

Volume 2, Issue 1, October 2026: DOI: <https://doi.org/10.5281/zenodo.22872229>. Article history:
Received: March 13, 2026; Revised: May 18, 2026; Accepted: August 27, 2026

Patterns and Extent of Artificial Intelligence Utilisation for Academic Activities Among Undergraduates

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Abstract

Background: The rapid proliferation of digital educational technologies has reshaped higher education, encouraging undergraduate students to incorporate automated applications into their study routines. Despite widespread discourse on digital transformation in Nigerian universities, empirical assessments of how students navigate specific functional tiers of artificial intelligence (AI) across diverse disciplines remain scarce.

Objective: Anchored on the Uses and Gratifications Theory (UGT), this study assessed the extent to which undergraduate students utilise distinct functional categories of AI—spanning basic computational tools, automated writing and language verifiers, adaptive tutoring platforms, and emerging autonomous systems—for their academic activities.

Methodology: A descriptive survey research design was adopted. From a population of 35,578 undergraduate students at the University of Port Harcourt, a sample size of 396 was determined using the

Page | 167

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Taro Yamane formula. An institutional network distribution yielded 381 valid responses via an online questionnaire. Data were analysed using frequency counts, percentage distributions, weighted mean scores, and a standard decision criterion benchmark of 2.50.

Result: Undergraduate students exhibited an overall low extent of AI utilisation for academic purposes (grand mean = 2.32). Relatively higher utilisation was restricted to basic mobile grammar checkers (mean = 2.61), instant computational tools (mean = 2.88), and digital scientific calculators (mean = 2.77). Conversely, institutional plagiarism detection suites (mean = 2.20), adaptive tutoring platforms (mean = 2.35), and advanced algorithmic algebra systems (mean = 1.97) recorded low to very low adoption. Awareness of fully autonomous systems remained conceptual, reflecting their absence from everyday academic workflows.

Conclusion: Undergraduate engagement with AI remains in an early developmental stage, characterised by a pragmatic reliance on accessible, zero-cost mobile applications to address immediate study tasks rather than advanced, research-driven systems. Consequently, university authorities should establish structured AI literacy programmes, secure institutional software licences, and formulate coherent policy frameworks for the ethical integration of emerging technologies into undergraduate learning.

Keywords: Academic Activities, Artificial Intelligence, Digital Literacy, Higher Education, Technology Adoption, Undergraduates.

Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technological innovations of the twenty-first century, fundamentally altering instructional paradigms and research methodologies within higher education. Broadly conceptualised, artificial intelligence denotes computer systems and algorithms designed to execute tasks that traditionally demand human cognitive faculties, including pattern recognition, linguistic processing, logical reasoning, and adaptive problem-solving (Russell & Norvig, 2021). Within contemporary tertiary education, intelligent technologies are increasingly embedded across curriculum delivery, assessment systems, and independent scholarship, offering undergraduates versatile platforms for literature synthesis, language refinement, mathematical computation, and self-paced study (Luckin et al., 2016; Holmes et al., 2019). As global universities accelerate digital infrastructure development, establishing empirical baselines on how undergraduates engage with varying tiers of automated systems has become an imperative avenue of scholarly enquiry (Zawacki-Richter et al., 2019).

In pedagogical computing literature, intelligent educational systems can be classified by functional complexity, ranging from basic computational and reactive utilities to generative language platforms, adaptive tutoring environments, and emerging autonomous architectures (Hintze, 2016; Kasneci et al., 2023). Basic reactive and computational tools operate on deterministic algorithms, delivering prompt outputs to user inputs without building longitudinal contextual profiles (Russell & Norvig, 2021). In day-to-day academic routines, students rely on these accessible tools for rapid numerical calculation, instant data parsing, and foundational literature retrieval (Holmes et al., 2019; Chen et al., 2020).

A more versatile tier consists of limited-memory architectures that leverage machine learning models and historical training data to generate tailored textual responses, refine grammar, detect textual similarities, and recommend relevant scholarly materials (Hintze, 2016; Dwivedi et al., 2023). Beyond language tools, educational development has introduced adaptive environments and intelligent tutoring systems designed

to monitor individual learning curves, identify diagnostic hurdles, and simulate interactive pedagogical guidance (Graesser et al., 2018; Holmes et al., 2022). At the conceptual frontier lie theoretical autonomous systems, which populate contemporary academic discourse regarding artificial general intelligence and independent machine consciousness (Bostrom, 2014; Kaplan & Haenlein, 2020).

Despite the expanding availability of these educational technologies, undergraduate engagement across developing economies remains heavily conditioned by technological infrastructure, device accessibility, subscription constraints, and uneven digital literacy. In sub-Saharan Africa, tertiary institutions frequently navigate acute digital divides, meaning that student technology adoption often unfolds along informal, self-directed trajectories rather than through coordinated institutional deployment. While empirical investigations in developed regions report sophisticated student adoption of integrated generative platforms and cognitive tutors (Baillifard et al., 2025; Prandner, 2025), there remains a distinct scarcity of empirical literature documenting the precise functional tiers of artificial intelligence utilised by Nigerian undergraduates. Determining whether students systematically leverage specialised academic platforms or merely depend on basic, zero-cost mobile applications is critical for informing university policy, curriculum design, and institutional infrastructure planning.

Research Questions

1. To what extent do undergraduate students utilise basic computational and reactive tools for academic activities?
2. To what extent do undergraduate students utilise automated language, writing verification, and recommendation tools for academic activities?
3. To what extent do undergraduate students utilise intelligent tutoring and adaptive learning systems for academic activities?
4. What is the extent of undergraduate engagement with emerging and conceptual autonomous artificial intelligence systems for academic activities?

Review of Related Literature

Conceptualising Artificial Intelligence and Functional Educational Tiers

Artificial intelligence encompasses computer systems designed to execute cognitive functions that traditionally require human intellect, including language interpretation, visual processing, structured reasoning, and problem resolution. Dauda et al. (2014) define artificial intelligence as the simulation of human intellectual processes by machines programmed to resolve problems through systematic computational pathways. In tertiary education, intelligent platforms facilitate individualised instruction, automated feedback, and self-directed inquiry, altering traditional learning routines (Verma, 2018). The integration of automated educational architectures can support student assessment outcomes and provide real-time feedback (Nwokorie & Onichakwe, 2024). As Johnson and Smith (2023) observe, modern adaptive tools utilise learner data analytics to adjust study content to individual pacing and competence levels. While intelligent tutoring systems deliver responsive instructional support, they serve as pedagogical complements rather than replacements for classroom educators, offering guided remediation within structured digital boundaries (Sasan & Kilag, 2023; Ukozor, 2025).

The conceptual progression of artificial intelligence is frequently categorised into functional developmental stages: reactive systems, limited-memory architectures, theory of mind models, and self-aware constructs

(Schroer, 2023). Reactive systems operate as fundamental computational engines that respond to direct operational inputs without retaining past interaction history (Johnson, 2024). In academic learning environments, these baseline utilities encompass deterministic calculation tools and static search mechanisms.

Limited-memory architectures represent the current backbone of applied educational artificial intelligence, retaining short-term contextual data to adapt future outputs (Kasneci et al., 2023). In higher education, this tier includes learning management systems that tailor academic content based on historical student progress, alongside generative writing assistants and automated similarity checkers (Dwivedi et al., 2023). Conversely, theory of mind artificial intelligence represents an advanced developmental horizon aimed at interpreting human emotional states, cognitive motivations, and social dynamics (González et al., 2021). While natural language conversational interfaces attempt to simulate conversational empathy, full affective computational comprehension remains confined to experimental computing (Kaplan & Haenlein, 2020). Finally, self-aware artificial intelligence denotes hypothetical machines endowed with subjective consciousness, independent identity, and autonomous intentionality (Lee, 2024). This tier remains strictly speculative, as contemporary computer science has not demonstrated empirical self-awareness in any physical or software architecture (Russell & Norvig, 2021; Lee, 2025).

Empirical Review

Basic Computational and Reactive Systems in Education

Reactive computational systems perform targeted tasks without drawing upon contextual historical profiles. Investigating intelligent learning frameworks, Chen et al. (2020) observed that undergraduates regularly interact with automated search engines and instant response interfaces to retrieve reference materials, demonstrating that basic reactive utilities enhance baseline study convenience. Similarly, Okonkwo and Ade-Ibijola (2021) examined student engagement with automated conversational chatbots and found that learners used conversational bots for course-related queries and administrative scheduling, improving study coordination.

The adoption rate of these fundamental tools diverges considerably across institutional resource contexts. Ferguson (2019) demonstrated that university students in technologically advanced environments actively integrate automated institutional feedback mechanisms and grammar-checking utilities into routine scholarship. Conversely, Okonkwo and Adeyemi (2022) found that undergraduates in Nigerian universities utilised specialised algorithmic software to a low extent, depending almost exclusively on handheld calculators and free mobile proofreading applications. They identified personal convenience, zero-cost mobile access, and bandwidth limitations as key factors shaping student preference for basic, reactive tools over sophisticated analytical software.

Generative Language and Writing Verification Tools

Applied machine-learning systems, often classified under limited-memory architectures, execute specialised academic tasks by processing massive training datasets (Kasneci et al., 2023). Benitez et al. (2025) evaluated the cognitive impact of generative tools on university students, concluding that while interaction with large language models significantly enhances task completion speed, it does not inherently expand underlying human critical reasoning. Within Nigerian universities, Olaleye and Eze (2021) noted that general student adoption of advanced digital learning platforms remained modest, constrained by

institutional licensing hurdles, minimal campus awareness, and uneven student technological literacy. By contrast, Ifenthaler and Schumacher (2020) demonstrated that undergraduates in well-funded international institutions make regular use of integrated learning analytics dashboards and institutional academic feedback platforms.

Examining localised usage, Hassan and Harande (2025) investigated students at Northwest University Kano, Nigeria, reporting widespread engagement with generative writing platforms and automated grammar tools for assignment composition, coursework drafting, and lexical correction. These observations are supported by Dwivedi et al. (2023), who established that tertiary students globally rely on generative language engines for text summarisation, drafting assistance, and self-directed study, illustrating that accessible limited-memory tools contribute positively to academic productivity when deployed with integrity.

Adaptive Tutoring Platforms and Conceptual AI Boundaries

Adaptive instructional platforms utilise learner modelling to detect comprehension bottlenecks and adjust pedagogical pacing. Graesser et al. (2018) reported that students utilising intelligent tutoring platforms showed marked gains in subject engagement and conceptual mastery, demonstrating the viability of adaptive agents in instructional delivery. Furthermore, Holmes et al. (2022) highlighted that educational technologies engineered to adjust instruction dynamically in response to student engagement patterns improve learner motivation and task persistence. However, as observed by Luckin et al. (2019), the broad deployment of intelligent tutoring platforms remains minimal across resource-constrained tertiary institutions due to elevated infrastructure costs and the absence of institutional integration.

Regarding autonomous systems, theoretical explorations into machine consciousness—such as mathematical formulations of artificial self-identity in large language models by Lee (2025)—continue to stimulate academic inquiry. Nevertheless, empirical assessments by Kaplan and Haenlein (2020) and Russell and Norvig (2021) confirm that fully self-aware artificial intelligence remains entirely hypothetical. Autonomous systems comparable to speculative cinema concepts like JARVIS do not exist in functional educational practice, meaning that university undergraduates do not engage with truly conscious technologies in their academic routines (Bostrom, 2014; Russell & Norvig, 2021).

Theoretical Framework

This investigation is anchored in the Uses and Gratifications Theory (UGT), formulated by Katz et al. (1974). UGT posits that individuals are active, goal-directed participants who purposefully select communication channels and emerging technologies to satisfy specific cognitive, affective, and practical needs. Rather than treating audiences as passive recipients of technological influence, the theory emphasises individual agency in seeking media to acquire information, facilitate learning, and accomplish personal objectives (Katz et al., 1973). As famously articulated by Katz (1959), the fundamental premise shifts enquiry from what media do to people to what people do with media.

A foundational assumption of UGT is that users sustain engagement with a technological medium only to the degree that it successfully gratifies their expectations. When a platform fails to deliver expected utility, users discontinue its use in favour of alternatives that provide more immediate or dependable functional benefits. This user-centric orientation is particularly appropriate for evaluating emerging digital educational tools, where adoption is largely voluntary and governed by practical utility.

Within this study, UGT clarifies the patterns and varying degrees to which undergraduate students utilise artificial intelligence technologies for academic activities. Undergraduates are conceptualised as discerning agents who engage with automated applications to complete course assignments, solve complex calculations, refine academic writing, and organise study tasks. The theory indicates that tools delivering immediate, accessible utility—such as free mobile grammar checkers or rapid computational solvers—will experience higher adoption rates than advanced systems that impose technological hurdles, complex interfaces, or financial subscriptions. UGT therefore provides a robust theoretical foundation for explaining why students demonstrate high utilisation of specific baseline utilities while underutilising specialised institutional platforms.

Research Methodology

Research Design

A descriptive survey research design was adopted for this study. This design is appropriate because it facilitates the systematic collection, description, and analysis of quantitative data regarding the perceptions, adoption behaviours, and extent of artificial intelligence utilisation across a cross-section of undergraduate students without experimental manipulation.

Population of the Study

The target population comprised all registered undergraduate students enrolled at the University of Port Harcourt during the 2023/2024 academic session. Official enrolment records from the institutional admissions office established the total undergraduate population at 35,578 students across all constituent faculties (University of Port Harcourt, 2024).

Sample Size and Sampling Technique

To ensure statistical adequacy, the sample size was determined using the Taro Yamane formula for finite populations at an error tolerance level of $e = 0.05$:

$$n = N / (1 + N(e)^2)$$

Where: n = required sample size N = finite population under study (35,578) e = margin of error (0.05)

Substituting the population parameters into the formula yielded:

$$n = 35,578 / (1 + 35,578(0.05)^2) = 35,578 / (1 + 35,578(0.0025)) = 35,578 / 89.945 = 395.55$$

Rounding up to the nearest whole integer established a target sample size of $n = 396$ respondents.

To recruit respondents across diverse departments, an institutional multi-stage network sampling framework was utilised. Initial contact was established with student leadership networks, specifically faculty and departmental executive officers, who served as primary distribution nodes. These student executives circulated the online survey protocol across departmental communication channels, class platforms, and faculty portals. Subsequent participants then disseminated the survey link across their

respective academic peer networks until 396 prospective respondents were engaged, ultimately yielding 381 completely filled and analytically valid submissions, representing an effective return rate of 96.2 per cent.

Measuring Instrument

The research instrument was a self-structured electronic questionnaire titled Utilisation of Artificial Intelligence for Academic Activities Questionnaire (UAIAAQ). The instrument comprised two distinct divisions:

Section A (Demographic Profile): Captured personal characteristics of respondents, including biological sex, age bracket, marital status, academic level, and faculty affiliation.

Section B (Psychographic and Utilisation Dimensions): Contained close-ended items structured around four functional tiers of educational technologies: basic computational tools, language and writing verification platforms, adaptive tutoring environments, and emerging autonomous systems.

Responses in Section B were measured using a modified four-point Likert scale weighted as follows: Strongly Agree (SA = 4), Agree (A = 3), Disagree (D = 2), and Strongly Disagree (SD = 1). Face and content validity of the instrument were ascertained through expert peer review by educational technology and measurement specialists, whilst internal consistency was established prior to full distribution.

Method of Data Collection

Data gathering was executed digitally using Google Forms to facilitate broad geographic access across university campuses and off-campus student residential zones. The survey instrument opened with a formal brief detailing the study objectives, guaranteeing participant anonymity, and obtaining digital informed consent. Respondents completed the survey items on internet-enabled smartphones or computers, with single-submission constraints applied to prevent multiple entries from the same user session. The digital protocol operated continuously until the target threshold was reached.

Method of Data Analysis

Empirical data were compiled and analysed using descriptive statistics, notably frequency distributions, percentage counts, and weighted mean scores. To interpret the research questions, a standard criterion mean benchmark was derived mathematically from the four-point scale weights:

$$\text{Mean } (\bar{x}) = \text{Total Weighted Score} / \text{Total Scale Points} = (4 + 3 + 2 + 1) / 4 = 10 / 4 = 2.50$$

Items or section clusters with a weighted mean score equal to or exceeding 2.50 were classified as high extent, denoting positive agreement and substantial utilisation. Conversely, mean scores falling below 2.49 were classified as low extent, indicating minimal adoption. To assess the gradations of utilisation with greater precision, mean scores were categorised across an operational continuum:

1.00 to 1.99 = Very Low Extent 2.00 to 2.49 = Low Extent 2.50 to 2.99 = High Extent 3.00 to 4.00 = Very High Extent

Results

Data gathered through the online questionnaire administration across the target population were collated and analysed. From the calculated target sample of 396 respondents, 381 copies of the instrument were duly completed and validated, representing an effective return rate of 96.2 per cent with a non-response rate of 3.8 per cent. The empirical analyses are based on these 381 valid responses.

Demographic Profile of Respondents

Table 1: Demographic Characteristics of Respondents (N = 381)

Variable	Classification Bracket	Frequency (f)	Percentage (%)
Biological Sex	Male	125	32.8
	Female	256	67.2
Age Bracket	16 to 18 years	55	14.4
	19 to 21 years	169	44.4
	22 to 24 years	108	28.3
	25 years and above	49	12.9
Marital Status	Single	362	95
	Married	19	5
Academic Level	100 Level	26	6.8
	200 Level	182	47.8
	300 Level	48	12.6
	400 Level	77	20.2
	500 Level	45	11.8
	600 Level	3	0.8
Total		381	100

Data in Table 1 reveal that female respondents formed the majority at 256 (67.2%), while males accounted for 125 (32.8%). The modal age bracket was 19 to 21 years with 169 respondents (44.4%), and 362 participants (95.0%) were single. Academically, the largest cohort comprised 200 level students at 182 (47.8%), followed by 400 level students at 77 (20.2%).

Empirical Analysis of Research Questions

Research Question 1: To what extent do undergraduate students utilise basic computational and reactive tools for academic activities?

Table 2: Extent of Utilisation of Basic Computational and Reactive Tools

S/N	Item Statement	SA (4)	A (3)	D (2)	SD (1)	Total fx	Mean ($\bar{x}$)	Extent
1	I use basic automated calculators providing instant computational feedback for assignments	97	172	81	31	1,097	2.88	High
2	I use digital scientific calculator software for academic problem-solving	98	136	107	40	1,054	2.77	High
3	I use programmable algorithmic calculators for coursework	34	80	172	95	815	2.14	Low
4	I use computer algebra system software (e.g. symbolic mathematical engines)	23	60	180	118	750	1.97	Very Low
5	I use web-based automated computational platforms	54	125	123	79	916	2.4	Low
6	I use rule-based automated grammar checkers for academic writing	42	156	126	57	945	2.48	Low
7	I use statistical proofreading applications for course assignments	21	113	173	74	843	2.21	Low
8	I use machine-learning writing assistants for sentence restructuring	36	107	167	71	870	2.28	Low
9	I use built-in word processor editing tools	49	145	130	57	948	2.49	Low
10	I use mobile-based grammar checking applications	52	174	110	45	995	2.61	High
	Cluster Grand Mean					9,233	2.42	Low

Table 2 shows an overall low utilisation of basic computational and reactive utilities (mean = 2.42). High adoption was limited to basic instant calculators (mean = 2.88), digital scientific tools (mean = 2.77), and mobile grammar applications (mean = 2.61), whereas specialised programmable calculators and algebraic engines recorded low adoption.

Research Question 2: To what extent do undergraduate students utilise automated language, writing verification, and recommendation tools for academic activities?

Table 3: Extent of Utilisation of Recommendation and Writing Verification Tools

S/N	Item Statement	SA (4)	A (3)	D (2)	SD (1)	Total fx	Mean ($\bar{x}$)	Extent
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11	I use content-based automated literature recommendation platforms	29	150	144	58	912	2.39	Low
12	I use collaborative filtering platforms that recommend academic texts	26	121	167	67	868	2.28	Low
13	I use hybrid recommendation platforms combining multiple databases	57	130	142	52	954	2.5	High
14	I use Turnitin similarity detection software for academic papers	50	75	158	98	839	2.2	Low
15	I use Grammarly plagiarism checking module for coursework	27	115	159	80	851	2.23	Low
16	I use hybrid similarity platforms combining repositories and web sources	22	77	168	114	769	2.02	Low
17	I use automated source-code similarity checkers	13	61	189	118	731	1.92	Very Low
18	I use real-time writing similarity and original verification engines	22	84	167	108	782	2.05	Low
	Cluster Grand Mean					6,706	2.2	Low

Data in Table 3 indicate an overall low extent of engagement with language verification and recommendation systems (mean = 2.20). Apart from hybrid recommendation platforms (mean = 2.50), institutional plagiarism suites and automated integrity tools recorded low to very low utilisation.

Research Question 3: To what extent do undergraduate students utilise intelligent tutoring and adaptive learning systems for academic activities?

Table 4: Extent of Utilisation of Adaptive Learning and Tutoring Systems

S/N	Item Statement	SA (4)	A (3)	D (2)	SD (1)	Total fx	Mean ($\bar{x}$)	Extent
19	I use cognitive tutoring systems that adjust instruction to learning pace	39	111	160	71	880	2.31	Low
20	I use intelligent tutoring platforms that identify comprehension bottlenecks	45	122	148	66	908	2.38	Low
	Cluster Grand Mean					1,788	2.35	Low

Table 4 shows that students utilise adaptive tutoring systems to a low extent (mean = 2.35). Both cognitive systems adapting instructional pace (mean = 2.31) and platforms diagnosing comprehension hurdles (mean = 2.38) fell below the 2.50 criterion benchmark.

Research Question 4: What is the extent of undergraduate engagement with emerging and conceptual autonomous artificial intelligence systems for academic activities?

Table 5: Extent of Engagement with Conceptual Autonomous AI Systems

S/N	Item Statement	SA (4)	A (3)	D (2)	SD (1)	Total fx	Mean ($\bar{x}$)	Extent
21	Perceived utilisation of autonomous systems operating with independent agency	33	81	138	129	780	2.05	Low
	Cluster Grand Mean					780	2.05	Low

Table 5 indicates a low mean score (mean = 2.05) regarding student interaction with autonomous AI systems. With 70.1 per cent of respondents rejecting operational reliance on such platforms, the findings show that student engagement with autonomous systems remains purely conceptual rather than functional in everyday academic routines.

Discussion of Findings

The empirical results of this study show that undergraduate students utilise artificial intelligence technologies for academic activities to an overall low extent, with functional usage heavily concentrated in accessible, consumer-oriented applications.

Regarding the first research question on basic computational and reactive tools, respondents demonstrated high utilisation of instant automated calculators and digital scientific tools, alongside mobile grammar applications. Conversely, specialised programmable algorithmic packages and symbolic computer algebra software recorded low to very low adoption. This division illustrates a clear student preference for readily accessible, offline, or low-bandwidth utilities that provide immediate answers for course assignments. These patterns align with the empirical findings of Okonkwo and Adeyemi (2022), who observed that undergraduates in Nigerian universities predominantly rely on simple handheld calculators and mobile-based writing tools, whilst rarely engaging with structured computational software due to limited technical training and software access. However, this contrasts with observations by Ferguson (2019), who reported substantial adoption of integrated institutional analytics and automated feedback systems among university students in well-resourced environments. As Chen et al. (2020) established, basic automated utilities enhance student access to foundational study support, but without formal training, advanced computational tools remain underutilised.

In relation to the second research question concerning language verification, literature discovery, and similarity detection tools, high utilisation was confined to hybrid recommendation platforms. Mainstream similarity detection platforms—such as Turnitin, Grammarly plagiarism verification, and code similarity engines—recorded uniformly low adoption levels. This outcome confirms the findings of Olaleye and Eze (2021), who reported modest adoption of advanced e-learning and AI platforms among Nigerian undergraduates due to institutional access barriers, lack of awareness, and limited digital competencies. Because institutional licences for enterprise plagiarism detection suites are typically managed by faculty administrators rather than distributed directly to students, undergraduates have few opportunities to embed these platforms into their personal writing workflows. While Hassan and Harande (2025) and Dwivedi et al. (2023) identified widespread use of generative language and writing assistants for academic coursework, the present findings show that when specialised verification tools require institutional subscriptions, student engagement drops markedly. As Benitez et al. (2025) argued, although automated language tools improve

task completion speed, students' selective use is governed heavily by interface convenience rather than institutional integration.

Regarding the third research question on intelligent tutoring and adaptive learning systems, respondents recorded low utilisation across both adaptive cognitive systems and diagnostic platforms. Although educational literature demonstrates that intelligent tutoring systems provide tailored feedback and improve learning engagement (Graesser et al., 2018; Holmes et al., 2022), their deployment within Nigerian universities is severely restricted. This finding corroborates Luckin et al. (2019), who documented that intelligent tutoring systems remain minimally integrated within university learning environments, particularly in resource-constrained contexts. As Sasan and Kilag (2023) and Ukozor (2025) observed, while adaptive platforms can effectively support instruction where human tutors are unavailable, their adoption requires stable digital infrastructure and deliberate institutional investment, conditions that are often lacking in federal universities.

With respect to the fourth research question addressing emerging autonomous systems, respondents reported low engagement. More than 70 per cent of participants rejected operational reliance on autonomous, self-directing systems for academic tasks. This outcome is consistent with the analyses of Russell and Norvig (2021), Bostrom (2014), and Kaplan and Haenlein (2020), which confirm that fully autonomous, self-aware artificial intelligence remains theoretical and has not been realised in functional educational platforms. While theoretical research into computational self-identity continues to evolve (Lee, 2025), the low score recorded here empirically validates that undergraduate study routines remain grounded in narrow, task-oriented software rather than speculative autonomous platforms.

The overall empirical patterns observed across all four tiers correspond directly with the Uses and Gratifications Theory (Katz et al., 1974). According to UGT, media audiences and technology users actively choose specific platforms that provide immediate gratification for identified psychological and practical needs (Katz, 1959; Katz et al., 1973). In this study, undergraduate students deliberately engaged with zero-cost, smartphone-compatible tools—such as basic calculators and mobile grammar checkers—because they immediately satisfy pressing needs for assignment completion, proofreading, and computational speed. Conversely, complex adaptive platforms and licensed plagiarism engines do not offer immediate, effortless gratification due to institutional paywalls, interface complexity, and inadequate connectivity. Undergraduates therefore exercise agency by bypassing inaccessible technologies in favour of tools that satisfy their academic demands with minimal friction.

Conclusion

This study evaluated the patterns and extent of artificial intelligence utilisation for academic activities among undergraduate students, using the University of Port Harcourt as an institutional study site. The empirical evidence indicates that undergraduate engagement with AI remains at an early developmental stage, characterised by an overall low extent of adoption.

Student interaction with automated technologies is heavily stratified. High utilisation is confined to basic, easily accessible, and zero-cost mobile applications, including instant calculators, digital scientific tools, and mobile grammar checkers. In contrast, higher-order academic tools—such as symbolic algebraic solvers, institutional plagiarism detection software, and adaptive cognitive tutoring systems—record low adoption due to institutional subscription barriers, inadequate digital infrastructure, and limited technological literacy. Furthermore, student engagement with autonomous systems remains purely

theoretical. Consequently, the potential of advanced artificial intelligence to foster critical inquiry, self-directed research, and academic integrity has not been systematically harnessed within the undergraduate learning environment.

Recommendations

Based on the empirical findings and conclusions of this study, the following recommendations are proposed:

- University authorities should acquire institutional campus licences for reputable academic writing, reference verification, and similarity detection platforms, providing verified access to undergraduate students to enhance research integrity and technical competence.
- The university management, through the Centre for Information and Telecommunication Engineering and related academic units, should establish structured workshops and digital literacy campaigns to train undergraduates in the practical use of advanced algorithmic solvers, academic literature search engines, and data analysis software.
- Academic departments should incorporate learning management systems with built-in adaptive tutoring modules into undergraduate coursework, encouraging lecturers to utilise interactive digital environments that reinforce personalised student learning.
- Faculty boards should formulate coherent policy frameworks and ethical guidelines regulating artificial intelligence usage in undergraduate scholarship, establishing transparent boundaries between acceptable automated study assistance and academic dishonesty.

Declarations

Ethical Approval: This study was conducted in accordance with the ethical guidelines of the Declaration of Helsinki. Informed consent was obtained electronically from all undergraduate participants prior to questionnaire administration. Participation was entirely voluntary, anonymous, and uncompensated, with no private identity markers or academic registration details recorded.

Artificial Intelligence (AI) Use Statement: During the preparation of this work, the authors used Claude (Anthropic) solely to improve language readability, style, and grammatical clarity. Following the use of this tool, the authors thoroughly reviewed, verified, and edited all text, and take full responsibility for the intellectual integrity, accuracy, and final content of the published manuscript.

Data Availability Statement: The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request.

Funding Statement: The authors received no specific grant or financial assistance from funding agencies in the public, commercial, or not-for-profit sectors for this research.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contributions: U.J Nwogu conceived the study, formulated the theoretical framework, and supervised data collection. C. M. Obinna designed the survey instrument, coordinated online participant recruitment, carried out the statistical analyses, and drafted the initial manuscript. B.C Nwandizee assisted with data cleaning, literature curation, and critical revision of the manuscript for substantial intellectual content. All authors read and approved the final manuscript.

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