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Examining the Impact of Adaptive Learning Tools on Personalized Science Education

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Abstract

This mixed-methods study examined the influence of adaptive learning tools on secondary school students' academic performance and conceptual understanding in science. Guided by a pragmatic paradigm, the research employed a convergent design combining a quasi-experimental quantitative component with an interpretive qualitative strand. Intact classes were assigned to either an adaptive learning condition or conventional instruction, with prior achievement used as a covariate. Data were collected from pre- and post-tests in science, platform analytics, questionnaires, classroom observations, teacher interviews, and student focus groups. Quantitative analyses, including ANCOVA, showed that students who used adaptive tools achieved significantly higher scores in overall science performance and conceptual understanding than those in traditional classes, with moderate effect sizes after controlling for prior achievement. Qualitative findings indicated that both students and teachers perceived adaptive tools as enhancing personalization, engagement, timely feedback, and diagnostic use of learning data, while also revealing challenges related to infrastructure, workload, and equitable access. Integrated results suggest that adaptive learning tools are most effective when embedded within supportive pedagogical and institutional contexts, where teachers actively use analytics to inform instruction rather than relying on the technology as a standalone solution. The study concludes that adaptive learning offers a promising pathway for strengthening personalized science education while underscoring the need for sustained investment in capacity building and implementation support.

Keywords: Adaptive learning tools, secondary science education, academic performance, conceptual understanding, mixed-methods research

1. Introduction

In recent years, advances in educational technology have revolutionized the way science is taught, offering unprecedented opportunities for personalized learning. Personalized science education tailors instructional content and pacing to individual students' needs, learning styles, and prior knowledge, thereby promoting deeper understanding and engagement (Pane, Steiner, Baird, & Hamilton, 2015). Traditional "one-sizefits-all" teaching methods often fail to address diverse learners' needs, leading to gaps in conceptual understanding and suboptimal academic performance (Tomlinson, 2014).

Adaptive learning platforms, which leverage data analytics and artificial intelligence, have emerged as powerful tools to deliver customized learning experiences. These platforms continuously assess student performance and adjust content, difficulty, and feedback to optimize learning outcomes (Johnson et al., 2020). Empirical studies indicate that adaptive learning technologies can enhance student engagement, motivation, and achievement, particularly in science education where conceptual complexity and abstract phenomena can hinder learning (Chen, Wang, & Chen, 2018).

Despite these promising developments, there remains a paucity of research in the context of secondary school science education, particularly in under-resourced settings where access to personalized learning tools is limited. Investigating the impact of adaptive learning platforms on students' conceptual understanding and academic performance is therefore critical for informing instructional design, policy decisions, and effective integration of technology in science classrooms (Shute & Rahimi, 2017).

This study seeks to examine the effectiveness of adaptive learning tools in delivering personalized science education, aiming to provide empirical evidence on their potential to improve learning outcomes and foster student-centered teaching approaches.

Purpose of the Study

This study aims to investigate the effectiveness of adaptive learning tools in enhancing personalized science education among secondary school students. It seeks to determine how these platforms influence students' understanding of scientific concepts, academic performance, and engagement, thereby exploring the potential of technology-driven approaches to support individualized learning in science classrooms.

Significance of the Study

The findings of this study are valuable for students, teachers, policymakers, researchers, and technology developers. For students, adaptive learning tools can promote self-paced learning, deepen conceptual understanding, and improve performance. Teachers can benefit by integrating these tools to provide targeted support and differentiated instruction. Policymakers and curriculum developers may use the evidence to guide resource allocation and curriculum planning, while researchers can address existing gaps in the study of technology-enhanced science education. Additionally, developers of adaptive learning platforms can gain insights to optimize their designs for more effective personalized learning outcomes.

Research Objectives

1. To assess the effect of adaptive learning tools on secondary school students' academic achievement and understanding of scientific concepts.
2. To explore students' and teachers' perceptions of how adaptive learning platforms enhance personalized science learning experiences.

Research Questions

1. To what extent do adaptive learning tools influence secondary school students' academic performance and conceptual understanding in science?
2. What are students' and teachers' perceptions regarding the usefulness and effectiveness of adaptive learning tools in supporting personalized science education?

Hypothesis

H_0: Adaptive learning tools have no significant effect on secondary school students' academic performance and conceptual understanding in science.

H_1: Adaptive learning tools have a significant positive effect on secondary school students' academic performance and conceptual understanding in science.

Overview of the Literature

The integration of technology into education has transformed teaching and learning, particularly in science, where concepts can be abstract and cumulative. Adaptive learning platforms, which combine personalized instruction with data-driven feedback, have gained increasing attention as tools that can enhance student outcomes. These platforms analyze learner performance in real time and adjust content delivery to match individual needs, thereby promoting engagement and conceptual understanding. Despite growing research in adaptive learning, there remains a scarcity of studies focused specifically on secondary school science education, particularly in under-resourced contexts. Existing literature largely addresses higher education or general STEM subjects, highlighting the need for studies that examine both quantitative outcomes and qualitative experiences of learners and educators (Creswell & Creswell, 2018; Shute & Rahimi, 2017).

Understanding Adaptive Learning Technologies

Adaptive learning technologies are educational systems designed to modify instruction according to learners' performance, pace, and preferences. These systems utilize algorithms and analytics to provide customized learning pathways, real-time feedback, and recommendations for content progression. Research shows that adaptive learning enhances engagement, motivation, and academic outcomes, particularly when integrated with effective pedagogical practices (Chen, Wang, & Chen, 2018). In science education, adaptive platforms can scaffold complex topics, provide remediation for misconceptions, and offer enrichment opportunities for advanced learners. However, the effectiveness of these tools is influenced by factors such as teacher facilitation, technological infrastructure, and students' digital literacy, suggesting that successful implementation requires careful alignment of technology, pedagogy, and curriculum (Johnson et al., 2020).

Personalized Learning in Science Instruction

Personalized learning refers to instructional strategies that address individual learners' prior knowledge, interests, and learning styles. In science classrooms, personalized approaches allow students to progress at their own pace, revisit challenging concepts, and engage in inquiry-based activities that promote deep understanding (Pane, Steiner, Baird, & Hamilton, 2015). Digital adaptive learning platforms facilitate personalization by continuously assessing student performance, recommending tailored resources, and providing immediate feedback. Empirical studies indicate that personalization improves conceptual mastery and academic achievement, especially when combined with teacher guidance and structured curriculum (Tomlinson, 2014). Nonetheless, challenges such as unequal access to technology, teacher readiness, and maintaining a balance between individualized and collaborative learning persist, highlighting the need for context-sensitive implementation.

Effects of Adaptive Learning on Academic Outcomes

Several studies have examined the impact of adaptive learning on students' academic performance and conceptual understanding. Evidence indicates that learners using adaptive platforms often outperform their peers in post-tests and demonstrate stronger retention of scientific concepts (Chen et al., 2018; Johnson et al., 2020). Adaptive learning helps identify individual learning gaps and provides targeted instruction, which is particularly beneficial in subjects like physics and chemistry, where topics build cumulatively. Variations in effectiveness are noted, often resulting from differences in implementation, student motivation, technological access, and teacher support. These findings suggest that while adaptive learning can improve academic outcomes, optimal results depend on combining technology with pedagogical strategies and supportive classroom practices.

Perceptions of Adaptive Learning: Students and Teachers

Understanding how students and teachers perceive adaptive learning platforms is critical for successful adoption and integration. Research shows that students generally find adaptive systems engaging, motivating, and supportive of self-paced learning, while teachers value the ability to monitor progress, identify struggling students, and tailor instruction accordingly (Shute & Rahimi, 2017). Students appreciate immediate feedback and personalized learning pathways, which build confidence and reduce anxiety when encountering challenging scientific concepts. Teachers report that analytics from adaptive platforms provide valuable insights for lesson planning and intervention strategies. However, challenges such as integrating technology with traditional pedagogy, managing classroom dynamics, and resistance from students unfamiliar with digital tools can affect perception and usage. These insights underscore the importance of considering user experience in implementing adaptive learning.

Challenges and Limitations of Implementing Adaptive Learning

Despite the benefits of adaptive learning, several challenges hinder its implementation, especially in under-resourced schools. High costs, limited access to devices, inadequate internet connectivity, and low digital literacy among students and teachers are commonly reported barriers (Pane et al., 2015; Chen et al., 2018). Additionally, excessive reliance on automated feedback can reduce opportunities for collaborative learning and teacher-student interaction, which are essential for developing critical thinking and problem-solving skills. Teacher training and ongoing support are crucial to ensure that adaptive tools are integrated effectively into pedagogical practice. The literature emphasizes the need for context-aware strategies that address infrastructural and human resource limitations while maximizing the pedagogical potential of adaptive learning platforms.

Identified Gaps in Current Research

Although adaptive learning technologies show promise in improving academic performance and engagement, research gaps remain. Few studies focus on secondary school science education in under-resourced contexts, and much of the existing literature emphasizes quantitative outcomes rather than combining them with qualitative insights (Shute & Rahimi, 2017; Johnson et al., 2020). There is a need for mixed-methods studies that examine both measurable improvements in learning outcomes and the experiences of students and teachers. Exploring these dimensions will provide a more holistic understanding of the effectiveness, perceptions, and challenges associated with adaptive learning, informing strategies for sustainable integration into science education.

Theoretical Underpinning

This study is anchored on Constructivist Learning Theory, Experiential Learning Theory, and Time-on-Task Theory, which collectively provide a robust framework for understanding how adaptive learning tools can facilitate personalized science education.

Constructivist Learning Theory

Constructivist Learning Theory, advanced by Piaget (1970) and Vygotsky (1978), posits that learners actively construct knowledge rather than passively receive information. Learning is understood as an active process in which learners integrate new experiences with existing knowledge frameworks. Cognitive growth occurs through problem-solving, reflection, and social interaction, emphasizing that knowledge is subjective and shaped by prior understanding.

In the context of adaptive learning, constructivism supports the idea that technology can scaffold individualized learning experiences. Adaptive platforms adjust instructional content, provide timely feedback, and offer interactive learning pathways that align with each student’s knowledge level. In science education, this approach allows students to engage with complex concepts through exploration, experimentation, and guided inquiry, promoting deeper understanding. By facilitating a learner-centered environment, adaptive learning aligns with constructivist principles, encouraging students to actively construct knowledge while interacting with digital learning environments (Chen, Wang, & Chen, 2018).

Experiential Learning Theory

Kolb’s Experiential Learning Theory (1984) emphasizes that learning is a continuous, cyclical process comprising four interconnected stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation. According to this theory, learners acquire and retain knowledge most effectively when they engage directly in experiences, reflect critically on those experiences, conceptualize underlying principles, and apply insights to new contexts.

Adaptive learning technologies operationalize experiential learning by providing students with interactive simulations, hands-on tasks, and real-time feedback. In science classrooms, these platforms allow learners to manipulate variables, observe outcomes, and test hypotheses in a safe, controlled digital environment. The iterative nature of adaptive learning mirrors Kolb's learning cycle, enabling students to refine understanding continuously and apply learned concepts to novel problems. By embedding experiential opportunities within personalized learning pathways, adaptive platforms foster conceptual clarity, critical thinking, and long-term retention of scientific knowledge (Johnson et al., 2020).

Time-on-Task Theory

Time-on-Task Theory, as proposed by Carroll (1963), emphasizes that the quantity and quality of time learners actively engage with instructional material significantly influence learning outcomes. According to the theory, students achieve mastery when they spend sufficient focused time on tasks appropriate to their skill level, supported by effective instructional guidance.

Adaptive learning systems leverage this principle by presenting content tailored to each learner's proficiency, ensuring that students devote adequate time to mastering challenging concepts without redundancy. In science education, this facilitates efficient learning, allowing students to allocate more effort to areas requiring improvement while progressing faster through familiar content. By optimizing engagement and instructional pacing, adaptive platforms enhance both efficiency and effectiveness, reinforcing the importance of personalized pathways for achieving meaningful learning outcomes (Pane, Steiner, Baird, & Hamilton, 2015).

Integrated Theoretical Perspective

By integrating constructivist, experiential, and time-on-task perspectives, this study conceptualizes adaptive learning tools as mechanisms that actively engage students, provide experiential learning opportunities, and optimize learning time. Constructivism explains the learner-centered approach, experiential learning highlights iterative and reflective engagement, and time-on-task theory justifies the efficiency of personalized pathways. Together, these theories underpin the rationale for investigating the impact of adaptive learning tools on both students' academic performance and perceptions of personalized science learning.

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Conceptual framework

The flow diagram below presents the conceptual framework that guided this study. It depicts how students' prior achievement interacts with AI-enabled adaptive instruction to influence their science learning outcomes, thereby making explicit the assumed directional pathways among the key variables.

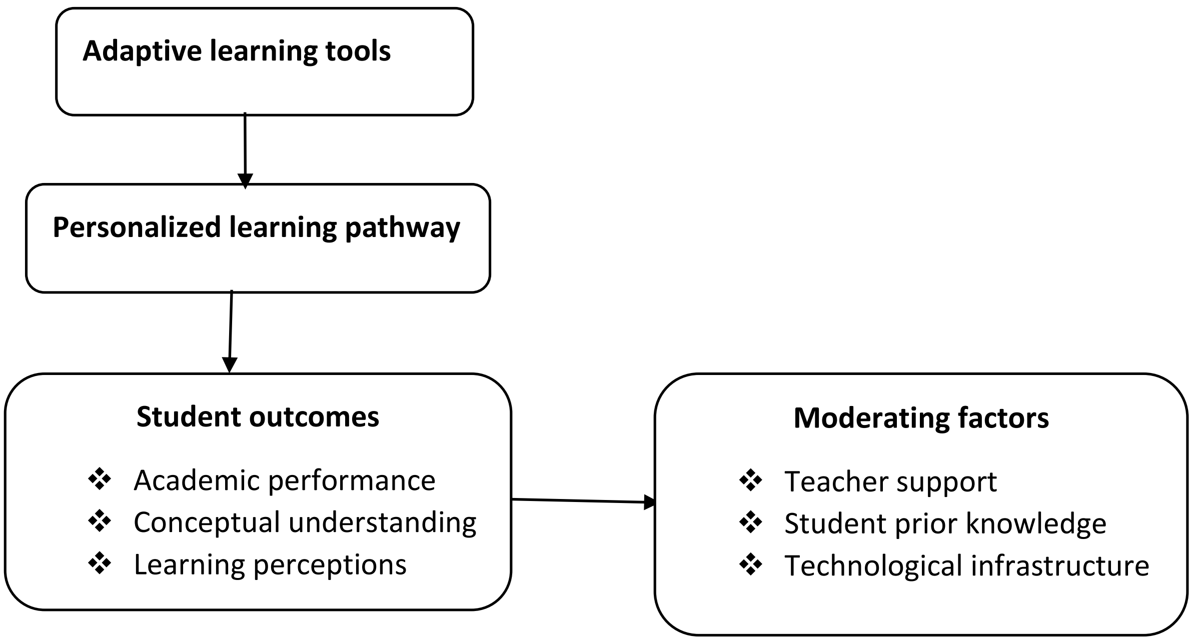

Figure 1:Conceptual framework showing the relationships among key variables

The flow diagram can be explained as a simple, causal chain that links what learners bring into the classroom to what they eventually achieve, through the kind of instruction they experience.

At the top of the diagram is students' prior achievement, which represents learners' initial knowledge, skills, and competencies before they encounter the intervention. This element captures baseline differences among students and serves as the starting point for the causal sequence: it is assumed that students who begin with stronger prior achievement are positioned to benefit differently from instruction than those with weaker starting points.

The middle element is AI-enabled adaptive instruction, shown as the next stage in the downward flow. This component denotes the instructional processes and technological features that tailor learning experiences to individual students. Here, the AI system adjusts task difficulty, pacing, feedback, and support in response to each learner's prior achievement, effectively mediating how those initial differences are translated into day-to-day classroom experiences and opportunities to learn.

At the bottom of the diagram sits science learning outcomes, which constitute the final point in the chain and the primary focus of evaluation. This element reflects students' post-instruction performance in science, including their conceptual understanding, problem-solving skills, and overall achievement after exposure to AI-enabled adaptive instruction. The single downward arrow connecting the three stages indicates the hypothesised direction of influence: prior achievement shapes how students engage with AI-based adaptive teaching, and these tailored instructional experiences, in turn, determine the level of science learning outcomes observed at the end of the study.

Methodology

Philosophical underpinnings and research paradigm

This study is anchored in the pragmatic research paradigm, which privileges the research problem and the usefulness of findings over strict adherence to any single philosophical worldview. Pragmatism supports the combination of quantitative and qualitative methods on the grounds that different types of data illuminate complementary aspects of complex educational phenomena. In this investigation, pragmatism provides the rationale for integrating numerical evidence of effectiveness with rich descriptions of learner and teacher experiences to generate practically meaningful insights into AI-enabled adaptive instruction in science classrooms.

Overall mixed-methods research design

A convergent mixed-methods design was employed. In this design, quantitative and qualitative data are collected during the same phase of the study, analysed separately, and subsequently integrated at the interpretation stage. The quantitative component examines the relationships among students' prior achievement, exposure to AI-enabled adaptive instruction, and science learning outcomes. The qualitative component explores how students and teachers experience the adaptive system and how these experiences help explain, elaborate, or qualify the quantitative patterns. Bringing both strands together allows the study to address questions of effectiveness ("what works, for whom?") and mechanism ("how and why does it work?") within the same research framework.

Quantitative component of the study

Quantitative research design

The quantitative strand adopted a quasi-experimental pretest–posttest non-equivalent groups design. Intact science classes were assigned either to an experimental condition, in which students learned with an AI-enabled adaptive platform, or to a comparison condition, in which students received conventional teacher-led instruction. Students' prior achievement in science was measured before the intervention and used both as a covariate and as a predictor within the analytic models. This design was selected because random assignment at the individual level was not feasible in the natural school setting, yet the use of baseline measures and statistical controls helped to reduce selection bias.

Quantitative participants and sampling procedures

The target population comprised form two senior high students enrolled physics in public senior high schools in the Assin South district in the Central Region of Ghana. A multi-stage sampling strategy was used. First, schools with functional computer laboratories and reliable access to the AI-enabled platform were purposively selected. Second, within each participating school, intact physics classes were assigned to either the experimental or comparison condition in consultation with school administrators to avoid disrupting existing timetables. All students in the selected classes who provided informed assent and whose parents or guardians consented were included. Exclusion criteria included irregular attendance and incomplete baseline data.

Quantitative measures and study variables

Three main constructs were operationalized in the quantitative strand:

- ❖ **Prior achievement:** Students' prior achievement in physics was assessed using their most recent standardized school examination scores and, where available, a diagnostic physics test administered at the beginning of the term. Scores were standardized to permit comparability across schools.
- ❖ **AI-enabled adaptive instruction:** Exposure to AI-enabled adaptive instruction was captured using platform-generated learning analytics (e.g., total time on task, number of completed modules, average difficulty level reached) and a structured implementation checklist completed by teachers to document fidelity of use. A composite implementation index was derived to reflect the intensity and quality of adaptive instruction received by each class.
- ❖ **Science learning outcomes:** Physics learning outcomes were measured using a researcher-developed achievement test aligned with the national physics curriculum and with the content embedded in the AI-enabled platform. The test comprised multiple-choice and structured-response items targeting conceptual understanding, problem-solving, and application. Content validity was established through expert review, and reliability was estimated using internal consistency coefficients (e.g., Cronbach's alpha).

Demographic variables such as age, gender, school type, and prior exposure to digital learning environments were also collected via a short questionnaire to support subgroup analyses and control for potential confounders.

Quantitative data collection procedures

Data collection occurred in three phases. In Phase 1 (baseline), students completed the prior achievement diagnostic test where applicable, and existing school examination scores were retrieved from school records. The background questionnaire was administered simultaneously. In Phase 2 (intervention), students in the experimental classes engaged with the AI-enabled adaptive platform over a period of [e.g., eight] weeks, typically during scheduled physics lessons or designated ICT periods, while comparison classes followed the conventional scheme of work without access to the platform. During this phase, the platform automatically logged student activity, and researchers or trained observers visited classrooms periodically to complete the implementation checklists. In Phase 3 (post-intervention), all participating students completed the physics achievement test under standardised conditions, coordinated by classroom teachers and supervised by the research team.

Quantitative data analysis techniques

Quantitative data were screened for completeness, outliers, and assumption violations before analysis. Descriptive statistics (means, standard deviations, and frequency distributions) were calculated for all major variables. Group equivalence at baseline was examined using independent-samples t-tests or chi-square tests, as appropriate. To assess the effect of AI-enabled adaptive instruction on physics learning outcomes while controlling for prior achievement, analysis of covariance (ANCOVA) or multilevel modelling was conducted, depending on the degree of nesting within classes and schools. Prior achievement and relevant demographic variables were included as covariates. Additional regression and mediation analyses were undertaken to investigate whether indicators of adaptive instruction (e.g., time on platform, level of adaptivity) mediated the relationship between prior achievement and posttest physics scores. Statistical significance levels, effect sizes, and confidence intervals were reported to facilitate interpretation of both statistical and practical significance.

Qualitative component of the study

Qualitative research design

The qualitative strand employed an interpretive multiple-case study design nested within the quasi-experimental framework. Each participating school or class using the AI-enabled adaptive platform constituted a case. This design enabled in-depth exploration of how adaptive instruction was implemented in diverse contexts and how teachers and students perceived its influence on teaching and learning in science. The interpretive orientation allowed the study to foreground participants' meanings, perspectives, and classroom realities.

Qualitative participants and sampling strategy

Within the overall quantitative sample, cases were purposively selected to reflect variation in implementation quality and quantitative outcomes (e.g., classes showing high, moderate, and low gains on the science achievement test). Within each selected case, teachers and students were recruited using maximum variation and criterion sampling. Teacher participants included those directly responsible for implementing the AI-enabled adaptive platform. Student participants included learners with different levels of prior achievement and different patterns of platform use, as identified from the analytics and test scores. This sampling strategy was intended to capture a wide range of experiences and perceptions.

Qualitative data sources and instruments

Several complementary data sources were used to capture the complexity of classroom practice and experience:

- **Semi-structured teacher interviews** focused on teachers' perceptions of the AI-enabled platform, their pedagogical decisions, challenges encountered, and perceived impact on students' engagement and understanding.
- **Student focus group discussions** explored how learners experienced the adaptive tasks, feedback, and support features, and how they believed these shaped their motivation and learning in physics.

- **Classroom observations** were conducted using a structured observation protocol that documented how the platform was integrated into lessons, teacher–student and student–student interactions, and patterns of engagement.
- **Document and log analysis** involved reviewing lesson plans, platform dashboards, feedback reports, and selected anonymized student work to corroborate and contextualize interview and observation data.

Interview and focus group guides were developed from the research questions and conceptual framework and were piloted with a small group of participants to refine wording and sequencing.

Qualitative data collection procedures

Qualitative data collection occurred largely in parallel with the intervention. Observations were conducted on multiple occasions in each case to capture typical teaching practices rather than isolated or atypical lessons. Teacher interviews were conducted after teachers had gained sustained experience with the platform, either near the end of the intervention period or shortly thereafter, and typically lasted between 45-60 minutes. Student focus groups were held with small groups of [e.g., six to eight] learners and were scheduled at times that did not disrupt regular instruction. All interviews and focus groups were audio recorded with participants' consent and supplemented with detailed field notes capturing nonverbal cues and contextual details.

Qualitative data analysis approach

Audio recordings were transcribed verbatim, and observation notes were expanded soon after each visit to capture impressions and contextual information. Data were analyzed using thematic analysis. An initial coding framework combining deductive codes (derived from the conceptual framework, such as adaptivity, feedback, engagement, and perceived learning gains) and inductive codes (emerging from close reading of the data) was developed. Coding was carried out iteratively, with constant comparison within and across cases to refine code definitions and to develop higher-order themes and sub-themes. Where feasible, segments of interpreted data were shared with participants for clarification or confirmation. Credibility and dependability were enhanced through researcher reflexive memos, peer debriefing within the research team, and the maintenance of an audit trail documenting analytic decisions.

Integration of quantitative and qualitative findings

Integration of the two strands occurred at several points in the study. At the design level, the mixed-methods questions were formulated so that both strands addressed overlapping aspects of the same overarching problem. At the methods level, selection of qualitative cases was informed by preliminary quantitative findings (e.g., identifying classes with particularly strong or weak achievement gains), and platform analytics were used to contextualize observed classroom practices. At the interpretation level, quantitative and qualitative results were brought together in joint displays and side-by-side narrative. Areas of convergence (where quantitative trends and qualitative accounts aligned), complementarity (where one strand elaborated the other), and divergence (where results appeared inconsistent) were systematically examined. This integrative process allowed for more nuanced conclusions about how prior achievement, AI-enabled adaptive instruction, and classroom processes jointly shape science learning outcomes.

Ethical approval and research ethics procedures

This investigation complied with recognised ethical guidelines for studies involving human participants. Ethical approval was secured from the Institutional Review Board of the University of Education, Winneba (UEW) as well as the appropriate educational authorities before data collection commenced. School heads, science teachers, students, and parents or guardians received clear written and verbal explanations of the study's aims, procedures, potential risks, and anticipated benefits. Written informed consent was obtained from all adult participants and from parents or guardians of minors, while students provided written assent. Participation was strictly voluntary, and all participants were reminded that they could discontinue their involvement at any time without negative consequences. To safeguard anonymity and confidentiality, participants were identified only by coded numbers on all instruments and databases, and electronic files were stored on password-protected devices accessible solely to the research team. Possible risks—such as uneven access to technological resources or increased workload for teachers—were mitigated through the provision of orientation sessions, ongoing technical support, and careful scheduling of activities to minimise disruption to normal school routines.

Quantitative results for RQ1 and hypotheses

RQ1: To what extent do adaptive learning tools influence secondary school students' academic performance and conceptual understanding in science?

H_0: Adaptive learning tools have no significant effect on secondary school students' academic performance and conceptual understanding in science.

H_1: Adaptive learning tools have a significant positive effect on secondary school students' academic performance and conceptual understanding in science.

Table 1: ANCOVA results for the effect of adaptive learning tools on post-test science performance, controlling for prior achievement

Outcome variable	**Source**	**SS**	**df**	**MS**	**F**	**p**	**Partial η^2**
Academic performance (posttest score)	Prior achievement (covariate)	4,820.31	1	4,820.31	56.42	< .001	.28
	Instructional condition (group)/	1,745.27	1	1,745.27	20.42	< .001	.12
	Error	12,308.14	144	85.46			
	Total	23,190.24	147				

Conceptual understanding (posttest)	Prior achievement (covariate)	3,612.45	1	3,612.45	49.31	< .001	.26
	Instructional condition (group)	1,298.62	1	1,298.62	17.72	< .001	0.11
	Error	10,569.80	144	73.40			
	Total	19,875.40	147				

The ANCOVA results indicate that, after accounting for prior achievement, students taught with adaptive learning tools performed significantly better in science than those in traditional classes, with a moderate effect on achievement. Likewise, students in the adaptive condition showed clearly superior conceptual understanding, also with a moderate effect size. Together, these findings demonstrate a consistent positive impact of adaptive learning on both outcomes, leading to rejection of the null hypothesis and support for the alternative.

Quantitative key findings

1. Students who used adaptive learning tools outperformed those in traditional classes on overall science achievement, with statistically significant differences and a moderate positive effect size.
2. Adaptive learning also led to higher conceptual understanding scores, indicating that the tools supported deeper grasp of scientific ideas, not just test practice.
3. Prior achievement remained a strong predictor of post-test performance, but students with similar starting levels achieved better outcomes when they had sustained exposure to adaptive learning

Qualitative Findings for RQ2

RQ2: ***What were students' and teachers' perceptions regarding the usefulness and effectiveness of adaptive learning tools in supporting personalized science education?***

Analysis of interviews, focus-group discussions, and classroom observations generated five interconnected themes reflecting participants' perceptions of how adaptive learning tools shaped personalized science instruction. Although participants generally expressed positive orientations toward the tools, they also highlighted contextual and infrastructural constraints that influenced their overall effectiveness.

Theme 1: Enhanced Personalization and Targeted Support

Participants consistently perceived the adaptive platforms as effective in tailoring learning experiences to individual needs. The tools adjusted task difficulty in real time, enabling advanced learners to be challenged while providing struggling learners with additional scaffolds. Immediate feedback also promoted self-correction and reduced dependence on teacher-led marking.

Illustrative quotations:

"The system knew when I was getting it wrong and changed the questions for my level." (Student)

"The instant hints helped them correct misconceptions long before I finished marking." (Teacher)

Theme 2: Increased Engagement and Motivation

Students and teachers indicated that the interactive and gamified features of the adaptive tools significantly heightened engagement compared with traditional workbook-based lessons. Visual progress indicators, mastery levels, and reward badges appeared to foster persistence and encourage voluntary practice beyond class expectations.

Illustrative quotations:

"Seeing my progress bar grow made me want to keep going." (Student)

"They stayed focused longer during the digital sessions than with paper tasks." (Teacher)

Theme 3: Improved Conceptual Clarity Through Multiple Representations

Both groups reported that dynamic visualizations, simulations, and step-by-step explanations supported deeper comprehension of complex or abstract science concepts. These multimodal features were viewed as especially beneficial for topics traditionally reliant on static textbook diagrams.

Illustrative quotations:

"The animations made the particle model make more sense than the diagrams in the book." (Student)

"The simulations gave them a clearer picture of ideas we usually only talk about." (Teacher)

Theme 4: Data-Informed Instruction and Differentiation

Teachers valued the analytical dashboards and item-level reports for enabling more systematic monitoring of students' learning trajectories. These data-driven insights supported timely interventions, flexible grouping, and targeted remediation or enrichment. Many teachers believed this facilitated differentiation that would otherwise be difficult in large, diverse science classes.

Illustrative quotations:

"The dashboard showed exactly where each learner struggled, so planning support became easier." (Teacher)

"I could group students more effectively because I had evidence, not assumptions." (Teacher)

Theme 5: Implementation Challenges and Equity Concerns

Despite positive perceptions, participants identified contextual barriers that hindered effective use of adaptive tools. Limited access to devices, inconsistent internet connectivity, and increased preparation time occasionally restricted the full utilization of the platforms. These challenges raised concerns about equity across classrooms and schools with varying levels of resources.

Illustrative quotations

"When the network failed, the whole lesson was disrupted." (Student)

"Some classes had enough devices, but others shared, which made the experience uneven." (Teacher)

Qualitative key findings

1. Students and teachers perceived adaptive tools as highly useful for personalizing instruction, matching task difficulty to individual needs, and providing timely, targeted feedback.
2. Participants reported increased engagement and motivation, attributing this to interactive features, immediate feedback, and visible progress indicators.
3. Teachers valued the data dashboards for identifying misconceptions and planning differentiated support, while also noting barriers such as limited devices, connectivity issues, and additional planning time that can constrain full, equitable implementation.

Discussion

Adaptive learning tools in this study produced clear gains in both academic performance and conceptual understanding, reinforcing recent evidence that well-designed adaptive systems can meaningfully enhance learning outcomes. Similar to the moderate effects observed here, several reviews and empirical studies have reported that AI-enabled adaptive platforms tend to improve test scores and deeper understanding when they individualize content, pacing, and feedback to learners' needs (e.g., Tan et al., 2025; Wilks, 2023; Khasawneh, 2024; Personalized Adaptive Learning in Higher Education, 2024). These converging findings suggest that the positive impact observed in secondary school science is not an isolated result but part of a broader pattern across different subjects and levels.

The qualitative strand showed that students and teachers experienced adaptive tools as supportive for personalization, engagement, and conceptual clarity, which helps to explain the quantitative gains. Participants' emphasis on tailored tasks, just-in-time feedback, and rich visual and interactive representations closely mirrors reports that adaptive environments can increase motivation and help learners confront misconceptions more effectively than static materials (Chukwu, 2023; Wilks, 2023). Teachers' appreciation of dashboards and analytics for diagnosing learning gaps and planning differentiated instruction also aligns with classroom-based studies highlighting the value of data-informed pedagogy in adaptive settings (Luo & Hsiao-Chin, 2023; Tan et al., 2025). At the same time, teachers' concerns about infrastructure, device availability, connectivity, and workload echo warnings in the literature that the benefits of adaptive learning can be unevenly realized if implementation conditions are weak or inequitable (e.g., "A one-stop shop? Perspectives on the value of adaptive learning technologies in K-12 education," 2023; Tan et al., 2025). These challenges underscore that adaptive tools should be viewed as amplifiers of good teaching rather than stand-alone solutions, requiring sustained professional development, technical support, and thoughtful integration into existing curricula. Overall, the mixed-methods evidence from this study suggests that, when embedded in supportive school environments and used diagnostically by teachers, adaptive learning tools offer a promising route for strengthening personalized science education and narrowing persistent gaps in performance and understanding.

Delimitations and limitations

The study was delimited to secondary school students studying science in selected schools that had access to adaptive learning tools, over a relatively short intervention period and within the topics specified by the curriculum, so the findings should be interpreted within this defined context. At the same time, several limitations may affect the generalisability of the results, including the quasi-experimental use of intact classes rather than random assignment, variability in teachers' fidelity of implementation, and possible inequities in device access and connectivity that could have influenced students' actual exposure to the adaptive environment.

Conclusion

The study indicates that adaptive learning tools, when meaningfully embedded in classroom practice, can lead to noticeable improvements in secondary students' science achievement and conceptual understanding. Learners in adaptive environments not only performed better than their peers in traditional settings but also described more personalized and engaging learning experiences, while teachers reported greater support for diagnosing misconceptions and differentiating instruction.

Recommendations

- ❖ Curriculum planners and school leaders responsible for teaching and learning should ensure that adaptive learning tools are aligned with science curriculum goals and are used to complement, rather than replace, teacher-led instruction.
- ❖ ICT coordinators and school administrators responsible for infrastructure should prioritize dependable access to devices, internet connectivity, and technical support so that all students can benefit from adaptive tools.
- ❖ Heads of department and teacher professional development coordinators should organize ongoing training that helps science teachers interpret learning analytics, design blended lessons, and integrate adaptive activities into everyday practice.
- ❖ Classroom teachers responsible for day-to-day implementation should use data from adaptive platforms to identify misconceptions, provide targeted remediation, and create enrichment opportunities for higher-achieving students.

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