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Challenges, Prospects and Readiness for AI-Powered Personalised Learning in Science Teacher Education: Evidence from Jigawa State College of Education, Gumel

Aminu Surajo Usman[1]*, Abdul Mati Gada[2], Muhammad Sunusi Ahmad[1], Yusuf Abdullahi Magama[1], and Ibrahim Sabitu[3]

[1] Department of Biology, Jigawa State College of Education, Gumel, Jigawa State, Nigeria
[2] Department of Mathematics, Jigawa State College of Education, Gumel, Jigawa State, Nigeria
[3] Department of Physics, Jigawa State College of Education, Gumel, Jigawa State, Nigeria

*Corresponding author: aminususman@jscoeg.edu.ng

Abstract

This study examined the challenges, prospects and readiness for AI-powered personalised learning in science teacher education at Jigawa State College of Education, Gumel. A cross-sectional descriptive survey was conducted among 50 science lecturers and 201 final-year science student-teachers, supported by an institutional ICT audit and frequency analysis of short open-ended responses. Internal consistency was good to excellent across the ten construct scales (Cronbach's α = .85–.93). Mean scores for awareness, readiness and perceived barriers were above the scale midpoint in both groups, whereas institutional support among lecturers (M = 2.30, SD = 0.86) and institutional access among students (M = 2.34, SD = 0.84) were below it. Awareness was not significantly associated with readiness among lecturers, r(48) = .135, p = .350, or student-teachers, r(199) = −.002, p = .979. The ICT audit yielded 35 of 54 points (64.8%), with notable deficiencies in internet and Wi-Fi access, staff computers and e-learning provision; no responsible AI policy was identified. Open-ended responses indicated interest in AI for access to scientific information, simulations and personalised learning, alongside concerns about cost, infrastructure, technical support and training. Overall, the findings suggest that interest in AI is present, but its responsible integration is constrained by institutional readiness.

Keywords: *Artificial intelligence; personalised learning; science teacher education; lecturer readiness; student-teachers; ICT infrastructure; Nigeria*

1. Introduction

Artificial intelligence (AI) is becoming increasingly visible in education, with growing interest in its capacity to support personalised learning and improve classroom efficiency. Within teacher education, its particular relevance lies in preparing future teachers to use AI-informed approaches in instructional planning and learner support (Guan et al., 2025; Kohnke et al., 2025).

These possibilities have emerged alongside persistent difficulties. Studies of teacher education report inadequate training, weak institutional support, limited infrastructure, ethical concerns and insufficient policy direction (Aliyu & Muhammad, 2025; Daher, 2025; Kohnke et al., 2025; Tsakeni & Nwafor, 2025). Access to digital tools is necessary, therefore, but is unlikely on its own to secure meaningful AI integration.

AI readiness is generally now understood as extending beyond simple awareness of the technology. It includes cognitive understanding, practical ability, professional vision and ethical judgement, while willingness to integrate AI may also be shaped by pedagogical knowledge, perceived usefulness and self-efficacy (Sun et al., 2024; Wang et al., 2023; Yue et al., 2024). An educator may consequently be familiar with AI yet lack the practical knowledge or confidence required to use it effectively.

The distinction is especially relevant in the preparation of pre-service teachers. Although many pre-service teachers recognise the value of AI for personalised learning and classroom efficiency, they often have an incomplete understanding of its basic principles, ethical implications and place in their future professional work (Guan et al., 2025; Kohnke et al., 2025). Teacher-education programmes have a responsibility, therefore, to prepare future teachers for critical, responsible and effective use of the technology.

Evidence from Nigeria gives weight to this concern. Ayanwale et al. (2024) found that knowledge and understanding of AI were important components of AI literacy among pre-service teachers and called for stronger preparation for future classrooms. Another Nigerian study identified basic AI knowledge as an important determinant of pre-service teachers' intention to learn AI (Sanusi et al., 2024). General awareness, it would appear, needs to be followed by organised opportunities for developing practical knowledge and competence.

Research from Nigeria and the wider region also points to inadequate infrastructure, limited training, ethical concerns and weak policy preparedness as continuing constraints on AI adoption. Such difficulties have been reported among teacher educators, college-of-education stakeholders and other groups involved in teacher preparation (Aliyu & Muhammad, 2025; Eke, 2024; Tsakeni & Nwafor, 2025). Institutional support sustained professional development and clear guidance on responsible use are consequently central to the adoption process.

The issue assumes added importance in science teacher education. Science teaching involves the explanation of difficult concepts, practical and inquiry-based work, simulations and attention to differences in how students learn. These features make it a potentially useful setting for AI-supported personalised learning, although effective application also requires subject-specific pedagogical judgement, practical competence and ethical awareness (Abdulayeva et al., 2025; Techakosit et al., 2026; Ugosor et al., 2025).

It is against this background, the present study examined the challenges, prospects and readiness for AI-powered personalised learning in science teacher education at Jigawa State

College of Education, Gumel. Specifically, it assessed AI awareness and literacy among science lecturers and student-teachers, examined digital access and institutional support, identified perceived barriers, tested the relationship between awareness and readiness, and examines views on the possible use of AI-supported personalised instruction in science and in future teaching practice.

2. Methodology

2.1 Study Design and Setting

A cross-sectional descriptive survey design was employed and supplemented by an institutional ICT-infrastructure audit and an analysis of short open-ended questionnaire responses. The study was conducted at Jigawa State College of Education, Gumel, Nigeria.

2.2 Participants and Sampling

The study population comprised 420 final-year science student-teachers and eligible lecturers in Biology, Chemistry, Physics and Integrated Science. A sample of 201 student-teachers was determined using a finite-population approach, allocated proportionately across the four areas of specialisation and selected through stratified random sampling. Because the lecturer population was comparatively small, a near-census approach was used: all eligible lecturers were invited, and 50 completed questionnaires were retained for analysis.

2.3 Study Instruments

Separate but parallel questionnaires were administered to lecturers and student-teachers. Each instrument included demographic and access variables, five construct scales rated from 1 (strongly disagree) to 5 (strongly agree), and three short open-ended questions. The lecturer questionnaire contained 35 Likert items measuring AI Awareness (8 items), Readiness (8 items), Institutional Support (7 items), Perceived Barriers (8 items) and Future Orientation (4 items). The student questionnaire contained 31 Likert items measuring AI Awareness (8 items), Learning Use (7 items), Institutional Access (5 items), Perceived Barriers (7 items) and Readiness (4 items). AI-supported personalised learning was represented by one readiness-related item in each instrument and was therefore interpreted at item level rather than as a separate validated scale.

2.4 Institutional ICT Audit

The institutional ICT audit comprised 18 indicators addressing computers, internet connectivity, electricity and backup power, e-learning facilities, technical support, institutional policies, digital training, data protection and accessibility support. Each indicator was scored from 0 (not available) to 3 (available and adequate), giving a maximum possible score of 54. The summed score was also expressed as a percentage of the maximum obtainable score. The audit was conducted through direct observation of ICT facilities and departmental units, review of relevant institutional documents, and verification with the head of ICT unit.

2.5 Validity, Reliability, and Ethical Considerations

Data validity was established through expert review of item relevance prior to administration. Internal consistency was assessed with Cronbach's alpha (95% CIs from 3,000 respondent-level bootstrap resamples); all ten construct scales showed good-to-excellent reliability (α = .85–.93; see Results, Table 2). Ethical clearance was obtained from the JSCOE Gumel

Research Directorate unit prior to data collection; participation was voluntary and anonymous, with no personally identifying information collected.

2.6 Data Analysis

The two datasets were checked for duplicate identifiers, missing responses and values outside the permitted Likert range. All 50 lecturer records and 201 student-teacher records satisfied these checks and were retained. Demographic and access variables were labelled according to the confirmed coding key. Construct scores were calculated as unweighted arithmetic means of their constituent items; no reverse-keyed items were identified in the supplied scoring information. Higher barrier scores therefore indicated stronger perceived barriers. Internal consistency was assessed separately for each construct and respondent group using Cronbach's alpha, with percentile 95% confidence intervals obtained from 3,000 respondent-level bootstrap samples. Descriptive statistics comprised frequencies, percentages, means and standard deviations. At item level, agreement was defined as a response of 4 (agree) or 5 (strongly agree). Pearson's product-moment correlation was used to examine the association between AI awareness and readiness, with two-sided p values and Fisher-transformed 95% confidence intervals; Spearman's rank correlation was used as a sensitivity analysis. Correlations among the remaining construct scores were exploratory. Identical open-ended statements were counted as recurring response categories after whitespace normalisation and summarised using frequencies and percentages; they were not treated as interview data or quoted as spontaneous narratives.

Data were prepared, coded and checked in Microsoft Excel. The cleaned datasets were subsequently analysed in Python using pandas 2.2.3, NumPy 2.3.5 and SciPy 1.17.0. Descriptive statistics, reliability estimates, bootstrap confidence intervals, correlation analyses and item-level agreement rates were calculated from the respondent-level data. Tables and figures were prepared from the verified analytical results. All statistical tests were two-tailed, with statistical significance set at $p < .05$.

3. Results

Results are presented separately for the 50 lecturers and 201 final-year science student-teachers. All completed questionnaires were included in the analysis.

3.1 Sample Characteristics

Of the 50 lecturers, 44 (88.0%) were male and 6 (12.0%) were female. Integrated Science accounted for the largest disciplinary group (n = 18, 36.0%), followed by Biology (n = 16, 32.0%), Chemistry (n = 11, 22.0%) and Physics (n = 5, 10.0%). Half held an M.Sc/M.Ed (n = 25, 50.0%), 20 (40.0%) held a B.Sc/B.Ed and 5 (10.0%) held a Ph.D. Most lecturers had at least 11 years of teaching experience (n = 33, 66.0%). Only 8 (16.0%) had received formal training related to AI or digital teaching tools; 28 (56.0%) owned a personal computer, and 15 (30.0%) had regular internet access for academic work.

Among the 201 student-teachers, 93 (46.3%) were male and 108 (53.7%) were female. Biology was the most common area of specialisation (n = 70, 34.8%), followed by Integrated Science (n = 55, 27.4%), Chemistry (n = 45, 22.4%) and Physics (n = 31, 15.4%). Their mean age was 21.96 years (SD = 2.55; range = 16–30). Formal AI-related training was reported by 24 (11.9%); 111 (55.2%) owned a personal computer and 112 (55.7%) had regular internet access for academic work. Although smartphone ownership was high (n = 187, 93.0%), only

30 (14.9%) owned a laptop. Slightly more than half had previously used an AI-supported tool for learning (n = 103, 51.2%). Table 1 presents the complete sample profile.

Table 1 *Sample Characteristics: Lecturers (N = 50) and Student-Teachers (N = 201)*

Characteristic	Lecturers, n (%)	Students, n (%)
Sex: Male	44 (88.0)	93 (46.3)
Sex: Female	6 (12.0)	108 (53.7)
Department/specialisation: Biology	16 (32.0)	70 (34.8)
Department/specialisation: Chemistry	11 (22.0)	45 (22.4)
Department/specialisation: Physics	5 (10.0)	31 (15.4)
Department/specialisation: Integrated Science	18 (36.0)	55 (27.4)
Qualification: B.Sc/B.Ed	20 (40.0)	—
Qualification: M.Sc/M.Ed	25 (50.0)	—
Qualification: Ph.D	5 (10.0)	—
Teaching experience: 1–5 years	7 (14.0)	—
Teaching experience: 6–10 years	10 (20.0)	—
Teaching experience: 11–15 years	17 (34.0)	—
Teaching experience: ≥16 years	16 (32.0)	—
Age (years), M (SD); range	—	21.96 (2.55); 16–30
Formal AI/digital-teaching training: Yes	8 (16.0)	24 (11.9)
Owns personal computer: Yes	28 (56.0)	111 (55.2)
Regular internet access for academic work: Yes	15 (30.0)	112 (55.7)
Owns smartphone: Yes	—	187 (93.0)
Owns laptop: Yes	—	30 (14.9)
Previously used an AI-supported learning tool: Yes	—	103 (51.2)

Note. Department refers to lecturers' department and students' area of specialisation. Age is reported as mean (standard deviation) and observed range. Dashes indicate that a characteristic was not applicable to that respondent group. Percentages may not total 100 because of rounding.

3.2 Reliability and Descriptive Statistics of Study Constructs

Internal consistency was good to excellent across the ten construct scales (α = .85–.93; Table 2). Among lecturers, the mean scores were 3.50 (SD = 0.78) for awareness, 3.64 (SD = 0.86) for readiness, 2.30 (SD = 0.86) for institutional support, 3.98 (SD = 0.79) for perceived barriers and 3.96 (SD = 0.76) for future orientation. Student-teachers recorded means of 4.04 (SD = 0.78) for awareness, 3.98 (SD = 0.72) for learning use, 2.34 (SD = 0.84) for institutional access, 4.02 (SD = 0.78) for perceived barriers and 3.96 (SD = 0.77) for readiness. Institutional support and access were the only construct means below the scale midpoint of 3.0. Full scale statistics are presented in Table 2, while Figure 1 illustrates the pattern across the two respondent groups.

Table 2 *Reliability and Descriptive Statistics of Study Constructs*

Group	Construct	Items	α	M	SD
Lecturer	Awareness	8	.92	3.50	0.78
Lecturer	Readiness	8	.93	3.64	0.86
Lecturer	Institutional Support	7	.93	2.30	0.86
Lecturer	Barriers	8	.93	3.98	0.79
Lecturer	Future Orientation	4	.88	3.96	0.76
Student	Awareness	8	.93	4.04	0.78
Student	Learning Use	7	.90	3.98	0.72
Student	Institutional Access	5	.90	2.34	0.84
Student	Barriers	7	.92	4.02	0.78
Student	Readiness	4	.85	3.96	0.77

Note. α = Cronbach's alpha; M = mean; SD = standard deviation. Construct scores ranged from 1 to 5, with higher barrier scores indicating stronger perceived barriers.

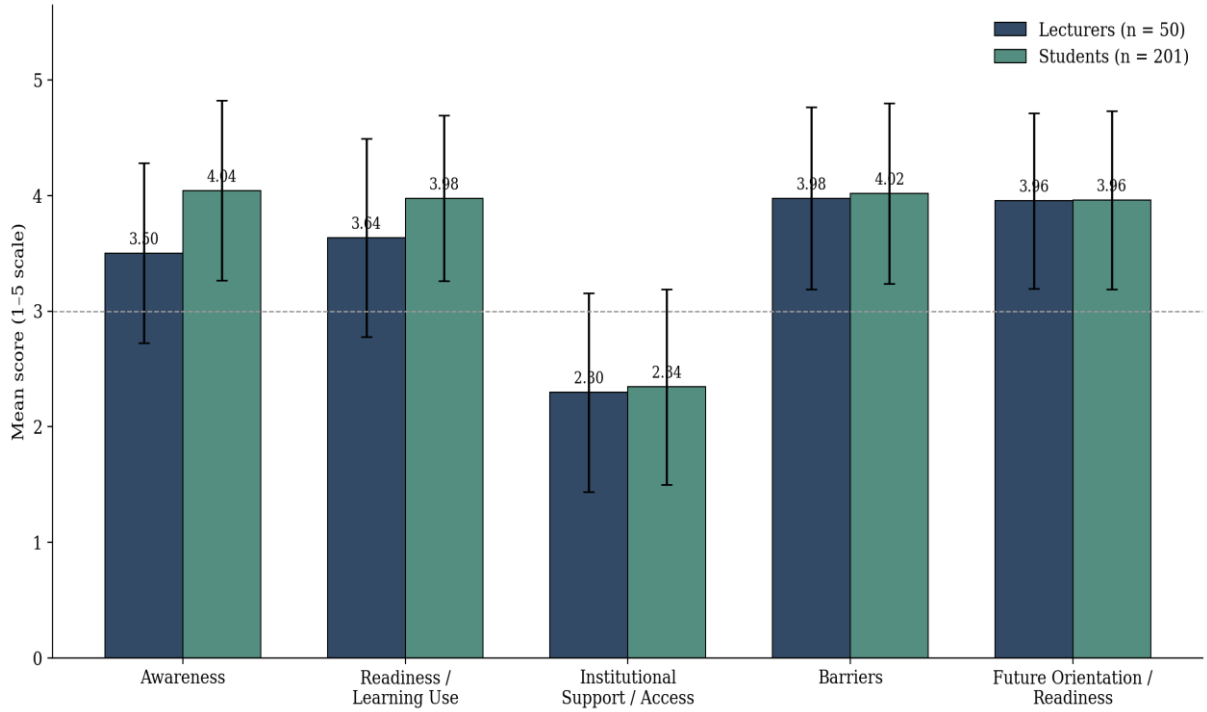


Figure 1. *Mean scores on parallel constructs, lecturers vs. students (error bars = ±1 SD; dashed line = scale midpoint, 3.0). Constructs are matched by parallel position across the two instruments (e.g., lecturers' Institutional Support and students' Institutional Access); construct wording differs slightly by respondent group.*

3.3 Item-Level Agreement and AI-Supported Personalised Learning

Item-level means and agreement rates were examined to identify the most and least strongly endorsed statements within each construct. Agreement was defined as selecting 4 (agree) or 5

(strongly agree) on the five-point scale. Table 3 presents the items with the highest and lowest agreement rates in each construct.

Among lecturers, agreement was highest for the ability to use AI-supported tools to generate practice questions for students (62.0%) and for the view that AI-supported personalised learning could improve science teaching at the college (60.0%). Agreement was lowest for the availability of training opportunities in new teaching technologies (8.0%).

Among student-teachers, agreement was highest for the belief that science teacher education should prepare students to use AI responsibly (74.6%) and the relevance of AI-supported tools to their future careers as teachers (74.6%). Agreement was lowest for the view that the college environment supported technology-based learning (12.9%). Agreement across the five-student institutional-access items varied only slightly, from 12.9% to 13.9%. The least endorsed statement was that the college environment supported technology-based learning (12.9%).

Concerns about inappropriate or excessive AI use received considerably stronger endorsement. Among lecturers, 82.0% expressed concern about students' misuse of AI for assignments, while 76.1% of student-teachers agreed that overdependence on AI could reduce independent thinking. Concerns about responsible use were therefore prominent alongside the reported infrastructural limitations.

The two personalised-learning items were interpreted separately because personalised learning was not measured as a multidimensional validated construct. Sixty per cent of lecturers agreed that AI-supported personalised learning could improve science teaching, while 72.6% of student-teachers agreed that it could improve their academic performance.

Table 3 Highest- and Lowest-Agreement Items within Each Construct

Group	Construct	Position	Item wording (code)	Agreement (%)
Lecturer	Awareness	Highest	I understand how AI can support lesson planning in science education. (B3)	56.0
Lecturer	Awareness	Lowest	I can judge whether information produced by AI tools is accurate. (B4)	42.0
Lecturer	Readiness	Highest	I can use AI-supported tools to generate practice questions for students. (C10)	62.0
Lecturer	Readiness	Lowest	I can use AI-supported tools to prepare lesson notes. (C9)	50.0
Lecturer	Readiness	Personalised learning	AI-supported personalised learning can improve science teaching in this college. (C16)	60.0
Lecturer	Institutional Support	Highest	There is institutional funding or support for digital innovation in teaching. (D23)	16.0
Lecturer	Institutional Support	Lowest	The college provides training opportunities on new teaching technologies. (D22)	8.0
Lecturer	Barriers	Highest	I am concerned about student misuse of AI for assignments. (E28)	82.0

Group	Construct	Position	Item wording (code)	Agreement (%)
Lecturer	Barriers	Lowest	The cost of devices and data is a major barrier to AI integration. (E31)	62.0
Lecturer	Future Orientation	Highest (tied)	I would participate in further training on AI integration if offered. (F33) / AI integration should be included in science teacher education curriculum planning. (F35)	72.0
Lecturer	Future Orientation	Lowest (tied)	I am ready to adopt AI-supported tools in my teaching. (F32) / I would recommend the gradual introduction of AI-supported personalised learning in science teacher education. (F34)	68.0
Student	Awareness	Highest (tied)	I have heard about AI tools used in education. (B1) / I believe I can learn how to use AI tools effectively. (B8)	75.1
Student	Awareness	Lowest (tied)	I understand some basic uses of AI in learning. (B2) / I can identify false or misleading information from digital tools. (B5)	71.1
Student	Learning Use	Highest	AI-supported tools are relevant to my future career as a teacher. (C12)	74.6
Student	Learning Use	Personalised learning	AI-supported personalised learning can improve my academic performance. (C13)	72.6
Student	Learning Use	Lowest	AI-supported tools can help me study at my own pace. (C10)	65.7
Student	Institutional Access	Highest	The college provides enough computer facilities for students. (D17)	13.9
Student	Institutional Access	Lowest	The college environment supports technology-based learning. (D20)	12.9
Student	Barriers	Highest	Overdependence on AI tools may reduce independent thinking. (E26)	76.1
Student	Barriers	Lowest (tied)	Irregular electricity supply affects my use of digital learning tools. (E22) / The cost of internet data and devices is a barrier to my use of such tools. (E27)	71.1
Student	Readiness	Highest	Science teacher education should prepare student-teachers to use AI responsibly. (F31)	74.6
Student	Readiness	Lowest	I am ready to use AI-supported tools for learning science. (F28)	67.2

Note. Agreement was defined as a response of 4 (agree) or 5 (strongly agree). Item wording is reproduced from the study questionnaires. Instrument codes are retained for traceability.

3.4 Relationship Between AI Awareness and Readiness

Among lecturers, AI awareness had a small positive but statistically nonsignificant relationship with readiness, $r(48) = .135$, 95% CI [−.149, .398], $p = .350$. The corresponding Spearman correlation was also nonsignificant, $\rho = .081$, $p = .574$. Among student-teachers, the relationship was negligible and statistically nonsignificant, $r(199) = -.002$, 95% CI [−.140, .137], $p = .979$; Spearman's $\rho = -.013$, $p = .854$. Thus, the findings provided no evidence of a statistically significant relationship between AI awareness and readiness in either respondent group.

3.5 Institutional ICT Infrastructure Audit

The 18-item institutional audit produced 35 of a possible 54 points (64.8%; mean item score = 1.94/3). Power supply, backup power, ICT policy, data privacy and security, and accessibility support each received a score of 3. Campus internet, Wi-Fi coverage, staff computers and the e-learning platform were rated 1/3, while responsible-AI policy provision received 0/3 (Figure 2). The overall score indicates that some institutional resources were available, but important weaknesses remained in the infrastructure most directly required for routine digital teaching and learning.

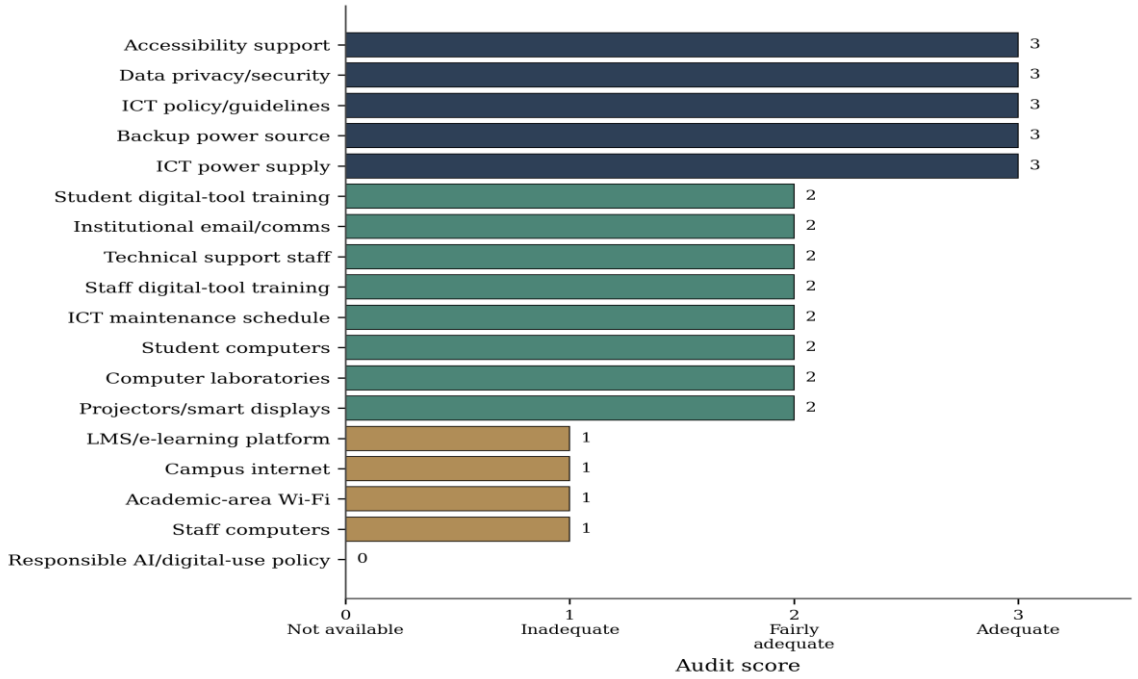


Figure 2. *Institutional ICT resource audit scores across 18 items (0 = not available, 3 = adequate).*

3.6 Open-Ended Response Categories

The short open-ended responses were organised as recurring response categories and reported using frequencies rather than as qualitative narratives. Table 4 summarises the leading response categories. Among lecturers, the most frequent perceived prospect was improved access to current scientific knowledge and simulations (20.0%). Provision of tools and facilities, and improvement of computer laboratories or internet infrastructure, were the leading support needs (18.0% each). Lecturers also referred to the possible contribution of AI to personalised learning and science teaching.

Table 4 *Leading Response Category per Open-Ended Field*

Group	Field	Leading response category	n	%
Lecturer	Prospects	Enhances access to up-to-date scientific knowledge/simulations	10	20.0
Lecturer	Obstacles	Lack of computers/internet access; insufficient AI tools; high cost (tied)	7	14.0
Lecturer	Support needed	Provision of tools/facilities; improved lab/internet infrastructure (tied)	9	18.0
Student	Benefits	Access to reliable information and low-cost learning resources	33	16.4
Student	Problems	Limited computer/internet access; poor internet/skills; tech support (tied)	25	12.4
Student	Training needed	Effective AI use, digital literacy, and critical-thinking training	28	13.9

Note. Categories represent recurring identical or standardised short responses and should not be interpreted as themes derived from interview data.

Among student-teachers, access to reliable information and low-cost learning resources was the most frequent perceived benefit (16.4%), while the leading training need concerned effective AI use, digital literacy and critical thinking (13.9%). Both groups identified limited computer and internet access, cost and inadequate technical support as important obstacles. Figure 3 presents the five most frequently reported obstacles or problems in each group. These frequencies describe the responses provided by participants and should not be interpreted as evidence of thematic saturation or as equivalent to interview-based qualitative themes.

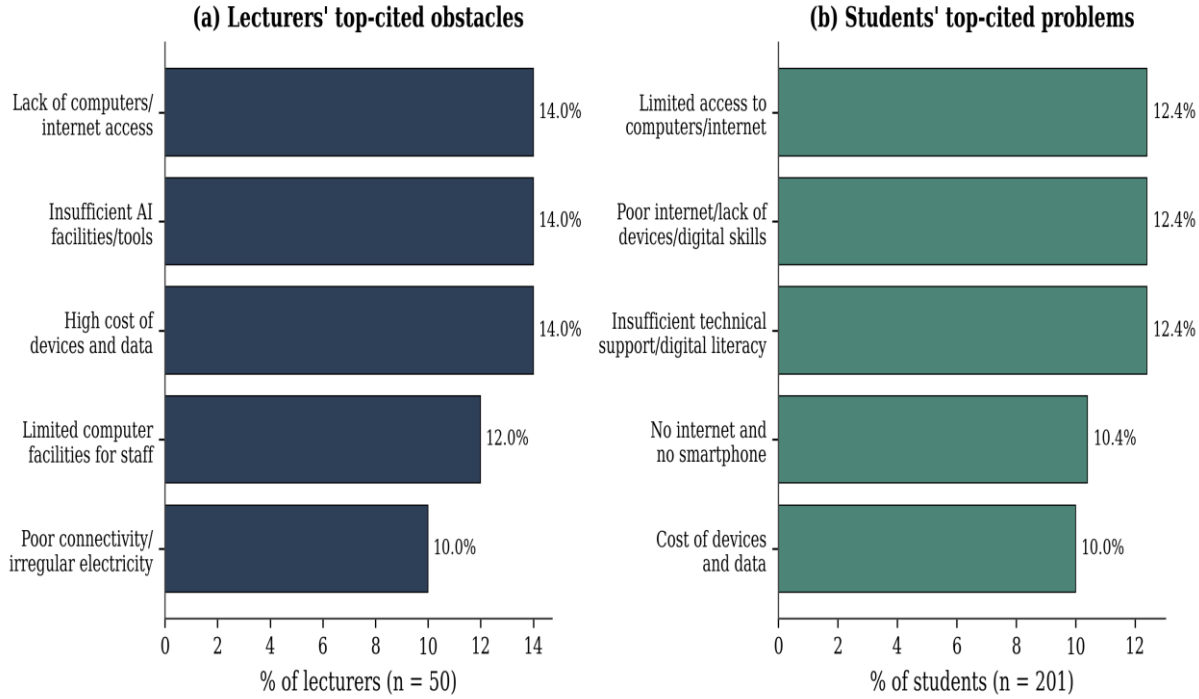


Figure 3. *Top five most frequently cited obstacles to AI integration reported by lecturers (a) and problems reported by students (b).*

4. Discussion

The findings portray AI integration in science teacher education at Jigawa State College of Education, Gumel, as an area of considerable promise operating within weak institutional conditions. Lecturers and student-teachers reported relatively favourable awareness and readiness, while also recognising substantial barriers to adoption. Institutional support and access received the lowest ratings in both groups. This pattern is consistent with Nigerian studies in which favourable attitudes towards AI coexist with inadequate training, limited infrastructure and poorly developed institutional policies (Aliyu & Muhammad, 2025; Eke, 2024; Tsakeni & Nwafor, 2025).

The low institutional ratings were consistent across the relevant questionnaire items. The ICT audit provided supporting evidence: internet connectivity, campus Wi-Fi, staff computers and e-learning facilities were inadequate, and no policy on responsible AI use was identified. Comparable barriers reported among pre-service science teachers include limited access to AI tools, unstable electricity, insufficient institutional support and inadequate AI-related coursework (Tsakeni & Nwafor, 2025). Evidence from Nigerian universities likewise suggests that institutional, technological and sociocultural conditions interact in limiting AI integration (Egbai et al., 2024).

The absence of a statistically significant relationship between AI awareness and readiness in either respondent group should be interpreted with caution. The association among lecturers was small and imprecise, whereas the association among student-teachers was effectively zero. Within these samples, awareness did not translate directly into readiness to use AI for teaching or learning. This finding should not be interpreted to mean that awareness is irrelevant. Rather, readiness may depend on additional factors, including self-efficacy, perceived usefulness, pedagogical competence, ethical judgement, access to digital resources and opportunities for structured training (Abdulayeva et al., 2025; Sun et al., 2024; Wang et al., 2023). Sanusi et al. (2024), for example, identified basic AI knowledge as an important determinant of the intention of pre-service teachers to learn AI. The weak associations also suggest that increasing awareness alone may not be sufficient to produce practical readiness.

The open-ended responses help to explain this quantitative pattern. Participants saw value in using AI to obtain scientific information, support simulations, prepare lessons and widen learning opportunities. Their reservations were also clear: they referred to the cost of devices and data, inadequate infrastructure and training, misuse of AI and overdependence on AI-generated information. Comparable concerns have been reported elsewhere, where pre-service teachers valued AI for personalised learning and classroom efficiency but remained concerned about overdependence, the possible loss of the human element in teaching and insufficient preparation (Guan et al., 2025; Kohnke et al., 2025).

The personalised-learning items nevertheless received favourable ratings. Sixty per cent of lecturers believed that AI-supported personalised learning could improve science teaching, and 72.6% of student-teachers thought it could improve their academic performance. These findings suggest that respondents recognised the possible value of adapting learning resources and support to individual needs. Application in science education would, however, require more than general familiarity with AI. Guidance would be needed for its use in scientific explanation, inquiry, simulations, practical work and assessment without weakening academic integrity or professional judgement.

A phased approach to integration appears appropriate. Priority should be given to reliable connectivity, adequate computer facilities and access to suitable digital tools. Lecturers and

student-teachers also require organised AI-literacy training covering practical use, critical appraisal of AI-generated material, academic integrity, data protection and ethical conduct. Science-specific professional development could then address lesson planning, simulations, formative assessment and differentiated instruction. Intervention research suggests that carefully designed professional development can improve AI literacy among pre-service teachers (Younis, 2024), although the present cross-sectional data cannot establish the likely effect of such training in this institution. The college would also require a policy defining acceptable uses of AI, responsibilities for human oversight and procedures for addressing misuse.

5. Conclusion

Science lecturers and student-teachers at Jigawa State College of Education, Gumel, were generally aware of AI and favourably disposed towards its use in science teaching and personalised learning. Their readiness was, however, incomplete and was not matched by adequate institutional provision. Limited formal training, weak digital infrastructure and the absence of clear guidance remain important constraints. Responsible integration will depend on sustained institutional support, relevant professional preparation and access to functional digital resources.

5.1 Recommendations

On the basis of the findings, the following recommendations are proposed:

1. First, the college should prioritise reliable internet connectivity, wider campus Wi-Fi coverage, adequate staff computers and stronger e-learning infrastructure, as these were among the clearest deficiencies identified through the survey and institutional audit.

2. Second, structured AI-literacy and professional-development programmes should be provided for lecturers and student-teachers, with emphasis on practical classroom applications, critical evaluation of AI-generated information and responsible use in science education.

3. Third, the institution should develop a policy to guide AI use in teaching and learning, addressing academic integrity, ethical practice, data protection, human oversight and acceptable educational applications.

4. Finally, AI-related knowledge and skills should be incorporated into the science teacher-education curriculum, particularly in relation to lesson planning, scientific simulations, inquiry-based learning and personalised instructional support.

5.2 Limitations and Directions for Future Research

The findings should be interpreted in the light of several limitations. The study was conducted in a single institution, and the results may not represent conditions in other Nigerian colleges of education. It also relied mainly on self-reported perceptions, which may differ from respondents' demonstrated competence or actual use of AI. In addition, the cross-sectional design does not permit causal conclusions about the effects of awareness, training or institutional support on readiness.

AI-powered personalised learning was represented by one item in each questionnaire rather than by a separate validated multidimensional scale. The short, recurring open-ended

responses also provided limited explanatory depth and should not be interpreted as equivalent to interview-based qualitative evidence. Future research should include several institutions, employ validated measures of AI readiness and personalised learning, and examine actual patterns of AI use. Longitudinal or intervention studies would provide stronger evidence of whether structured training and improved institutional support lead to sustained changes in classroom practice.

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