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DISCOVERING PATTERNS OF GENERATIVE AI USE AMONG UNIVERSITY STUDENTS: EVIDENCE FROM AN ONLINE SURVEY AND ASSOCIATION RULE MINING

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Abstract

Generative artificial intelligence tools are gradually reshaping how university students read, write, and prepare for academic tasks. However, within Nigerian universities, there is still limited empirical evidence on how students actually use these tools and how such use relates to verification practices, institutional policy awareness, and learning experiences. This study examined patterns of generative AI use among university students in Nigeria using an online survey and association rule mining. A total of 700 valid responses collected between 18 December 2025 and 18 January 2026 were analyzed. Descriptive statistics were used to examine the extent to which AI tools are used, how frequently students rely on them, which tools they prefer, and the academic activities for which they are used. Association rule mining was then employed to identify recurring relationships among AI use behaviour, checking and editing practices, perceived policy communication, policy understanding, and students' learning experiences. The findings show that generative AI has already become part of the everyday academic routine for many students. Most respondents reported using AI to clarify difficult concepts, summarize learning materials, organize assignment ideas, and prepare for examinations. The analysis also indicates that students who perceived clearer communication about institutional AI policies were more likely to understand acceptable AI use. At the same time, frequent use sometimes appeared alongside signs of reliance that may affect deeper engagement with learning. These results highlight the need for clearer guidance and practical AI literacy support within Nigerian universities.

Keywords: generative artificial intelligence, university students, association rule mining, Nigeria.

Introduction

In recent years, generative artificial intelligence has quickly moved from being a technological novelty to becoming a tool that many students now use in their everyday academic work. Across universities, students increasingly rely on AI to explain difficult concepts, summarize readings,

organize ideas for assignments, and support early stages of research. As a result, higher education institutions are facing growing pressure to determine how to use these tools responsibly while still supporting meaningful learning. Evidence from a large-scale survey in the United Kingdom shows how quickly this shift is taking place. In 2025, about 88 per cent of students reported using generative AI for assessments, compared with 53 per cent in 2024, with the most common uses including explaining concepts, summarizing readings, and generating research ideas (Freeman, 2025). Despite this rapid adoption, universities are still grappling with questions about appropriate policies, clear guidelines, and student support systems, as well as concerns about unequal access to these technologies (Tsao, 2025). These developments highlight the growing need for evidence-based institutional responses that combine clearer guidance and communication, practical AI literacy support focused on verification and transparency, and student support structures that reflect how quickly generative AI has moved from a novelty to an everyday academic tool (Revesai, 2025).

In Nigerian universities, this development unfolds in a context where digital access is expanding, though unevenly (Ogar et al., 2025). Nigeria had about 103 million internet users at the start of 2024, with internet penetration estimated at 45.5 percent, suggesting a large and growing population of students who can access AI tools through smartphones and internet-enabled platforms (Emmason, 2024). For many students, generative AI can function as informal academic support, especially for clarification of difficult concepts and rapid drafting or summarization. (Lo et al., 2025). At the same time, concerns persist about overreliance, academic integrity pressures, and unequal access to better-paid tools or a stable internet connection (Rane et al., 2024). UNESCO has warned that education systems need governance, human capacity development, and safeguards to ensure a human-centred and responsible approach to generative AI in education and research (UNESCO, 2025).

Although research on generative AI in higher education is expanding, many studies still treat AI use as a single behaviour and link it to a single outcome at a time (McDonald et al., 2025). Yet student use is rarely that simple. Students differ by frequency of use, purpose of use, whether they verify AI outputs, how they understand institutional rules, and how AI use relates to learning confidence and wellbeing (Ma'amor et al., 2024). Evidence on perceptions of AI use in assessment and feedback also points to policy ambiguity and mixed acceptance, underscoring the importance of studying how policy awareness and usage behaviours co-occur (Tierney et al., 2025). Scholarly discussions of generative AI in education similarly emphasize both opportunities and risks, including the need to protect deep learning and critical thinking while acknowledging practical benefits (Ali et al., 2024).

This is why a pattern-focused approach is timely. Association rule mining is designed to identify frequent co-occurrences in data without imposing linear assumptions or causal claims. In education research, data mining approaches are widely used to detect meaningful behavioural patterns that may be missed when variables are analyzed in isolation, making association rules suitable for

mapping how multiple study behaviours cluster in real student life. By applying association rule mining to online survey responses, this study moves beyond simply reporting how many students use AI and instead examines the combinations of behaviours and perceptions that tend to occur together among university students in Nigeria.

The research questions are as follows.

1. What are the dominant patterns of generative AI use among university students in Nigeria in terms of frequency and academic purposes?
2. How do AI use behaviours co-occur with verification habits and awareness of institutional rules on acceptable AI use?
3. What behavioural combinations are most strongly associated with heavy reliance on generative AI and with self-reported learning experience and wellbeing indicators?

The study is guided by the following objectives.

1. To describe the prevalence, frequency, and academic purposes of generative AI use among university students in Nigeria using online survey data.
2. To identify frequent co-occurring patterns linking AI use behaviours, verification practices, policy awareness, and student learning experiences using association rule mining.
3. To draw evidence-based implications for responsible AI guidance and student support within Nigerian universities, consistent with emerging governance recommendations.

Methodology

Study design

This study adopted a cross-sectional online survey design. The study combined descriptive analysis and association rule mining to examine the prevalence, frequency, and academic purposes of generative AI use, and to identify frequent co-occurring patterns linking AI use behaviours, verification practices, policy awareness, and student learning experiences.

Study setting and target population

The study focused on university students in Nigeria. Eligible participants were undergraduate and postgraduate students currently enrolled in Nigerian universities during the study period. Participation was voluntary and anonymous.

Sampling approach and recruitment

A non-probability sampling approach was used because the study was administered online. The questionnaire link was primarily disseminated through departmental, faculty, course, and level-based WhatsApp groups for Nigerian university students. Students were instructed to forward the link to their classmates in order to connect with a diverse student body from different institutions.

Data collection procedure and timeframe

The Google Forms questionnaire was used to gather information (data) from respondents online. The response window was from 18 December 2025 to 18 January 2026. Google Forms

automatically recorded timestamps for each submission within this period. A total of 700 valid responses were retained for analysis after basic screening.

Instrument and measures

The questionnaire contained 30 items and was designed to be completed in approximately 5 to 7 minutes. It covered seven measurement areas:

1. respondent background and digital access: age group, gender, level of study, faculty or college, smartphone ownership, laptop ownership, internet access quality, and frequency of data purchase
2. AI exposure and intensity: whether the student had ever paid for an AI subscription, what their primary tool was how often they used it for schoolwork, and whether they had used generative AI
3. Academic uses of AI include concept clarification, reading material summaries, assignment ideas and outlines, assignment draughting, exam practice, and research assistance.
4. Verification and study techniques: confirming AI responses, identifying incorrect AI outputs, reviewing and revising outputs, and keeping up with course readings
5. Perceived policy communication, individual comprehension of permissible use, integrity perspective on submitting AI output as one's own, and perceived peer noncompliance with regulations comprise policy awareness and integrity orientation.
6. Indicators of the student learning experience include perceived diminished deep-thinking effort, dependence on AI to initiate or finish tasks, and perceived unfair advantage because of unequal access.
7. A five-point Likert scale was used to measure items 14 through 30: strongly disagree, disagree, neutral, agree, strongly agree.

Data preparation and coding

Before analysis, the dataset was screened to retain only records with consent. The Likert items were recoded for association rule mining using a binary scheme consistent with the study aim of identifying clear co-occurrence patterns:

Agree and strongly agree were coded as 1, representing high endorsement of the item Neutral, disagree, and strongly disagree were coded as 0

Frequency of AI use was further recoded to reflect meaningful intensity for pattern analysis:

Frequent use was defined as daily or a few times a week

Other categories were treated as not frequent for the binary frequent use item

These coding choices were applied consistently across the dataset to create a transaction-like basket of items for each respondent.

Data analysis

Analysis was carried out in two stages.

Stage 1: Descriptive Analysis

Frequencies and percentages were computed to describe the prevalence of generative AI use, frequency of use, tool preference, and the main academic purposes of use. These results addressed Objective 1.

Stage 2: Association Rule Mining

Association rule mining was used to identify patterns of behaviours and perceptions that tend to occur together in the data. The apriori algorithm was applied to the binary item basket derived from the survey responses. To ensure clarity for readers who may not be familiar with data mining terminology, the three rule evaluation measures are explained in practical terms below.

Support indicates how common a particular pattern is in the dataset. It represents the proportion of respondents for whom both the antecedent and the consequent occur together. In a sample of 700 students, a support value of 0.05 means that the pattern applies to at least 35 students. This measure helps ensure that reported rules are not based on very small or unstable subgroups.

Confidence reflects how likely the consequent is to occur when the antecedent is present. In simple terms, it answers the question: if students report X, how likely are they also to report Y? For example, a confidence value of 0.80 indicates that 80 percent of students who report X also report Y. Confidence therefore captures the strength of the conditional relationship between behaviours or perceptions.

Lift compares the observed co-occurrence of two items with what would be expected if they were unrelated. A lift value of 1 suggests no meaningful association beyond chance. Values greater than 1 indicate that the items occur together more often than expected under independence, while values below 1 indicate the opposite. For instance, a lift of 2.0 suggests that the combination appears twice as frequently as would be expected if the two items were statistically independent.

Given the sample size and the aim of identifying stable and substantively meaningful patterns, conservative rule selection thresholds were applied. A minimum support of 0.05 ensured that each retained rule applied to at least 35 students. A minimum confidence of 0.70 was selected to retain only relatively strong conditional relationships. A minimum lift of 1.20 ensured that reported rules represented associations that were meaningfully stronger than what would occur by chance alone. Rules were ranked primarily by lift, followed by confidence and support. All identified patterns are interpreted as co-occurring relationships rather than causal effects.

To retain interpretable and stable rules, given the sample size, the rule selection thresholds were set as follows:

Minimum support: 0.05

Minimum confidence: 0.70

Minimum lift: 1.20

Rules were ranked primarily by lift, then by confidence and support. The mined rules were interpreted as co-occurring patterns rather than causal effects.

Threshold Justification

Given the exploratory nature of the study and the sample size of 700 respondents, the threshold values were selected to balance stability, interpretability, and substantive relevance. A minimum support of 0.05 ensured that each retained rule applied to at least 35 students. This decision reduced the likelihood of highlighting patterns driven by very small subgroups that may not be practically meaningful within the broader student population. Lower support thresholds would have generated a larger number of rules, including rare combinations that may reflect noise rather than consistent behavioural tendencies.

A minimum confidence of 0.70 was chosen to retain only relatively strong conditional relationships. In practical terms, this means that at least 70 percent of students exhibiting the antecedent also exhibited the consequent. This threshold helps ensure that reported rules represent consistent behavioural co-occurrence rather than weak or unstable associations. Using a lower confidence threshold would increase rule quantity but reduce interpretive strength, while a much higher threshold could eliminate meaningful but slightly more moderate patterns.

A minimum lift of 1.20 was applied to ensure that retained rules reflected associations meaningfully stronger than chance. Lift values close to 1 indicate little deviation from statistical independence. By requiring lift to exceed 1.20, the analysis focused on behavioural combinations that occur at least 20 percent more frequently than expected under independence. This improves substantive interpretation by highlighting patterns that are not merely common, but structurally linked within student responses.

Together, these thresholds shaped rule interpretation by prioritizing patterns that are sufficiently frequent, conditionally strong, and meaningfully different from chance. As a result, the reported rules represent stable co-occurring behavioural tendencies within the student population rather than isolated or incidental combinations. However, it is important to note that different threshold choices would yield different sets of rules, reflecting the exploratory nature of association rule mining.

Ethical considerations

Participation was voluntary, and informed consent was obtained at the beginning of the questionnaire. No identifying information, such as names, phone numbers, or matric numbers, was collected. Data were used strictly for academic research purposes and were analyzed in aggregate.

Results

Table 1. Descriptive characteristics of respondents (n = 700)

Variable	Category	Frequency	Percentage (%)
Age group	18–20 years	236	33.7
	21–23 years	272	38.9
	Other age groups	192	27.4
Gender	Male	359	51.3
	Female	323	46.1

	Prefer not to say	18	2.6
Level of study	200–400 level	450	64.2
	Other levels	250	35.8
Faculty/College	Sciences and Engineering	198	28.3
	Social Sciences and Education	211	30.1
	Other faculties	291	41.6

Note. "Other age groups" include respondents below 18 years and above 23 years. "Other levels" include 100-level, 500-level and above, and postgraduate students. Faculty groupings were collapsed to improve clarity and reduce table length.

The descriptive statistics indicate that the respondents were largely within the core undergraduate age range, with most aged 18-23 years. Gender representation was fairly balanced, suggesting that the sample reflects both male and female student experiences. A majority of the respondents were at the 200-400 level, which is typically associated with a higher academic workload and sustained engagement with coursework. Participation was drawn from a wide range of faculties, with notable representation from both science-oriented disciplines and social science and education-related fields. This spread across levels and disciplines suggests that the findings are not confined to a narrow academic group. Overall, the demographic profile indicates a diverse, academically active student population, providing a suitable foundation for examining patterns of generative AI use among university students in Nigeria.

In addressing the question1 and Objective 1, the tables below show the prevalence status of the use of AI

Table 2. Prevalence, frequency, most used tools, and academic purposes of generative AI use (n = 700)

Panel A. Prevalence and paid use (all respondents)

Indicator	**Category**	**N**	**Percentages**
used generative AI before	yes	592	84.6
used generative AI before	no	108	15.4
Total		700	
ever paid for an AI subscription	yes	67	9.6
ever paid for an AI subscription	no	633	90.4
Total		700	

Prevalence of generative AI use was high among the students surveyed. Out of the 700 respondents, 592 students (84.6 percent) reported that they had used a generative AI tool before, while 108 students (15.4 percent) reported they had not. Paid subscription use was relatively low, as only 67 students (9.6 percent) indicated they had ever paid for any AI subscription, compared to 633 students (90.4 percent) who had not.

Panel B. Frequency of use for academic work (all respondents)

Frequency category	**N**	**Percentages**
Daily	146	20.9
a few times a week	189	27.0
about once a week	114	16.3
a few times a month	97	13.9
Rarely	40	5.7
Never	114	16.3

In terms of frequency, regular use was common. Daily use was reported by 146 students (20.9 percent), while 189 students (27.0 percent) reported using AI a few times a week. Taken together, 47.9 percent of respondents fell into the frequent use category (daily or a few times a week). A further 114 students (16.3 percent) used AI about once a week, 97 students (13.9 percent) used it a few times a month, and 40 students (5.7 percent) used it rarely. Those reporting never using AI were 114 students (16.3 percent), which is consistent with the 15.4 percent who indicated they had never used generative AI before, suggesting a small level of response variation across the two items.

Panel C. Most used generative AI tool (all respondents)

Tool	**N**	**Percentages**
Chatgpt	323	46.1
Gemini	110	15.7
Copilot	56	8.0
Claude	37	5.3
Other	37	5.3
i am not sure	137	19.6

Regarding the most commonly used tools, ChatGPT was the dominant option, selected by 323 respondents (46.1 percent). This was followed by Gemini (110 respondents, 15.7 percent) and Copilot (56 respondents, 8.0 percent). Claude and Other tools were each reported by 37 respondents (5.3 percent). Notably, 137 respondents (19.6 percent) selected “I am not sure,” which suggests that a sizeable number of students use generative AI through shared links, embedded platforms, or informal access routes without paying attention to specific tool names.

Panel D. Academic purposes (agree or strongly agree), among AI users only (n = 592)

Academic purpose	**N**	**Percentages**
understand difficult topics	389	65.7
generate assignment or project ideas and outlines	358	60.5
exam practice questions	341	57.6
summarise lecture notes or readings	332	56.1
research support	317	53.5
draft parts of assignments or project write ups	313	52.9

Note: Panel D percentages are computed using only respondents who reported having used generative AI (n = 592).

The academic purposes for which students used generative AI were also clear. Focusing on those who agreed or strongly agreed with each purpose item, the highest reported use was for understanding difficult topics (65.7 percent among AI users), followed by generating assignment or project ideas and outlines (60.5 percent), and practicing for exams through practice questions (57.6 percent). Summarizing lecture notes or reading materials was also common (56.1 percent), while research support activities such as identifying keywords, structuring topics, or simplifying journal articles were reported by 53.5 percent of AI users. Drafting parts of assignments or project write-ups, though still substantial, was comparatively lower but remained prominent (52.9 percent among AI users). Overall, the pattern suggests that students are not using AI for a single, narrow purpose; rather, they span both learning support activities and assessment-related tasks, with a stronger emphasis on comprehension and study preparation than on outright drafting.

Association rule mining was applied to the binary item basket derived from the survey (Agree or Strongly agree coded as 1, otherwise 0). Rules were retained using a minimum support of 0.05, a minimum confidence of 0.70, and a minimum lift of 1.20. The results below present the most meaningful co-occurring patterns linking AI use behaviours, verification practices, policy awareness, and learning experiences. These patterns are interpreted as associations and not as cause and effect.

Table 2A. Policy communication and policy understanding rules

Rule (antecedent → consequent)	**support**	**confidence**	**lift**
Laptop_Yes and PolicyComm_High → PolicyAware_High	0.109	0.864	2.786
PolicyComm_High → PolicyAware_High	0.161	0.813	2.622
Internet_Good and PolicyComm_High → PolicyAware_High	0.083	0.806	2.599
CheckEdit_High and PolicyComm_High → PolicyAware_High	0.107	0.824	2.659

The clearest policy signal in the data is that communication of rules goes together with students' understanding of what acceptable AI use means. The rule PolicyComm_High → PolicyAware_High has strong confidence (0.813) and high lift (2.622), showing that policy understanding is far more common among students who report that rules were communicated than would be expected by chance. Access-related factors also strengthen this pattern. For example, where students have a laptop and also perceive policy communication, policy awareness is even more likely (confidence 0.864, lift 2.786). Taken together, these rules suggest that when institutions actually communicate guidance and students have the basic digital capacity to engage with it, understanding of acceptable use tends to be higher.

Table 2B. Frequent AI use and academic use patterns with verification and editing

Rule (antecedent → consequent)	**support**	**confidence**	**lift**
Use_Draft_High and Verify_High → AI_Frequent	0.287	0.893	1.867
Use_Summarise_High and CheckEdit_High → AI_Frequent	0.280	0.841	1.758
AI_Frequent and Verify_High → Use_Draft_High	0.287	0.810	1.807

These rules show that the frequent AI use in this sample is not casual. It clusters around serious academic purposes such as drafting and summarizing, and it also co-occurs with quality control practices for a meaningful proportion of students. For instance, among students who report using AI for drafting and also report verifying AI answers, a very large share are frequent AI users (confidence 0.893). Similarly, students who use AI for summarizing and report checking and editing outputs are also likely to be frequent users (confidence 0.841). This pattern is important because it indicates that frequent use is often tied to deliberate academic workflows, where students combine AI assistance with some level of review and verification.

Table 2C. Frequent AI use, reliance, and learning experience patterns

Rule (antecedent → consequent)	**support**	**confidence**	**lift**
Use_Draft_High and Reliance_High → AI_Frequent	0.259	0.938	1.960
Use_Summarise_High and Reliance_High → AI_Frequent	0.266	0.930	1.943
Use_Summarise_High and DeepThinkingReduced_High → AI_Frequent	0.289	0.922	1.927
Use_Draft_High and Use_ResearchSupport_High → AI_Frequent	0.283	0.925	1.933
Use_Draft_High and StillRead_Low → AI_Frequent	0.131	0.929	1.942

The learning experience side of the rules suggests that frequent AI use tends to come with bundled behaviours that matter for student development. Strong patterns connect frequent use with reliance. Where students report that it becomes harder to start or complete tasks without AI, they are very likely to also be frequent users, especially when they use AI for drafting or summarizing (confidence about 0.93 to 0.94, lift about 1.94 to 1.96). Another important co-occurrence is between summarizing use and the perception that AI reduces the effort of deep thinking, which also strongly links to frequent use (support 0.289, confidence 0.922). The rule involving StillRead_Low has limited coverage but is still notable. It suggests that a subgroup of frequent users combines drafting with weaker engagement with course materials. In practical terms, the pattern is not that all AI users neglect reading, but that when lower reading discipline co-occurs with drafting, it almost always falls within the frequent user segment.

Objective 3 was addressed by translating the observed prevalence patterns and the strongest association rules into practical, evidence-based implications for guidance and student support within Nigerian universities. The emphasis is on what the data suggest universities should prioritize, rather than making causal claims.

Table 3A. Evidence signals from the data and what they imply for responsible guidance

evidence signal from survey and rules	**what it implies for university guidance and support**
High AI uptake in the sample and a large share of frequent users	AI use is already part of students' learning routines, so silence or prohibition without support may be unrealistic. Universities need clear, practical guidance that recognizes current student practice.
Low perceived policy communication and modest policy understanding	Many students appear to be learning AI use informally. This supports the need for visible, repeated communication of rules in student-friendly language, not just policy documents.
Strong rule showing policy communication co occurs with policy understanding (PolicyComm_High → PolicyAware_High; confidence 0.813; lift 2.622)	Policy communication is a core leverage point. When guidance is communicated, students are much more likely to report that they understand acceptable use. This suggests that strengthening communication channels can improve compliance and clarity.
Frequent AI use clusters with checking and editing, and also with verification	Student practice includes both responsible and risky elements. Support should focus on strengthening verification skills, source checking, and responsible referencing, rather than treating all use as misconduct.

Frequent AI use strongly co-occurs with reliance and reduced deep thinking effort	Student support should include guidance on balanced use, encouragement of independent problem-solving, and the development of habits that prevent overdependence.
Students report unequal access concerns, and only a small share pay for subscriptions	Universities should consider equity. Guidance should not assume that all students can afford premium tools. Basic support, free resources, and digital access strategies are needed to reduce unfair advantage.

The strongest practical message from the results is that universities are not starting from zero. Students are already using generative AI widely, and many use it frequently for core academic purposes. At the same time, policy visibility and clarity appear weak, and this matters because policy communication shows a strong association with policy understanding. The implication is straightforward. If institutions want responsible use, they must first ensure students actually see and understand the rules. In addition, the co occurring patterns show that frequent AI use has two sides. It often comes with checking, editing, and verification, but it also appears alongside reliance and reduced deep thinking effort for a substantial subgroup. This points to a support approach that strengthens academic skills and responsible practice rather than relying only on enforcement.

Table 3B. Suggested student support package mapped to the pattern evidence

Support area	**What the university can provide**	**Pattern evidence this responds to**
Clear acceptable use guidance	short departmental guidelines, examples of allowed and not allowed uses, assessment-specific rules, simple FAQs	low policy communication and understanding, plus strong co-occurrence between communication and understanding
AI literacy and verification training	short modules on fact checking, using credible sources, asking AI for references and verifying them, identifying hallucinations	frequent use co-occurring with verification and editing, plus reported awareness that AI can be wrong
Responsible referencing and transparency	guidance on how to acknowledge AI assistance, integrity reminders, sample statements for disclosures	high agreement that submitting AI work as own is wrong, but mixed policy clarity suggests students need practical direction
Study skills support to prevent overreliance	sessions on independent thinking, structured learning routines, problem solving without AI first, then using AI for support	reliance high and reduced deep thinking effort co-occurring with frequent AI use

Equity and access support	improve campus WiFi, create digital support hubs, provide free access to learning resources, avoid requiring paid AI tools for coursework	unequal access concerns and low paid subscription rate
Lecturer and departmental alignment	short staff briefings so lecturers communicate consistent rules and expectations	policy communication is a major leverage point and works better when consistent across lecturers and departments

The support package above is designed to match what the data are already showing about student behaviour. Nigerian university students are using AI as part of their academic survival strategy, especially to understand difficult topics, summarize materials, and prepare for exams. A policy response that focuses only on punishment may not address the reality of use. Instead, the results support a balanced strategy that combines communication, literacy building, academic integrity and clarity, and student support services. The goal is to guide behaviour toward responsible use while protecting core academic outcomes such as independent reasoning and deep learning.

Discussion

The findings from this study indicate that generative AI has already become part of the everyday academic routine of many university students in Nigeria. Rather than remaining a distant or emerging technology, AI tools are now actively used by students to support their learning activities. This pattern reflects a broader global shift in higher education where students increasingly rely on generative AI for tasks such as explaining difficult concepts, summarizing academic materials, generating ideas, and supporting assignment preparation. The high prevalence observed in this study, together with the sizeable proportion of frequent users, suggests that institutional responses based solely on avoidance or blanket restriction may not adequately reflect the realities of student practice within Nigerian universities.

A key insight from the findings is the noticeable gap between student behaviour and institutional clarity regarding AI use. While many students reported using generative AI for academic purposes, levels of perceived policy communication and understanding of acceptable AI use were relatively low. At the same time, the association rule analysis revealed a strong relationship between perceived policy communication and students' understanding of institutional expectations. In practical terms, students who reported that their university or department had communicated guidance on AI use were considerably more likely to report understanding what constitutes acceptable use. This highlights policy communication as a critical leverage point for institutions. Improving the visibility and clarity of guidance is therefore not merely a procedural step but an important strategy for promoting responsible AI use among students. This observation aligns with UNESCO's call for educational institutions to move beyond broad statements about AI and instead

prioritize practical actions that build human capacity and support a human-centered approach to the use of generative technologies in education.

The behavioural patterns identified in the study also reveal a more nuanced picture of how students integrate AI into their learning processes. Frequent use of AI was commonly associated with academically meaningful activities such as drafting ideas, summarizing materials, preparing for examinations, and supporting research-related tasks. Importantly, many students also reported engaging in responsible practices such as checking, editing, and verifying AI generated responses before using them for academic work. This suggests that for many students, AI is incorporated into deliberate study routines rather than being used purely as a shortcut. However, the findings also show that frequent use sometimes co-occurs with reliance on AI and with the perception that AI can reduce the effort required for deep thinking. These patterns do not necessarily imply that AI use automatically weakens learning outcomes. Rather, they suggest that without appropriate guidance and support, some students may gradually become overly dependent on these tools. Consequently, institutional responses should go beyond simple regulation and instead adopt a balanced approach that combines clear rules with practical AI literacy training. Such training could focus on verification skills, transparency in AI use, and responsible referencing practices, while assessment designs may need to emphasize reasoning, originality, and independent engagement with course material.

Another important issue emerging from the findings concerns equity in access to AI technologies. Although generative AI tools were widely used among the respondents, only a small proportion reported paying for AI subscriptions. At the same time, many students expressed concern that unequal access to devices, internet connectivity, or premium AI tools could create unfair academic advantages. This reflects broader concerns in higher education about the digital divide and how disparities in technological access can shape learning opportunities. Nigerian universities, therefore, need to remain mindful of these inequalities when developing policies or teaching practices related to AI use. Practical steps may include avoiding course requirements that assume access to paid AI tools, strengthening campus internet connectivity where possible, and providing guidance that helps students make effective use of freely available AI platforms.

It is also important to recognize that the patterns identified in this study represent associations rather than causal relationships. Association rule mining is designed to reveal behaviours that frequently occur together, but it does not determine whether one factor directly causes another. For example, the strong relationship observed between perceived policy communication and policy understanding suggests that students who report seeing guidance are more likely to report understanding institutional expectations. However, the analysis cannot establish whether communication itself produces this understanding, or whether students who are already more attentive to institutional information simply report both. Similarly, the associations linking frequent AI use to reliance and reduced effort in deep thinking should be interpreted as behavioural tendencies rather than direct cause-and-effect relationships. These findings, therefore, highlight

areas that warrant further investigation, particularly through longitudinal or experimental research designs that can examine causal pathways more directly.

Despite these limitations, the study provides several useful insights for policy and practice within Nigerian universities. The strong association between policy communication and policy understanding suggests that clearer, more visible guidance could significantly improve students' responsible AI use. Institutions may therefore benefit from integrating AI guidance into course outlines, departmental orientations, learning management systems, and assessment instructions so that students encounter these expectations consistently throughout their academic experience.

In addition, the patterns linking frequent AI use to verification and editing practices suggest that many students are already aware of the need to critically evaluate AI-generated outputs. Universities can build on this awareness by introducing targeted AI literacy initiatives such as short workshops or training modules that focus on fact-checking, identifying inaccurate AI responses, verifying sources, and properly acknowledging AI assistance in academic work. Such interventions would help students move from informal experimentation toward more responsible and academically sound use of AI tools.

At the same time, the association between frequent AI use, reliance on it, and reduced effort in deep thinking highlights the need for complementary support for study skills. Universities may need to encourage learning practices that balance the benefits of AI with the development of independent reasoning. This could include assessment designs that require students to explain their thought processes, reflective components in assignments, or classroom activities that emphasize problem solving and conceptual understanding. By strengthening these learning structures, institutions can harness the advantages of generative AI while safeguarding key educational goals such as critical thinking and intellectual independence.

Finally, the concerns raised by students about unequal access to digital resources underscore the importance of addressing equity in AI related policies. Expanding campus internet access, supporting digital learning hubs, and ensuring that course expectations do not assume access to premium AI tools may help reduce disparities among students. Addressing these structural issues will be essential for ensuring that the benefits of generative AI are shared more fairly across the student population.

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QUESTIONNAIRE

Discovering Patterns of Generative AI Use Among University Students: Evidence from an Online Survey and Association Rule Mining

Hello. You are invited to take part in a short academic survey on how university students use generative AI tools such as ChatGPT, Gemini, Copilot, Claude, and similar apps for learning and schoolwork. This survey is strictly for research purposes. Participation is voluntary. Your responses are anonymous and no name, phone number, or matric number is required. You can stop at any time. The questionnaire takes about 5 to 7 minutes to complete. Please answer honestly and fill it only once. Thank you.

Questions

1. I have read the information above and I agree to participate.
   Options: Yes, No
2. Age group
   Options: Under 18, 18 to 20, 21 to 23, 24 to 26, 27 and above
3. Gender
   Options: Male, Female, Prefer not to say
4. Level of study
   Options: 100 level, 200 level, 300 level, 400 level, 500 level and above, Postgraduate
5. Faculty or college
   Options: Arts, Social Sciences, Education, Sciences, Engineering, Agriculture, Law, Medicine and Health Sciences, Business Administration, Other
6. Do you have a personal smartphone
   Options: Yes, No
7. Do you have a personal laptop
   Options: Yes, No
8. How would you rate your internet access for academic work
   Options: Very poor, Poor, Fair, Good, Very good
9. On average, how often do you buy data in a week
   Options: Rarely, 1 to 2 times, 3 to 4 times, Almost daily, Daily
10. Have you ever used a generative AI tool
    Options: Yes, No
11. Which tool do you use most often
    Options: ChatGPT, Gemini, Copilot, Claude, Other, I am not sure

12. How often do you use generative AI for academic work
    Options: Daily, A few times a week, About once a week, A few times a month, Rarely, Never
13. Have you ever paid for any AI subscription
    Options: Yes, No
14. I use generative AI to understand difficult topics when I study.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
15. I use generative AI to summarise lecture notes or reading materials.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
16. I use generative AI to generate assignment or project ideas and outlines.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
17. I use generative AI to draft parts of my assignments or project write ups.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
18. I use generative AI to practise for exams, including generating practice questions.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
19. I use generative AI to support research tasks such as keywords, structure, or simplifying journal articles.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
20. I usually verify AI answers using lecture notes, textbooks, lecturers, or credible websites.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
21. I have noticed that AI sometimes gives wrong or misleading answers.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
22. I check and edit AI output properly before I use it for schoolwork.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
23. Even when I use AI, I still read my course materials properly.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
24. My university or department has communicated rules or guidance on acceptable AI use.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
25. I personally understand what counts as acceptable AI use in assignments in my institution.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
26. Submitting AI generated work as my own without acknowledgment is wrong.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
27. Many students use AI in ways that may not align with university rules.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
28. Using AI sometimes reduces my effort to think deeply before answering academic questions.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree

29. When I do not have access to AI, it becomes harder for me to start or complete academic tasks.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
30. Unequal access to data, devices, or paid AI tools creates unfair academic advantage among students.
    Options: Strongly disagree, Disagree, Neutral, Agree, Strongly agree