident, and highly readable responses. The interface therefore lowers the behavioural threshold for use while leaving the epistemic burden with the learner. In other words, GenAI makes it easy to ask, but not necessarily easy to judge. For university students, the educational value of GenAI depends partly on whether they can interrogate an output, compare it with credible sources, identify uncertainty, and recognise when use crosses an ethical or assessment boundary [8, 12].

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a complementary perspective. UTAUT

proposes that technology use is shaped by performance expectancy, effort expectancy, social influence, and facilitating conditions [18]. In the GenAI context, awareness may help students recognise possible academic uses and develop confidence in engaging with the technology, but it should not be expected to explain use completely. Access to devices and data, perceived usefulness, peer practices, lecturer guidance, assessment rules, and institutional policy may all influence whether an aware student actually incorporates GenAI into learning. This theoretical combination suggests an awareness-use pathway that is plausible but necessarily partial.

1.3. Generative AI in Health Professions Education

Evidence from health professions education suggests that GenAI is already part of students' learning environments. In a survey of medical students in the United States, Ganjavi et al. [7] reported near-universal awareness of ChatGPT, although use for medical coursework was lower. Students recognised potential benefits for learning while also expressing concern about inaccurate responses, privacy, and plagiarism. Similar patterns have been reported across health professions programmes, where students use GenAI for information retrieval, clarification, academic writing, study support, and examination preparation, yet remain uncertain about appropriate boundaries of use [9, 13, 16].

For allied health students, the combination of classroom learning, clinical placements and discipline-specific records makes these risks particularly consequential. For example, learning tasks in radiography, rehabilitation and health information management may draw on patient images, functional assessments or case records. Entering identifiable placement material or confidential case-study details into a public GenAI service could disclose information beyond the authorised care or teaching setting. Removing names alone may leave identifying details in an image or narrative. These risks are shared with medical education; their relevance here lies in the variety of allied health tasks and data formats. Teaching should therefore use fictional or appropriately de-identified cases, approved systems and explicit confidentiality guidance, consistent with World Health Organization guidance [19]. This is a contextual rationale, not evidence that the participating first-year students disclosed patient data.

The African evidence base is expanding. Ajalo et al. [2] found widespread use of ChatGPT and other AI tools among medical students in Uganda, including use for assignments, tutorials, examinations, and research writing. In Nigeria, Orok et al. [15] reported substantial familiarity and use among pharmacy students, while Iliyasu et al. [10] found that medical and allied health students with stronger knowledge of ChatGPT were more likely to use it academically. These studies show that GenAI adoption is not confined to high-income settings and that knowledge appears to matter. They also indicate that institutional guidance, AI literacy, and infrastructure remain uneven.

1.4. The Nigerian Context and the Unresolved Awareness-use Question

Nigerian universities are encountering GenAI at a time when digital learning opportunities and constraints coexist. Students increasingly access AI-enabled search, writing, and conversational tools through smartphones and web platforms, but the quality of access, institutional guidance, and formal AI literacy education varies. Aiyebilehin et al. [1] reported that awareness and digital literacy predicted ChatGPT use among Nigerian undergraduates, while Chigozie [6] described how students use AI to clarify concepts, locate learning resources, and support independent study but also encounter misleading information, limited AI literacy, and the risk of overdependence.

Three gaps remain consequential. First, much of the available Nigerian evidence focuses on ChatGPT, even though students now use a wider GenAI ecosystem. Second, several studies operationalise use as whether a student has ever used a tool, which may conceal substantial variation in learning-oriented engagement. Third, evidence remains limited on whether a multidimensional form of GenAI awareness - including capabilities, verification, privacy, bias, and academic integrity - is associated with how frequently students use GenAI across specific learning tasks in a specialised allied health sciences environment.

Addressing these gaps can contribute to both theory and practice. If awareness is strongly connected with academic use, AI literacy initiatives may help students move from accidental or recreational exposure towards purposeful learning. If the relationship is modest, institutions will need to look beyond awareness to the broader conditions that enable or constrain use. The present study therefore examines the awareness-use relationship while also attending to the specific aspects of awareness and learning activity that are most and least developed among students.

1.5. Research Questions and Hypothesis

The study was guided by three research questions: (1) What is the level of GenAI awareness among the participating undergraduates? (2) To what extent do the participating undergraduates utilise GenAI for learning? and (3) What relationship exists between GenAI awareness and utilisation for learning, and to what extent does awareness statistically predict utilisation? The null hypothesis tested for the third question was that GenAI awareness would not significantly predict utilisation for learning.

2. Methodology

2.1. Study Design and Setting

The study employed an analytical cross-sectional survey design. Data were collected at the Federal University of Allied

Health Sciences, Enugu, Nigeria, a specialised federal university offering programmes across health sciences, allied health, biomedical, behavioural, technological, and related fields. The survey was administered from 6 to 10 September 2026. The design was appropriate because the study sought to describe current levels of GenAI awareness and learning-oriented utilisation and to test the statistical relationship between these constructs at a defined point in time.

2.2. Participants

The study focused on first-year undergraduates enrolled in selected academic programmes. A total of 220 students provided electronic informed consent and submitted complete questionnaires during the data-collection period; all complete consenting records were retained in the primary analysis. Participants represented 14 programmes, providing a broad view of students entering a specialised health sciences environment. Nursing Sciences contributed the largest programme group, followed by Biomedical Engineering, Prosthetics and Orthotics, Healthcare Management, and Health Information Management. Because the available study records did not include a complete sampling frame or a documented probability-sampling procedure, the findings are interpreted as evidence from the participating students rather than as population estimates for all undergraduates in the institution. Programme representation was uneven: Nursing Sciences contributed 45 respondents, whereas Physiology and Medical Laboratory Sciences contributed one each. Consequently, the pooled estimates give greater weight to the larger participating programme groups and cannot establish programme-specific patterns or represent each programme equally, even within this institution.

2.3. Instrument

Data were collected using a study-specific online questionnaire organised into demographic and GenAI-use questions, a 10-item GenAI Awareness scale, and a 12-item GenAI Utilisation for Learning scale. Awareness items addressed understanding of GenAI, familiarity with common tools and capabilities, the influence of prompt quality, the possibility of hallucinated or fabricated information, the need to verify outputs, privacy and security risks, potential bias or misleading information, and academic-integrity concerns. Responses ranged from 1 (Not aware) to 4 (Highly aware).

The utilisation scale focused on concrete learning activities rather than a single indicator of prior use. Items asked how often students used GenAI to obtain explanations, clarify unfamiliar terms, summarise learning materials, generate study notes, brainstorm ideas, obtain worked examples, generate practice questions, prepare for examinations, improve academic writing, obtain problem-solving guidance, check answers, and support independent learning. Responses ranged from 1 (Never) to 4 (Very often). Composite scores were calculated as the mean of the completed items for each construct.

Internal consistency in the present sample was good for awareness (Cronbach's $\alpha = .859$) and excellent for utilisation ($\alpha = .945$). The awareness content was conceptually aligned with the knowledge, use, evaluation, and ethical dimensions emphasised in AI-literacy scholarship [14].

The questionnaire was researcher-developed to operationalise the study objectives through items about GenAI capabilities, critical evaluation and specific learning tasks. Its awareness content was conceptually aligned with the AI-literacy domains described by Ng et al. [14], rather than adopted as a fully validated standardised scale. The questionnaire was face-validated by three experts: two in Computer Science Education and one in Measurement and Evaluation, all from the Department of Mathematics and Computer Science Education, Enugu State University of Science and Technology, Agbani, Enugu State, Nigeria. This face-validation process does not establish construct validity; the quantitative reliability evidence reported here remains limited to internal consistency within the present sample.

2.4. Data Management and Quality Checks

The analysis workbook supplied for verification contained 220 consenting respondent records, all of which were retained; the separate empty worksheet was excluded. There were no missing responses across the 10 awareness and 12 utilisation items. Response labels were converted to their numeric codes from 1 to 4, and the two composite scores were calculated as the unweighted means of their respective items, with no reverse scoring. The derived respondent-level file uses anonymous analysis identifiers and omits demographic fields; it includes item scores, composite means, prior-use responses, fitted values and residuals.

A data-consistency issue was identified in the prior-use question. Twelve students selected 'No' when asked whether they had ever used a GenAI tool, yet all 12 completed the task-specific utilisation items and 11 selected a named GenAI application or reported non-zero use. Because the 12-item utilisation scale was the prespecified multi-item measure of academic use and the survey had not applied skip logic, these records were retained in the primary analysis. To determine whether they materially influenced the result, a sensitivity analysis was also conducted among the 208 respondents who explicitly reported prior GenAI use.

2.5. Data Analysis

The analysis followed the research questions. Frequencies and percentages described participant characteristics, prior awareness, prior use, and the most frequently used GenAI tools. Means and standard deviations summarised the individual awareness and utilisation items and the composite scores. Pearson's product-moment correlation was used to assess the bivariate association between awareness and utilisation. Simple linear regression then estimated the statistical contribution

of awareness to utilisation, specified as $Utilisation = \beta_0 + \beta_1 (Awareness) + \varepsilon$. The two-sided 95% confidence interval for Pearson’s correlation was calculated using Fisher’s z transformation, with standard error $1/\sqrt{(N - 3)}$, and back-transformed to the correlation scale.

Because the utilisation outcome was bounded by a four-point response scale and the model residuals were negatively skewed, heteroscedasticity-consistent type 3 (HC3) standard errors were reported for the regression coefficient. A Spearman rank correlation was used as a non-parametric robustness check, and the regression/correlation analyses were repeated among the 208 respondents who explicitly reported prior GenAI use. Statistical significance was set at $\alpha = .05$. Analyses were conducted with SciPy and statsmodels in Python. The respondent-level scoring, correlations and regression estimates were independently verified during revision using NumPy and SciPy; HC3 coefficient intervals used the t distribution with 218 residual degrees of freedom.

2.6. Ethical Considerations

Ethical approval was granted by the Faculty of Healthcare Management and Leadership, Federal University of Allied

Health Sciences, Enugu (Approval No. FHML/RD/VOL.1/023). All included respondents indicated that they had read the participant information and voluntarily agreed to participate before completing the questionnaire. Participation was voluntary, and directly identifying information is not reported in this manuscript.

3. Results

3.1. Participant Profile and GenAI Exposure

The sample was predominantly female (76.4%). Just over half of the participants were aged 18-20 years (54.5%), while 41.4% were aged 21-23 years. GenAI exposure was already widespread among these first-year students: 213 participants (96.8%) had heard of GenAI before the survey and 208 (94.5%) reported prior use. ChatGPT was the most frequently used tool (60.0%), followed by Google Gemini (21.4%), Meta AI (9.1%), and Claude (5.9%). The distribution suggests that ChatGPT remained dominant, but students were engaging with a broader platform ecology rather than a single application.

Table 1. Participant characteristics and GenAI exposure (N = 220).

Characteristic	Category	n	%
Gender	Female	168	76.4
	Male	52	23.6
Age	18-20 years	120	54.5
	21-23 years	91	41.4
	24-27 years	7	3.2
	28 years and above	2	0.9
	Nursing Sciences	45	20.5
	Biomedical Engineering	31	14.1
Academic programme	Prosthetics & Orthotics	26	11.8
	Healthcare Management	23	10.5
	Health Information Management	22	10.0
	Dental Technology	20	9.1
	Social Work	19	8.6
	Microbiology	14	6.4
	Speech Therapy	10	4.5
	Radiography	4	1.8
	Physiotherapy	2	0.9
	Dental Therapy	2	0.9
	Medical Laboratory Sciences	1	0.5

Characteristic	Category	n	%
Heard of GenAI	Physiology	1	0.5
	Yes	213	96.8
	No	7	3.2
Prior GenAI use	Yes	208	94.5
	No	12	5.5
Most frequently used tool	ChatGPT	132	60.0
	Google Gemini	47	21.4
	Meta AI	20	9.1
	Claude	13	5.9
	Perplexity	3	1.4
	Microsoft Copilot	2	0.9
	Other GenAI tool	2	0.9
	No GenAI tool	1	0.5

3.2. What Students Knew About GenAI

Overall GenAI awareness was high (mean (M) = 3.48, standard deviation (SD) = .45). The strongest awareness concerned GenAI's visible academic capabilities: students were highly aware that GenAI could explain difficult academic concepts (M = 3.74, SD = .45), were familiar with common GenAI tools (M = 3.73, SD = .47), and recognised that GenAI

can generate new content (M = 3.65, SD = .54). Awareness was comparatively weaker for privacy and security risks (M = 3.21, SD = .85), the potential for bias or misleading information (M = 3.22, SD = .83), and academic-integrity concerns arising from unacknowledged AI-generated content (M = 3.30, SD = .73). Descriptively, the pattern suggests a capability-criticality gap: students appeared more certain about what GenAI could do for them than about the risks and responsibilities that should govern its use.

Table 2. GenAI awareness item statistics.

Item	Abbreviated content	Mean	SD
A1	Meaning of generative AI	3.52	0.61
A2	Common GenAI tools	3.73	0.47
A3	Ability to generate new content	3.65	0.54
A4	Use for explaining difficult concepts	3.74	0.45
A5	Prompt quality affects response quality	3.50	0.70
A6	Outputs may be inaccurate or fabricated	3.44	0.77
A7	AI outputs should be verified	3.45	0.73
A8	Privacy/security risks of sharing personal or confidential information	3.21	0.85
A9	Potential bias or misleading information	3.22	0.83
A10	Academic-integrity concerns from unacknowledged AI content	3.30	0.73
	Overall awareness composite	3.48	0.45

3.3. How Students Used GenAI for Learning

Learning-oriented utilisation was also high ($M = 3.44$, $SD = .52$). The most frequent uses were clarifying unfamiliar words, terms, or concepts ($M = 3.55$, $SD = .61$), generating examples to support understanding ($M = 3.53$, $SD = .61$), and obtaining explanations of difficult concepts taught in class (M

$= 3.51$, $SD = .62$). These activities place GenAI primarily in an explanatory and scaffolding role. The lowest mean, although still indicating frequent use, was for checking or improving answers to academic questions ($M = 3.34$, $SD = .71$). Overall, the pattern depicts GenAI as an embedded study aid used across comprehension, revision, writing, problem solving, and independent learning.

Table 3. GenAI utilisation-for-learning item statistics.

Item	Abbreviated content	Mean	SD
U1	Obtain explanations of difficult concepts	3.51	0.62
U2	Clarify unfamiliar words, terms or concepts	3.55	0.61
U3	Summarise lecture notes, textbooks or learning materials	3.42	0.67
U4	Generate study notes or outlines	3.38	0.69
U5	Brainstorm ideas for assignments or projects	3.38	0.65
U6	Generate examples to understand difficult topics	3.53	0.61
U7	Generate practice questions or revision exercises	3.42	0.67
U8	Prepare for tests or examinations	3.43	0.66
U9	Improve grammar, clarity or organisation of academic writing	3.38	0.71
U10	Obtain guidance when solving academic problems	3.46	0.64
U11	Check or improve answers to academic questions	3.34	0.71
U12	Support independent learning outside the classroom	3.46	0.63
	Overall utilisation composite	3.44	0.52

3.4. From Awareness to Academic Use

GenAI awareness was moderately and positively associated with utilisation for learning ($r = .427$, 95% confidence interval (CI) [.313, .530], $p < .001$). The non-parametric sensitivity analysis produced a consistent and somewhat stronger relationship (Spearman's $\rho = .512$, $p < .001$). Thus, students who reported greater awareness of GenAI also tended to report more frequent use of it for learning. Figure 1 displays the observed respondent-level scores and the fitted regression line.

The simple linear regression model was statistically signif-

icant. Awareness explained 18.3% of the variance in utilisation ($R^2 = .183$; adjusted $R^2 = .179$). Using HC3 robust standard errors, a one-point increase in mean awareness was associated with an estimated .49-point increase in mean utilisation ($B = .490$, HC3 SE = .073, $\beta = .427$, 95% CI [.346, .634], $t = 6.72$, $p < .001$). The conventional ordinary least-squares (OLS) model yielded $F(1, 218) = 48.67$, $p < .001$. When the analysis was restricted to the 208 respondents who explicitly reported prior GenAI use, the relationship remained comparable ($r = .462$, $B = .499$, $R^2 = .214$, $p < .001$). The central result was therefore not dependent on the logically inconsistent responses to the prior-use screening item.

Table 4. Regression of GenAI utilisation for learning on GenAI awareness ($N = 220$).

Predictor	B	HC3 SE	β	t	p	95% CI	R^2
Constant	1.735	.250	-	6.94	<.001	1.242-2.227	
GenAI awareness	.490	.073	.427	6.72	<.001	.346-.634	.183

Note. Outcome = mean utilisation-for-learning score. HC3 SE = heteroscedasticity-consistent type 3 standard error; B = unstandardised coefficient; β = standardised coefficient; CI = confidence interval; OLS = ordinary least squares; R^2 = coefficient of determination. Conventional OLS model: $F(1, 218) = 48.67$, $p < .001$; adjusted $R^2 = .179$.

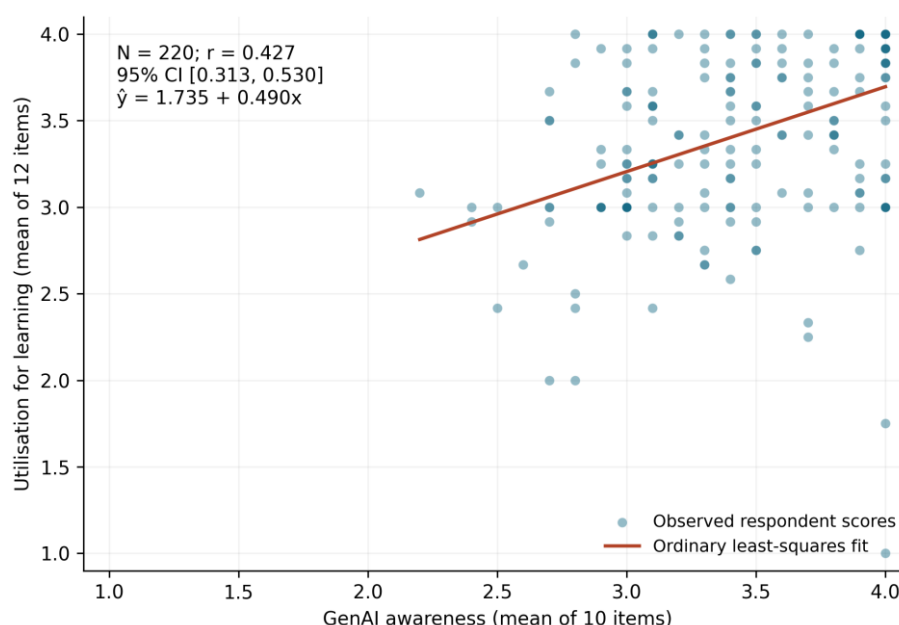


Figure 1. GenAI awareness and utilisation for learning among 220 respondents.

Note. Each point represents a respondent's awareness mean (10 items) and utilisation mean (12 items), both on a 1–4 scale. Coincident observations overlap; transparency indicates overplotting, and no jitter or simulated observations were used. The line is the ordinary least-squares fit, $\hat{y} = 1.735 + 0.490x$, shown over the observed awareness range. The displayed 95% interval is the Fisher-z confidence interval for Pearson's correlation, not a regression confidence band.

4. Discussion of Findings

The study set out to determine whether awareness of GenAI is merely a companion to academic use or whether it makes a measurable contribution to the way students engage with these tools for learning. The findings point to a clear but nuanced answer. GenAI had already become part of the learning environment of most participants, students reported high awareness and frequent use, and awareness significantly predicted utilisation. Yet awareness explained less than one-fifth of the variance in use. The results therefore support an awareness-use relationship while cautioning against the assumption that knowing more about GenAI is, by itself, sufficient to shape how students use it.

4.1. The Near-universal GenAI Learner

The first striking finding is the scale of exposure. Almost all respondents had heard of GenAI and more than nine in ten reported prior use. This level of penetration is higher than that reported in several earlier health-professions studies. Ganjavi et al. [7], for example, found that although 96% of surveyed US medical students had heard of ChatGPT, 52% had used it

for medical-school coursework. Iliyasu et al. [10] reported that 61.9% of medical and allied health students in Kano had used ChatGPT for academic purposes, while Ajalo et al. [2] found that 75.7% of Ugandan medical students had used AI tools. Orok et al. [15] reported substantial use among Nigerian pharmacy students, particularly for assignments and study.

The present prevalence should be interpreted in its temporal context. Data were collected in September 2026, several years after the public release of ChatGPT and after major technology companies had integrated GenAI functions into search, productivity, mobile, and communication ecosystems. Students entering university in this period may therefore arrive with prior GenAI experience acquired outside formal instruction. This creates a new institutional reality: universities are increasingly teaching students who have already formed habits of AI use before institutions have necessarily taught them how to evaluate those habits.

ChatGPT remained the most frequently used platform, but its 60% share also reveals diversification. More than one-third of the sample primarily used alternatives such as Gemini, Meta AI, Claude, Perplexity, or Copilot. This matters pedagogically. Policies and training that equate GenAI with one named platform risk becoming obsolete as tools change. What students need are transferable practices - verification, prompt

refinement, confidentiality, bias recognition, appropriate attribution, and disciplinary judgement - that remain relevant across platforms.

4.2. A Capability-criticality Gap in Students' Awareness

The item-level pattern provides a second important insight. Students were most aware of the visible capabilities of GenAI: that common tools exist, that they can generate content, and that they can explain difficult academic concepts. Awareness was lower for privacy and security, bias and misleading information, and the academic-integrity implications of unacknowledged AI-generated content. Although the present instrument was not designed to validate separate latent dimensions, this descriptive imbalance can be understood as a capability-criticality gap - stronger awareness of what GenAI can do than of how its outputs should be scrutinised and governed.

This pattern resonates with wider research. Students often value GenAI for speed, accessibility, explanation, and productivity while expressing uncertainty about accuracy, plagiarism, privacy, and responsible use [3, 5, 8]. Health-professions students have similarly recognised inaccurate information, privacy risks, and ethical concerns as important limitations [7, 13, 16]. The current findings suggest that exposure may develop faster than critical literacy: students encounter the benefits repeatedly and directly, while the risks may remain abstract unless they are explicitly taught.

For allied health education, that asymmetry deserves attention. A learner who is highly skilled at eliciting a fluent answer but less alert to fabrication or confidentiality may carry a weak verification habit into later professional learning. The educational task is therefore not to suppress GenAI use, but to make critical judgement as routine as prompting. In this sense, AI literacy should be treated as an epistemic and ethical competence, not merely as familiarity with a set of digital tools.

4.3. GenAI as an On-demand Learning Scaffold

Students' most frequent learning uses were concept clarification, explanation, and the generation of examples. These practices suggest that GenAI is functioning primarily as an on-demand scaffold: a resource students consult when lecture content, terminology, or a difficult concept requires another explanation. Similar uses have been documented in higher education and health-professions research, where students turn to GenAI for explanations, summarisation, information retrieval, brainstorming, and study support [3, 7, 9].

This use can be educationally productive when GenAI extends rather than replaces cognitive effort. An additional explanation may help a student reorganise a difficult idea; a generated example may make an abstract principle concrete; practice questions may support retrieval and revision. The same activities can become educationally weak when students outsource interpretation, accept outputs without verification, or

use generated answers in place of disciplinary reasoning. The finding that use is already frequent therefore strengthens, rather than reduces, the case for explicit instruction in how to work critically with GenAI.

4.4. Why Awareness Predicts Use - and Why it Does Not Explain Everything

The central statistical finding was that awareness positively predicted utilisation. This is consistent with the idea that students are more likely to integrate a technology into their learning when they understand what it is, what it can do, and how it can be applied. Nigerian evidence points in the same direction. Iliyasu et al. [10] found that stronger knowledge of ChatGPT was associated with greater likelihood of use among medical and allied health students, while Aiyebelehin et al. [1] reported that awareness and digital literacy predicted ChatGPT use among Nigerian undergraduates. Pallivathukal et al. [16] similarly found that knowledge and attitudes were associated with academic ChatGPT use among healthcare students.

The contribution of the present study lies in showing this relationship with continuous, multi-item measures of both awareness and learning-oriented utilisation and across a broader GenAI ecosystem. Rather than asking only whether students had ever used an AI tool, the analysis captured how often they used GenAI for 12 concrete learning activities. The moderate correlation and regression effect suggest that awareness is not merely background knowledge; it is connected with academic behaviour.

At the same time, the R^2 of .183 is theoretically instructive. Awareness mattered, but most of the variation in utilisation remained unexplained. This is consistent with UTAUT, which positions actual use within a wider configuration of perceived usefulness, effort, social influence, and facilitating conditions [18]. For contemporary students, additional influences may include the cost of data or subscriptions, quality of internet access, device availability, peer norms, lecturer attitudes, confidence in prompting, assessment design, institutional rules, and perceptions of academic-integrity risk. The result therefore argues against awareness-only interventions. Universities may increase knowledge of GenAI without necessarily changing how students use it if the surrounding learning environment remains unchanged.

4.5. Implications for Allied Health Education

The practical implication is not simply that universities should 'teach AI'. They should teach students how to think with and about AI. A structured AI-literacy curriculum for allied health students should combine four elements. First, students need functional competence: what GenAI systems can and cannot do and how prompts can be refined. Second, they need verification competence: how to test claims against textbooks, peer-reviewed research, professional guidance, and

other authoritative sources. Third, they need ethical and privacy competence: what information should not be entered into public systems, how bias can appear, and when AI assistance should be disclosed. Fourth, they need disciplinary competence: when GenAI can support reasoning and when reliance on it may weaken the development of professional judgement.

Assessment policy is equally important. Students require clear distinctions between legitimate learning support and unacceptable substitution of their own work. Ambiguous rules can produce two undesirable outcomes: uncritical use by students who assume anything technically possible is permitted, and avoidance by students who fear that any AI use will be treated as misconduct. Clear, task-specific guidance can support responsible experimentation while preserving authorship and academic standards [8, 12].

The findings also suggest that AI literacy should begin early. Because these were first-year students and most had already used GenAI, waiting until advanced coursework to introduce responsible-use principles may be too late. Orientation programmes, first-year digital literacy courses, library instruction, academic writing support, and introductory professional courses provide practical entry points for institution-wide guidance.

5. Conclusion and Recommendations

GenAI has already moved from the margins of student technology use into the everyday learning practices of the undergraduates studied here. Students reported high awareness and frequent use, particularly for clarifying concepts, obtaining explanations, generating examples, and supporting independent study. Awareness was a statistically significant predictor of utilisation, confirming that what students know about GenAI is meaningfully related to how they use it for learning. However, awareness accounted for only 18.3% of the variance in utilisation, showing that it is one part of a broader adoption ecology rather than a complete explanation.

The item-level results sharpen this conclusion. Students' strongest awareness concerned GenAI's capabilities, while privacy, bias, misleading information, and academic integrity were comparatively weaker. Institutions should therefore resist equating frequent use with mature AI literacy. The more appropriate goal is informed use: students who can exploit the educational affordances of GenAI while questioning its outputs, protecting confidential information, acknowledging AI assistance appropriately, and preserving their own disciplinary reasoning.

On the basis of these findings, allied health universities should embed structured AI literacy early in undergraduate programmes; design guidance around transferable principles rather than a single named platform; integrate verification, privacy, bias, and academic-integrity instruction into digital and research literacy; and align assessment rules with clearly communicated expectations for permitted and prohibited AI assis-

tance. Such measures would respond to the reality that students are already using GenAI while addressing the more difficult task of ensuring that use becomes educationally responsible.

6. Limitations and Future Direction

The findings should be interpreted within several limitations. The cross-sectional design does not establish temporal ordering or causality; 'prediction' in this study is statistical rather than causal. Data were obtained from one institution, and programme representation was uneven, which limits generalisability. The available records did not document a probability-sampling procedure or permit calculation of a population response rate. All measures were self-reported and may be affected by recall, social-desirability, and common-method bias.

The awareness instrument was study-specific. Although its internal consistency was good and its content aligns with established AI-literacy themes, external validation, factor-analytic confirmation, and measurement invariance testing were not available. The high awareness and utilisation scores also produced ceiling effects and non-normal regression residuals, although HC3 robust errors, a rank-based correlation, and the prior-user sensitivity analysis supported the substantive conclusion. In addition, GenAI tools change rapidly, so prevalence estimates and platform preferences are time-sensitive.

Future research should therefore test the awareness-use pathway in larger, multicentre samples and follow students longitudinally to determine whether changes in AI literacy precede changes in academic use. Validated GenAI-literacy instruments should be used or developed, with attention to capability knowledge, critical evaluation, ethics, privacy, and discipline-specific competence. More explanatory models should examine perceived usefulness, digital competence, internet and device access, lecturer guidance, peer norms, institutional policy, assessment conditions, and prompting self-efficacy. Experimental or quasi-experimental studies could then test whether structured AI-literacy interventions improve not only the frequency of GenAI use, but the quality, verification, and ethical appropriateness of that use.

Abbreviations

AI	Artificial Intelligence
GenAI	Generative Artificial Intelligence
UTAUT	Unified Theory of Acceptance and Use of Technology
HC3	Heteroscedasticity-consistent Type 3
SE	Standard Error
SD	Standard Deviation
CI	Confidence Interval
OLS	Ordinary Least Squares
M	Mean
B	Unstandardised Regression Coefficient

β	Standardised Regression Coefficient
R^2	Coefficient of Determination
ORCID	Open Researcher and Contributor ID
US	United States

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Data Availability Statement

A de-identified version of the analytic dataset may be made available by the corresponding author subject to institutional and ethical requirements.

Conflicts of Interest

The authors declare no conflicts of interest.

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