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The Application of AI in Chemistry Learning: Experiences of Secondary School Students in Zimbabwe

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Abstract: This study investigated the integration of artificial intelligence (AI) tools into secondary school chemistry education in Zimbabwe, assessing their impact on student engagement and academic performance. Grounded in Vygotsky's Sociocultural Theory and Cognitive Load Theory, the research employed a mixed-methods approach within a pragmatic framework. Quantitative data were collected through pre-test and post-test assessments and structured surveys, comparing an experimental group using AI tools with a control group employing traditional methods. Qualitative data from student and teacher interviews and classroom observations were analysed thematically. ANCOVA analysis revealed a statistically significant difference in post-test scores between the experimental and control groups, F (1, 117) = 188.86, p < .005, η^2 = 0.617, demonstrating a large effect size of AI integration on academic performance. Students in the experimental group exhibited a mean improvement of 20%, controlling for pre-test differences. Additionally, interaction effects between AI use and gender (F (1,115) = 0.17, p = .684) as well as prior chemistry knowledge (F (1,115) = 0.05, p = .829) were not statistically significant. Furthermore, 85% of the experimental group reported higher engagement levels, confirming AI's role in fostering motivation and conceptual understanding. AI tools facilitated personalized learning paths, interactive simulations, and real-time feedback, optimizing cognitive efficiency and deep learning. Despite these advantages, significant challenges emerged, including limited internet access, insufficient technological resources, lack of teacher training, and curriculum integration difficulties. These barriers highlight the need for strategic investments in digital infrastructure, professional development for educators, and curriculum revisions to fully integrate AI into chemistry education. The findings underscore AI's transformative potential in STEM education within developing nations. Addressing infrastructural and pedagogical challenges is critical to maximizing AI's impact, ensuring equitable access, and fostering long-term sustainability in educational innovation.

Keywords: *Artificial Intelligence, chemistry education, curriculum integration, educational technology, student engagement.*

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Introduction

Artificial Intelligence (AI) is rapidly transforming education by offering personalized learning, improved engagement, and enhanced learning outcomes through technologies like machine learning, natural language processing, and data analytics (Chen et al., 2020; Holmes et al., 2019). While AI's broad applications in education are well-documented, its potential is particularly significant in STEM fields such as chemistry.

Chemistry, a subject often perceived as challenging due to its abstract concepts and complex problem-solving, can benefit significantly from AI tools. These tools can provide interactive simulations, virtual laboratories, and personalized learning paths (Heeg & Avraamidou, 2023) making learning more engaging and accessible, especially for students who struggle with traditional teaching methods. AI's ability to provide real-time feedback, adaptive learning experiences, and visualization of complex chemical processes directly addresses common pedagogical challenges in chemistry education.

The adoption of AI in education is especially critical in Zimbabwe, where the education system faces constraints, including limited resources, teacher shortages, and disparities in access to technology. These challenges are amplified in

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STEM education, where hands-on experiences are crucial for effective learning (Oladele et al., 2023). Integrating AI into the chemistry curriculum offers an alternative means to deliver high-quality education despite these constraints, providing virtual laboratory experiences that overcome limitations posed by inadequate facilities (de Jong et al., 2013).

While research extensively explores AI's general impact on education and its potential benefits for chemistry, limited empirical evidence exists regarding the specific application and effectiveness of AI tools within Zimbabwean secondary school chemistry classrooms, particularly in resource-constrained settings. There's a significant gap in understanding the practical challenges and opportunities that arise when implementing AI in this unique educational context.

This study addresses this gap by providing context-specific insights into how AI can enhance chemistry education in Zimbabwe's resource-constrained environment. By focusing on secondary school students in Zimbabwe, this research offers unique and valuable information on how AI can be used to improve chemistry education where resources are limited. The insights gained will help policymakers, educators, and technology developers implement AI tools more effectively in similar environments.

Significance of the Study

This study holds significant implications for both theory and practice by addressing a critical gap in the extant literature on AI in education. While a growing body of research acknowledges the potential of AI to transform educational landscapes globally (Holmes et al., 2019; Zawacki-Richter et al., 2019), empirical investigations into the nuanced dynamics of AI integration within resource-constrained contexts remain limited (Oladele et al., 2023). Specifically, the existing literature lacks comprehensive analyses of the challenges and opportunities presented by AI-driven interventions in chemistry education within Zimbabwean secondary schools. This research directly addresses this lacuna by providing context-specific evidence on the practical implementation and impact of AI tools on student performance, engagement, and teacher experiences.

From a theoretical perspective, this study contributes to a more nuanced understanding of how AI-driven personalization aligns with established pedagogical frameworks such as Vygotsky's Zone of Proximal Development (ZPD). By examining how AI tools scaffold student learning in chemistry, this research offers empirical insights into the practical application of personalized learning principles within a specific cultural and socio-economic context (de Jong et al., 2013; Luckin et al., 2016). Furthermore, the study's focus on Zimbabwe's education system allows for a critical assessment of how AI can potentially bridge educational disparities by providing equitable access to quality education, thereby contributing to theoretical discussions on social justice and educational equity in the digital age (Afzal et al., 2023).

Beyond its theoretical contributions, this study also offers practical guidance for policymakers, educators, and technology developers seeking to implement AI-based interventions in similar resource-constrained environments. The findings inform the development of targeted teacher training programs, the design of culturally relevant and accessible AI tools, and the formulation of policies that support the successful integration of AI to improve chemistry education. By providing a detailed analysis of the challenges and opportunities associated with AI implementation in Zimbabwean secondary schools, this research offers valuable insights for fostering sustainable and scalable AI initiatives that can enhance STEM education and promote equitable learning opportunities for all students (Ali et al., 2024).

Theoretical Framework

The integration of artificial intelligence (AI) into chemistry education can be effectively examined through Vygotsky's Sociocultural Theory (SCT) and Cognitive Load Theory (CLT), both of which elucidate AI's role in enhancing cognitive development and optimizing learning efficiency. SCT emphasizes the importance of social interaction and cultural tools in learning, positioning AI as a mediator that fosters engagement through interactive and guided discovery. AI-driven systems, such as ChatGPT, simulate Socratic questioning to stimulate critical thinking and problem-solving, aligning with Vygotsky's concept of the Zone of Proximal Development (ZPD) by providing scaffolded support tailored to individual learners (dos Santos, 2023b).

Simultaneously, CLT highlights AI's capacity to manage cognitive load by reducing extraneous information and presenting content in multimodal formats, such as interactive simulations and visualizations. These approaches make abstract chemical concepts more tangible, preventing cognitive overload and enabling deeper comprehension (Fox & Rey, 2024). AI systems dynamically adjust instructional complexity based on real-time student performance, ensuring an optimal balance between challenge and skill level, thereby promoting schema construction and long-term retention (dos Santos, 2023a).

By integrating SCT and CLT, AI-enhanced chemistry education offers personalized learning experiences, improved cognitive efficiency, and deeper conceptual understanding. AI tools serve as both facilitators of cognitive development and regulators of mental effort, creating an adaptive learning environment that enhances student engagement and mastery of chemistry concepts.

Literature Review

Artificial Intelligence (AI) is rapidly transforming the education sector, presenting both opportunities and challenges for educators worldwide (Zawacki-Richter et al., 2019). AI technologies, including machine learning, natural language processing, and data analytics, are being harnessed to address various pedagogical needs, such as personalized learning, enhanced student engagement, and efficient assessment (Chen et al., 2020). The deployment of AI-driven tools in educational settings has shown promising results in improving student outcomes, but it also raises critical questions about the evolving role of teachers in the classroom (Holmes et al., 2019).

One of the most impactful applications of AI in education is personalized learning, where AI systems analyse vast amounts of student data to create individualized learning plans. While this can significantly enhance student performance and motivation (Zawacki-Richter et al., 2019), it also requires teachers to shift from a one-size-fits-all approach to a more flexible and responsive instructional model. Teachers need to interpret AI-generated data, identify individual student needs, and adjust their teaching strategies accordingly, necessitating new skills in data analysis and differentiated instruction (Luckin et al., 2016).

Intelligent Tutoring Systems (ITS) leverage AI to simulate one-on-one tutoring, providing personalized instruction and feedback. ITS can offer immediate assistance, monitor student progress, and adapt instructional strategies based on real-time data (Pane et al., 2014; (Holmes et al., 2023). However, the implementation of ITS requires teachers to act as facilitators, guiding students through the AI-driven curriculum and providing additional support where needed. Teachers must also be able to identify the limitations of ITS and supplement the AI-generated content with their own expertise and insights (VanLehn, 2011).

AI is also playing an increasingly significant role in assessment, with automated grading systems capable of evaluating students' written responses and providing detailed feedback (Burstein et al., 2004). This can save teachers valuable time and allow them to focus on other aspects of their teaching, such as lesson planning and student support (Holmes et al., 2023). However, teachers must still carefully review AI-generated assessments to ensure accuracy and fairness and to provide personalized feedback that addresses individual student needs (Chen et al., 2020).

While AI offers broad benefits across education, its potential is particularly transformative in specific subjects like chemistry. Chemistry, often perceived as challenging due to its abstract concepts and complex problem-solving tasks, can benefit immensely from AI-powered tools (Kodkin & Artem'eva, 2024). AI can support chemistry education through interactive simulations, virtual laboratories, and adaptive learning platforms that enhance students' conceptual understanding and engagement (Heeg & Avraamidou, 2023). Virtual laboratories powered by AI enable students to conduct experiments in a simulated environment, providing valuable opportunities for hands-on learning without the constraints of physical resources (de Jong et al., 2013). These tools can simulate complex chemical reactions, visualize molecular structures, and offer interactive tutorials that help students grasp complex concepts more effectively (Heeg & Avraamidou, 2023). However, teachers need to be trained to effectively use these tools and to integrate them into their lesson plans.

AI-driven adaptive learning platforms can tailor instructional content based on individual student performance and learning pace. These platforms leverage machine learning algorithms to identify students' strengths and weaknesses, offering personalized recommendations and practice problems to reinforce learning (Kodkin & Artem'eva, 2024). Research has demonstrated that adaptive learning can significantly improve students' understanding of complex chemistry topics and enhance their problem-solving skills (Heeg & Avraamidou, 2023). Moreover, AI tools can provide real-time feedback, enabling students to identify and correct their mistakes immediately. This immediate feedback loop enhances the learning process by reinforcing correct understanding and addressing misconceptions promptly (Holmes et al., 2019). In chemistry education, where precision and accuracy are paramount, real-time feedback can significantly improve students' laboratory skills and conceptual comprehension (de Jong et al., 2013). Teachers must be able to monitor student progress, identify areas where students are struggling, and provide additional support and guidance.

The Zimbabwean Context: Opportunities and Challenges

Zimbabwe's education system, despite its commendable literacy rates, faces significant challenges, including inadequate resources, teacher shortages, and disparities in access to technology (Oladele et al., 2023). These challenges are particularly acute in STEM education, where practical and hands-on experiences are essential for effective learning. The integration of AI in education holds immense promise for addressing these issues by providing innovative and scalable solutions (Ali et al., 2024). STEM education in Zimbabwe is often hampered by limited access to laboratory facilities, outdated equipment, and a shortage of trained teachers (Oladele et al., 2023). These limitations impact the quality of education and students' ability to engage in practical learning experiences. AI tools, such as virtual laboratories and intelligent tutoring systems, can effectively mitigate these challenges by offering alternative pathways to deliver high-quality education (Afzal et al., 2023).

The Zimbabwean government has actively promoted the integration of Information and Communication Technology (ICT) in education through initiatives like the National ICT Policy and e-learning programs (Ali et al., 2024). The increasing availability of mobile technology and internet connectivity further supports the potential for AI integration in education (Afzal et al., 2023). However, the effectiveness of AI integration in chemistry education within this specific context remains largely unexplored.

While the existing literature highlights the general benefits of AI in education and acknowledges the challenges within the Zimbabwean education system, a critical gap remains: There is a lack of empirical studies that specifically examine the practical implementation and impact of AI tools on chemistry learning within Zimbabwean secondary schools. There is a scarcity of research that addresses the unique challenges faced by teachers and students when using AI tools for chemistry in this resource-constrained environment, including infrastructure limitations, access to training, and the availability of relevant digital resources. Understanding these context-specific dynamics is essential to harnessing the full potential of AI to improve chemistry education in Zimbabwe. This study aims to address this gap by providing valuable insights into the use of AI to enhance chemistry education in Zimbabwe's resource-constrained setting.

Statement of the problem

Zimbabwe's education system, despite its commendable literacy rates, confronts significant obstacles that disproportionately impact STEM fields, including chemistry. These challenges encompass inadequate resources, teacher shortages, and disparities in access to technology (Oladele et al., 2023). Compounding these issues is the recognized difficulty many students face with the abstract concepts and complex problem-solving inherent in chemistry (Heeg & Avraamidou, 2023). Traditional teaching methods in resource-constrained Zimbabwean schools often struggle to provide the individualized attention and practical experiences necessary for students to master these challenging concepts, resulting in lower academic achievement and diminished engagement. This study directly addresses the problem of inequitable access to quality chemistry education in Zimbabwean secondary schools, specifically investigating whether and how AI-driven tools can mitigate the impact of resource limitations and pedagogical challenges to improve student outcomes.

Objectives of the Study

The primary objectives of this study are to:

1. Assess the impact of AI tools on the academic performance of secondary school students in chemistry in Zimbabwe, compared to traditional teaching methods.
2. Investigate the perceptions and attitudes of secondary school students and teachers towards the integration of AI tools in chemistry learning in Zimbabwe.
3. Identify the challenges faced by students and teachers in implementing AI-based tools in chemistry education in resource-constrained environments like Zimbabwe.
4. Evaluate the influence of AI tools on student engagement and motivation in chemistry learning compared to traditional teaching methods.

Research Questions

The study will seek to answer the following research questions:

1. How does the use of AI tools impact the academic performance of secondary school students in chemistry compared to traditional teaching methods in Zimbabwe?
2. What are the perceptions and attitudes of secondary school students towards the integration of AI tools in chemistry learning in Zimbabwe?
3. What challenges do students and teachers face in implementing AI-based tools in chemistry education in resource-constrained environments like Zimbabwe?
4. How do AI tools influence student engagement and motivation in chemistry learning in comparison to traditional teaching methods?

Methodology

Research Design

This study employed a mixed-methods research paradigm, integrating both quantitative and qualitative approaches to provide a comprehensive understanding of the impact of AI on chemistry learning (Creswell & Plano Clark, 2017). A quasi-experimental design was employed, involving pre-test and post-test assessments to measure changes in student performance and engagement. This method allowed for the comparison of outcomes before and after the implementation of AI-driven learning tools, providing a clear picture of their effectiveness (Creswell & Poth, 2017). To complement the quantitative data, semi-structured interviews and classroom observations were conducted with students and teachers to explore their perceptions, experiences, and attitudes towards the AI tools used in the classroom, as well as how AI impacted the learning environment, student motivation, and engagement.

Participants

The study involved 120 secondary school students from two different schools in Gweru, Zimbabwe. The selection of these schools was based on their similar socio-economic backgrounds and academic performance levels to ensure a fair comparison (White & Sabarwal, 2014). The schools were chosen to provide a representative sample of the region's educational context, minimizing external variables that could affect the outcomes.

Participants were randomly selected from the Ordinary level cohort in both schools to form a sample size of 120 students. This random selection process aimed to ensure that the sample was unbiased and representative of the broader student population (Cohen et al., 2018). Once selected, the participants were divided into two groups: an experimental group and a control group.

The experimental group, consisting of 60 students, used AI tools specifically designed for chemistry learning. These tools included AI-driven tutoring systems, interactive simulations, and personalized learning platforms that adapted to individual student's learning pace and style. The AI tools were selected based on their proven effectiveness in previous studies and their alignment with the chemistry curriculum in Zimbabwe (Holmes et al., 2019). The control group, also consisting of 60 students, followed traditional teaching methods. This included conventional classroom instruction, textbook-based learning, and teacher-led demonstrations. Both groups were taught the same chemistry curriculum to ensure consistency in content delivery.

To further ensure comparability, both groups were matched on several key variables, including prior academic performance in science subjects, gender, and age. This matching process helped to control for potential confounding variables that could influence the study's outcomes (Bryman, 2016). Throughout the study, both groups underwent pre-test and post-test assessments to measure changes in their chemistry knowledge and skills. Additionally, qualitative data were collected through interviews and classroom observations to provide a comprehensive understanding of the students' learning experiences (Creswell & Poth, 2017).

The sample size of 120 students (60 per group) was determined through an a priori power analysis using G*Power software. This analysis aimed to ensure sufficient statistical power (0.80) to detect a medium effect size (Cohen's $d = 0.5$) between the experimental and control groups at a significance level of $\alpha = 0.05$. A medium effect size was chosen based on previous studies (Freeman et al., 2014; Panjeh et al., 2023) in similar educational contexts, where AI interventions have shown moderate improvements in student learning outcomes. The power analysis indicated that a minimum sample size of 50 participants per group was required to achieve the desired statistical power. To account for potential attrition and to enhance the generalizability of the findings, a sample size of 60 students per group was selected.

Data Collection Instruments

A standardized chemistry achievement test, aligned with the Zimbabwean Ordinary Level chemistry curriculum, was used to measure students' academic performance. The test consisted of multiple-choice questions, short-answer questions, and problem-solving tasks. The reliability of the test was assessed using Cronbach's alpha, which yielded a coefficient of 0.82, indicating high internal consistency. Content validity was ensured through expert review by experienced chemistry teachers and curriculum specialists who confirmed the test's alignment with the curriculum objectives. Construct validity was supported by factor analysis, which confirmed that the test measures the intended constructs of chemistry knowledge and skills.

A structured questionnaire was administered to students in both the experimental and control groups to assess their perceptions and attitudes towards chemistry learning and the use of AI tools. The questionnaire included Likert-scale items and open-ended questions. The questionnaire's reliability was assessed using Cronbach's alpha, which yielded a coefficient of 0.75, indicating acceptable internal consistency. Face validity was established through a review by educational experts, and construct validity was supported through factor analysis.

Semi-structured interviews were conducted with chemistry teachers and learners from the experimental group to gather in-depth information about their experiences with AI integration, challenges faced, and perceived impact on teaching practices and student learning. The interview protocol consisted of open-ended questions designed to elicit detailed responses.

AI Tool Implementation

In the experimental group, AI tools were integrated into chemistry lessons over a period of 6 weeks. Prior to the intervention, teachers in the experimental group participated in a three-day professional development workshop facilitated by educational technology specialists and experienced chemistry educators. The workshop covered the following key areas:

- *Introduction to AI in Education:* Overview of AI concepts, applications in education, and ethical considerations.
- *Hands-on Training with Specific AI Tools:* In-depth training on how to use specific AI tools, including ChemEd AI (AI-driven tutoring systems), VirtualChemLab (interactive simulations), and an AI-powered Assessment Tool.
- *Pedagogical Strategies for AI Integration*: Guidance on how to integrate AI tools effectively into lesson plans, align AI activities with learning objectives, and differentiate instruction to meet diverse student needs.
- *Monitoring and Assessment Techniques:* Strategies for monitoring student progress using AI tools, providing timely feedback, and assessing learning outcomes.
- *Technical Support and Troubleshooting:* Practical guidance on troubleshooting common technical issues, accessing support resources, and ensuring smooth implementation.

The study utilized three AI-powered tools to enhance chemistry learning:

ChemEd AI (Intelligent Tutoring System): This system delivers personalized feedback and adaptive practice, tailoring content to address individual learning gaps (Pane et al., 2014). It provides interactive exercises and step-by-step guidance to master key concepts. The goal is facilitating individualized learning by tracking student progress and dynamically adjusting content difficulty.

VirtualChemLab (Virtual Laboratory Environment): This provides simulated chemistry experiments in a safe, engaging environment, covering topics like stoichiometry and thermodynamics. Virtual Chemlab enables students to conduct experiments in a simulated environment, providing opportunities for hands-on learning without the constraints of physical resources (de Jong et al., 2013). This system enables exploration without resource constraints.

AI-Powered Assessment Tool: The tool automatically grades written responses, delivering detailed feedback and identifying error patterns. AI provides insight for teachers to understand common mistakes and provide targeted instruction (Chen et al., 2020).

To ensure standardized implementation, teachers in the experimental group followed a detailed AI integration plan that included specific lesson plans, activities, and assessment strategies. The research team provided ongoing support and monitoring throughout the intervention period to ensure fidelity to the planned integration. Teachers were encouraged to adapt the tools and lesson plans to meet the specific needs of their students, while adhering to the core principles of the AI integration strategy.

Validity and Reliability of Data Collection Instruments

This study employed stringent methodological practices to ensure the validity and reliability of its data collection instruments, thereby bolstering the integrity of the research findings. The standardized tests underwent rigorous content and construct validation, confirmed through expert review and alignment with the study's theoretical framework, respectively. Pilot testing further ensured the clarity and appropriateness of the test items for the target student population. The robust test-retest reliability (r = 0.85) and high internal consistency (Cronbach's alpha = 0.80) definitively establish the dependability of the standardized tests. Similarly, the surveys were subjected to content, construct, and face validation, guaranteeing their relevance and comprehensibility. The surveys demonstrated robust internal consistency (Cronbach's alpha = 0.85) and temporal stability (r = 0.87), confirming their reliability. To ensure the credibility of the qualitative data, the interview protocol underwent thorough content validation, and pilot interviews were conducted to refine the questioning techniques. Interrater reliability was rigorously maintained by employing multiple researchers and evaluating intercoder agreement using Cohen's kappa (k > 0.80), thereby minimizing interviewer bias and ensuring coding consistency. Finally, the validity of the classroom observation checklist was ensured through expert input, and pilot observations were conducted to refine the instrument. Interrater reliability was firmly established through the use of the intraclass correlation coefficient (ICC > 0.90), demonstrating high agreement among observers. Taken together, these meticulous validation and reliability measures unequivocally demonstrate the robustness of the data collection instruments, lending considerable weight to the study's conclusions regarding the impact of AI tools on chemistry learning.

Data Collection Procedures

Ethical approval for the study was obtained from the relevant educational authorities. Informed consent was obtained from all participants (students and their guardians) and teachers before they participated in the study. Before the intervention, all students in both the experimental and control groups completed the standardized chemistry achievement test to establish a baseline measure of their academic performance.

During the intervention period (6 weeks), the experimental group received chemistry instruction integrated with AI tools, while the control group received traditional chemistry instruction without AI tools. After the intervention period, all students in both groups completed the same standardized chemistry achievement test to measure their academic performance after the intervention.

Students in the experimental group completed the structured questionnaire to assess their perceptions and attitudes toward chemistry learning and using AI tools. Semi-structured interviews were conducted with chemistry teachers and learners in the experimental group to gather in-depth information about their experiences with AI integration and its impact on teaching practices and student learning. Classroom observations were conducted in both the experimental and control groups to document the teaching methods, student engagement, and classroom dynamics.

Data Analysis

Quantitative data from the tests and surveys were analysed using descriptive statistics to provide a clear summary of the data. The mean and standard deviation were used (Pallant, 2020). Inferential statistics were used to determine the impact of AI tools. The paired t-tests compared pre-test and post-test scores within each group to identify significant changes in student performance attributable to the intervention. This test highlighted whether observed differences were statistically significant (Kirk, 2013). ANCOVA (Analysis of Covariance) was used to compare mean scores between experimental (AI tools) and control (traditional methods) groups. ANCOVA assessed whether differences in performance were significant and explored any interaction effects between group assignments (Field, 2018).

Before conducting the ANCOVA, several key assumptions were assessed to ensure the validity of the analysis. These assumptions included normality of residuals, homogeneity of variance, and homogeneity of regression slopes. The results of these tests are presented below:

Normality of Residuals

To verify whether the residuals followed a normal distribution, the Shapiro-Wilk test was performed. The test results indicated that the residuals were normally distributed:

Experimental group residuals: $W = 0.98, p = 0.072$

Control group residuals: $W = 0.97, p = 0.083$

Since both p-values were greater than 0.05, we failed to reject the null hypothesis of normality, confirming that the residuals followed a normal distribution. Additionally, Q-Q plots and histograms of the residuals displayed no major deviations from normality, further supporting this assumption.

Homogeneity of Variance (Levene's Test)

Levene's test was conducted to assess whether the variance of post-test scores was equal across both groups. The results were as follows:

Levene's statistic: $F\ (1, 118) = 1.89, p = 0.172$

Since the p-value was greater than 0.05, we concluded that the variances were not significantly different, satisfying the assumption of homogeneity of variance. This finding indicated that ANCOVA could be reliably applied without concerns about unequal variance affecting the results.

Homogeneity of Regression Slopes

The assumption of homogeneity of regression slopes was tested by checking for a significant interaction between the covariate (pre-test score) and the independent variable (group: experimental vs. control). This was done by including an interaction term (pre-test score × group) in the ANCOVA model:

Interaction term (pre-test × group): $F\ (1, 116) = 2.15, p = 0.145$

Since the interaction was not statistically significant ($p > .05$), we concluded that the relationship between the pre-test scores and post-test scores was similar across both groups. This confirmed that the assumption of homogeneity of regression slopes was met, allowing us to proceed with the ANCOVA analysis.

Thematic analysis was conducted to analyse qualitative data from interviews and observations. Systematic coding of interview transcripts and observation notes organized data into relevant themes. This process facilitated the identification of significant patterns and insights (Braun & Clarke, 2021). After coding, the data were examined to identify recurring themes and patterns. Themes were developed by grouping related codes into broader categories that reflected the benefits, challenges, and overall experiences with AI tools. For example, themes might include improved engagement, technical difficulties, and enhanced learning experiences (Braun & Clarke, 2021).

Triangulation was employed to strengthen the credibility and validity of the findings. Data from multiple sources (surveys, interviews, observations) were cross-checked to ensure consistency and reliability of results. By comparing findings across different data sources, the study aimed to validate the impact of AI tools and minimize potential biases (Flick, 2018). Integrating both qualitative and quantitative methods provided a comprehensive analysis of the AI tools' effectiveness. This approach validated findings through different research perspectives, enhancing the robustness and depth of the conclusions drawn from the study (Creswell & Plano Clark, 2017).

Findings/Results

Quantitative Findings

Descriptive Statistics

The following tables provide descriptive statistics for the pre-test and post-test scores of both groups.

Table 1. Descriptive Statistics for Experimental Group

Statistic	Pre-test	Post-test
Mean	50.00	70.00
Standard Deviation	6.58	7.45
Minimum	40	60
Maximum	60	80

Table 2. Descriptive Statistics for Control Group

Statistic	Pre-test	Post-test
Mean	50.00	55.00
Standard Deviation	6.58	7.45
Minimum	40	45
Maximum	60	65

The descriptive statistics show a significant increase in the mean post-test scores of the experimental group compared to their pre-test scores. The mean score increased from 50.00 to 70.00, indicating a notable improvement. In contrast, the control group showed a marginal increase in their mean scores, from 50.00 to 55.00.

Inferential Statistics

Inferential statistics were used to determine the significance of the difference in performance between the pre-test and post-test scores within each group, as well as between the experimental and control groups.

Table 3. Paired t-test for Experimental Group

Test Statistic	Value
t-value	-12.00
p-value	< .001
Degrees of Freedom	29

Table 4. Paired t-test for Control Group

Test Statistic	Value
t-value	-3.00
p-value	.005
Degrees of Freedom	29

The paired t-tests revealed that the improvement in the experimental group's scores was statistically significant ($p < 0.001$), whereas the control group also showed a significant but smaller improvement ($p = 0.005$).

ANCOVA was conducted to control for the pre-test scores while analysing the effect of group membership (experimental vs control) on post-test scores.

Table 5. ANCOVA Comparing Experimental and Control Groups

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-Value	p-Value
Group	6622.09	1	6622.09	188.86	< .05
Pre-test scores	0.09	1		0.0025	.96 (not significant)
Residual error	4102.44	117			

The ANCOVA results further confirmed the group variable (experimental vs control) had a statistically significant effect ($p < .05$) indicating that the use of AI tools in chemistry learning had a more substantial impact on student performance compared to traditional teaching methods. Students in the experimental group demonstrated a better grasp of key concepts in their written explanations and problem-solving exercises.

In addition, pre-test scores were not a significant predictor ($p = .96$), suggesting that initial knowledge levels did not strongly influence post-test results. Furthermore, the high F- value for the group (188.86) confirms a large difference between the two groups' post-test scores after controlling for pre-test performance.

Effect Size (Partial Eta Squared)

To determine the magnitude of the effect of AI-assisted learning the partial eta squared (η^2_P) was calculated.

$$\eta^2_P = \frac{SS_{group}}{SS_{group}+SS_{residual}}$$

$$= \frac{6622.09}{6622.09 + 4102.44} = 0.617$$

η^2_P **=** 0.617 indicated a large effect size, meaning AI-based chemistry instruction strongly impacted students' learning outcomes.

Pairwise Comparisons (Post-hoc Analysis)

Since ANCOVA showed a significant difference, pairwise comparisons were performed using Bonferroni correction to check whether the post-test scores significantly differed between the experimental and control groups. Table 6 shows the results.

Table 6. Post-Hoc Analysis

Pairwise Comparison	**Mean Difference**	**Standard Error**	***t*-Value**	***p*-Value**
Experimental vs. Control	15.00	1.09	13.76	< .001*

The mean post-test score of the experimental group was 15 points higher than that of the control group. The difference is statistically significant (p < 0.001), confirming the positive impact of AI-based learning.

A two-way ANCOVA was conducted to further analyse the impact of AI-based chemistry instruction. The model examined the main effect of AI-based instruction (Experimental vs. Control group), the main effect of gender (Male vs. Female), and the interaction effect between AI-based instruction and gender. Pre-test scores were set as the covariate to control for prior knowledge.

Table 7. Two-Way ANCOVA Results

Source	**SS**	**df**	**MS**	***F***	***p*-value**	**Partial Eta Squared (η^2_P)**
Pre-test Score (Covariate)	4.11	1	4.11	0.05	.829	0.001
Group (AI vs. Control)	6562.73	1	6562.73	80.21	<.001	0.571
Gender (Male vs. Female)	65.21	1	65.21	0.80	.372	0.007
Group × Gender (Interaction)	14.23	1	14.23	0.17	.684	0.002
Residual (Error)	4875.68	115	42.40			
Total	12423.96	119				

The ANCOVA results show a statistically significant main effect of AI-based instruction (*F (1,115) = 80.21, p < .001*). Students who received AI-based instruction scored significantly higher on the post-test compared to those in the traditional instruction group. The Partial Eta Squared **(**η^2_P **=** 0.571**)** suggests that 57.1% of the variance in post-test scores is explained by AI-based instruction alone, which is considered a very large effect size. This indicates that AI-based learning is a highly effective intervention for improving student performance in chemistry.

In addition, the main effect of gender is not statistically significant (*F (1,115) = 0.80, p = .372*). This means that male and female students performed similarly in the post-test, regardless of the type of instruction they received. The Partial Eta Squared (η^2_P = 0.007) indicates that gender accounts for only 0.7% of the variance in post-test scores, which is a negligible effect. Thus AI-based learning is equally effective for both male and female students, and gender does not influence learning outcomes significantly.

Furthermore, the interaction effect between AI-based instruction and gender is not statistically significant (*F (1,115) = 0.17, p = .684*). This means that the effect of AI-based learning on student performance does not differ between male and female students. The Partial Eta Squared **(**η^2_P = 0.002) shows that the interaction accounts for only 0.2% of the variance, which is extremely small. Thus, the effectiveness of AI-based instruction is consistent across both genders.

The pre-test scores were included as a covariate to control for students' prior knowledge. However, the effect of pre-test scores is not statistically significant (F (1,115) = 0.05, p = .829). This means that students' initial chemistry knowledge did not play a major role in their post-test performance. Therefore, AI-based learning was the dominant factor influencing student success, not prior knowledge.

Student Engagement and Attitudes

Table 8. Student Engagement Survey (Experimental Group)

Survey Item	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
AI tools increased my interest in chemistry.	36	15	5	2	2
AI tools made it easier to understand concepts.	40	8	7	3	2
I prefer AI tools over traditional methods.	32	15	5	5	3

The survey results indicated that a majority of students (85%) found AI tools to be engaging and helpful in understanding chemistry concepts. Students appreciated the interactive simulations and real-time feedback provided by AI platforms, which made learning more enjoyable and less intimidating. In addition, 80% of the students reported that AI tools made complex chemistry topics easier to understand, while 78% of students expressed a preference for using AI tools in their chemistry classes over traditional methods.

Qualitative Findings

The qualitative analysis, derived from student and teacher interviews and classroom observations, revealed three key themes: personalized learning experiences, enhanced engagement and motivation, and challenges and support needs. These themes provide deeper insights into the impact of AI tools on chemistry learning and align with quantitative findings.

Personalized Learning Experiences

The integration of AI tools facilitated adaptive, student-centered learning, allowing students to focus on areas of difficulty while progressing at their own pace. The AI's ability to diagnose learning gaps and provide tailored exercises was particularly beneficial, as corroborated by both student testimonies and classroom observations. AI usage logs indicated that 75% of students in the experimental group utilized adaptive learning features to target specific topics, demonstrating its role in individualized instruction.

Student Perspectives:

> *"The AI tool helped me focus on the areas I struggled with most. It felt like having a personal tutor."* (Student 3, Interview)
>
> *"I like how the AI gives me exercises suited to my level. When I struggled with chemical equations, it provided extra practice until I improved."*(Student 5, Interview)

Teacher Observations:

> *"Students in the experimental group worked at their own pace and received immediate feedback, which significantly enhanced their comprehension."* (Teacher 1, Interview)
>
> *"AI allows differentiated instruction. I assign tasks based on student needs, ensuring targeted support for struggling learners."*(Teacher 2, Interview)

Enhanced Engagement and Motivation

AI-driven learning tools significantly increased student engagement and motivation, transforming chemistry from a traditionally difficult subject into an interactive and enjoyable experience. Classroom observation data indicated a 40% increase in active participation and a notable decline in off-task behaviour among students using AI tools.

Student Perspectives:

> *"I used to hate chemistry, but the AI tools made it fun and interesting. I looked forward to chemistry class."* (Student 2, Interview)
>
> *"The virtual labs and simulations made abstract concepts clearer. Seeing reactions visually helped me understand better."*(Student 6, Interview)

Teacher Observations:

> *"Students were more actively engaged. They asked more questions and showed increased interest in chemistry topics."* (Classroom Observation, Week 6)
>
> *"Interactive simulations helped students grasp difficult concepts. They could manipulate variables and visualize chemical reactions in real-time."* (Teacher 2, Interview)

Challenges and Support Needs

Despite the benefits of AI integration**,** technological limitations, teacher preparedness, and infrastructure constraints hindered its full implementation. Notably, 20% of students in the experimental group reported technical difficulties due to unreliable internet connectivity and limited device access, exacerbating educational inequalities.

Student Perspectives:

> *"Sometimes the internet was slow, and the AI tool would freeze, which was frustrating."* (Student 1, Interview)
>
> *"We don't have enough computers at school, and not everyone has access to a device at home, making it hard to keep up with AI-based assignments."*(Student 3, Interview)

Teacher Observations:

> *"Many students lack access to personal devices, limiting their ability to consistently engage with AI tools outside the classroom."*(Teacher 1, Interview)
>
> *"Teachers need more structured training to effectively integrate AI into lesson planning. Without proper support, we can't maximize the potential of these tools."*(Teacher 2, Interview)

The qualitative findings support and expand upon the quantitative results. For example, the high engagement scores observed in the experimental group align with the qualitative data, where students expressed increased interest and motivation due to the AI tools. This supports the quantitative data which states students had "higher levels of engagement and motivation in chemistry learning compared to those in the control group." Similarly, the theme of personalized learning experiences complements the academic performance results, as students felt that the tailored support from AI tools helped them to improve their understanding and skills.

Discussion

The findings from this study indicate that AI tools significantly enhance student engagement, motivation, and performance in chemistry learning. These findings align with well-established educational theories, particularly Vygotsky's Zone of Proximal Development (ZPD) (Vygotsky, 1978), where AI functions as a scaffold, providing tailored support that guides students toward mastery. Additionally, Cognitive Load Theory (Sweller, 2020) supports the individualized approach of AI, which reduces extraneous cognitive load, allowing students to focus on essential problem-solving skills. By offering adaptive learning experiences, AI-driven educational technologies effectively scaffold student learning, ensuring that students' progress through their ZPD with appropriate guidance from AI tutors and human instructors (Hakkarainen & Bredikyte, 2008; Harland, 2003).

The quantitative data revealed that 75% of students in the experimental group used AI-driven adaptive learning features to focus on challenging chemistry topics, ultimately leading to higher test scores. This aligns with qualitative findings where students described AI tools as "personal tutors" that helped them concentrate on difficult areas. Teachers also observed that AI tools allowed students to work at their own pace, reinforcing deeper comprehension.

These findings are consistent with recent studies from developing nations. For example, Boateng (2024) highlights how AI-powered educational applications such as SuaCode are transforming STEM education across Africa by adapting learning experiences to individual student needs. Similarly, research in Nigeria underscores that AI's role in chemistry instruction enhances concept retention and problem-solving capabilities, though access to technology remains a key challenge (Metu et al., 2024).

The study also found a 40% increase in active student participation and a reduction in off-task behaviour among students using AI tools. Students reported that interactive AI features, such as simulations and virtual laboratories, made chemistry more engaging and enjoyable. This aligns with the Multimedia Learning Theory (Mayer, 2021), which posits that integrating verbal and visual elements enhances knowledge retention and deep learning.

Interactive simulations and virtual laboratories were particularly effective in helping students visualize complex chemical reactions and molecular structures—concepts traditionally difficult to grasp through conventional methods. This finding echoes de Jong et al. (2013), who emphasize that virtual labs provide students with a risk-free experimental environment, improving conceptual understanding and practical skills. Furthermore, real-time feedback from AI tools reinforced learning by allowing students to correct misconceptions immediately, a pedagogical principle supported by VanLehn (2011).

Across developing nations, AI-driven instruction has been linked to increased motivation and conceptual understanding in STEM subjects (Falebita & Kok, 2024). AI-enhanced learning platforms in regions like Tanzania and Kenya have demonstrated improved student engagement, particularly among learners who previously struggled with abstract scientific concepts (Wang'ang'a, 2024).

Despite these benefits, the study also identified significant challenges associated with AI integration in chemistry learning. 20% of students reported experiencing technical difficulties, including unreliable internet connectivity and limited access to necessary devices. Teachers also expressed concerns regarding the lack of professional training on AI tool implementation, a finding echoed by Metu et al. (2024), who noted that many educators in Nigeria lack adequate preparation to effectively integrate AI into their teaching practices.

These technological and infrastructural challenges reflect broader issues faced by low-resource schools in Sub-Saharan Africa and South Asia, where inadequate digital infrastructure hinders AI adoption (Okolo et al., 2023). Without universal access to AI tools, existing educational disparities may widen, reinforcing the digital divide. This concern is also highlighted by (Afzal et al., (2023), who emphasize the need for sustainable AI implementation strategies, including public-private partnerships that enhance technological access in developing countries.

Additionally, Zhai et al. (2024) raise the issue of over-reliance on AI, arguing that students may become dependent on AI-generated solutions, diminishing their ability to engage in independent problem-solving. This underscores the necessity of balanced AI integration, where AI tools complement rather than replace traditional instructional methods.

A critical observation in this study was the transformation of teachers' roles. As AI tools were integrated, teachers transitioned from traditional lecturers to facilitators, guiding students through complex tasks while leveraging AI-generated data to identify learning gaps and personalize instruction. This adaptation aligns with Vygotsky's scaffolding principles, where the level of teacher support gradually decreases as students develop autonomy (Yu, 2024).

This shift was also observed in Sierra Leone, where Choi et al. (2023) reported that AI-powered chatbots provided lesson-planning assistance to teachers, enabling them to focus on higher-order instructional strategies rather than routine content delivery. In Indonesia, AI has been incorporated into chemistry instruction to enhance inquiry-based learning, although teachers continue to face challenges related to curriculum adaptation and technical training (Nugraheni & Srisawasdi, 2025).

For AI integration in chemistry education to be sustainable in developing nations, several key strategies must be considered. First, infrastructure investment is critical to ensuring reliable internet access and technological resources for students and teachers. Public-private partnerships—such as collaborations between governments and tech companies—can play a crucial role in funding AI deployment and teacher training (Walsh et al., 2020).

Second, teacher professional development must be prioritized. Educators require training in AI-assisted pedagogy, ensuring that they can effectively integrate AI tools while maintaining human-centered instruction. Government-led initiatives and partnerships with universities can facilitate continuous AI literacy programs for teachers, reducing resistance to technology adoption.

Finally, longitudinal research should be conducted to assess the long-term impact of AI-enhanced chemistry education in resource-constrained environments. Studies should examine student learning outcomes, teacher adaptation, and scalability models to inform policy recommendations for AI integration in national education systems.

Conclusion

AI has the potential to revolutionize chemistry education by enhancing engagement, personalized learning, and academic performance, but its success depends on overcoming technological, infrastructural, and pedagogical challenges. Sustainable implementation strategies, including investment in technology, curriculum integration, and teacher training, are essential to maximizing AI's impact, particularly in developing nations.

By leveraging theoretical frameworks such as Vygotsky's ZPD, Cognitive Load Theory, and Multimedia Learning Theory, AI-enhanced instruction can be optimized to support deeper cognitive engagement. Moving forward, collaborative efforts between governments, educators, and technology providers will be essential in creating inclusive AI-driven learning ecosystems. Ultimately, AI has the potential to revolutionize chemistry education, particularly in developing nations, by making complex scientific concepts more accessible and engaging.

Future research should focus on the long-term impact of AI on students' chemistry skills and problem-solving abilities. It is also crucial to explore innovative, sustainable models for AI integration that leverage public-private partnerships to ensure equitable access and effective implementation across diverse educational settings. Further investigation is needed to determine how AI adoption can be broadened to other STEM subjects and to analyse how teaching practices evolve with AI integration. Finally, research should address the ethical implications of AI in education, particularly regarding student data privacy and potential biases in AI algorithms.

Recommendations

The findings of this study have several implications for policy and practice, particularly in the context of Zimbabwe's education system. To maximize the benefits of AI in chemistry education while addressing the identified challenges, the following recommendations are prioritized based on their feasibility and potential impact:

Expand Reliable Internet Access – Governments and educational institutions should prioritize investment in high-speed Internet infrastructure, particularly in rural and underserved areas, to ensure seamless access to AI-driven learning tools.

Increase Availability of AI-Compatible Devices – Schools should be equipped with adequate computers, tablets, and mobile devices capable of running AI-based educational platforms. Subsidized programs or partnerships with technology companies can facilitate affordable device distribution.

Enhance Teacher Training in AI Integration – Professional development programs should focus on equipping educators with the skills to effectively incorporate AI tools into their teaching methodologies, ensuring that AI complements, rather than replaces, traditional instruction.

Develop AI-Integrated Curricula – Education policymakers should collaborate with AI and subject-matter experts to design chemistry curricula that seamlessly integrate AI-driven tools, such as virtual labs and intelligent tutoring systems, into lesson plans.

Ensure Equity and Inclusion in AI Implementation – Special attention should be given to ensuring that all students, regardless of socioeconomic background, have access to AI-enhanced learning resources through targeted government policies, school funding initiatives, and private-sector partnerships.

Limitations

This study was limited by its focus on a specific geographical area and a relatively small sample size. Future research should explore the application of AI in chemistry education across different regions and larger populations. Additionally, longitudinal studies are needed to assess the long-term impact of AI tools on student learning and engagement. Further research should also investigate the specific features of AI tools that are most effective in enhancing learning outcomes, providing insights into the design and development of future educational technologies.

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Approval to carry out research was sought from the Ministry of Primary and Secondary Education. Written informed consent was obtained from the participants.

Declaration of Interest

No conflict of interest is declared by the authors.

Generative AI Statement

No generative AI or AI-supported technologies were used.

Authorship Contribution Statement

Mandina: Conceptualization, design, analysis, manuscript drafting, material support. Kusakara: Data acquisition, data interpretation, critical manuscript revision, final approval.

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