Original Research Article

**OPTIMIZING STEM CURRICULUM DESIGN THROUGH ARTIFICIAL INTELLIGENCE: A COMPARATIVE STUDY OF PERSONALIZED LEARNING ALGORITHMS IN SECONDARY EDUCATION**

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**ABSTRACT**

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| --- |
| The research compares AI-driven personalized learning algorithms and traditional learning in Science, Technology, Engineering and Mathematics curriculum design optimization, with emphasis on secondary-level biology class in West Wendover High School, Nevada, United States. Using a two-shot quasi-experimental design, the research investigates the academic performance of 60 Grade 10 students, who are divided into an experimental group (AI-driven learning) and a control group (traditional learning). Pre and post-tests assessed student performance in two biology units—Energy in the Ecosystem and Heredity and Variation—while surveys tracked the influence of student engagement, prior knowledge, and learning preferences on AI-driven learning effectiveness. Results show that the AI group participants' post-tests were considerably higher, with high levels of mastery (83.0% for Unit 3 and 90.9% for Unit 4), in contrast with the moderate mastery of the traditional group (69.2% for Unit 3 and 70.9% for Unit 4). Paired and independent samples t-tests statistical analysis proved to the superiority of AI-driven learning compared to traditional learning in terms of improving academic performance, particularly in complex subjects like genetics, heredity, and variation. Be-sides, AI-driven learning improved learners' engagement by facilitating real-time feedback, adaptive learning paths, and interactive digital tools, while the study highlights the importance of consolidating foundational knowledge along-side AI integration. The paper concludes that AI-driven personalized learning considerably improves STEM learning because it meets personal learning requirements, stimulates interest, and makes complex ideas simpler. For optimum AI-driven teaching, though, STEM curricula should integrate personalized AI platforms with interactive, peer-to-peer learning exercises to promote greater conceptual comprehension.  Based on these findings, this study recommends the use of AI-driven tools in STEM courses, the development of advanced adaptive learning features, and the implementation of hybrid approaches to AI-driven and traditional learning. It also recommends district leaders, curriculum designers, and instructors to explore AI-driven personalized learning to enhance curriculum optimization and continue re-searching to design and test these methods for large-scale implementation. |

*Keywords: Artificial intelligence, Personalized learning, AI-driven learning, Comparative study*

**1. INTRODUCTION**

The fast development and evolution of science and technology fields necessitate the implementation of new approaches in academia. These methods are meant to address the rising need for better learning experiences that more effectively resonate with the current generation of students. New learning practices are linked to higher student engagement since they promote active involvement through shared problem-solving, critical thinking, and creativity (Tomkova, 2024). As the global learning environment is undergoing radical transformation, schools are increasingly being urged to leave conventional practices behind and adopt contemporary learning pedagogies that equip students for a world with advanced technologies.

Traditional learning methods, often characterized by teacher-centered instruction, structured curricula, and standardized assessments, emphasize direct instruction, where teachers deliver content through lectures, textbooks, and class-room discussions (Johnson, S., & Aragon, S., 2021). These methods have proven effective in establishing foundational knowledge, particularly in sub-jects like mathematics, science, and language arts, where mastery of basic concepts is critical for advanced learning. Traditional learning environments provide a clear and predictable framework for acquiring knowledge and skills, fostering discipline, focus, and respect for authority—qualities that are essential for academic and professional success.

Despite these strengths, traditional learning methods have limitations. Critics argue that their rigid structure and one-size-fits-all approach often fail to address the diverse needs, learning styles, and paces of individual students. For ex-ample, students who struggle with certain concepts may fall behind, while those who grasp material quickly may be-come disengaged due to a lack of challenge (Johnson, S., & Aragon, S., 2021). Furthermore, traditional methods often prioritize rote memorization over critical thinking, creativity, and problem-solving, which are increasingly valued in the 21st-century workforce. These limitations highlight the need for more flexible and personalized approaches to education, which is where innovative methods, particularly those driven by Artificial Intelligence (AI), come into play.

Artificial Intelligence (AI) has also become a compelling driving force, impacting not just the business and communication arenas but also the educational landscape (Ruiz-Rojas et al., 2023). The worldwide spread of AI technologies in the 21st century has profoundly changed the manner in which individuals engage with information and one another at both an individual and organizational scale (Southworth et al., 2023). In the field of education, artificial intelligence offers new ways of personalizing learning, automating administrative processes, and supporting teachers with real-time decision-making. The developments have created wide interest in the potential of AI to enhance learning and teaching while at the same time raising important questions about its broader impact on educational equity and access (Kamalov et al., 2023).

In Science, Technology, Engineering, and Mathematics (STEM) education, AI is particularly crucial. Personalized learning software has the potential to tailor content to the individual learning profiles of learners, which can improve learner performance and engagement (Anderson & Zhang, 2023; Kim, Park, & Lee, 2021). Artificial intelligence-based systems can provide immediate feedback, adjust tests, and provide differentiated instruction (Shete & Pujari, 2024). Nonetheless, there are a number of challenges to navigate, such as the urgent necessity for large-scale teacher training, data privacy issues, and disparities in technological access—especially in under-resourced environments (Rukadikari & Khandelwal, 2023; Dela Cruz & Santos, 2022). It is imperative to mitigate these challenges in order to maximize the transformative power of artificial intelligence in education.

With increased worldwide focus on STEM education, the development of successful and engaging curricula is becoming increasingly vital (Ruiz-Rojas et al., 2023). Among the notable trends is the incorporation of artificial intelligence-driven personalized learning algorithms, which have the potential to transform teaching methods according to the specific learning requirements of every individual student. Such systems allow adaptive learning pathways, providing personalized guidance and support with the aim of optimizing academic success for students. STEM education programs adopting such strategies aim to equip students for advanced learning and professional endeavors while expecting to cultivate essential life skills in problem-solving and innovation (Lutkevich, 2022).

Use of artificial intelligence in biology education has high potential to foster higher levels of student engagement by providing interactive and inquiry-based learning approaches. Tools like virtual laboratories, auto-grading systems, and real-time performance feedback improve the delivery of intricate biological concepts (Holmes et al., 2022; Chen et al., 2021). Such technology innovations permit the simulation of scientific processes, thus allowing students to learn genetics, cellular biology, and ecosystems in experiential and cost-effective manner (Luckin et al., 2018). Furthermore, the automation of routine tasks by artificial intelligence releases educators to design practical activities and facilitate greater student involvement in STEM inquiry.

Across the globe, nations are incorporating artificial intelligence into K–12 biology education to raise curriculum efficiency and boost educational equality. In China, Japan, and Singapore, among other countries in Asia, there has been massive investment in adaptive learning technologies that personalize learning experiences and provide instant feedback (Zhu et al., 2022; Tanaka & Ito, 2021; Lim & Chua, 2023).

Furthermore, Alonzo and Reyes (2020) researched the effect of AI-based learning systems on student engagement in STEM subjects in a rural Philippine high school and reported that the use of such technology greatly enhanced engagement, particularly among students who were previously disengaged or underperforming. The research noted the need to customize AI tools to the local cultural and educational environment in order to render them accessible and beneficial. These results are reinforced by Martinez-Maldonado et al. (2017), who highlighted the importance of AI and learning analytics in developing personalized, adaptive learning spaces that facilitate collaboration and adjust to heterogeneous learning needs. Collectively, the research highlights the potential of AI-based tools to improve inclusivity and close education gaps in low-resource contexts.

Additionally, in various African nations, including Kenya and Nigeria, artificial intelligence technologies are being utilized to address infrastructural challenges, employing mobile learning platforms and virtual science laboratories to provide superior biology education in regions with limited resources (Nyamari et al., 2021; Okoye & Adewale, 2022). The diverse implementations of these technologies highlight the flexibility of AI in distinct educational environments, simultaneously exposing the multiple approaches employed to tackle localized difficulties.

Notwithstanding the global trend within the field, there exists a significant research gap for the organized incorporation of AI-driven personalized learning algorithms in secondary school biology curricula, particularly where resources are scarce. Although numerous studies stress the promising benefits of AI in the overall STEM education process, fewer studies concentrate on biology education at the secondary level, particularly on the issues of student performance, teacher readiness, and adequacy of infrastructure. In addition, empirical evidence on the effectiveness of these artificial intelligence tools in personalizing instruction to address diverse learning needs and interests is scarce. This study seeks to bridge this gap through an investigation of the impact of AI-supported personalized learning in the context of biology education, identifying ideal approaches for its implementation and assessing its role in promoting inclusive learning environments.

This shift from conventional, teacher-directed methods to contemporary, student-directed methods is being further propelled by artificial intelligence and adaptive technology advancements (Johnson & Aragon, 2021; OECD, 2020). Such technologies support data-driven teaching that is responsive in the moment, thereby facilitating personalized learning pathways and promoting essential 21st-century competencies like collaboration, creativity, and problem-solving (Nguyen et al., 2022). As the learning landscape is redesigned to address the needs of the digital era, the incorporation of artificial intelligence into STEM education—and particularly that of biology—shows tremendous potential for preparing a future-ready generation of students. But this change must be wisely implemented, supported by sustained professional development, and accompanied by a commitment to closing current disparities in access and opportunity.

**Research Questions:**

The purpose of this study is to compare the academic performance of students in a biology subject under traditional learning methods and those utilizing AI-driven personalized learning algorithms, with the goal of optimizing STEM curriculum design.

Specifically, the study seeks the following specific research questions:

1. What is the mean score of pre-tests in the following:

1.1. utilization of AI driven personalized learning algorithms?

1.2. traditional method?

2. What is the mean score of post-tests in the following:

2.1. utilization of AI driven personalized learning algorithms?

2.2. traditional method?

3. Is there a significant difference between the pretest and post-test among students exposed to AI-driven personalized learning algorithms compared to traditional methods?

4. What is the level of influence of the following factors on the effectiveness of AI-driven personalized learning in biology subject, as to:

4.1 student engagement,

4.2 prior knowledge, and

4.3 learning preferences?

**2. methodology**

The study utilized experimental research design specifically two-shots quasi-experimental and descriptive research design. Specifically, non-equivalent control group design was used, where the experimental group was subjected to exposure of AI-driven personalized learning platforms, while the control group proceeds with traditional STEM instructional practices.

The two-shots pre-test and post-test non-random quasi-experimental design is a research design where two groups of subjects are measured on a dependent variable at two different times prior to an intervention (pre-tests) and then are measured at two different times following the intervention (post-tests). The procedure, which is essentially "two shots" at measurement of the variable at each time, provides a clearer picture of possible changes over time and reduces some threats to internal validity present in conventional pre-test/post-test designs. This design is appropriate considering the limitations that are associated with carrying out genuine experiments in school environments, where randomization of people into groups is usually not possible (Cook & Campbell, 1979).

List 1 below shows the non-random two-shots pre-test and post-test quasi-experimental research design.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1st Shot | | | | 2nd Shot | | | |
|  | Time 1 | | Time 2 | | Time 1 | | Time 2 | |
|  | Assignment | Pre-test | Intervention | Post-test | Assignment | Pre-test | Intervention | Post-test |
| G1 | N | O1 | X | O2 | N | O1 | X | O2 |
| G2 | N | O3 |  | O4 | N | O3 |  | O4 |

**List 1. Pre-test-Post-test Design**

Legend:

N = Non-random selection

G1 = Experimental Group

G2 = Control Group

O1 = Pretest

O2 = Posttest

O3 = Pretest

O4 = Posttest

X = Treatment/Intervention (AI-driven personalized learning algorithm)

This two-shots non-random quasi-experimental design is being used regularly for measuring the effect of an intervention by comparing the performance of two groups, a treatment and a control group in two distinct units or phases in lesson under investigation. Both of the groups were given a pretest to identify their starting performance (O1 and O3), and the intervention for Group 1 (X). After the intervention, both groups were given a posttest (O2 and O4) to identify any difference in their performance level. This was then followed by the entire procedure being replicated for the second study phase. This design permits the exploration of the influence of AI-driven personalized learning algorithms on student performance via the comparisons within and between the groups of changes in pretest and posttest scores over two distinct phases or units of the instructional content.

The design illustrated is akin to those utilized in contemporary educational studies of the impact of technology-supported learning resources (Anderson & Zhang, 2023; Kim et al., 2021), whose efficacy in identifying causal links between interventions and learning outcomes has been established.

The current research used a descriptive research design to assess the various factors influencing the effectiveness of artificial intelligence-driven personalized learning algorithms for enhancing STEM course development in American high school education. The use of a quantitative methodology suits the current research because it enables the structured exploration of variable relationships, testing of hypotheses, and gathering of measurable data that is amenable to statistical analysis (Creswell & Creswell, 2018).

The study was conducted at West Wendover High School in the Elko County, State of Nevada in the United States of America during the first semester of the 2024-2025 school year. The school caters grades 9 to 12 and offers various curricular subjects both for diploma for K-12 learning and advance college subjects. West Wendover High School is a Title 1 school that receives funding from the government to help give students from low-income families a quality education. Students who were enrolled in STEM classes that were taking biology were the participants involved.

The research uses a non-random sampling technique, i.e., convenience sampling, of 60 students from Grade 10 aged 15 to 16 years from two classes, each containing 30 students. The school administration chose the participants, thereby providing ease of access and feasibility within the given timeframe for the study. The constituents of each class were extremely heterogeneous. This pre-decided selection was used to safeguard the study from bias.

The two classes have a diverse membership, which is indicative of a broad range of academic abilities, learning styles, and socio-economic backgrounds. This range is in line with the aims of the study to determine the effectiveness of the intervention for a heterogeneous population of students.

Although the sampling method employed restricts generalizability of findings because of the lack of random selection, it is deemed acceptable under practical constraints and with the aim of achieving in-depth understanding in a real educational environment.

Prior to participation, the students' parents or guardians were provided with informed written letter of consent. Privacy and confidentiality of participants were strictly upheld throughout the whole inquiry. The study was conducted at West Wendover High School in the state of Nevada but only with grade 10. The results might not be applicable in other school environments or grades.

The Pre-Test/Post-Test method and questionnaires were used by the researcher in carrying out the research.

Pre-tests and Post-tests: The researcher created a teacher-made test instrument to test how AI-driven personalized learning algorithms would fare against traditional teaching methods. The test was meticulously crafted following the researcher's experience in test construction and matched the criteria and objectives stipulated by the New Generation Science Standards (NGSS) curriculum. The selection and distribution of test items were dictated by a detailed table of specifications (TOS) so that the examination covered a representative sample of cognitive levels and major learning objectives.

The test was comprised of forty (40) items and was designed to measure students' knowledge and ability in the fields of STEM. To determine its validity, the test underwent expert review so that every item was properly measuring the intended learning outcomes. Reliability analysis was also performed to establish student performance consistency across administrations. The test was administered as a pre-test and a post-test to members of the experimental (AI-driven) and control (traditional method) groups.

Every correct answer was worth one point, giving a total potential score of forty points. The scores derived from these tests allowed for a comparison of the performance of the students pre- and post-intervention, and therefore gave valuable feedback on the effects of AI-driven personalized learning. The test's systematic construction and validation guaranteed that the test was effective as a valid tool for gauging students' progress and the effectiveness of AI implementation in STEM education.

The tool was validated by five experts from different fields. It was pretested on thirty (30) Grade 11 students of West Wendover High School who are not the beneficiaries of the study. The result of the test was utilized in order to come up with the validity indexes like the indexes of discrimination and difficulty of the items and test reliability. The student scores were ordered systematically in terms of increasing values. The lower and upper 27% of the class will be utilized for validation. Each subgroup contains 30 students.

To estimate the reliability of the test, the researcher employed the Kuder-Richardson Formula 20 (KR-20). Miller, Linn, and Gronlund (2009) state that the classification of the reliability index must be done according to the correlation coefficients.

After the pilot tests, it was found out that the unit three has a reliability of 0.8797, interpreted as good for classroom test. Furthermore, when the unit four was pilot test and calculated, it was found out that it has a reliability of 0.8951, interpreted as good for classroom test as well.

A questionnaire of student survey was administered to identify the various factors that affect the performance of AI-driven personalized learning algorithm in biology subject like: student engagement, prior knowledge, and learning preferences. The survey consisted of 10- items of 5- Likert scale.

The researcher submitted the teacher-made test to five experts in test construction. Once the five experts confirmed the validity of the teacher constructed test, it was discovered that the unit three: Flow of Energy in Ecosystem test was highly valid with a mean rating of 4.68. Also, unit four: Genetics was also discovered to be highly valid with a mean rating of 4.74.

Additionally, the researcher-created data collection questionnaire that were distributed to the five (5) experts for the content validation. They were requested to appraise the relevance of the questions in the research-developed tool in relation to content.

Once the five experts approved the questionnaire, it was revealed that the tool was highly valid with a mean rating of 4.70.

Gathering information was initiated in a timely manner. First, the researcher obtained approval from the principal of West Wendover High School through the presentation of the research proposal and discussion of its implementation with the principal. Once approved by the principal, the proposal was given to the Assistant Principal for High School for approval. Following approval from both administrators, the researcher requested the approval of the Elko County School District Superintendent to carry out the experimental study. After the final approval, the researcher proceeded with preparation, dissemination of printed letters to respondents, consent to parents and study implementation with permission and approval from the Ethical Committee for standards and guidelines in conducting research.

The research concentrated on two learning modules: Unit Three – Energy in the Ecosystem and Unit Four – Heredity and Variation, which were both taught for the second quarter of the first semester. The duration of the research extended over nine weeks, with four weeks devoted per module and one week for testing. In order to have valid and reliable assessment, a Table of Specifications (TOS) for a 40-item teacher-made test was developed by the researcher and then tried out on 30 Grade 11 students. The test was reviewed by a panel of five test construction experts. Furthermore, a researcher-developed questionnaire was designed to determine the determinants of AI-driven learning effectiveness among students.

The same panel of expert reviewers validated this instrument.

The study employed an experimental design wherein two groups of Grade 10 students (n = 60) were exposed to one of the following: a control group (n = 30) that was subjected to routine lecture-based instruction and an experimental group (n = 30) that was subjected to AI-driven personalized instruction. The experimental group utilized various AI-driven personalized learning algorithm, including Brisk Teaching for lesson and activity planning, Khanmigo for AI-driven interactive explorations, ChatGPT 4.0 Turbo for knowledge search and synthesis, and Quizizz AI for automatic assessment question gamification, and quiz generation. The control group used the traditional method of teaching and learning. Both groups were given the same pre-tests and post-tests, and student scores were compared to determine whether there were statistically significant performance differences between the two instructional types.

The Preliminary Phase involved identifying the instructional units, developing the Table of Specifications (TOS), constructing the teacher-made test, designing survey forms, validation of tests and surveys, and developing AI-driven lesson plans and activities. The traditional learning approach, however, followed the same process except that the lesson plans were not developed with AI, and no AI technologies were integrated.

The preparation stage included the selection of instructional methods, preparation of AI-supported lessons and activities, and orientation of student participants to study routines. However, the traditional learning group were informed and exposed only to collaborative learning and inquiry approach.

The evaluation phase consisted of pre-test administration, execution of the nine-week experimental treatment, post-test administration, and analysis of students' performance data to assess the effect of AI-driven personalized learning.

On the other hand, the traditional learning group underwent the identical tests as the AI-based group; however, they did not undergo any type of intervention. Their performance was also assessed and analyzed.

The results of this study gave useful information regarding the level of the variables that impact the performance of AI-driven personalized learning algorithms on the engagement of students, prior knowledge, and learning preferences in the field of STEM education.

The collected data was analyzed using statistical methods appropriate for comparing the performance and engagement levels between the experimental and control groups.

**Sub-problems 1 and 2:** What is the mean percentage scores of pre-tests and post-test in the utilization of AI-driven personalized learning algorithms?

To describe the academic performance level of students before and after the intervention, mean scores were used for both the pretest and posttest.

Equation for Mean:

x̄=ΣX/N

Where:

x̄ = Mean score

∑X = Sum of all student scores

N = Number of students

Additionally, Mean Percentage Score or MPS was also used for both pre-test and post-test to describe students’ performance better.

Equation for Mean Percentage Score:

MPS=(Total Score)/(Total number tested x Total number items )\*100

Where:

MPS = mean percentage score

Total score = sum of scores of students

Total number tested = number of students tested

Total number of items = total items in the test

The table below shows how to interpret the MPS for pre-test and post-test of students under AI-driven personalized learning algorithm and traditional learning.

List 2-Mean Percentage Score Adjectival Interpretation

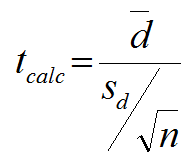
|  |  |
| --- | --- |
| **Mean Percentage Score** | **Adjectival Interpretation** |
| 75% to 100% | High mastery |
| 54% to 75% | Moderate mastery |
| 0% to 49% | Low mastery |

*Source: Nurul & Suziyani (2018)*

**Sub-problem 3:** Is there a significant difference between the pretest and post-test among students exposed to AI-driven personalized learning algorithms compared to traditional methods?

To answer sub-problem number 3 on the test of difference between the pre-test and post-test among students exposed to AI-driven personalized learning algorithms compared to traditional methods, paired samples t-test was used.

Equation for Paired t-test:



Where:

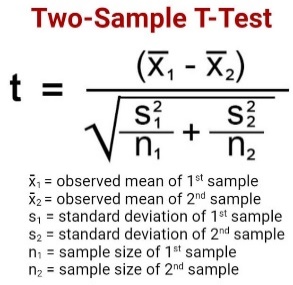
x̄d = Mean of the differences between paired scores (posttest - pretest)

sd = Standard deviation of the differences

n = Number of paired scores

Independent Samples t-test was also calculated (for between-group comparison). This to compare the post-test scores of the group exposed to AI-driven learning and a group exposed to traditional methods.

Equation for Independent Samples t-test:



Where:

x̄₁ , x̄2 = Mean scores of the two groups

"s₁²" , "s₂²" = Variance of the two groups

n1 , n2 = Sample sizes of the two groups

**Sub-problem 4:** What is the level of the factors influence the effectiveness of AI-driven personalized learning in biology subject, as to: student engagement, prior knowledge, and learning preferences? To answer sub-problem number 4 on the level of factors that influence the effectiveness of the AI-driven personalized learning in biology subject, weighted mean was used.

Equation for Mean:

x̄=ΣX/N

Where:

x̄ = Mean score

∑X = Sum of all student scores

N = Number of students

The table shows how to interpret the results on the factors that influence the effectiveness of AI-driven personalized learning algorithm in biology subject, the Likert scale was used.

List 3- Interpretation of results on the factors that influence the effectiveness of an AI-driven personalised learning algorithm in biology based on the responses using the Likert Scale

|  |  |  |  |
| --- | --- | --- | --- |
| **Scale** | **Range of Mean** | **Descriptive Equivalence** | **Descriptive Interpretation** |
| 5 | 4.21 – 5.00 | Very highly influenced | The factor has a very significant impact on learning. |
| 4 | 3.41 – 4.20 | Highly influenced | The factor has a substantial impact on learning. |
| 3 | 2.61 – 3.0 | Moderately influenced | The factor has a moderate impact on learning. |
| 2 | 1.81 – 2.60 | Slightly influenced | The factor has a minor impact on learning. |
| 1 | 1.00 – 1.80 | Not influenced | The factor has no significant impact on learning. |

**3. results and discussion**

**Mean Percentage Scores of Pre-tests**

The students' mean percentage scores in the pretest yield a baseline data for quantifying their prior knowledge of the biology content of the research. The 2-shot pretest was administered through two successive administrations of a 40-item multiple-choice test for unit three and unit four. Both the exposed class to the AI-driven personalized learning algorithm and the traditional learning condition class took part in the pretests. This guarantees a strong comparison of the academic performance of the students before the intervention.

**1.1. Implementation of AI-Powered Personalized Learning Algorithm**

Pretest in the application of the AI-driven personalized learning algorithm is a fundamental baseline measure of the students' prior knowledge and skills in biology. By their measurement before the implementation of the algorithm, the pretest gives important information of where they are starting from, hence allowing for customization of learning pathways and also assessment of the effectiveness of the algorithm in improving academic performance.

Table 1 below presents pre-test mean percentage scores (MPS) of students exposed to AI-driven personalized learning algorithm for Unit three: Energy in the Ecosystem and Unit four: Heredity and Variation.

The findings show poor performance in both units, with 39.0% MPS percentage in Unit 3 and 37.9% in Unit 4. The findings imply that before the intervention, the students poorly understood the content conceptually.

**Table** **1 Pre-test: Mean Percentage Score of AI-Driven Learning**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Unit** | **Total Number of Students** | **Total Number Tested** | **Total Number of Items** | **Highest Score** | **Lowest Score** | **Total Scores** | **Mean** | **MPS** | **Adjectival Interpretation** |
| 3 | 30 | 30 | 40 | 21 | 6 | 468 | 15.60 | 39.0 | Low mastery |
| 4 | 30 | 30 | 40 | 20 | 10 | 455 | 15.17 | 37.9 | Low mastery |

These findings complement research like Rukadikari & Khandelwal (2023) and Dela Cruz & Santos (2022), which highlight that students perform poorly in STEM material under ordinary conditions, calling for adaptive and personalized learning approaches. Likewise, Shete & Pujari (2024) concluded that AI-based tutoring significantly impacts learning gains, with a specific benefit for low prior knowledge students. The pre-tests in this research serve as a baseline to understand the effect of AI-driven learning, validating earlier research that suggests learning algorithms personalized for individuals can close knowledge gaps and enhance the performance of students in the long run.

**1.2. Traditional Learning**

The pretest percentage score is a necessary baseline to determine student knowledge and understanding of biology before instruction. Through the administration of a 40-question multiple-choice test, the test accesses basic concepts and prepares the students for the classes ahead.

Table 2 shows pre-test mean percentage scores (MPS) of students for Unit 3: Energy in the Ecosystem and Unit 4: Heredity and Variation under the traditional learning.

**Table 2** **Pre-test: Mean Percentage Score of Traditional Learning**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Unit** |  | **Total Number of Students** | **Total Number Tested** | **Total Number of Items** | **Highest Score** | **Lowest Score** | **Total Scores** | **Mean** | **MPS** | **Adjectival Interpretation** |
| 3 |  | 30 | 30 | 40 | 26 | 4 | 460 | 15.33 | 38.3 | Low mastery |
| 4 |  | 30 | 30 | 40 | 21 | 6 | 414 | 13.80 | 34.5 | Low mastery |

The findings show poor performance in both units, with a 38.3% MPS percentage in Unit three and 34.5% in Unit four. These are similar to those in AI-driven learning (Table 1), showing that the students in both groups had little knowledge of the subjects beforehand.

The results are consistent with studies by Alonzo & Reyes (2020), which demonstrate that the students perform poorly in difficult STEM material under regular learning settings. Further, relatively lower pre-test scores for Unit four confirm studies such as Luckin et al. (2018), which demonstrate that material that addresses abstract genetic principles are more difficult to the students without personalized instructional support and limited resources (Nyamari et al. 2021; Okoye & Adewale, 2022).

These results offer an essential baseline to which comparisons should be made, confirming the imperative to investigate whether AI-driven personalized learning can lead to significant improvements in post-test scores over regular instruction.

**Mean Percentage Scores of Post-tests**

The students' mean percentage scores in the post-tests are a reflection of their learning outcomes following the instructional treatments. Being a 2-shot post-test, the tests were comprised of 40 multiple-choice items each, testing Unit three and Unit four. Both the class that used the AI-driven personalized learning algorithm and the class using traditional learning took part in the tests. Post-test results are information regarding the efficacy of each instructional approach in fostering students' comprehension of the selected biology concepts.

**2.1. Implementation of AI-Powered Personalized Learning Algorithm**

The posttest under the application of the AI-driven personalized learning algorithm is one of the most important measures to ascertain the success of the algorithm in enhancing student understanding and academic achievement in biology. The 40-item multiple-choice posttest, which is given after the intervention, assesses students' knowledge of major concepts acquired during the learning period.

Table 3 shows the post-test mean percentage scores (MPS) of students who received AI-driven personalized learning for Unit three: Energy in the Ecosystem and Unit four: Heredity and Variation.

**Table 3** **Post-test: Mean Percentage Score of AI-Driven Learning**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Unit** | **Total Number of Students** | **Total Number Tested** | **Total Number of Items** | **Highest Score** | **Lowest Score** | **Total Scores** | **Mean** | **MPS** | **Adjectival Interpretation** |
| 3 | 30 | 30 | 40 | 39 | 27 | 996 | 33.20 | 83.0 | High mastery |
| 4 | 30 | 30 | 40 | 40 | 29 | 1056 | 36.37 | 90.9 | High mastery |

The outcomes show a dramatic increase from the pre-test, with an MPS of 83.0% (high mastery) for Unit three and 90.9% (high mastery) for Unit four.

This profound improvement in scores indicates that AI-driven personalized learning made a considerable difference in student performance, which is corroborated by research like Anderson & Zhang (2023) and Shete & Pujari (2024), which established that AI-driven personalized learning systems improve student engagement and retention in STEM. In addition, the greater mastery in Unit four is consistent with research by Dela Cruz & Santos (2022) that highlights how AI-powered platforms serve to demystify intricate genetic principles using individualized explanations as well as interactive simulations.

The noteworthy disparity between post-test and pre-test scores validates the viability of AI-based learning algorithms in satisfying personal learning requirements, especially in STEM learning. Findings identify AI integration as an effective method of enhancing student mastery of conventional learning.

**2.2. Traditional Learning**

The post-test mean percentage scores under the traditional method is a major assessment to ascertain the understanding and retention of biology concepts acquired from traditional modes of instruction. Taken at the completion of learning units, the 40-item multiple-choice post-test evaluates the knowledge and expertise gained by the learners. The post-test results provide the foundation for comparing the effectiveness of traditional methods and AI-driven personalized learning approaches in achieving learning objectives.

Table 4 shows the post-test mean percentage scores (MPS) of the students who experienced conventional learning for Unit three: Energy in the Ecosystem and Unit four: Heredity and Variation.

**Table 4** **Post-test: Mean Percentage Score of Traditional Learning**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Unit** | **Total Number of Students** | **Total Number Tested** | **Total Number of Items** | **Highest Score** | **Lowest Score** | **Total Scores** | **Mean** | **MPS** | **Adjectival Interpretation** |
| 3 | 30 | 30 | 40 | 36 | 21 | 831 | 27.70 | 69.2 | Moderate mastery |
| 4 | 30 | 30 | 40 | 38 | 19 | 851 | 28.37 | 70.9 | Moderate mastery |

The findings show improvement from the pre-test with an MPS of 69.2% (moderate mastery) in Unit three and 70.9% (moderate mastery) in Unit four.

While these scores represent learning gains, they are lower than those that have been measured for the AI-driven personalized learning, as is seen in Table 3. These results affirm results like Kim, Park, & Lee (2021) and Anderson & Zhang (2023), where it was discovered that while traditional lecture-based learning is effective, it may not be capable of catering to individual learning rates and thereby end up achieving lower mastery levels than adaptive AI-driven interventions.

The findings also confirm Alonzo & Reyes's (2020) study in the Philippines that found students in the traditional setting learn and improve over time but lag in more complicated content because of the one-size-fits-all approach of traditional learning. The disparity between AI-driven and traditional post-test scores confirms the necessity of more interactive and personalized learning modes to optimize student comprehension, specifically in STEM learning.

**Difference Between the Performance of Students Expose to AI-driven and Traditional Learning on their Pre-test and Post-test**

This chapter highlights the major differences in the pretest and posttest scores of students who have been exposed to AI-driven personalized learning algorithms and students who have been taught based on conventional methods. From these differences, the effectiveness of AI-driven personalized learning in improving the performance of students is determined in comparison with conventional methods of teaching. The results offer an insight into how new pedagogical methods affect academic attainments in the field of biology.

Table 5 shows the paired samples t-test of pre-test and post-test scores of AI-driven personalized learning and traditional learning for Unit three: Energy in the Ecosystem and Unit four: Heredity and Variation.

**Table 5** **Significant Difference Between the Performance of Students Expose to AI-Driven Personalized Learning Algorithm and Traditional Learning on their Pre-test and Post-test Using Paired Samples t-test**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Groups** | **Tests** | **Unit 3 (1st shot)** | | | | **Unit 4 (2nd shot)** | | | |
| **ẍ** | **SD** | **t** | **P** | **ẍ** | **SD** | **t** | **P** |
| AI-Driven | Pre-test | 15.60 | 4.21 | **24.9996** | **0.0001\*** | 15.17 | 3.06 | **33.5167** | **0.0001\*** |
| Post-test | 33.20 | 3.48 | 36.37 | 4.92 |
| Traditional | Pre-test | 15.33 | 5.14 | **13.3463** | **0.0001\*** | 13.80 | 3.95 | **16.3169** | **0.0001\*** |
| Post-test | 27.70 | 4.84 | 28.37 | 4.93 |

*Paired Samples t-test results of AI-driven and Traditional Learning pre-test and post-test*

Within the AI-driven group, the mean scores shifted significantly from 15.60 (SD = 4.21) to 33.20 (SD = 3.48) in Unit three and from 15.17 (SD = 3.06) to 36.37 (SD = 4.92) in Unit four. The respective t-values (24.9996 for Unit three and 33.5167 for Unit four) and p-values (0.0001) reveal highly significant improvement, implying that AI-based personalized learning had a very strong positive impact on student performance.

For the control learning group, a rise in scores was also statistically significant but not as high. The mean scores went up from 15.33 (SD = 5.14) to 27.70 (SD = 4.84) for Unit three and from 13.80 (SD = 3.95) to 28.37 (SD = 4.93) for Unit four. The t-values (13.3463 for Unit 3 and 16.3169 for Unit 4) and p-values (0.0001) indicate that the learning gains were significant, though not as high as in the AI-driven group.

These results align with Kim, Park, & Lee (2021) and Luckin et al. (2018), which attested that AI adaptive learning systems retain knowledge and understanding more than conventional instructional methodologies. Likewise, research by Dela Cruz & Santos (2022) in Philippine settings emphasizes that AI-driven personalized learning attains greater mastery levels since it responds to personal learning requirements and rates.

Table 6 shows the difference between AI-driven and traditional learning on their pre-test and post-test using independent samples t-test.

**Table 6 Significant Difference Between the Performance of Students Expose to AI-Driven Personalized Learning Algorithm and Traditional Learning on their Pre-test and Post-test Using Independent Samples t-test**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Pre-test Results** | **AI-driven** | | **Traditional** | | **t** | **P** |
| **ẍ** | **SD** | **ẍ** | **SD** |
| Unit 3 | 15.60 | 4.21 | 15.33 | 5.14 | **0.2199** | **0.8268** |
| Unit 4 | 15.17 | 3.06 | 13.80 | 3.95 | **1.4971** | **0.1398** |
|  | | | | | | |
| **Post-test Results** | **AI-driven** | | **Traditional** | | **t** | **P** |
| **ẍ** | **SD** | **ẍ** | **SD** |
| Unit 3 | 33.20 | 3.48 | 27.70 | 4.84 | **5.0570** | **0.0001\*\*** |
| Unit 4 | 36.37 | 4.92 | 28.37 | 4.93 | **6.2887** | **0.0001\*\*** |

*Independent Samples t-test results of AI-driven and Traditional Learning Pre-test and Post-test Unit 3 t=5.0570, p<0.05 Unit 4 t=6.2887, p<0.05 significant at 0.05 level of significance*

**Pre-test Comparison**

The two groups did not differ significantly before instruction. Unit three pre-test mean scores were 15.60 (SD = 4.21) for the AI-based group and 15.33 (SD = 5.14) for the control group. The t-value (0.2199) and p-value (0.8268) show that the difference is statistically not significant, suggesting that both groups began with the same amount of knowledge.

Likewise, in Unit four, the AI group scored a pre-test mean of 15.17 (SD = 3.06), whereas that of the traditional group was 13.80 (SD = 3.95). The t-value (1.4971) and p-value (0.1398) indicate that the two groups were not different prior to the intervention.

**Post-test Comparison**

After instruction, the two groups varied considerably. The post-test mean score of the AI-driven group in Unit three increased to 33.20 (SD = 3.48), while that of the conventional group increased to 27.70 (SD = 4.84). The t-value (5.0570) and p-value (0.0001) indicate a highly significant difference in favor of AI-driven learning.

Likewise, in Unit four, the AI-driven group achieved a mean post-test score of 36.37 (SD = 4.92), whereas the traditional group achieved 28.37 (SD = 4.93). Both the t-value (6.2887) and p-value (0.0001) indicate a statistically significant difference at the 0.05 level of significance in support of AI-based personalized learning.

**Validation with Prior Research**

These findings are aligned with studies by Anderson & Zhang (2023) and Shete & Pujari (2024), which determined that AI-driven adaptive learning contributes more positively to academic performance compared to traditional methods. These are also aligned with a study conducted by Dela Cruz & Santos (2022) in the Philippine context, where it was proven that students using AI-driven learning platforms have greater mastery levels due to real-time feedback and individualized learning.

**Level of the Factors that Influence the effectiveness of AI-Driven Personalized Learning**

The effectiveness factors of AI-driven personalized learning covered in this chapter are student engagement, prior knowledge, and learning preferences. These are the key factors in identifying the success of personalized learning methods since they address the individual needs and learning styles of students. Their levels assist in analyzing further how each factor plays a role in the overall effect of AI-driven learning in academic performance improvement and learning process improvement.

**4.1. Student Engagement**

The success of AI-driven personalized learning depends on a group of interrelated factors, and student engagement is among their foundations. Engagement, or the degree to which a learner is interested, motivated, and actively involved in learning, has a direct influence on how they respond to and learn from AI-assisted platforms. Highly motivated students will more likely discover adaptive functions, react to personalized feedback, and engage in personalized activities, which results in better learning outcomes (Nguyen et al., 2022). On the other hand, low engagement can negate the benefits of AI-driven learning because students won't reap maximum advantage from the platform's functionality. Educators and AI systems can enhance engagement, render the entire process of learning effective, and enhance academic achievement by creating a motivating and nurturing environment.

Table 7 illustrates the student engagement findings in AI-driven personalized learning settings. The responses were measured on a five-point Likert scale where 5 was 'very highly influenced' and 1 was 'not influenced.' The findings based on this would be that AI-driven personalization has a positive influence on student motivation and engagement in learning processes.

**Table 7** **Summary Results of the Student Engagement on AI-driven Personalized Learning Algorithm Survey**

|  |  |  |
| --- | --- | --- |
| **Questions** | **Mean Rating** | **Descriptive Equivalence** |
| I actively participate in STEM-related activities and discussions in class. | 4.19 | Highly influenced |
| I am interested in learning about how artificial intelligence can be applied to education and STEM fields. | 4.26 | Very highly influenced |
| I enjoy using AI-powered tools (e.g. adaptive learning platforms) to support my learning in STEM subjects. | 4.55 | Very highly influenced |
| I feel motivated to improve my knowledge and skills in STEM subjects through engaging learning activities. | 4.43 | Very highly influenced |
| I feel challenged and engaged by STEM problems and tasks that are personalized to my skill level using AI. | 4.51 | Very highly influenced |
| I enjoy collaborating with my peers on STEM projects and activities, both in person and through digital platforms. | 4.58 | Very highly influenced |
| I feel more engaged in STEM learning when I can use technology, including AI-driven platform and tools. | 4.66 | Very highly influenced |
| I find personalized learning paths (adapted by AI) more engaging than traditional learning methods. | 4.57 | Very highly influenced |
| I feel more engaged when I receive timely feedback on my performance through AI-driven platforms, helping me improve. | 4.80 | Very highly influenced |
| I explore STEM-related topics outside of class time because I am interested and engaged in the subject matter. | 4.22 | Very highly influenced |
| **Overall Mean** | **4.48** | **Very highly influenced** |

*Interpretation: 5- very highly influenced, 4- highly influenced, 3-moderately influenced, 2- slightly influenced, 1-not influenced*

The grand mean rating of 4.48 belongs to the "Very Highly Influenced" category, indicating that the students reacted positively toward AI-based personalized learning for STEM subjects.

The highest-rated statement was "I feel more engaged when I receive timely feedback on my performance through AI-driven platforms, helping me improve" (Mean = 4.80). This shows that timely, data-driven feedback greatly improves student engagement and motivation.

Students also agreed highly with "I feel more engaged in STEM learning when I can use technology, including AI-driven platform and tools" (Mean = 4.66) (Johnson & Aragon, 2021) and "I enjoy working with my peers on STEM activities and projects, both face-to-face and through digital platforms" (Mean = 4.58). These results highlight peer collaboration and digital tools in maintaining student interest in STEM (Zhu et al., 2022; Tanaka & Ito, 2021; Lim & Chua, 2023).

The statement that "I find personalized learning paths (adapted by AI) more engaging than traditional learning methods" (Mean = 4.57) indicates that the students perceive AI-driven personalized learning as more effective compared to traditional learning methods (Kamalov, 2023).

These results are also corroborated by Holmes et al., (2022); Chen et al., (2021) and Shete & Pujari (2024), which highlight that adaptive learning using AI enables interaction due to real-time feedback, individualized activities, as well as interactivity. Alonzo & Reyes (2020) also discovered that in the Philippines, students interacted more and showed better motivation in STEM subjects when they utilized AI-driven personalized learning versus traditional methods.

**4.2. Prior Knowledge**

Prior knowledge serves as the baseline to which new learning is aligned, essential to a student's capacity to process, retain, and utilize new knowledge. In STEM education, insight into a learner's prior knowledge base enables instructors to craft lessons that close gaps, make connections, and deepen understanding. With AI-driven personalized learning algorithms, current knowledge data can be utilized to tailor content and modify instruction so learning experiences are pertinent and challenging in a suitable way. The pairing of current knowledge and new knowledge is key to provoking engagement and achieving meaningful learning outcomes. Moreover, awareness of the role of prior knowledge enables the identification of misconceptions early enough for intervention to avert the reinforcement of incorrect ideas. Finally, the tactical utilization of prior knowledge in learning enables learners to go into new concepts with confidence, which enhances their general academic performance and long-term retention.

Table 8 presents the summary results of the prior knowledge of students’ on AI-driven personalized learning algorithm survey.

**Table 8** **Summary Results of the Prior Knowledge of Students on AI-driven Personalized Learning Algorithm Survey**

|  |  |  |
| --- | --- | --- |
| **Questions** | **Mean Rating** | **Descriptive Equivalence** |
| I am familiar with the core concepts of the STEM (Science, Technology, Engineering, Math) curriculum. | 2.78 | Moderately influenced |
| I have a basic understanding of what artificial intelligence (AI) is. | 3.45 | Highly influenced |
| I am aware of how AI is being used in education to support learning. | 4.19 | Highly influenced |
| I understand the concept of personalized learning in the context of education. | 4.15 | Highly influenced |
| I am familiar with how AI-driven algorithms can adapt lessons to individual learning needs. | 4.10 | Highly influenced |
| I understand the role of curriculum design in improving student outcomes in STEM subjects. | 3.79 | Highly influenced |
| I know how technology is integrated into the STEM curriculum to enhance learning. | 4.25 | Very highly influenced |
| I am aware of AI applications in STEM fields, such as in data analysis, automation, and robotics. | 4.23 | Very highly influenced |
| I believe AI has the potential to improve student learning outcomes in STEM subjects. | 4.82 | Very highly influenced |
| I understand the challenge or limitations of using AI in education. | 4.55 | Very highly influenced |
| **Overall Mean** | **4.03** | **Highly influenced** |

*Interpretation: 5- very highly influenced, 4- highly influenced, 3-moderately influenced, 2- slightly influenced, 1-not influenced*

Table 8 shows students' prior knowledge of STEM concepts, artificial intelligence (AI), and its application in education. The results show a total mean rating of 4.03, which is "Highly Influenced," demonstrating that students have high prior knowledge regarding AI and its usefulness in STEM education (Lutkevich, 2022). However, the lowest ranked statement, "I am familiar with the core concepts of the STEM (Science, Technology, Engineering, Math) curriculum" (Mean = 2.78, Moderately Influenced), indicates that students might need to be reinforced in basic STEM principles prior to full implementation of AI-driven learning.

Notwithstanding this gap, the students exhibited high awareness of AI's use in education, as shown by items like " I am aware of how AI is being used in education to support learning." (Mean = 4.19) and "I understand the concept of personalized learning in the context of education" (Mean = 4.15). This suggests students are aware of AI's application in tailoring lessons to meet individual learning requirements. In addition, the top-rated statement, "I believe AI has the potential to improve student learning outcomes in STEM subjects" (Mean = 4.82, Very Highly Influenced), shows high conviction in AI's effectiveness. Astonishingly, students also acknowledged the challenge of AI in education, as shown by the high ranking of "I understand the challenge or limitations of using AI in education" (Mean = 4.55, Very Highly Influenced).

These results are consistent with research by Kim, Park, & Lee (2021), which identifies that learners with AI backgrounds are more comfortable interacting with adaptive learning systems. In the same way, Dela Cruz & Santos (2022) concluded that in the Philippines, learners who were already exposed to technology integration in STEM education had an easier time adjusting to AI-driven learning systems. Though AI and its applications are familiar to students in this research, the limited knowledge that they have on core STEM concepts only indicates that they need to be reinforced more. That would mean that AI-driven learning must be introduced alongside core STEM learning in order for it to have its optimum impact and for the students to gain the full advantage of personalized learning.

**4.3. Learning Preferences**

Learning styles are individual approaches to processing, taking in, and perceiving information. Learning styles can be quite different for different students and include visual, auditory, kinesthetic, and other learning styles. Knowing a student's learning style enables teachers to design instruction in ways that will optimize engagement and effectiveness by presenting content in a manner that is available to each learner. Technological response and personalization of learning pathways based on individual preference are possible through personalized learning with AI. The alignment of teaching approaches with learning preference by teachers enables them to develop more inclusive and effective learning environments that lead to student achievement. The integration of learning preference into lesson planning enhances participation among students as well as active engagement due to the fact that the learners are more attached to the content.

Table 9 presents the summary results of the personal learning preferences of students’ survey.

Table 9 presents the results of students’ personal learning preferences, highlighting their inclination toward AI-driven and interactive learning methods. The overall mean rating of 4.63, classified as "Very Highly Influenced," indicates a strong preference for adaptive, technology-enhanced learning experiences in STEM education.

**Table 9 Summary Results of the Personal Learning Preferences of Students Survey**

|  |  |  |
| --- | --- | --- |
| **Questions** | **Mean Rating** | **Descriptive Equivalence** |
| I prefer using interactive tools (e.g. simulations, virtual labs) to learn STEM subjects. | 4.59 | Very highly influenced |
| I am open to using AI-powered platforms that personalize learning content based on my progress and performance. | 4.65 | Very highly influenced |
| I prefer learning at my own pace, with materials that adapt to my learning speed. | 4.53 | Very highly influenced |
| I learn best when I can engage in hands-on activities, such as experiments or projects. | 4.75 | Very highly influenced |
| I value immediate feedback and insights from AI-driven platforms that track my learning progress. | 4.71 | Very highly influenced |
| I prefer collaborative learning experiences, such as group work or discussions, to enhance my understanding of STEM topics. | 4.69 | Very highly influenced |
| I find video tutorials and lectures helpful in understanding complex STEM concepts. | 4.50 | Very highly influenced |
| I am comfortable following AI-generated personalized study plans based on my strengths and areas for improvements. | 4.81 | Very highly influenced |
| I enjoy problem-solving activities, such as quizzes or challenges, that are tailored to my skill level by AI. | 4.30 | Very highly influenced |
| I prefer a variety of learning resources (e.g. videos, articles, quizzes) that I can choose from depending on my learning needs. | 4.78 | Very highly influenced |
| **Overall Mean** | **4.63** | **Very highly influenced** |

*Interpretation: 5- very highly influenced, 4- highly influenced, 3-moderately influenced, 2- slightly influenced, 1-not influenced*

Among the items, the highest-rated feedback was "I am comfortable following AI-generated personalized study plans based on my strengths and areas for improvement" (Mean = 4.81), reflecting students' high acceptance of AI-driven learning pathways. Similarly, students highly valued instant feedback from AI-powered platforms (Mean = 4.71), reflecting students' preference for continuous evaluation and real-time feedback to enhance their learning. Their strong preference for practical work, including experiments or projects (Mean = 4.75), supports research highlighting the importance of experiential learning in STEM.

In addition, students indicated a high preference level for interactive learning activities (Mean = 4.69) and a variety of learning materials (Mean = 4.78), indicating that while they like personalized AI-driven learning, they also like social interaction and diversity of instructional materials. Notably, their high preference level for interactive tools such as simulations and virtual labs (Mean = 4.59) indicates that technology is necessary to maintain engagement and promote deeper understanding.

These results are consistent with research by Shete & Pujari (2024), emphasizing the efficacy of AI-driven personalized learning in meeting individual students' needs. In a similar study, Holmes et al., (2022) and Chen et al., (2021) discovered that students who were exposed to adaptive learning technologies were more engaged and motivated in STEM education. In the Philippines, Rukadikar & Khandelwal, (2023) and Dela Cruz & Santos (2022) discovered that students preferred AI-driven platforms for their capacity to deliver adaptive and flexible learning.

In general, the findings indicate that students learn optimally in an educational setting with a mixture of AI-driven personalization, interactive software, group projects, and varied learning materials. The findings highlight how STEM curriculum development with AI-driven adaptive learning in combination with hands-on and collaborative learning helps to enhance student interest and learning to the fullest.

**4. Conclusion**

Results show that AI-driven group students achieved significantly better post-test scores with high mastery levels (83.0% for Unit 3 and 90.9% for Unit 4), whereas moderate mastery was achieved in the traditional group (69.2% for Unit 3 and 70.9% for Unit 4). Independent and paired samples t-tests confirmed the superiority of AI-driven learning in enhancing academic performance, especially in challenging subjects such as genetics, heredity, and variation. Further, AI-driven learning enhanced students' interest with instant feedback, adaptive learning pathways, and interactive virtual tools, although the study suggests strengthening foundation knowledge in conjunction with AI adoption. In addition, through the conduct of the study, a concept paper for the improvement of the AI-driven personalized learning algorithm in biology was created, this concept paper is also part of the outputs of the study with the aim of determining major limitations of current AI-based personalized learning in biology, design framework in integrating innovative features that promote student engagement, react to current knowledge, and support learning styles, suggest approaches for the integration of real-time feedback and contextual learning features in the algorithm. Suggest ways to measure the effectiveness of the improved algorithm at attaining better academic performance.

The research concludes that AI-driven personalized learning algorithm considerably improves STEM education as it caters to individual learning needs, improves engagement, and clarifies abstract concepts. However, to maximize AI-driven learning, STEM education needs to combine personalized AI coursework with interactive, experiential learning sessions to augment deeper conceptual comprehension. From these findings, this study suggests the incorporation of AI-driven tools in STEM education, developing very sophisticated adaptive learning functions, and instituting hybrid models of learning that merge AI-driven and traditional approaches. It also suggests that district administrators, curriculum developers, and teachers investigate AI-driven personalized learning in curriculum development and research more to develop and pilot these practices for large-scale adoption.

**Consent**

All authors declare that ‘written informed consent was obtained from the patient (or other approved parties) for publication of this case report and accompanying images. A copy of the written consent is available for review by the Editorial office/Chief Editor/Editorial Board members of this journal.

**Ethical approval**

All authors hereby declare that all experiments have been examined and approved by the appropriate ethics committee and have therefore been performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki.

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**APPENDI****X**