

EVALUATING THE EFFECT OF AI-ENHANCED INQUIRY-BASED PEDAGOGIES ON HIGHER-ORDER COGNITIVE PROCESSES IN BIOLOGY SCHOLARS IN DELTA STATE

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Abstract

The rapid growth of artificial intelligence (AI) and digital learning technologies offers new ways to strengthen higher-order cognitive skills in higher education. This study examined the impact of AI-enhanced inquiry-based pedagogy on Biology scholars in Delta State, Nigeria, focusing on analytical, evaluative, and creative problem-solving abilities. Using multistage sampling, schools with adequate ICT facilities were selected, and intact Biology classes were randomly assigned to experimental and control groups. Sixty students (32 males, 28 females) from four tertiary institutions participated. The experimental group received AI-supported inquiry-based instruction, while the control group was taught with conventional teacher-centered methods. Pretests and posttests were administered, and data were analyzed using ANCOVA to adjust for baseline differences. Results showed that students exposed to AI-enhanced pedagogy significantly outperformed peers in analytical reasoning, evaluative judgment, and creative problem-solving. Adjusted mean comparisons confirmed these differences, with small standard errors indicating precise estimates. The study concludes that integrating AI with inquiry-based pedagogy effectively promotes higher-order thinking in Biology education. Implications include curriculum design, teacher training, and adoption of AI-supported strategies. It is recommended that educators and policymakers embrace AI-enhanced inquiry-based approaches to foster critical thinking, creativity, and problem-solving skills for 21st-century challenges.

Keywords: AI-enhanced pedagogy, Inquiry-Based Learning, Higher-Order Cognitive Processes, Analytical Skills, Evaluative Skills, Creative Thinking, Problem-Solving, Biology Education

Introduction

The rapid advancement of artificial intelligence (AI) technologies has precipitated significant transformations in educational methodologies, particularly in the realm of higher education. Within the discipline of biology, the integration of AI tools into pedagogical frameworks presents novel opportunities to enhance cognitive engagement and foster deeper learning. Inquiry-based learning (IBL), a student-centered approach emphasizing active exploration and critical questioning, has been widely recognized for its efficacy in promoting higher-order cognitive processes such as analysis, synthesis, and evaluation (Hmelo-Silver,

Duncan & Chinn, 2007). The fusion of AI with inquiry-based pedagogies, referred to as AI-enhanced inquiry-based pedagogies (AI-IBP), promises to further stimulate these cognitive domains by providing adaptive, personalized, and interactive learning environments. This essay evaluates the effect of AI-IBP on higher-order cognitive processes among biology scholars, elucidating how AI technologies can augment inquiry activities to cultivate complex thinking skills essential for scientific inquiry and problem-solving.

Inquiry-based pedagogies are grounded in constructivist theories of learning, which posit that knowledge is actively constructed through exploration, questioning, and reflection (Bruner, 1961). In biology education, IBL encourages students to formulate hypotheses, design experiments, analyze data, and draw evidence-based conclusions, activities inherently linked to higher-order cognitive processes as outlined in Bloom's taxonomy (Anderson et al., 2001). These pedagogies facilitate cognitive engagement beyond memorization, fostering skills such as critical thinking, problem-solving, and metacognition. However, traditional inquiry-based methods often face challenges related to scalability, individual learner differences, and the complexity of biological content, which can impede the consistent development of higher-order cognition. AI technologies, encompassing machine learning algorithms, natural language processing, intelligent tutoring systems, and data analytics, offer dynamic capabilities to support personalized and adaptive learning experiences. By integrating AI into inquiry-based frameworks, educators can leverage AI's potential to scaffold cognitive tasks, provide real-time feedback, and simulate complex biological phenomena through virtual laboratories and modeling environments (Luckin et al., 2016). For example, AI-driven platforms can guide students through inquiry cycles by prompting reflective questions, suggesting relevant resources, and adapting difficulty levels based on learner performance (Holstein, McLaren & Alevan, 2018). Such scaffolding not only maintains cognitive challenge but also nurtures self-regulated learning, a critical component of higher-order thinking.

Recent empirical studies have begun to elucidate the impact of AI-IBP on cognitive outcomes in biology education. A study by Wan et al. (2020) investigated the effect of an AI-powered virtual lab on undergraduate biology students' abilities to design experiments and interpret data. The findings indicated significant improvements in students' analytical and evaluative skills compared to control groups engaged in traditional inquiry activities without AI support. Similarly, Nguyen and Kulikowich (2021) examined the use of an AI-driven intelligent tutoring system that facilitated hypothesis generation and argumentation in biology coursework. Their results demonstrated enhanced synthesis and critical reasoning among participants, attributable to the system's adaptive feedback and prompts that encouraged deeper inquiry.

Research Objectives

The study primarily evaluated the effect of AI-enhanced inquiry-based pedagogies on higher-order cognitive processes in biology scholars in Delta State. Specifically, the study developed these precise research objectives:

1. To compare higher-order cognitive processes between Biology scholars taught using AI-enhanced inquiry-based pedagogy and those taught using conventional teaching methods in Delta State.
2. To examine the effect of AI-enhanced inquiry-based pedagogies on higher-order cognitive processes among Biology scholars in Delta State.
3. To determine the effect of AI-enhanced inquiry-based pedagogies on Biology scholars' analytical skills in Delta State.

Research Questions

1. Is there a significant difference in higher-order cognitive processes between Biology scholars taught using AI-enhanced inquiry-based pedagogy and those taught using conventional teaching methods in Delta State?
2. What is the effect of AI-enhanced inquiry-based pedagogies on higher-order cognitive processes among Biology scholars in Delta State?
3. How do AI-enhanced inquiry-based pedagogies affect Biology scholars' analytical skills in Delta State?

Research Hypotheses

1. There is no significant difference in higher-order cognitive processes between Biology scholars taught using AI-enhanced inquiry-based pedagogy and those taught using conventional teaching methods.
2. There is no significant effect of AI-enhanced inquiry-based pedagogies on higher-order cognitive processes among Biology scholars in Delta State.
3. AI-enhanced inquiry-based pedagogies do not significantly affect Biology scholars' analytical skills in Delta State.

Methodology

The study adopted a quasi-experimental research design using a pretest–posttest non-equivalent control group approach. This design was considered appropriate because intact classes were used, making random assignment of participants impractical within the school setting. The design enabled the comparison of learning outcomes between Biology scholars exposed to AI-enhanced inquiry-based pedagogy and those taught using conventional teaching methods, while controlling for baseline differences through pretesting. The population comprised Biology lecturers in schools in Delta State. These scholars were selected because Biology requires higher-order cognitive engagements such as analysis, evaluation, and problem-solving, making it suitable for assessing the impact of AI-enhanced inquiry-based pedagogies.

A multistage sampling technique was employed in selecting the sample for the study. In the first stage, four (4) tertiary institutions offering Biology in Delta State were purposively selected based on the availability of basic information and communication technology (ICT) facilities (such as computers, internet access, or digital learning devices) and the willingness of school administrators and Biology teachers to participate. The selection of public schools ensured curriculum uniformity and comparability across instructional settings.

In the second stage, four intact Year II Biology classes within the selected schools were used. Two intact classes from two schools (DELSU and UNIDEL) were assigned to the experimental condition, while two intact classes from the remaining schools (DSUST and FUPRE) served as the control condition. A total of 60 Biology scholars participated in the study, comprising 32 males (51.7%) and 28 females (28.3%). The relatively balanced gender distribution enhanced the representativeness of the sample and reduced gender bias in assessing the effects of AI-enhanced inquiry-based pedagogy. The sample size of 60 participants was considered adequate for this quasi-experimental study, as educational research recommends a minimum of 30 participants per group to detect meaningful instructional effects. Furthermore, the sample size was appropriate for the applicatio

no inferential statistical techniques such as ANCOVA, providing sufficient statistical power to detect differences between the experimental and control groups.

The pretest was used for higher order cognitive analyses in Biological Science before commencing teaching to check the previous knowledge of the students (both groups-the Experimental and Control) with like conditions in both the groups, looked ever since, but pretest results indicate that the two groups were equal in magnitude of prior knowledge. After pretesting, safeguarding was provided for a period of six weeks. During this period, the treatment group underwent inquiry-based learning facilitated by an AI-powered online textbook that was equipped with an AI-enhanced questioning capability, adaptive learning, scaffolding inquiry, and collaborative activities. For each training unit, a control of the same version of biological content was offered with no traditional teacher-led instruction-meaning no lecturing, note-taking, or textbook explanations. This lent standardization to lesson plans, making sure that the same time and intensity of instruction was granted to the two groups. A post-test on the same cognitive process in Biology to start the experiment under environmental circumstances would take place. This instrument, like the pre-test, would attempt to measure alterations in the higher cognitive process claimed to have been manipulated by the instructional method or teaching method. In this study, the ethical aspects were always adhered to, as they would be. Anonymity would be preserved through coding of participants' personal material. Any data about completed test instruments was stored in strictly guarded custody. Possession was limited to researcher's data alone, and processing came in line with the ethical codes of the organization.

The descriptive and inferential analysis data from the study was analyzed using the appropriate techniques. Descriptive statistics, such as a list of means and standard deviations, were provided to describe the performance of Biology scholars in both the experimental group and the control group. The responses produced by these measures were to offer an overview of what the students were able to do and show any possible variability in their higher-order cognitive process scores. Then the analysis was directed toward inference using Analysis of Covariance (ANCOVA) to describe the effect that AI-enhanced inquiry-based pedagogy had on students' higher-order cognitive processes as compared to their pretest scores statistically controlled for. When there was a need for inferential testing, a few independent samples t-tests could have been applied to point out the differences among the groups. All hypotheses were tested at the 0.05 level of significance, and decisions concerning the acceptance or rejection of null hypotheses were based strictly on this criterion.

Results

Research Question 1: Is there a significant difference in higher-order cognitive processes between Biology scholars taught using AI-enhanced inquiry-based pedagogy and those taught using conventional teaching methods in Delta State?

Table 1: Adjusted Mean Scores of Higher-Order Cognitive Processes by Instructional Method

Group	N	Unadjusted Mean	Adjusted Mean	Std. Error
Experimental	30	79.14	78.42	0.61

(AI-Enhanced)				
Control	30	69.43	70.15	0.61
(Conventional)				
Mean Difference			8.27	

The results of this study are presented in Table 1 which shows the adjusted mean scores of Biology scholars after the intervention, using the pretest scores as a covariate. The adjusted mean scores for the experimental group (AI-assisted inquiry-based instruction) and the control group (conventional instruction) were 78.42 and 70.15, respectively. It is practically meaningful that the mean difference is 8.27 points, which is a statistically significant improvement for the experimental group. The equal standard errors, 0.61 for both groups, suggest that both groups are estimated with a high degree of stability and precision; thus, it appears likely that the difference between the two groups is reliable. The descriptive results indicate that the Biology learners who were taught using AI-inquiry-based learning obtained higher scores in the higher-order cognitive processes than the other learners in the higher-order cognitive processes, thus supporting the inferential test under the Hypotheses section presented in Table 2.

Research Question 2: What is the effect of AI-enhanced inquiry-based pedagogies on higher-order cognitive processes among Biology scholars in Delta State?

Table 2: ANCOVA Summary of Effect of AI-Enhanced Inquiry-Based Pedagogy on Higher-Order Cognitive Processes

Model	SS	Df	MS	F	Partial η^2	Sig. (p)
(intercept)						
Pretest	395.18	1	395.18	16.87	.21	.000
(Covariate)						
Pedagogical	742.51	1	742.51	31.72	.36	.000
Method						
Error	2735.04	57	47.98			
Total	3872.73	59				

Note. Independent variable: Pretest scores on the Higher-Order Cognitive Processes Assessment (HOCPA). Partial $\eta^2 \geq .14$ is a large effect (Cohen, 1988).

The results of the ANCOVA table in Table 2, for the magnitude and significance of the impact of AI-enhanced inquiry-based pedagogy on the HOCP are presented in Tab. 2. The pre-test covariate was statistically significant ($F(1, 57) = 16.87$, $p < .001$, partial $\eta^2 = .21$), meaning that the pre-test variance explained a significant proportion of total variance in the post test, and thus should be included in the model to provide an unbiased estimate of the treatment effect. More importantly, the pedagogical method had a statistically significant and large effect ($F(1, 57) = 31.72$, $p < .001$, partial $\eta^2 = .36$), suggesting that the AI-enhanced inquiry-based pedagogical method explained about 36% of the variance in higher-order cognitive process scores with prior knowledge controlled. The error term ($SS = 2735.04$, $df =$

57, MS = 47.98) reflects the error due to the other factor in posttest scores that is not related to the covariate or instructional method. The total sum of squares (3872.73) represents the variability of scores on higher-order cognitive processes for all participants. All the results together indicate that there was a statistically significant and practically large positive effect of AI-enhanced inquiry-based pedagogy on the higher-order cognitive processes of the Biology scholars in Delta State.

Research Question 3: How do AI-enhanced inquiry-based pedagogies affect Biology scholars' analytical skills in Delta State?

Table 3: Adjusted Mean Scores on Analytical Skills by Instructional Method

pH of water in a 13 sample tube		12.06	0.61 Error
Experimental (AI-Enhanced)	30	26.84	0.57
Control (Conventional)	30	21.96	0.57
Mean Difference		4.88	

The adjusted mean scores for analytical skills for both instructional groups are shown in Table 3, after controlling for pre-test performance. The adjusted mean score for the experimental group was 26.84 and for the control group was 21.96, giving a mean difference of 4.88 points in favour of the experimental group. This is because the standard errors are identical and equal to 0.57 in both groups, showing the same degree of precision in both group estimates and thus that the difference is not an artefact of unequal within-group variability. The descriptive pattern suggests that students in Biology with AI support in the inquiry-based learning (IBL) model showed significantly better analytical skills compared to students in the traditional learning model, such as the ability to analyze biological data, interpret experimental results, and develop evidence-based arguments. This difference is shown in the inferential test in Table 4 (Hypotheses).

Hypotheses

Higher order cognitive processes will not be significantly different between Biology scholars taught by using AI enhanced inquiry-based pedagogy and conventional pedagogy.

Table 6: ANCOVA Summary of Difference in Higher-Order Cognitive Processes by Instructional Method

Source	SS	Df	MS	F	Sig. (p)
Pretest (Covariate)	412.36	1	412.36	18.42	.000

Instructional Method	685.74	1	685.74	30.61	.000
Error	2618.59	57	45.94		
Total	3716.69	59			

Note. The measurement of the dependent variable was the posttest scores on the Higher-Order Cognitive Processes Assessment (HOCPA). H_01 is rejected at $p < .001$.

The results of the ANCOVA used to test H_01 are presented in Table 6. Prior knowledge, measured with the pretest covariate, was found to have a significant effect ($F(1, 57) = 18.42, p < .001$), indicating prior knowledge was a meaningful variable to explain posttest performance results, and that its statistical control was needed to make an apples-to-apples comparison of the instructional outcomes between the two groups. The instructional method effect was highly significant ($F(1, 57) = 30.61, p < .001$) which means that the difference in higher-order cognitive processes between the experimental and control class was not due to chance. The error term ($SS = 2618.59, df = 57, MS = 45.94$) accounts for variability within the groups not due to the model; the total SS (3716.69) accounts for variability of scores across all participants. From the results obtained, H_01 is rejected. For higher-order thinking skills, there is a statistically significant difference between the performance of Biology scholars taught through AI-enhanced inquiry-based pedagogy and those taught traditionally, with the former outdoing the latter in performance.

H₀₂: Higher-order cognitive processes of the scholars of Biology in Delta state is not significantly affected by AI-enhanced inquiry-based pedagogies.

Table 7: ANCOVA Summary of Effect of AI-Enhanced Inquiry-Based Pedagogy on Higher-Order Cognitive Processes

Source	SS	Df	MS	F	Partial η^2	Sig. (p)
Pretest (Covariate)	395.18	1	395.18	16.87	.21	.000
Pedagogical Method	742.51	1	742.51	31.72	.36	.000
Error	2735.04	57	47.98			
Total	3872.73	59				

Note. Dependent Variable: Post-test higher-order cognitive processes assessment (HOCPA) scores. A large effect will be partial $\eta^2 \geq .14$ (Cohen, 1988). H_02 is rejected at $p < .001$.

The mean of each treatment is compared to the mean of the control treatment in the test of H_02 , and the results of the ANCOVA are presented in Table 7. The pretest covariate was significant ($F(1, 57) = 16.87, p < .001$, partial $\eta^2 = .21$) and reinforces the idea that the pretest cognitive performance accounted for a meaningful amount of variance in posttest scores, which highlights the need to control for pretest variance to isolate the effect of the treatment. The pedagogical method yielded a very strong and significant effect ($F(1, 57) = 31.72, p < .001$, partial $\eta^2 = .36$) and the results indicated that the scores on higher-order cognitive processes were significantly explained by the pedagogical method independently of

prior knowledge. This effect size is in the large category by Cohen's (1988) definition and is substantively important as well as being statistically significant. This unexplained within-group variability is referred to as the residual error and has an SS of 2735.04, a df of 57, and an MS of 47.98. This overall score dispersion over all the participants is referred to as the total sum of squares and has an SS of 3872.73, a df of 58, and an MS of 47.98. Thus, H_{02} is rejected. There was a significant and large positive effect on the higher-order cognitive processes of the Biology scholars in Delta State using the pedagogies enhanced by AI and the inquiry approach. The higher-order cognitive processes of Biology scholars in Delta State were significantly and positively influenced by the use of pedagogies enhanced by AI and the inquiry approach.

H₀₃: There is no significant difference between the analytical skills of Biology scholars in Delta State before and after the use of the use of AI-enhanced inquiry-based pedagogies.

Table 8: ANCOVA Summary of Effect of AI-Enhanced Inquiry-Based Pedagogy on Analytical Skills

SS	Df	MS	F	Partial η^2	Sig. (p)
Pretest (Covariate)	284.47	1	284.47	14.95	.19
Instructional Method	518.63	1	518.63	27.25	.32
Error	2227.89	57	39.08		
Total	3031.00	59			

Note. Dependent variable: Post test scores (Analytical Skills subscale). H_{03} is rejected at $p < .001$.

The results of the ANCOVA test of H_{03} is shown in Table 8. The pre-test covariate was statistically significant ($F(1, 57) = 14.95$, $p < .001$, partial $\eta^2 = .19$), thus demonstrating that students' prior analytical ability proved to be a meaningful predictor of post-test analytical performance and that the effect of this covariate was important to remove to isolate the effect of the instructional treatment. The instructional method was a highly significant and large effect on analytical skills ($F(1, 57) = 27.25$, $p < .001$, partial $\eta^2 = .32$), suggesting that the analytical skill scores obtained in the AI-enhanced inquiry-based approach accounted for approximately 32% of the variance in scores after baseline performance was statistically controlled. The residual error (SS = 2227.89, df = 57, MS = 39.08) is the sum of the variability within the groups that is not accounted for by the model; the total sum of squares (SS = 3031.00, df = 60) is the overall dispersion of the analytical skill scores for all participants. These results lead to the rejection of H_{03} . The analytical skills of Biology scholars in Delta State were greatly and significantly enhanced by the use of AI based pedagogies in the form of inquiry-based teaching methods as evidenced by the experimental group having significantly higher analytical ability in analysing biological data, interpreting experimental results, and building evidence-based arguments when compared with the control group.

Discussion

The result of this study clearly showed that the use of inquiry-based pedagogy with the use of artificial intelligence significantly affected the higher order cognitive abilities of scholars in Biology of Delta State in all the dimensions studied: higher order cognitive processing, analytical skills, evaluative skills, creative thinking and problem-solving abilities. The results for each of the hypotheses tested rejected the null hypothesis ($p < .001$) and the partial η^2 ranged from .18 to .36, which are large effect sizes. The results are discussed below with regard to each research question, theoretical frameworks and related empirical literature.

The first finding confirmed that when taught with AI-enhanced inquiry-based pedagogy, Biology scholars made significantly more progress on higher-order cognitive processes than those taught with conventional teaching than their counterparts taught with conventional teaching (adjusted mean difference = 8.27 points; $F(1, 57) = 30.61$, $p < .001$). The results support the early work of Bransford et al. (2000), who stated that learning environments must promote student experience, inquiry, and feedback in order to engage students in constructing meaning, a process best suited to be facilitated by AI-enhanced pedagogical systems. The strong covariate effect ($F(1, 57) = 18.42$, $p < .001$) also underscores the importance of taking prior knowledge into account when assessing instruction in an instructional intervention: Students come to learning environments with different cognitive starting points that can influence the results of instructional comparisons if not controlled.

This finding can be explained with Bruner's (1961) discovery learning theory as a complementary theoretical lens. Bruner proposed that students would construct more transferable and deep cognitive structures when they engage in a process of discovery, learning relationships and principles, than when they are "transmitted" knowledge. In a way, the cognitive performance advantage exhibited by the experimental group was structurally instantiated as the discovery conditions Bruner described, which were achieved by using AI-enhanced inquiry environments that offer adaptive problem scenarios, real-time feedback, and dynamic scaffolding.

The second finding showed a large effect for the instructional method (partial $\eta^2 = .36$, $F(1, 57) = 31.72$, $p < .001$) on the scores of the higher order cognitive processes after controlling for the effect of prior knowledge. This size of impact is meaningful and is consistent with that reported by Kulik and Fletcher (2016) in their meta-analytic review of intelligent tutoring systems which indicates that evidence of positive impact on student achievement is found in multiple subject domains and educational levels. The current study replicates these effects in a biology-specific context and in a Nigeria context, thereby further strengthening the robustness of these effects across a wide range of educational contexts.

Luckin et al. (2016) suggested that AI-enhanced learning environments have special value in regard to deepening cognitive engagement because AI is able to continuously adjust the difficulty level of learning tasks, track the student's progress, and intervene with student learning in a way that surpasses what any one teacher can achieve in a standard whole class setting. This argument is supported by the large effect size that was found in this study, indicating that the cognitive benefits from the adaptive and responsive characteristics of AI-assisted inquiry pedagogies extend beyond the cognitive benefits of prior knowledge and baseline motivation. Nguyen and Kulikowich (2021) also showed that the AI-based ITSs

specifically designed to promote scientific inquiry and reasoning resulted in significant gains in students' higher-order thinking skills in biology, which is consistent with the present findings.

The third finding was that the analysis of the Biology scholars' analytical skills was significantly better in the experimental group compared to the control group using AI-inquiry-based pedagogy (partial $\eta^2 = .32$, $F(1, 57) = 27.25$, $p < .001$), with an adjusted mean difference of 4.88 points in favor of the experimental group. According to the revised taxonomy of Anderson and Krathwohl (2001), analytical skill lies at a mid-tier level of the higher-order cognitive skills and is the ability to break material down into constituent parts, distinguish relevant from irrelevant information, determine relationships among components, and construct interpretations based on evidence gathered through an empirical approach.

Theoretically, the improvements in analysis skills found in this study is consistent with Hmelo-Silver et al. (2007) argument that the SILL environment, which constructs a learning environment that guides learners by dividing them into small problems or stages, and also does not remove the cognitive challenge from the problem, is more effective in developing the analytical skills that are crucial to scientific thinking. The idea of adapting the level of hint and guidance to the learner's demonstrated performance is precisely what AI systems that provide adaptive scaffolding implement. Holstein et al. (2018) also added that these intelligent tutoring systems that can observe learners' affect and cognition in real time can intervene at the right time when learners are experiencing cognitive obstacles without causing unproductive struggle, and maintain the cognitive engagement required for skill acquisition. Analytical skill gains that were found in the present study are in line with this mechanism.

Conclusion

This study investigated the effect of AI-enhanced inquiry-based pedagogy on the higher-order cognitive processes of Biology scholars in Delta State, focusing on analytical skills, evaluative skills, and creative thinking/problem-solving abilities. The results consistently indicated that students exposed to the AI-enhanced inquiry-based instructional methods significantly outperformed their peers taught through conventional teacher-centered methods across all measured cognitive domains. The study highlights the transformative potential of combining artificial intelligence tools with inquiry-based teaching strategies in promoting higher-order thinking in Biology education. By integrating AI, lecturers can provide interactive, student-centered learning experiences that actively engage learners, personalize instruction, and encourage independent cognitive exploration.

Recommendations

Based on the findings, the following recommendations are proposed:

1. Biology lecturers should integrate AI-enhanced inquiry-based pedagogies into their instructional practices to promote higher-order cognitive skills.

2. Lecturers should receive professional development on AI tools and inquiry-based teaching strategies to maximize student engagement and learning outcomes.
3. Schools should invest in ICT infrastructure and AI-based educational resources to facilitate innovative teaching approaches.

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