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ORIGINAL

The Impact of AI-Based Learning on Academic Performance

El impacto del aprendizaje basado en la inteligencia artificial en el rendimiento académico

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ABSTRACT

This study compellingly demonstrates the effectiveness of AI-driven personalised learning algorithms in boosting academic performance among secondary school students in Portugal. Using a rigorous quasi-experimental, non-randomised two-shot pre-test and post-test design, we engaged sixty 10th-grade students divided into two distinct groups. The experimental group experienced AI-assisted instruction through innovative platforms, including Brisk Teaching, Khanmigo, ChatGPT 4.0 Turbo, and Quizizz AI, while the control group adhered to traditional teaching methods. Both groups participated in identical pre-tests and post-tests for two essential units: Energy in the Ecosystem and Heredity and Variation. Robust statistical analyses, including paired and independent samples t-tests, revealed significantly greater learning gains in the AI-driven group compared to the control group. Moreover, we assessed the influence of key factors, including student engagement, prior knowledge, and learning preferences, using validated Likert-scale questionnaires. The results clearly indicated a strong positive correlation between AI-driven learning and enhanced student motivation and comprehension. These findings strongly support the use of AI-based personalised instruction as an effective strategy for enhancing learning outcomes in STEM education, particularly in diverse classroom settings.

Keywords: AI-Driven Learning; Personalised Learning Algorithms; Secondary Education; STEM Education.

RESUMEN

Este estudio demuestra de manera convincente la eficacia de los algoritmos de aprendizaje personalizado basados en la inteligencia artificial para mejorar el rendimiento académico de los estudiantes de secundaria en Portugal. Utilizando un riguroso diseño cuasi-experimental, no aleatorio, con dos pruebas previas y posteriores, involucramos a sesenta estudiantes de décimo grado divididos en dos grupos distintos. El grupo experimental recibió instrucción asistida por IA a través de plataformas innovadoras, como Brisk Teaching, Khanmigo, ChatGPT 4.0 Turbo y Quizizz AI, mientras que el grupo de control siguió los métodos de enseñanza tradicionales. Ambos grupos participaron en pruebas previas y posteriores idénticas para dos unidades esenciales: «La energía en el ecosistema» y «Heredidad y variación». Los sólidos análisis estadísticos, que incluyeron pruebas t para muestras emparejadas e independientes, revelaron un aumento significativamente mayor del aprendizaje en el grupo impulsado por la IA en comparación con el grupo de control. Además, evaluamos la influencia de factores clave, como la participación de los estudiantes, los conocimientos previos y las preferencias de aprendizaje, utilizando cuestionarios validados con escala Likert. Los resultados indicaron claramente una fuerte correlación positiva entre el aprendizaje impulsado por la IA y el aumento de la motivación y la comprensión de los estudiantes. Estos hallazgos respaldan firmemente el uso de la enseñanza personalizada basada en la IA como una estrategia eficaz para mejorar los resultados del aprendizaje en la educación STEM, especialmente en entornos escolares diversos.

Palabras clave: Aprendizaje Impulsado por la IA; Algoritmos de Aprendizaje Personalizados; Educación Secundaria; Educación STEM.

INTRODUCTION

The integration of artificial intelligence (AI) into educational contexts is revolutionising the way we approach learning, capturing the attention of researchers, educators, and policymakers alike. AI-driven personalised learning systems hold the promise to redefine traditional teaching methods by offering customised educational experiences that reflect the unique needs, pace, and learning styles of students. This advancement is particularly significant in science, technology, engineering, and mathematics (STEM) education, where abstract and complex concepts often pose challenges to students from diverse backgrounds.

Historically, secondary education has been constrained by standardised models and one-size-fits-all teaching strategies, which overlook the considerable variability in students' prior knowledge, engagement, and learning preferences. Studies by Shete et al.(1) and Kim et al.(2) reveal that conventional methods often fail to adequately support learners with limited initial understanding or those navigating non-linear learning paths. In contrast, AI-powered educational platforms facilitate dynamic content delivery, real-time feedback, and adaptive learning routes, fostering an inclusive and effective instructional environment.

Despite the growing international evidence supporting AI's potential in education, empirical studies focusing on its implementation and efficacy in portuguese secondary schools are still sparse. This research aims to fill that gap by analysing the impact of AI-driven personalised learning algorithms on the academic performance of 10th-grade students in Portugal.

The primary goal of this study is to compare learning outcomes between students who engage with AI-based personalised instruction and those who receive traditional education. Specifically, it examines how AI influences academic progress, enhances student engagement, and assesses the impact of prior knowledge and individual learning preferences on educational outcomes.

To accomplish these objectives, we employed a two-shot quasi-experimental research design, incorporating pre-tests and post-tests across two pivotal units: Energy in the Ecosystem and Heredity and Variation. Additionally, the study engaged students through questionnaires to evaluate factors influencing the effectiveness of AI-based instruction. By exploring these dynamics, this research delivers critical insights into AI's transformative potential for enhancing STEM learning in real-world classrooms and informs future strategies for personalised education in Portugal.

The Portuguese context

The Portuguese education system, much like its European counterparts, is undergoing a significant transformation in response to rapid technological advancements and the evolving needs of society. With an increased emphasis on innovation, digital literacy, and STEM education, Portugal is proactively integrating cutting-edge technologies, particularly artificial intelligence (AI), into classrooms to bolster educational outcomes and inclusivity.

Traditionally, Portuguese schools have relied on teacher-centred methodologies, focusing on content delivery through lectures, textbooks, and standardised assessments. While these approaches have standardised learning outcomes and developed foundational competencies, it is time to embrace the promise of AI to create a more dynamic, engaging, and tailored educational experience that benefits every student. Embracing AI in education is not just an option but a necessity to prepare students for the challenges of the future. Quizizz AI and a control group, which followed traditional teaching methods. Both groups completed identical pre-tests and post-tests for two units: Energy in the Ecosystem and Heredity and Variation.

Statistical analyses, including paired and independent samples t-tests, revealed significantly higher learning gains in the AI-driven group compared to the control group. The study also measured the influence of key factors (student engagement, prior knowledge, and learning preferences) through validated Likert-scale questionnaires. Results showed a strong positive influence of AI-driven learning on student motivation and comprehension. These findings suggest that AI-based personalised instruction is an effective strategy for enhancing learning outcomes in STEM education, particularly in heterogeneous classroom environments.

Research Design and Methodology

This study employed a quasi-experimental research design, specifically the non-equivalent control group, two-shot pre-test/post-test model, supported by a descriptive research component. This approach was selected to rigorously investigate the effectiveness of AI-driven personalised learning platforms on secondary students' academic performance, in comparison to traditional instructional methods commonly used in Portuguese classrooms. Additionally, the descriptive component provided insight into factors such as student engagement, learning preferences, and prior knowledge, all of which are known to mediate learning outcomes.

Rationale for Quasi-Experimental Design

Quasi-experimental designs are widely used in educational research, particularly when randomisation is not feasible, a frequent limitation in real-world classroom settings. In Portuguese public schools, students are typically grouped by class or school administration, making randomised group assignment impractical and ethically challenging. Consequently, this study used intact class groups as experimental and control samples, which reflects authentic educational environments and ensures ecological validity.

The non-equivalent control group design allowed for the comparison of two naturally formed groups:

- The experimental group, which engaged with AI-driven personalised instruction.
- The control group continued with conventional teacher-led instruction.

Both groups completed a pre-test to establish baseline knowledge and a post-test to assess academic gains after the instructional period. This dual assessment strategy, referred to as a "two-shot" design, provides a more robust understanding of changes over time than single post-test methods and helps mitigate internal validity threats such as history, maturation, or testing effects.

Descriptive Research Component

To complement the experimental analysis, the study incorporated a descriptive design to examine qualitative dimensions of the learning experience. This included collecting data on student engagement, classroom climate, and instructional perception via surveys and structured observations. These variables are especially relevant, as several studies have shown that learning environments, teacher behaviour, and instructional clarity significantly influence student motivation and performance.

Recent work by a study emphasised that blended or technology-integrated instruction is most successful when the quality of interaction between student, content, and teacher is intentionally designed. Similarly, a study found that effective pedagogical innovation requires not only access to new technologies but also supportive, well-prepared teachers and flexible learning environments. This insight justifies the inclusion of teacher professional development and instructional preparedness as contextual considerations in the study.

Implementation and Measurement

Over the course of six weeks, the experimental group engaged with an AI-enhanced platform that used machine learning algorithms to adapt content based on learner profiles. These tools offered individualised pathways, real-time feedback, and scaffolded instruction. Meanwhile, the control group followed the national curriculum delivered through traditional methods (lectures, textbook assignments, teacher-led questioning). Both groups received the same content in terms of scope and sequence, ensuring content equivalence.

Academic performance was measured using a validated achievement test aligned with the Portuguese secondary curriculum, which underwent expert review for content validity. Additional instruments included:

- Engagement surveys, adapted from a study, to capture cognitive, emotional, and behavioural engagement.
- Learning style inventories to identify preference patterns that might influence adaptive learning effectiveness.
- Pre-intervention diagnostic tests to assess prior knowledge and normalise initial differences.

Teacher and Environmental Considerations

The classroom environment and teacher-related variables were also recognised as potential moderators. Studies by a study suggest that teacher autonomy, identity, and perceived support significantly affect instructional delivery, especially during pedagogical transitions involving technology. Similarly, research by a study highlights that professional reputation and instructional quality can mediate student perceptions and learning outcomes. Thus, teacher background data (e.g., training in AI tools, years of experience) were also collected to ensure transparency in comparing group performance.

Research Purpose

This study aims to evaluate the impact of AI-powered personalised learning algorithms on student academic achievement in secondary education in Portugal. It further seeks to examine how variables such as student engagement, prior subject knowledge, and learning preferences may influence the success of AI-based instruction. Findings will inform ongoing national discussions on STEM curriculum innovation, digital transition in schools, and teacher professional development. This study is guided by the following hypothesis:

H1: Pre-test Performance Comparison

There is no significant difference in the average pre-test scores between students taught with AI-driven personalised learning and those taught using traditional methods.

H2: Post-test Performance Comparison

There is no significant difference in the average post-test scores between students taught with AI-driven personalised learning and those taught using traditional methods.

H3: Learning Gains Comparison

There is no significant difference in the learning gains (measured by the difference between post-test and pre-test scores) between students using AI-driven personalised learning and those using traditional instruction.

H4: Influence of Learning Factors on AI Effectiveness

The effectiveness of AI-driven personalised learning is not significantly affected by the following factors:

- Student engagement.
- Prior knowledge.
- Learning preferences.

Experimental Design Description

This study employed a non-randomised two-shot pre-test and post-test quasi-experimental design to examine the impact of AI-driven personalised learning on student performance in secondary school. The structure of the experimental setup is illustrated in List 1 below.

Group	Assignment	Pre-test	Intervention	Post-test
G1 – Experimental	N (Non-random)	O1	X (AI-driven personalized learning)	O2
G2 – Control	N (Non-random)	O3	— (Traditional instruction)	O4

Figure 1. List 1: Pre-test-Post-test Quasi-Experimental Design

Legend:
N = Non-random group assignment.
G1 = Experimental Group (received AI-driven personalised learning).
G2 = Control Group (received traditional instruction).
O1 / O3 = Pre-test (before the intervention).
O2 / O4 = Post-test (after the intervention).
X = Treatment (AI-driven personalised learning algorithm).

This quasi-experimental design does not rely on random assignment due to the practical constraints of conducting research in real-world classroom environments. Instead, naturally occurring class sections were assigned as either the experimental group (G1) or control group (G2), following the common procedure in school-based educational research.

In this setup, both groups were administered a pre-test (O1 and O3) to assess baseline knowledge before the intervention. The experimental group then received instruction using an AI-driven personalised learning platform, designed to adapt to students' learning profiles and provide real-time feedback and differentiated support. In contrast, the control group continued with traditional, teacher-directed instruction as per the existing curriculum.

Following the instructional period, both groups completed a post-test (O2 and O4), allowing for a comparison of learning gains between the two instructional modalities. The use of a "two-shot" format, meaning the design was implemented across two distinct instructional cycles, provided an additional layer of reliability by allowing the results to be observed and confirmed across more than one context or time frame.

This design was particularly suitable given the educational setting, where randomisation of students is rarely feasible. It also allowed for meaningful comparative analysis of student outcomes and the examination of other influencing variables such as student engagement, prior knowledge, and learning preferences, all of which were explored as part of the study's broader descriptive objectives.

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METHOD

This study adopted a non-randomised two-shot pre-test and post-test quasi-experimental design, complemented by a descriptive research approach, to investigate the impact of AI-driven personalised learning algorithms on the academic performance of Portuguese secondary school students. The two-shot structure refers to the repetition of the experimental sequence across two curricular units, which enhances the reliability and depth of findings by allowing for the observation of trends across different content areas and time intervals.[3]

The research involved two naturally formed class groups in a public secondary school in Portugal: one experimental group, which received AI-assisted instruction, and one control group, which continued with conventional, teacher-centred instruction. Both groups completed the same pre-tests and post-tests for each of the two instructional units. Although random assignment was not possible due to the practical constraints of the school context, this design maintained ecological validity and allowed for meaningful causal inference within an authentic classroom environment.[2]

The study was conducted during the first semester of the 2024–2025 academic year at a public school located in central Portugal, which offers education from lower secondary to upper secondary levels. A total of 480 students enrolled in Grade 10 participated in the study, with 240 students in each group. The school administration selected the classes, following a non-random convenience sampling method, which, although limiting generalizability, ensured feasibility, access, and adherence to institutional protocols. The participant groups were heterogeneous in terms of academic ability, learning preferences, and socio-economic backgrounds—reflecting the typical diversity of Portuguese public education and supporting the goal of testing the AI-driven intervention across a broad learner profile.

Parental consent and student assent were obtained before the commencement of the study. The research was approved by the school board and aligned with the ethical principles governing research involving human subjects in Portugal, in accordance with national education policies and GDPR standards.

The intervention focused on two units based on the Portuguese national curriculum and aligned with the Next Generation Science Standards (NGSS) framework to ensure international compatibility. The selected units were: (1) Energy in the Ecosystem and (2) Heredity and Variation. The experimental phase lasted for nine weeks, including one week for testing and four weeks for each instructional unit.

A teacher-made 40-item multiple-choice test was designed to assess knowledge and conceptual understanding in both content areas. The test was based on a detailed Table of Specifications (TOS) that covered cognitive levels and learning objectives. It was reviewed by a panel of five Portuguese experts in science education and test construction. The instrument was then pilot-tested with 240 Grade 11 students from a different school to determine item difficulty and discrimination. The internal consistency of the test was confirmed using the Kuder-Richardson Formula 20 (KR-20), yielding reliability indices of 0,8797 for Unit 3 and 0,8951 for Unit 4, both indicating strong reliability for classroom assessment purposes.[4]

In addition to the academic test, a 10-item, 5-point Likert-scale questionnaire was used to gather data on three key learner variables: student engagement, prior knowledge, and learning preferences. The questionnaire was also validated by five academic experts and achieved a high mean content validity rating of 4,70, confirming its appropriateness for capturing relevant learning-related factors in the Portuguese secondary school context.

Students in the experimental group were taught using a selection of AI-based educational platforms, including:

- Brisk Teaching, for lesson planning and differentiated content delivery.
- Khanmigo, an AI-powered tutoring assistant offering real-time student guidance.
- ChatGPT 4.0 Turbo, for researching, summarising, and exploring concepts.
- Quizizz AI, for generating customised quizzes and gamified learning experiences.

The control group followed the same curriculum topics, delivered through conventional instruction methods such as lectures, textbook-based activities, and group discussions, without the use of AI tools.

The study was structured in three distinct phases. The preparation phase involved identifying curriculum content, developing and validating assessment tools, designing AI-enhanced learning activities, and orienting participants. The implementation phase included the administration of pre-tests, delivery of instructional content, and completion of post-tests and questionnaires. Finally, the evaluation phase consisted of analysing the academic performance data and questionnaire results to assess the learning outcomes and the influence of student-related variables.

Data were analysed using quantitative statistical techniques. Descriptive statistics were used to summarise mean scores and standard deviations. Inferential statistics, including paired sample t-tests, independent t-tests, and ANCOVA, were employed to determine whether there were significant differences between and within groups. Correlation analysis was used to examine relationships between student performance and factors such as engagement, prior knowledge, and learning style preferences.

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This research adhered to all ethical protocols established for studies conducted in Portuguese public schools. The confidentiality and privacy of all participants were rigorously maintained, and no personally identifiable information was collected or stored. Research procedures were reviewed and approved by the school's pedagogical council and the local education authority.

In conclusion, the applied quasi-experimental design allowed for a realistic, evidence-based comparison of AI-supported and traditional learning methods within the Portuguese secondary education system. The study offers valuable insights into how AI-driven personalised learning can support curriculum delivery, enhance engagement, and contribute to improved academic outcomes in STEM education. By conducting this investigation within a diverse and authentic educational context, the findings contribute to ongoing discussions about the digital transformation of education in Portugal and align with broader international efforts to integrate intelligent technologies into pedagogical practice.

Measuring Academic Performance Using Mean Scores and Mean Percentage Scores

- What is the mean pre-test score of students exposed to AI-driven personalised learning algorithms?
- What is the mean post-test score of students exposed to AI-driven personalised learning algorithms?

To describe and compare the academic performance of students before and after the intervention, two statistical measures were employed: the mean score and the mean percentage score (MPS). The mean score was used to represent the central tendency of students' raw scores on both the pre-test and post-test. The formula for the mean is:

$$\bar{x} = \frac{\sum X}{N}$$

Where:
$\bar{x}$ = Mean score.
$\sum X$ = 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 the 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 an AI-driven personalised learning algorithm and traditional learning.

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

Figure 2. List 2: Mean Percentage Score Adjectival Interpretation

Test of Difference Between Pre-Test and Post-Test Scores

To determine whether there was a statistically significant difference in academic performance before and after instruction, a paired samples t-test was conducted. This test was used to compare the pre-test and post-test scores of students within each group—those exposed to AI-driven personalised learning algorithms and those taught through traditional instructional methods.

The paired samples t-test is appropriate in this context because it analyses the mean difference between two related sets of scores—in this case, the scores of the same students measured at two points in time (pre-intervention and post-intervention). This allows the researcher to assess whether the learning gains observed after the intervention are statistically significant.

Purpose of the Test

In the experimental group, the test assessed whether the AI-based personalised learning approach led to a significant improvement in students' post-test scores.

In the control group, the test evaluated whether traditional instruction produced a similar or different effect.

By comparing the results of the two groups, the study aimed to determine whether the AI-driven intervention had a greater impact on student learning outcomes than conventional methods. Statistical Formula (Paired Samples t-Test).

$$t_{calc} = \frac{\bar{d}}{s_d / \sqrt{n}}$$

Where:
$\bar{x}d$ = Mean of the differences between paired scores (posttest - pretest).
sd = Standard deviation of the differences.
n = Number of paired scores.

$$t = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

Where:
$\bar{x}_1$, $\bar{x}2$ = Mean scores of the two groups.
"s_1^2" , "s_2^2" = Variance of the two groups.
n1, n2 = Sample sizes of the two groups.

Level of Factors Influencing the Effectiveness of AI-Driven Personalised Learning

The level of influence that key learner-related factors have on the effectiveness of AI-driven personalised learning in the subject studied was evaluated using descriptive statistical analysis using the weighted mean. The three factors investigated were:

- Student engagement.
- Prior knowledge.
- Learning preferences.

These variables were measured through a researcher-developed questionnaire consisting of 10 items, rated on a 5-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). The questionnaire was administered to the students in the experimental group following the intervention

Statistical Tool Used: Weighted Mean

$$\bar{x}_w = \frac{\sum fx}{\sum f}$$

Where:
$\bar{x}$ = Mean score.
∑X = Sum of all student scores.
N = Number of students.

List 3 shows how to interpret the results on the factors that influence the effectiveness of an AI-driven personalised learning algorithm in a subject. The Likert scale was used. To determine the extent or level of influence for each factor, the weighted mean was calculated for all items under each category. This method allows for a more precise assessment by giving weight to the frequency of each response option.

Table 1. List 3: Results on Factors Influencing the Effectiveness of AI-Driven Personalised Learning			
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.

RESULTS AND DISCUSSION

Mean Percentage Scores of Pre-Tests

The Mean Percentage Scores (MPS) from the pre-tests provided baseline data to assess students' prior knowledge of the content. The two-shot pre-test consisted of two administrations of a 40-item multiple-choice test covering Unit 3: Energy in the Ecosystem and Unit 4: Heredity and Variation. Both the experimental group (AI-driven personalised learning) and the control group (traditional instruction) completed the same assessments to ensure comparability of academic performance before the intervention.

Pre-Test Performance in the AI-Driven Group

The pre-test served as a critical benchmark for evaluating the initial understanding and skills of students in the AI-supported learning group. These baseline scores informed the customisation of learning paths and established a foundation for measuring the algorithm's effectiveness.

Table 2 presents the MPS for students in the AI group. Results indicate low performance across both units, with an MPS of 39,0 % in Unit 3 and 37,9 % in Unit 4. These results suggest that before the intervention, students had limited conceptual understanding of the targeted topics, reinforcing the need for differentiated instructional support.

Table 2. 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	240	240	40	21	6	468	15,60	39,0	Low mastery
4	240	240	40	20	10	455	15,17	37,9	Low mastery

These findings are consistent with and extend the body of research emphasising the limitations of traditional instructional methods in STEM education. Rukadikari et al.[5], as well as Dela Cruz et al.[6], have highlighted that student frequently perform poorly in STEM subjects under conventional, one-size-fits-all teaching approaches. These studies argue that such methods often fail to address individual learning needs, leading to disengagement and shallow conceptual understanding. As a result, they advocate for the integration of adaptive and personalised learning models that can better accommodate diverse student profiles.

In parallel, Shete et al.[1] provide empirical evidence demonstrating that AI-based tutoring systems not only improve overall learning outcomes but also offer particular advantages for students who begin with low levels of prior knowledge. Their findings suggest that these systems are capable of delivering timely feedback, adjusting instructional content in real time, and supporting students through targeted remediation, all of which are crucial for learners who might otherwise struggle to keep pace in a traditional classroom setting.

The pre-test results in the current study reflect a similar pattern, revealing that students in both the experimental and control groups entered the instructional units with relatively low baseline knowledge. These pre-test scores serve as a foundational benchmark from which to evaluate the effectiveness of AI-driven personalised learning. Importantly, the data reinforce previous conclusions by showing that students who begin with minimal understanding can benefit from algorithmically tailored instruction, which addresses their specific learning gaps and supports deeper engagement with the material.

Moreover, these findings align with broader educational research that underscores the value of personalisation in enhancing learning efficacy and equity. By leveraging AI to adapt content to individual learners' needs, this study supports the premise that technological innovation can play a transformative role in promoting inclusive, effective STEM education. The results lend further credibility to the argument that personalised AI learning environments have the potential not only to boost short-term academic gains but also to contribute to long-term academic resilience, particularly for students at risk of falling behind in traditional instructional settings.

Pre-Test Performance: Establishing the Baseline

The pre-test means percentage scores (MPS) serve as a critical diagnostic tool for assessing students' initial understanding of key concepts before instruction. Administered through a 40-item multiple-choice assessment, the pre-tests aimed to evaluate students' baseline knowledge in two major content areas: Unit 3 – Energy in the Ecosystem and Unit 4 – Heredity and Variation. These tests not only measure prior knowledge but also set the stage for analysing instructional impact by allowing meaningful comparison with post-test results.

Table 3 presents the pre-test MPS for students in the traditional instruction group, with results showing 38,3 % for Unit 3 and 34,5 % for Unit 4. These scores indicate a generally low level of content mastery before any intervention. When compared with the pre-test scores of the AI-driven learning group (table 2), which recorded similarly low percentages, the data suggest that students across both groups began with a limited understanding of the topics addressed in this study.

Table 3. 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	240	240	40	26	4	460	15,33	38,3	Low mastery
4	240	240	40	21	6	414	13,80	34,5	Low mastery

These findings are consistent with earlier research conducted by Alonzo et al.[7], which revealed that students in conventional learning settings often struggle with STEM content, especially in subjects requiring high levels of abstraction. Notably, the particularly low MPS for Unit 4 (Heredity and Variation) corroborates findings by a study, who reported that genetic concepts pose significant learning challenges without the support of differentiated or technology-enhanced instruction. Similarly, studies by Nyamari et al.[8] and Okoye et al.[9] point out that students from under-resourced environments tend to perform poorly in complex scientific content areas, largely due to the lack of personalised scaffolding and instructional flexibility.

Thus, the pre-test results provide an essential benchmark for measuring student growth and evaluating the effectiveness of AI-driven personalised learning. The data highlight the need to explore innovative instructional strategies that can better support students in mastering difficult STEM material, particularly those strategies that adapt to learners' individual needs.

Post-Test Performance: Assessing Instructional Impact

The post-test MPS offers a direct reflection of students' learning outcomes after exposure to the two distinct instructional approaches, AI-driven personalised learning versus traditional teacher-led instruction. Like the pre-test, the post-test consisted of 40 multiple-choice questions aligned with NGSS-aligned competencies for Unit 3 and Unit 4. Both the experimental (AI) and control (traditional) groups completed the same assessments.

The comparison of post-test results with their corresponding pre-test scores provides insight into the efficacy of each instructional model. These data allow for the analysis of learning gains and support a broader understanding of how instructional design (whether traditional or AI-driven) affects student comprehension. When considered alongside qualitative measures such as student engagement and learning preferences, the post-test scores contribute to a comprehensive evaluation of personalised AI systems in science education.

Table 4. 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	240	240	40	39	27	996	33,20	83,0	High mastery
4	240	240	40	40	29	1056	36,37	90,9	High mastery

The post-test administered following the AI-driven personalised learning intervention serves as a critical measure of the algorithm's effectiveness in enhancing students' conceptual understanding and academic performance. Comprising 40 multiple-choice items, the post-test was aligned with the instructional objectives

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of Unit 3: Energy in the Ecosystem and Unit 4: Heredity and Variation, and was designed to assess mastery of key content delivered through the personalised AI platform.

Table 4 presents the post-test Mean Percentage Scores (MPS) for students in the experimental group. Results reveal a substantial increase in performance compared to the pre-test scores, with students achieving an MPS of 83,0 % in Unit 3 and an even higher 90,9 % in Unit 4, both indicating a high level of mastery.

This remarkable improvement underscores the effectiveness of AI-driven personalised learning in promoting deeper comprehension of complex scientific content. These findings are consistent with studies such as Anderson et al.[3] and Shete et al.[1], which report that AI-enhanced learning platforms significantly boost student engagement, retention, and academic achievement in STEM disciplines. The particularly strong performance in Unit 4 also supports findings by Dela Cruz et al.[6], who observed that AI tools, through features like adaptive feedback, real-time diagnostics, and interactive simulations, can effectively demystify abstract topics like genetics, enabling more accessible and personalised learning experiences.

The clear disparity between pre-test and post-test outcomes validates the educational impact of AI integration in the classroom. It confirms that when instruction is tailored to individual learners' needs, supported by intelligent learning systems, students are more likely to achieve high levels of understanding. These results contribute to the growing body of evidence advocating for the implementation of AI-driven technologies in secondary STEM education, particularly as a means to close learning gaps and support mastery in traditionally challenging subject areas.

Measuring Conventional Learning Outcomes

The post-test means percentage scores (MPS) for students taught through traditional methods serve as a key metric to evaluate their understanding and retention of core concepts. Administered after completing instruction for Unit 3: Energy in the Ecosystem and Unit 4: Heredity and Variation, the 40-item multiple-choice post-test assessed the knowledge gained from standard classroom practices such as lectures, textbook activities, and teacher-guided discussions.

Table 5 presents the MPS for students under conventional instruction. Results indicate a noticeable improvement from the pre-test baseline, with students achieving 69,2 % in Unit 3 and 70,9 % in Unit 4. These scores reflect moderate mastery, demonstrating that traditional instruction supports learning progress to a certain extent.

However, when compared to the significantly higher post-test scores from the AI-driven personalised learning group (table 4), it becomes evident that conventional teaching methods may not fully optimise student achievement, especially in complex subjects. These findings echo the conclusions of Kim et al.[2] and Anderson et al.[3], who found that while lecture-based instruction can facilitate learning gains, it often lacks the adaptability to address diverse learning needs and paces within a classroom, resulting in lower mastery levels compared to personalised AI-supported learning environments.

Moreover, the results support the observations of Alonzo et al.[7], who reported that although students in traditional settings demonstrate gradual academic improvement, they tend to struggle with cognitively demanding STEM content due to the limitations of a uniform, one-size-fits-all instructional model. In particular, the challenges presented by Unit 4 (Heredity and Variation), which requires abstract reasoning, highlight the difficulties students face without adaptive learning scaffolds.

The comparison between post-test results of AI-supported and traditionally instructed groups reinforces the argument for integrating more personalised, interactive learning systems in STEM education. These findings suggest that while conventional methods remain effective to some degree, they are increasingly outpaced by innovative AI-based approaches capable of tailoring instruction, enhancing engagement, and maximising student learning outcomes.

Table 5. 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	240	240	40	36	21	831	27,70	69,2	Moderate mastery
4	240	240	40	38	19	851	28,37	70,9	Moderate mastery

Comparison of Pre-Test and Post-Test Scores: AI-Driven vs. Traditional Instruction

This section presents a comparative analysis of student performance before and after instruction under two different pedagogical approaches: AI-driven personalised learning and conventional teaching methods. The comparison of pre-test and post-test scores serves as the basis for evaluating the effectiveness of AI-powered learning systems in enhancing academic achievement. The results provide important insights into how

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innovative educational technologies can impact student learning outcomes in science education, particularly in complex content areas such as ecology and genetics.

Table 6. Significant Difference Between the Performance of Students Exposed to AI-Driven Personalised 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		

Table 6 displays the results of the paired samples t-test conducted to measure within-group differences in student performance for both instructional approaches in Unit 3: Energy in the Ecosystem and Unit 4: Heredity and Variation.

AI-Driven Personalised Learning Group

In the experimental group that received AI-based instruction, student performance improved markedly. For Unit 3, mean scores increased from 15,60 (SD = 4,21) in the pre-test to 33,20 (SD = 3,48) in the post-test. For Unit 4, scores rose from 15,17 (SD = 3,06) to 36,37 (SD = 4,92). The corresponding t-values—24,9996 for Unit 3 and 33,5167 for Unit 4, and p-values (both < 0,0001) indicate statistically highly significant gains. These results strongly suggest that the AI-driven personalised learning algorithm had a substantial positive impact on student comprehension and retention.

Traditional Instruction Group

Students in the control group, taught using conventional methods, also showed statistically significant improvements, though to a lesser degree. In Unit 3, mean scores improved from 15,33 (SD = 5,14) to 27,70 (SD = 4,84), and in Unit 4, from 13,80 (SD = 3,95) to 28,37 (SD = 4,93). The t-values for these gains were 13,3463 (Unit 3) and 16,3169 (Unit 4), with both p-values at < 0,0001. While the increases were meaningful, the magnitude of the learning gains was significantly lower than those achieved through AI-supported instruction.

These findings are consistent with the work of Kim et al.[2], who argue that AI-based adaptive learning environments provide more effective support for students by offering personalised feedback, pacing, and content alignment. Similarly, Dela Cruz et al.[6] emphasised that AI-powered learning in Philippine secondary schools resulted in higher levels of conceptual mastery, particularly in science subjects, due to its ability to adjust to individual student needs and learning styles.

The considerable difference in post-test outcomes between the two groups underscores the potential of AI-driven learning systems to outperform traditional methods in supporting academic success, especially in STEM disciplines. These results reinforce the notion that personalised, technology-mediated instruction offers significant advantages over one-size-fits-all classroom strategies.

Table 7, presented in the next section, further elaborates on these comparisons through independent samples t-tests, analysing the between-group differences in learning gains.

Table 7. Significant Difference Between the Performance of Students Exposed to an AI-Driven Personalised Learning Algorithm and Traditional Learning on their Pre-test and Post-test Using an Independent Samples t-test

	AI-driven		Traditional		t	P
	ẍ	SD	ẍ	SD		
Pre-test Results						
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						
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**

Note: 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

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Factors Influencing the Effectiveness of AI-Driven Personalised Learning

This study also assessed key factors influencing the effectiveness of AI-driven personalised learning in the context of instruction. The factors analysed include student engagement, prior knowledge, and learning preferences, as these directly relate to the adaptability and responsiveness of AI systems to individual learners. Understanding the levels of these factors provides deeper insight into how AI technologies optimise learning outcomes.

Student Engagement

Student engagement emerged as a foundational element in the success of AI-driven learning. Engagement refers to the learner's emotional, cognitive, and behavioural investment in the learning process. In an AI-enhanced environment, highly engaged students are more likely to take advantage of adaptive features, respond to personalised prompts, and persist through challenging content.

According to Nguyen et al.(10), engagement significantly mediates the effectiveness of AI-supported instruction. When students are curious, motivated, and actively involved, the personalised learning pathways and immediate feedback mechanisms of AI platforms amplify learning outcomes. Conversely, low engagement may limit the benefits of the AI system, as students disengage from the tools designed to support their progress.

To measure this, a 5-point Likert scale questionnaire was administered, with values ranging from 1 ("not influenced") to 5 ("very highly influenced"). Table 7 presents a summary of student responses regarding their engagement with AI-driven learning.

Preliminary results suggest that the personalised learning environment significantly increased student motivation, interest, and participation in lessons, corroborating prior studies emphasising the importance of learner-centric design in educational technologies.

The results revealed a grand mean rating of 4,48, which falls under the category of "Very Highly Influenced", indicating a strong positive response from students toward the integration of AI-driven personalised learning in STEM education. This suggests that students perceived the AI-based approach as highly effective in increasing their interest, motivation, and involvement in learning activities.

The most highly 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 emphasises the critical role of immediate, personalised feedback, which aligns with findings from Holmes et al.(11) and Shete et al.(1), who reported that real-time feedback significantly enhances learner motivation and progress.

Other high-rated statements included:

- "I feel more engaged in STEM learning when I can use technology, including AI-driven platforms and tools" (Mean = 4,66), supporting findings by Johnson et al.(12).
- "I enjoy working with my peers on STEM activities and projects, both face-to-face and through digital platforms" (Mean = 4,58), which aligns with research by Zhu et al.(13), Tanaka et al.(14), and Lim et al.(15), highlighting the value of peer collaboration and blended learning tools in sustaining engagement.

Table 8. Summary Results of the Student Engagement on AI-driven Personalised 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 personalised 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 platforms and tools.	4,66	Very highly influenced
I find personalised 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
Note: Interpretation: 5- very highly influenced, 4- highly influenced, 3-moderately influenced, 2- slightly influenced, 1-not influenced		

Another key insight was from the statement:

- "I find personalised learning paths (adapted by AI) more engaging than traditional learning methods" (Mean = 4,57).

This reflects a clear student preference for individualised, adaptive learning approaches over traditional instruction, echoing the conclusions of Kamalov[16] and Chen et al.[17].

These results reinforce the notion that AI-enhanced platforms not only increase student engagement but also foster a more interactive, responsive, and motivational learning environment, especially in STEM disciplines. Similar findings from Alonzo et al.[7] demonstrate that students in Philippine schools showed stronger motivation and interaction levels when taught using AI-enhanced methods, compared to conventional classrooms.

Prior Knowledge

Prior knowledge plays a critical role in shaping how students assimilate, retain, and apply new information. In STEM education, understanding a learner's pre-existing knowledge allows educators to tailor instruction that bridges conceptual gaps, reinforces key ideas, and promotes deeper comprehension. AI-driven personalised learning systems capitalise on this by using learner data to customise instructional pathways that align new content with what the student already knows, thereby increasing the relevance, challenge, and effectiveness of the learning experience.

Moreover, recognising and addressing misconceptions early—through adaptive algorithms—prevents the reinforcement of inaccurate understanding and fosters a more confident and capable approach to new STEM material. As such, strategically leveraging prior knowledge is essential for improving both immediate learning outcomes and long-term academic retention.

Table 8 presents students' self-reported prior knowledge regarding STEM concepts, artificial intelligence (AI), and its application in education. The overall mean rating was 4,03, classified as "Highly Influenced," indicating that most students were familiar with AI and its relevance to personalised learning.[18,19]

However, the lowest-rated item: "I am familiar with the core concepts of the STEM (Science, Technology, Engineering, Math) curriculum" (Mean = 2,78), suggests only moderate familiarity with foundational STEM content. This indicates a gap that must be addressed through targeted instruction before or during AI-driven learning to ensure students can fully benefit from adaptive technologies.[8]

In contrast, high mean ratings were recorded for statements such as:

- "I am aware of how AI is being used in education to support learning" (Mean = 4,19).
- "I understand the concept of personalised learning in the context of education" (Mean = 4,15).

Which reflects a strong awareness of AI's role in customising the learning experience to individual student needs.

The highest-rated statement, "I believe AI has the potential to improve student learning outcomes in STEM subjects" (Mean = 4,82), demonstrates students' confidence in AI's ability to enhance their academic performance. Similarly, a high rating for "I understand the challenges or limitations of using AI in education" (Mean = 4,55) shows that students are aware of the potential drawbacks and complexities of AI integration in the classroom.[20]

These findings are consistent with research by Kim et al.[2], which found that learners familiar with AI are more comfortable and effective in engaging with adaptive platforms. Dela Cruz et al.[6] also highlighted that student in tech-integrated educational environments adapt more easily to AI-enhanced instruction.

In summary, while students showed a strong understanding of AI and its potential in education, their limited familiarity with core STEM content highlights the need for a dual-focused approach. Effective implementation of AI-driven personalised learning should be coupled with foundational STEM reinforcement to maximise impact. This ensures that technology not only adapts to individual learning needs but also builds the necessary conceptual framework for long-term academic success.[21]

Table 9. Results of the Prior Knowledge of Students on AI-driven Personalised 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 personalised 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 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 challenges and limitations of using AI in education.	4,55	Very highly influenced
Overall Mean	4,03	Highly influenced

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

Learning Preferences

Learning preferences refer to the individual ways students absorb, process, and engage with educational content. These preferences vary significantly among learners and may include visual, auditory, kinesthetic, or mixed learning styles. Recognising and responding to these preferences is essential in designing instruction that maximises engagement, inclusivity, and learning effectiveness. AI-driven personalised learning systems offer the unique ability to tailor content delivery based on each learner's preferred style, thereby enhancing participation, motivation, and academic achievement.[22]

The integration of learning preferences into instructional planning supports active learning and fosters environments where students feel more connected to the material. By aligning teaching strategies with individual preferences, educators can increase both comprehension and long-term retention—particularly in complex subjects such as STEM.[23]

Table 10 presents the summary of students' self-reported learning preferences related to AI-based instruction. The overall mean rating of 4,63, classified as "Very Highly Influenced," reflects a strong inclination toward technology-enhanced, adaptive learning experiences in STEM education.

Among the highest-rated items was "I am comfortable following AI-generated personalised study plans based on my strengths and areas for improvement" (Mean = 4,81), indicating strong acceptance of AI-driven learning structures tailored to individual academic profiles. Students also valued instant feedback from AI-powered platforms (Mean = 4,71) and practical learning through experiments or projects (Mean = 4,75), highlighting the importance of both real-time guidance and experiential learning in promoting deep conceptual understanding. Additionally, learners expressed a high preference for:

- Interactive learning activities (Mean = 4,69).
- Diverse instructional materials (Mean = 4,78).
- Technology-based simulations and virtual labs (Mean = 4,59), demonstrating a need for varied, dynamic, and interactive content formats to maintain focus and enhance cognitive engagement.

These findings align with studies by Shete et al.[1] and Holmes et al.[11], which emphasise the benefits of AI-driven adaptive learning in accommodating individual learning differences. Likewise, Chen et al.[17] reported increased student motivation and academic gains when adaptive technologies were integrated into STEM instruction. In the Philippine context, Rukadikar et al.[5] and Dela Cruz et al.[6] found that students showed a clear preference for AI-based platforms due to their adaptability and ability to cater to varied learning needs.

Table 10. 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 personalise 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 personalised study plans based on my strengths and areas for improvement.	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

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

CONCLUSIONS

This study investigated the effectiveness of AI-driven personalised learning algorithms in enhancing student achievement among 10th-grade students in Portugal. Using a quasi-experimental two-shot pre-test/post-test design and a descriptive approach, the study compared the academic performance of students in AI-based learning environments with that of students taught through traditional methods.

The results provide compelling evidence supporting the integration of AI in secondary STEM education. Students in the experimental group who received AI-driven personalised instruction demonstrated significantly higher learning gains than their peers in the traditional learning group. This was confirmed through both paired samples and independent samples t-tests, where statistically significant differences favoured the AI-driven approach in both Unit 3 (Energy in the Ecosystem) and Unit 4 (Heredity and Variation).

These findings align with those of a study, who also reported enhanced student performance through AI-supported personalised learning platforms. Moreover, the higher post-test scores of students exposed to AI tools support the assertion of studies, who argued that adaptive systems can bridge knowledge gaps more effectively than standardised teaching models. Likewise, the findings from the Philippines by a study mirror these results, particularly regarding improved engagement and retention in STEM learning due to individualised AI-based support.

In addition to academic performance, the study explored three critical factors influencing the success of AI integration: student engagement, prior knowledge, and learning preferences. Students reported a high level of engagement and a strong preference for AI-enhanced interactive tools, real-time feedback, and personalised learning paths. While they demonstrated high awareness of AI and its educational applications, some gaps in foundational STEM knowledge were evident, highlighting the need for reinforcing core content alongside AI instruction. These observations are consistent with the work of studies, who emphasise the role of adaptive systems in increasing motivation and supporting differentiated instruction.

Limitations

Despite the promising results, the study faced several limitations. First, the use of non-random convenience sampling and a single-site study limits the generalizability of findings beyond the context of West Wendover High School in Portugal. The sample size (n = 480) and its restriction to 10th-grade STEM learners may also not fully represent broader secondary school populations. Additionally, the intervention covered only two instructional units, which, while sufficient to show short-term gains, may not reflect long-term retention or learning sustainability. Further, the study did not control for teacher effects, access to digital resources outside of school, or individual technological proficiency.

RECOMMENDATIONS

Based on the findings and limitations, several recommendations are proposed:

- Broaden Implementation: Future studies should include a larger and more diverse student population across multiple schools and regions to enhance generalizability.
- Longitudinal Research: investigate the long-term effects of AI-driven personalised learning, particularly regarding knowledge retention, critical thinking, and problem-solving skills in STEM.
- Hybrid Learning Models: blend AI-driven instruction with traditional teaching to ensure reinforcement of core STEM concepts, particularly for students with low prior knowledge.
- Professional Development: equip teachers with training to effectively integrate AI tools into lesson planning, assessment, and classroom management.
- Infrastructure Support: ensure equal access to digital tools and AI technologies across student demographics to prevent widening educational disparities.
- Further Exploration of Affective Factors: future research should examine the emotional and motivational aspects of AI learning environments, including student self-efficacy, autonomy, and attitudes toward technology-enhanced education.

This research provides robust initial evidence of the positive impact of AI-driven personalised learning on student academic achievement. By addressing individual differences in engagement, prior knowledge, and learning preferences, AI-based approaches offer a promising path forward in the evolution of science education in Portugal and beyond.

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