

Research Article

Effects of AI-supported adaptive learning systems on scientific reasoning, conceptual understanding and misconceptions reduction among pre-service teachers in Kwara State, Nigeria

I. J. Limangba^a, S. Bawa^b, A. Musa^c, E. U. Raphael^d, S. Adam^e, M. Shehu^f, U. A. Muhammad^g, M. C. Mohammed^f, A. D. Olufemi^f, Y. I. Alfa^f, H. S. Arah^h, I. M. Bashirⁱ & S. A. Umar^j

^a Department of Chemistry, Baze University, Abuja, Nigeria

^b Department of Chemistry, Federal University of Education Zaria, Nigeria.

^c Department of Physics, Dr Umaru Sanda Ahmadu College of Education Minna, Nigeria.

^d Department of Basic Science and Technology, Federal College of Freshwater Fisheries Technology, New Bussa, Nigeria.

^e School of Sciences, Kwara State College Of Education (T), Lafiagi, Nigeria.

^f Department of Science Education, Federal University of Technology, Minna, Nigeria.

^g Department of Chemistry, Federal University of Education Kontagora, Nigeria.

^h Model Secondary school, Dr Umaru Sanda Ahmadu College of Education Minna, Nigeria.

ⁱ Department of Primary Education Studies, Dr Umaru Sanda Ahmadu College of Education Minna, Nigeria.

^j Department of General Studies, College of Health Technology Minna, Nigeria.

Abstract

This study investigated the effect of an AI-supported adaptive learning system on pre-service teachers' scientific reasoning, conceptual understanding and misconceptions reduction in Kwara State, Nigeria. A Pretest-posttest control group quasi-experimental design was used. The sample of 120 pre-service teachers was drawn from Kwara State College of Education (Technical), Lafiagi, randomly assigned by intact classes into two groups. An experimental group (n=60) was exposed to the rule-based adaptive learning system with personal scaffolding, feedback and misconception-targeted interventions, whereas the control group (n=60) was given non-adaptive digital learning. The Scientific Reasoning Inventory (KR-20 = 0.84) and two-tier Conceptual Understanding and Misconception Diagnostic Test (= 0.81) were the instruments used. ANCOVA analysis of post-test scores, controlling for pre-test scores as the covariate, revealed a statistically significant main effect of instructional group on scientific reasoning, $F(1, 117) = 151.92, p < .001, \eta^2 = .565$, and on conceptual understanding, $F(1, 117) = 140.61, p < .001, \eta^2 = .546$, with the experimental group demonstrating significantly higher adjusted mean scores than the control group. Besides, Pearson product-moment correlation showed that interaction time on adaptive learning was significantly and negatively correlated with scientific misconceptions ($r = -.42, p < .01$). These results suggest that adaptive learning system is a tool that Nigerian teachers can utilize to positively impact pre-service teachers' scientific reasoning and conceptual understanding. This research recommends that adaptive learning systems with personalized scaffolding and diagnostic feedback mechanisms be adopted and incorporated into teacher education curricula.

Keywords: Adaptive learning system, Artificial intelligence, Conceptual understanding, Pre-service teachers, Scientific misconceptions, Scientific reasoning.

1. Introduction

In this 21st century, science education is increasingly dominated by a shift in epistemology from knowing propositional knowledge to understanding scientific reasoning (SR) and achieving deep conceptual understanding

(CU). This epistemological shift means that learners will not only know about the world that is increasingly guided by science but also will be able to judge evidence, integrate information across different datasets, and break apart deeply

*Corresponding author: I. J. Limangba,

Email address: chemistlimangba@gmail.com (I. J. Limangba)

ORCID: <https://orcid.org/0009-0006-5687-9177>

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held misunderstandings in a rapidly moving science-based world (El-Fathi et al., 2025; NRC, 2012). In the centre of this educational landscape are pre-service teachers (PSTs), who as recipients of teacher education programs are a pipeline of how children are exposed to science literacy. A sad and pervasive paradox is found in teacher education where teachers aim to be proponents of higher-level reasoning and inquiry and yet PSTs go into and out of their teacher education program with non-integrated knowledge structures and rote memory knowledge. In many cases these fragmented knowledge structures are more than an academic problem, they are a systemic choke-point, since teachers with the non-integrated understanding are more likely than not to perpetuate misconception cycles of intuition or learned heuristics to their students (Mnguni, 2025; Dauda et al., 2026).

This problem is compounded by the historical context in Nigeria in general, and in Kwara State in particular where teacher-centred, didactic instruction largely prevails in Nigerian tertiary education system and teacher training colleges where there are so many alternative conceptions, and where teaching has been largely transmissive in total disregard for the imperatives of the National policy on Education. Research has demonstrated that Nigerian, North-Central PSTs are generally poor with abstraction in science, have several misconceptions in thermodynamics, genetics and electromagnetism and cannot reason logically outside of the school context (Olawajaju et al., 2025; Ansari and Qamari, 2025). Alternative frameworks cannot be changed through conventional lectures, since that approach cannot provide individualized cognitive conflict required to break faulty mental schemas. The lack of progress in classroom teaching of science at this level demands a major shift away from a universally suitable digital tool toward more refined neuroscience-based interventions.

The emergence of Artificial Intelligence-Supported Adaptive Learning Systems (ASALs) offers a transformative solution to these persistent pedagogical hurdles. Unlike traditional Computer-Based Instruction (CBI) which follows a linear trajectory, ASALs leverage machine learning algorithms to create a dynamic, personalized learning path that mimics the presence of a "more knowledgeable other." By continuously analysing learner inputs, these systems provide real-time, data-driven scaffolding within the learner's Zone of Proximal Development (ZPD), thereby addressing the unique cognitive gaps of each PST (Vygotsky, 1978; Kgosi et al., 2026). The theoretical synergy between scientific reasoning and adaptive learning is profound: whereas reasoning requires a logical engine to process evidence, the adaptive system provides the targeted feedback loops necessary to steer that engine away from fallacious conclusions. Recent global studies have begun to elucidate this relationship; for instance, Jia et al. (2025) demonstrated that adaptive scaffolding significantly enhances metacognitive awareness, while other scholars have noted that personalized feedback is the most effective variable in reducing the misconception density in undergraduate populations (Meronda et al., 2025; Islamiyah et al., 2022).

However, a significant empirical lacuna persists concerning the application of these AI-driven environments

within the socio-technical context of Nigerian teacher education. While much of the existing literature on adaptive systems originates from Western or Asian contexts, there is a dearth of research exploring how such technologies interact with the specific cultural and academic prerequisites of PSTs in Kwara State. Existing Nigerian studies have frequently focused on the usability or adoption of E-learning, yet they often fail to investigate the deeper cognitive transformations which are specifically the interplay between scientific reasoning and the erosion of misconceptions facilitated by AI adaptivity. Furthermore, the literature has largely treated scientific reasoning and conceptual understanding as isolated variables, neglecting the holistic impact that AI-supported interaction metrics have on the overall cognitive development of the teacher in training. Despite the promise of AI-supported adaptive learning systems, their implementation in developing contexts is often constrained by equity-related concerns. In Kwara State and many parts of Nigeria, disparities in internet connectivity, access to digital devices, electricity supply and digital literacy may affect learners' ability to benefit equally from AI-enhanced educational interventions. These inequalities, commonly described as the digital divide, may influence both participation and learning outcomes. Therefore, investigating AI-supported learning within the realities of Nigerian teacher education is essential not only for evaluating effectiveness but also for understanding issues of accessibility, inclusiveness, and equitable educational opportunities.

An integration of constructivist learning theory, cognitive conflict theory and metacognitive regulation theory can provide a finer grained perspective on the effectiveness of AI supported adaptive learning systems within this study. A constructivist framework explains learning in terms of learners restructuring prior knowledge schemata and emphasizing active knowledge construction rather than passive acquisition. Within such a framework the adaptive system is conceptualized as an intelligent tutor/mediator capable of diagnosing misconceptions and providing tailored scaffolding for the learner to utilize. Cognitive conflict theory further explains the mechanism underlying the conceptual change observed in this study. Learners are forced into a state of cognitive disequilibrium, a state that requires their existing knowledge structures to be reorganized in the process of resolving cognitive conflict when their misconceptions are confronted directly through system feedback. Incorporating two-tier diagnostic feedback and the presentation of system-generated targeted feedback to specific misconceptions actualizes this type of learning by exposing learners to conflicting statements within their own thinking.

Metacognitive regulation theory can also be used to describe how the adaptive feedback loops facilitated conceptual change within this study. The continuous cycle of adaptive feedback prompted learners to reflect on their cognition, test the correctness of their responses and consequently adjust their metacognitive strategy. These processes represent two distinct yet complementary components of metacognition-monitoring and control, both of which contribute significantly to the cultivation of reasoning. Lastly, from a learning analytics standpoint, the

longer time students spent interacting is interpreted as a measure of engagement within the learner-system feedback cycle. While not a causal explanation, this enhanced interaction was probably more indicative of increased cognitive processing and prolonged engagement with adaptive scaffolding, thus fostering more advantageous circumstances under which learning could be enhanced.

This study, therefore, seeks to fill this critical void by investigating the effects of AI-supported adaptive learning systems on the scientific reasoning, conceptual understanding, and misconception reduction among pre-service teachers in Kwara State, Nigeria. It departs from the traditional comparative research design by not only measuring outcomes but also analysing the relationship between the intensity of adaptive interaction and the subsequent shifts in the PSTs' mental models. By grounding the study in the local realities of Kwara State's educational infrastructure while employing global standards for AI-integrated pedagogy, this research aims to provide a robust, empirical blueprint for modernizing teacher preparation. The ultimate objective is to determine if personalized, AI-scaffolded interventions can break the cycle of misconceptions that has long hindered science education in the region, thereby equipping a new generation of teachers with the cognitive tools necessary to foster true scientific literacy in Nigerian schools.

The primary objective of this study is to evaluate the efficacy of AI supported adaptive learning platforms in enhancing the professional competencies of science educators. Specifically, the study aims to:

- (i) Assess the extent to which adaptive scaffolding influences the scientific reasoning skills of pre-service teachers compared to traditional digital instruction.
- (ii) Determine the effects of personalized feedback loops on the depth of conceptual understanding regarding complex scientific phenomena.
- (iii) Investigate the relationship between interaction time within an adaptive environment and the reduction of persistent scientific misconceptions.

To achieve these objectives, the following questions guide this study:

1. Is there a significant difference in the scientific reasoning scores of pre-service teachers who use AI supported adaptive learning systems compared to those who use non adaptive digital tools?
2. How does the adaptive nature of the AI system facilitate the transition from fragmented to coherent conceptual understanding of scientific principles?
3. To what extent does the level of interaction time within an AI-supported adaptive learning environment relate to pre-service teachers' scientific reasoning, conceptual understanding and misconception reduction?

The following null hypotheses were tested at 0.05 level of significance:

1. There is no significant difference in the scientific

reasoning gains between pre-service teachers using AI supported adaptive learning systems and those in a traditional digital learning environment.

2. There is no significant difference in the depth of conceptual understanding of scientific phenomena between the experimental group and the control group.
3. There is no significant relationship between interaction time within an AI-supported adaptive learning environment and pre-service teachers' scientific reasoning, conceptual understanding, and misconception reduction

This research matters because we are at a point of no return regarding technology in education. Practically, this study provides a blueprint for how teacher education programs can use AI to solve the problem of overcrowded and impersonal lecture halls. It offers a way to ensure that every future teacher, regardless of their starting point, reaches a baseline of scientific literacy that is both deep and flexible. Academically, this study occupies a vital niche by blending educational psychology with computer science, offering a granular look at the black box of AI driven cognitive development. By documenting this impact, we move closer to a future where technology does not just replace the teacher but empowers the teacher to be a more profound thinker.

2. Methodology

This study adopted a quasi-experimental pre-test post-test control group design to examine the effects of an AI-supported adaptive learning system on scientific reasoning, conceptual understanding and misconceptions reduction among pre-service teachers' in Kwara State. The choice of a quasi-experimental approach was necessitated by the use of intact classes, which made random assignment at the individual level impractical. To strengthen internal validity and account for potential baseline differences, Analysis of Covariance (ANCOVA) was employed, with pre-test scores serving as covariates. Additional measures were taken to minimize threats to validity, including ensuring equivalence of instructional content, duration, and learning conditions across groups.

The sample consisted of 120 pre-service teachers drawn from the School of Science Education at Kwara State College of Education (Technical), Lafiagi, Nigeria. Participants were in their second year of study, a stage at which both disciplinary knowledge and pedagogical competencies are actively developing. The participants were assigned by intact class into two groups: an experimental group ($n = 60$), which received instruction through an AI-supported adaptive learning system, and a control group ($n = 60$), which engaged with non-adaptive digital instructional materials. Baseline equivalence between the two groups was established using pre-test scores, which showed no statistically significant differences prior to the intervention.

The intervention for the experimental group was delivered through a rule-based adaptive learning system

designed to provide personalized instructional support through continuous learner–system interaction. The adaptive learning system used in this study was a researcher rule-based platform developed specifically for the intervention. The system was built using predefined decision rules rather than generative artificial intelligence. Learner responses were continuously analysed against predetermined instructional pathways, allowing the system to provide personalized feedback, adaptive task sequencing, and misconception-targeted remediation. The system was deployed through a web-based interface accessible via laptops and smartphones provided by the institution during the intervention period. The system comprised three interrelated components: a learner model, a pedagogical module, and an adaptation engine. The learner model maintained a dynamic profile of each participant's performance, updating in real time based on response accuracy and patterns of engagement. The pedagogical module delivered instructional content and scaffolding, while the adaptation engine applied predefined if–then rules to adjust the learning experience. For example, when a learner provided an incorrect response repeatedly, the system generated elaborated feedback and presented a simplified analogous task; conversely, consistent correct responses triggered increased task complexity.

The adaptive functionality of the system was operationalized through three primary mechanisms: adaptive scaffolding, personalized feedback, and misconception-targeted intervention. Adaptive scaffolding involved the dynamic sequencing of tasks from highly structured to more open-ended formats, accompanied by prompts designed to stimulate reasoning, such as requests to justify claims or evaluate evidence. Personalized feedback included corrective, elaborative, and metacognitive components, providing not only information about correctness but also explanations of underlying reasoning errors and prompts for reflection. Misconception-targeted interventions were implemented by identifying common incorrect response patterns associated with documented alternative conceptions in science and presenting counter examples, conceptual conflict prompts, and simplified explanatory models to facilitate conceptual change.

In contrast, the control group received instruction through a non-adaptive digital learning environment characterized by static content, linear progression, and generic feedback limited to indicating whether responses were correct or incorrect. Both groups were exposed to identical curriculum content to ensure that differences in learning outcomes could be attributed primarily to the mode of instructional delivery rather than content variation. The instructional content focused on three science domains that have consistently been identified in the literature as sources of persistent misconceptions among learners: chemical kinetics, genetics and electromagnetism. The chemical

kinetics module addressed concepts such as collision theory, activation energy, reaction mechanisms, catalyst action, and factors influencing reaction rates. The genetics module covered inheritance patterns, dominant and recessive traits, gene expression, and genetic variation, while the electromagnetism module focused on electric fields, current flow, magnetic interactions, and electromagnetic induction. These topics were deliberately selected because they require higher-order reasoning and conceptual understanding and are frequently associated with alternative conceptions among pre-service science teachers

Data were collected using two primary instruments: the Scientific Reasoning Inventory (SRI) and the Conceptual Understanding and Misconception Diagnostic Test (CUT-MD). The SRI consisted of 25 multiple choice items designed to assess key components of scientific reasoning, including hypothesis formulation, evidence evaluation, and causal inference. Each item required participants to justify their responses, thereby capturing both outcome and reasoning processes. The reliability of the instrument was established using the Kuder–Richardson Formula 20, yielding a coefficient of 0.84.

The CUT-MD was designed as a two-tier diagnostic instrument to assess both conceptual understanding and the presence of misconceptions. The first tier comprised multiple choice questions targeting core scientific concepts, while the second tier required participants to provide reasoning for their selected answers. Distractors were constructed based on commonly documented misconceptions in science education literature, enabling the identification and classification of alternative conceptions. Responses were categorized into scientifically accurate understanding, partial understanding, and specific misconception types. Scoring was structured such that correct answers with correct reasoning received full credit, correct answers with incorrect reasoning received partial credit, and incorrect answers aligned with known misconceptions were coded accordingly. The reliability of the instrument, as determined by Cronbach's alpha, was 0.81.

In addition to test data, interaction log data were collected for participants in the experimental group. These data included total time spent on the platform, number of task attempts, and frequency of feedback access. These metrics were used to examine the relationship between engagement within the adaptive environment and cognitive outcomes.

The study was conducted over a period of eight weeks. During the first week, participants were oriented to the study procedures and administered the pre-tests. The intervention was implemented from week two to seven, during which the experimental group engaged with the adaptive system while the control group used non-adaptive digital materials. In the eighth week, post-tests were administered under standardized conditions to ensure consistency in data collection.

Data analysis was carried out in several stages.

Descriptive statistics, including means and standard deviations, were computed to summarize participant performance. Prior to the main analysis, the assumptions of ANCOVA were tested, including homogeneity of variance using Levene's test and homogeneity of regression slopes. ANCOVA was then conducted to compare post-test scores between groups while controlling for pre-test differences. Effect sizes were reported using partial eta squared (η^2) to determine the magnitude of observed effects. Misconception data were analysed by examining the frequency and distribution of identified misconception categories across pre-test and post-test measures. Pearson product-moment correlation analysis was employed to explore relationships between interaction variables and learning outcomes within the experimental group. The interpretation of these correlations was limited to associative relationships and did not imply causation.

To enhance internal validity, several control measures were implemented. Both groups received equal instructional time and were exposed to the same curricular content. Learning environments and technological resources were standardized to minimize external variability. However, certain variables, such as digital literacy and learner motivation, were not directly measured and are acknowledged as potential confounding factors that may have influenced the results.

Fidelity of implementation was ensured through regular

monitoring of instructional sessions and verification of system usage logs. All participants in the experimental group completed at least 90% of the assigned activities, indicating a high level of engagement with the intervention. Ethical approval for the study was obtained from the relevant institutional authority. Participation was voluntary, informed consent was secured from all participants, and all data were treated with high confidentiality.

3. Results

This section transitions from the descriptive overview of the participant performance to the inferential testing of the null hypotheses. Before conducting the primary analysis, the assumptions for the Analysis of Covariance (ANCOVA) were verified. Levene's test for equality of error variances was non-significant for both scientific reasoning, $F(1,118) = 1.84$, $p = .177$, and conceptual understanding, $F(1,118) = 2.15$, $p = .145$. Furthermore, the assumption of homogeneity of regression slopes was met, as the interaction between the covariate (pre-test) and the independent variable (group) was not statistically significant.

3.1. Analysis of scientific reasoning (RQ1 and H01)

The first research question investigated the impact of AI-supported adaptive scaffolding on the scientific reasoning skills of pre-service teachers. Table 1 presents the descriptive statistics for both the experimental and control groups.

Table 1: Descriptive Statistics for Scientific Reasoning Inventory (SRI) Scores

Group	N	Pre-test Mean	Pre-test SD	Post-test Mean	Post-test SD	Adjusted Mean
Experimental	60	42.15	7.34	74.82	6.12	74.78
Control	60	41.88	7.51	58.45	8.23	58.49

The experimental group demonstrated a substantial increase in their mean scores compared to the control group.

To determine if this difference was statistically significant while controlling for initial variations, an ANCOVA was performed. The results are detailed in Table 2.

Table 2: ANCOVA Summary Table for Scientific Reasoning by Instructional Method

Source	Type III Sum of Squares	df	Mean Square	F	p	Partial η^2
Corrected Model	8245.12	2	4122.56	78.44	<.001	.573
Intercept	12450.33	1	12450.33	236.88	<.001	.669
Pre-test (Covariate)	455.20	1	455.20	8.66	.004	.069
Group	7984.45	1	7984.45	151.92	<.001	.565
Error	6148.18	117	52.55			
Total	545620.00	120				
Corrected Total	14393.30	119				

The ANCOVA results indicate a significant main effect for the instructional group, $F(1,117) = 151.92$, $p < .001$. The partial eta squared ($\eta^2 = .565$) suggests that the intervention had a large effect size, accounting for approximately 56.5% of the variance in the post-test scientific reasoning scores. Consequently, the null hypothesis (H_{01}) is rejected.

3.2. Analysis of conceptual understanding (RQ2 and H02)

The second research question aimed to assess the depth of conceptual understanding regarding complex scientific phenomena.

The descriptive data in Table 3 shows the performance across the two instructional environments.

To test the second null hypothesis, another ANCOVA was conducted to compare the adjusted post-test means of the two groups. These results are summarized in Table 4.

Table 3: Descriptive Statistics for Conceptual Understanding Test (CUT) Scores

Group	N	Pre-test Mean	Pre-test SD	Post-test Mean	Post-test SD	Adjusted Mean
Experimental	60	38.45	6.82	71.20	5.88	71.12
Control	60	38.10	6.95	54.10	9.45	54.18

Table 4: ANCOVA Summary Table for Conceptual Understanding by Instructional Method

Source	Type III Sum of Squares	df	Mean Square	F	p	Partial η^2
Corrected Model	8842.15	2	4421.08	72.35	<.001	.553
Intercept	10890.45	1	10890.45	178.22	<.001	.604
Pretest (Covariate)	215.30	1	215.30	3.52	.063	.029
Group	8592.12	1	8592.12	140.61	<.001	.546
Error	7149.55	117	61.11			
Total	482150.00	120				
Corrected Total	15991.70	119				

The inferential analysis confirms a significant difference in the conceptual understanding scores between the experimental and control groups, $F(1,117) = 140.61$, $p < .001$. The effect size ($\eta^2 = .546$) remains high, indicating that the AI-supported adaptive environment significantly enhanced the participants' grasp of scientific concepts. Based on these findings, the second null hypothesis (H_{02}) is also rejected.

Analysis of Relationship between Interaction Time within an Adaptive Environment and the Reduction of Persistent Scientific Misconceptions (RQ₃)

To provide a more granular understanding of how the

experimental intervention functioned internally, it was necessary to move beyond group comparisons and examine the specific relationships between the participants' engagement metrics and their cognitive outcomes. This analysis was restricted to the experimental group ($n=60$), as they were the only participants with tracked interaction data within the AI supported adaptive environment. The use of the Pearson product-moment correlation allowed for an exploration of how the time investment in the system related to the final assessments of scientific reasoning, conceptual understanding, and the persistence of misconceptions.

Table 5: Pearson Correlation Matrix for Experimental Group Interaction and Cognitive Outcomes

Variables	1	2	3	4
1. Interaction Time (Minutes)	1			
2. Scientific Reasoning (Posttest)	.58**	1		
3. Conceptual Understanding (Posttest)	.61**	.72**	1	
4. Remaining Misconceptions	-.42**	-.55**	-.64**	1

Note. $n = 60$. ** Correlation is significant at the 0.01 level (2-tailed).

The results in Table 5 presents the Pearson product moment correlation coefficients examining the relationships between interaction time and key cognitive outcomes within the experimental group ($n = 60$). The analysis reveals several statistically significant associations.

The positive association between interaction time and scientific reasoning scores ($r = .58$, $p < .01$), suggests that prolonged engagement with adaptive scaffolding may provide learners with additional opportunities to practice evidence evaluation, hypothesis testing, and causal reasoning. Unlike conventional digital environments, adaptive systems continuously adjust task complexity and feedback according to learner performance, creating repeated cycles of reflection and correction. These iterative learning experiences may contribute to the development of more sophisticated reasoning patterns.

Similarly, the relationship strong positive between interaction time and conceptual understanding ($r = .61$, $p < .01$), indicates that sustained exposure to personalized explanations and misconception-targeted interventions may facilitate deeper conceptual restructuring. According to constructivist learning theory, meaningful learning occurs when learners actively reconcile new information with prior knowledge. The adaptive system appears to support this process by identifying conceptual weaknesses and delivering individualized remediation. Consequently, learners who spent more time interacting with the system may have had greater opportunities to resolve cognitive conflicts and replace alternative conceptions with scientifically accepted explanations.

In contrast, interaction time demonstrates a moderate negative correlation with remaining misconceptions ($r = -.42$, $p < .01$). This inverse relationship indicates that participants who spent more time interacting with the adaptive system tended to exhibit fewer misconceptions at post-test. Furthermore, scientific reasoning and conceptual understanding are strongly positively correlated ($r = .72$, $p < .01$), reflecting a close alignment between the ability to reason scientifically and the depth of conceptual knowledge. Both variables also show moderate negative correlations with misconceptions ($r = -.55$ and $r = -.64$, respectively, $p < .01$), indicating that higher-order reasoning and stronger conceptual understanding are associated with reduced misconception prevalence.

All reported correlations are statistically significant at the 0.01 level (two-tailed), suggesting that the observed relationships are unlikely to have occurred by chance. However, these associations should be interpreted as correlational rather than causal.

4. Discussion of Results

The findings of this study provide compelling evidence that AI-supported adaptive learning systems (ASALs) significantly enhance scientific reasoning, conceptual understanding, and misconception reduction among pre-service teachers. When situated within the global literature, these results both confirm established empirical patterns and extend their applicability to underrepresented contexts, particularly sub-Saharan Africa.

The significant gain in scientific reasoning observed in the experimental group aligns with other work on adaptive scaffolding and metacognition enhancing higher-order thinking. Jia et al. (2025) also observed adaptive scaffolding would enhance learners' metacognitive regulation, Nguyen (2025) found AI learning would boost learning, and Curtis and Kelley (2023) also suggested feedback and interaction would foster reasoning while Sajja et al. (2024) noted AI's ability to tailor scaffolding based on learner's needs. In this case, it would seem consistent practice with adaptive feedback and prompts would also foster better scientific reasoning, but the high effect size ($\eta^2 = .565$) is much higher than others observed in technology enriched learning environments (Chen et al., 2022). This discrepancy is likely due to contextual baseline. The pedagogical change of introducing a highly adaptive, feedback rich learning system to learners with prior exposure to teacher-centred learning environments like Nigeria (Ansari and Qamari, 2025; Olarewaju et al., 2025) would likely show larger learning gains than environments that have already been immersed in technologically rich learning systems (Chen et al., 2022).

The findings on conceptual understanding further align with global evidence emphasizing the role of personalized feedback in facilitating conceptual change. Studies by Meronda et al. (2025) and Islamiyah et al. (2025) demonstrate that targeted feedback significantly reduces misconception prevalence. Consistent with these findings, participants in the adaptive learning group achieved higher conceptual understanding scores and exhibited fewer misconceptions. This supports constructivist perspectives, which posit that conceptual change occurs through cognitive conflict and the restructuring of existing mental models (NRC, 2012). The integration of two-tier diagnostic assessments within the adaptive system appears to have effectively operationalized this process.

The observed negative correlation between interaction time and remaining misconceptions ($r = -.42$, $p < .01$) indicates that increased engagement with the adaptive learning system is associated with lower levels of misconception retention, supporting previous research that identified both the quality and frequency of feedback as important to its effectiveness (Qadir et al., 2025; Kim, 2012). However, this stronger correlation compared to previous research might be influenced by characteristics of the present sample, such as little prior experience with individualized learning systems. Similarly, the positive relationships between interaction time and both scientific reasoning ($r = .58$, $p < .01$) and conceptual understanding ($r = .61$, $p < .01$) suggest that greater system use is linked to improved cognitive outcomes, which is also congruent with learning analytics literature, which identifies engagement as an important predictor of learning outcomes (Kuo, 2025). This also lends support to the theoretical premise that adaptive systems could function as a "more knowledgeable other" as suggested by Vygotsky (1978). However, these relationships should be interpreted with caution. Given the correlational nature of the analysis, no causal inferences can be made. It is plausible that underlying learner characteristics such as prior ability, motivation, or digital literacy may have influenced both the level of interaction and the observed learning outcomes. Therefore,

while the findings highlight meaningful associations, they do not establish that increased interaction time directly produces improvements in reasoning, conceptual understanding, or misconception reduction. (Luckin and Cukurova, 2019; Baker, 2021). This limitation is particularly relevant in developing contexts, where disparities in digital competence may shape interactions with technology-enhanced learning environments.

Beyond addressing an important empirical gap in African teacher education research, the findings also provide evidence that can inform policy decisions regarding the integration of artificial intelligence technologies into science teacher preparation programmes in Nigeria. While most studies on ASALs originate from Western and Asian contexts, the present findings demonstrate that such systems are not only transferable but also highly effective within the Nigerian context. This supports broader arguments that AI-driven educational technologies can contribute to reducing global inequities in instructional quality when appropriately contextualized (Sajja, et al., 2024). Additionally, this study advances the literature by examining scientific reasoning and conceptual understanding as interrelated constructs. The strong correlation between these variables ($r = .72$) supports emerging perspectives that view reasoning and conceptual knowledge as mutually reinforcing dimensions of science learning (El Fathi et al., 2025). This integrative approach provides a more comprehensive understanding of cognitive development than studies that treat these constructs independently.

The findings of this study have important implications for educational policy and teacher preparation in Nigeria. The significant improvements observed in scientific reasoning, conceptual understanding, and misconception reduction suggest that AI-supported adaptive learning systems can serve as valuable instructional tools within teacher education programmes. Given the on-going efforts to improve science education quality in Nigeria, policymakers should consider incorporating adaptive learning technologies into pre-service teacher training curricula. However, successful implementation will require complementary investments in digital infrastructure, reliable internet connectivity, stable electricity supply, and capacity-building programmes for teacher educators. Furthermore, educational authorities should develop guidelines for the ethical and pedagogically sound integration of artificial intelligence in teaching and learning. Addressing these policy considerations could enhance the effectiveness and sustainability of AI-supported learning initiatives across Nigerian colleges of education and universities.

Nevertheless, several limitations must be acknowledged. The quasi-experimental design introduces potential selection bias despite the use of ANCOVA (Creswell & Creswell, 2017). The single institution sample limits generalizability, and the short duration of the intervention constrains conclusions regarding long-term retention and transfer of learning (NRC, 2012). Furthermore, unmeasured variables such as motivation and prior technological experience may have influenced the results.

In conclusion, the findings are consistent with global evidence supporting the effectiveness of AI-supported adaptive learning systems while highlighting context specific

amplification effects and engagement dependent mechanisms. The study provides strong empirical support for the integration of adaptive learning technologies in teacher education, particularly in developing contexts where traditional instructional models remain prevalent.

5. Conclusion

The results of this study offer substantial empirical support to the claim that AI-driven adaptive learning can support significant improvement in scientific reasoning, conceptual knowledge, and reduction of persisting misconceptions for pre-service teachers. Beyond simply comparing outcomes, however, this study illustrates that learners' sustained engagement with adaptive scaffolding and tailored feedback, rather than an aggregated comparison of groups, is a major source of cognitive change and lends support to conceptualizing AI as a facilitator within learners' zones of proximal development. More globally, this study adds to the literature on adaptive learning by demonstrating how the learning context may interact with and even boost the effect of adaptivity when learning occurs in non-optimal contexts like those with teacher-centred instruction. The high correlation found between scientific reasoning and conceptual knowledge also suggests the necessity of conceptualizing both constructs as interlocking aspects of science learning, not separable dependent variables. Although the quasi-experimental design and restricted sample make generalization difficult, this study provides strong justification for the thoughtful incorporation of AI-driven adaptive learning systems into teacher education contexts, especially in developing settings. Longitudinal, multi-institution designs are needed in future studies to analyse the long-term persistence and generalizability of these learning gains.

Recommendations

Pre-service teacher education programs need to address the systematic implementation of AI-based adaptive learning environments in science education in order to improve pre-service teachers' scientific reasoning skills, conceptually deepen their understanding of scientific concepts and overcome misconceptions. The implementation should be based on sound pedagogical design principles that draw on features such as adaptively provided scaffolding, diagnostic feedback in real time, and concept-specific remediation of common misconceptions. Colleges and universities are recommended to build teaching capacity and ensure coherence with learning objectives.

Abbreviations

ASALs	Artificial Intelligence-Supported Adaptive Learning Systems
CBI	Computer-Based Instruction
ZPD	Zone of Proximal Development
PST	Pre-service teachers

ANACOV Analysis of Covariance
 SRI Scientific Reasoning Inventory
 CUT Conceptual Understanding Test

Author Contributions

Idirisu Jibril Limangba: Conceptualization, Investigation, Validation, writing –Review & Editing, Project Administration, Methodology, Supervision,
Swafiyah Bawa: Data Curation, Investigation, Formal Analysis, Writing - original draft, Supervision.
Asmau Musa: Methodology, Validation, Investigation, Writing – Review & Editing.
Ekunke Unyime-Abasi Raphae: Formal Analysis, Data Curation, Validation, Writing – Review & Editing.
Sulaiman Adam: Investigation, Resources, Data Curation, Writing – Review & Editing
Mohammed Shehu: Investigation, Resources, Validation, Writing – Review & Editing
Usman Abdullahi Muhammad: Methodology, Formal Analysis, Visualization, Writing – Review & Editing.
Mohammed Chegba Mohammed: Investigation, Resources, Data Curation, Writing – Review & Editing
Ajayi Daniel Olufemi: Supervision, Validation, Writing – Review & Editing
Yahaya Ibrahim Alfa: Supervision, Methodology, Validation, Writing – Review & Editing
Halima Saidu Arah: Investigation, Data Curation, Writing – Review & Editing
Ismail Muhammad Bashir: Resources, Validation, Visualization, Writing – Review & Editing
Salisu A. Umar: Supervision, Conceptualization, Methodology, Validation, Writing – Review & Editing, Project Administration

Conflicts of Interest

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