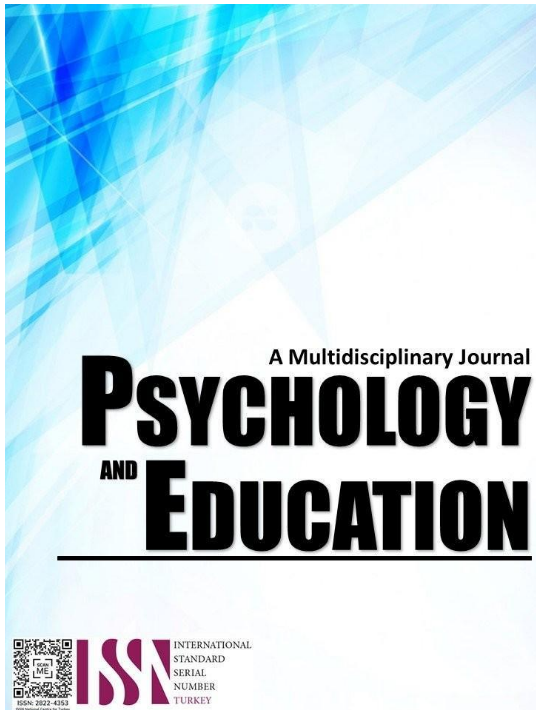
EFFECTIVENESS OF AI-ASSISTED INSTRUCTION, CONVENTIONAL TEACHING AND STUDENTS' ACADEMIC PERFORMANCE IN SCIENCE EDUCATION



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Research Article

Effectiveness of AI-Assisted Instruction, Conventional Teaching, and Students' Academic Performance in Science Education

Genna Maro G. Dapiroc
For affiliations and correspondence, see the last page.

Abstract

The science curriculum in the Philippines aims to promote lifelong experience among the students and equip them with the proper knowledge, skills, and values. This research assessed the effectiveness of AI-assisted instruction, conventional teaching, and students' academic performance in science education. AI-assisted instruction engages the students during discussion and helps them understand the lesson. The study participants were two intact blocks of first-year nursing students from Christ the King College. Using a quasi-experimental design, one block was introduced to AI-assisted instruction, and the other section was exposed to Conventional Teaching Instruction. Pretest and posttest were administered to both groups using standardized tests for performance. Findings revealed that there was no significant difference between the two modes of instruction. It highlighted the inconsistencies in student understanding of scientific concepts, with traditional teaching methods potentially limiting engagement, critical thinking, and hands-on learning. Differences in student performance between AI and conventional students are closely related to disparities in each group's accessibility to resources, especially access to the Internet. Educational institutions must invest in better digital infrastructure with reliable Wi-Fi and devices that ensure student access and maximize AI-assisted instructional opportunities.

Keywords: *AI- assisted instruction, conventional teaching, science curriculum, student performance*

Introduction

The science curriculum in the Philippines aims to promote lifelong experience among the students and equip them with the knowledge, skills, and values necessary to engage with a purpose in this globally changing world. It also focuses on administering creative and critical thinking, promoting scientific inquiry, and understanding scientific concepts related to real-life situations. The scientific curriculum encourages a close relationship between science and technology, especially local technology, protecting the nation's cultural legacy (K–12 Science Curriculum, 2016).

Machine learning in the era of artificial intelligence encompasses many areas, specifically in Education. It allows supervised, unsupervised, and reinforcement learning among the students. To customize instructional materials to each student's needs, AI systems assess each student's learning preferences and areas of strength and weakness. Real-time task difficulty adaptive learning platforms make adjustments in response to student performance. Students receive individualized teaching and feedback from these systems. AI tutors may mimic one-on-one tutoring by adjusting to each student's unique learning style and offering focused assistance.

The Program for International Student Assessment (PISA) 2022 results for the Philippines were released on December 5, 2023, and the country's mathematics, reading, and science performance was assessed. However, the country's performance in science is lower than the OECD average, with only 16% of students attaining at least Level 2 proficiency in mathematics, compared to the OECD average of 69% (OECD, 2023). This outcome demonstrated how the Philippines performed compared to other Asian nations, particularly in science. It is recommended for countries whose science, mathematics, and reading scores are under the OECD average to use new digital technologies, and providing students access to Education with the required help can help them increase their PISA scores (İdil et al., 2024).

The PISA results proved that many college and high school students still struggle to understand basic scientific concepts. The biochemistry subject is a significant course among nursing students that institutions of higher learning must offer by the Commission on Higher Education. It has been noted that students are struggling to comprehend lessons involving cells, chemical bonding, hydrocarbons, and even macronutrients. This is concerning because these fundamental ideas should be taught in high school.

Like other nations, the Philippines faces challenges in disseminating scientific knowledge, and numerous causes exist. The Philippines' science education system lacks basic supplies, including labs, textbooks, lab guides, etc. These are crucial to help students learn, especially regarding laboratory work. John Dewey's "Learning by Doing" theory provides a strong foundation for promoting in-depth, significant learning experiences. His theories emphasize the value of social interaction, problem-solving, and active engagement in the learning process. The socioeconomic condition of the students, which prevents them from giving their best effort in the classroom and widens the achievement gap between students from wealthy and underprivileged groups in terms of scientific education outcomes, is another issue we may investigate.

Substantial reforms at multiple levels are needed to tackle these issues, such as curriculum development, teacher preparation, infrastructure development, and policies that support equal access to high-quality science education for all students. Machine-assisted instruction in the era of artificial intelligence is dedicated to building a paradigm connecting teachers, machines, and students, emphasizing the cooperation and evolution among teachers, machines, and students, and promoting man-machine integration and teaching (Li et al., 2022). AI-assisted instruction can benefit the students and the teachers as it engages the students during discussions and helps them understand the lesson. It will empower them to reach their full potential.

With the above-mentioned information about the problematic status of Science Education in the Philippines, this study investigated the effect of AI-assisted instruction on students' academic performance in science. The study was conducted since no local study is conducted similar to this in the school where the researcher is employed. Although AI-assisted instruction is becoming more popular in the field of Education, it is still unknown how successful it is in teaching science compared to traditional methods. This study fills these gaps by assessing whether AI enhances student performance and engagement in science education or only acts as a supplemental tool. The results will assist teachers in identifying the best teaching practices to improve student learning.

Research Questions

This research aimed to investigate the effect of AI-assisted instruction strategy on college students' performance in science. Specifically, it answered the following questions. Specifically, it will answer the following questions:

1. What is the level of performance before and after the intervention for students exposed to traditional teaching in terms of:
    1.1 observing;
    1.2 predicting;
    1.3 analyzing;
    1.4 problem-solving; and
    1.5 experimenting?
2. What is the level of Science performance before and after the intervention for students exposed to AI-assisted teaching in terms of:
    2.1 observing;
    2.2 predicting;
    2.3 analyzing;
    2.4 problem-solving; and
    2.5 experimenting?
3. Is there a significant difference between the pretest and posttest performance of students exposed to conventional teaching?
4. Is there a significant difference between the pretest-pretest and posttest performance of students exposed to AI-assisted teaching?
5. Is there a significant difference in Science performance between those students exposed to traditional and AI-assisted teaching?

Methodology

Research Design

This research utilized a quasi-experimental design. Quasi-experimental research designs, as the name suggests, use non-experimental (or non-researcher-induced) variation in the primary independent variable of interest, essentially mimicking experimental conditions in which some subjects are exposed to treatment and others are not on a random basis (Gopalan et.al, 2020). Quasi-experimental designs can be used to answer implementation science questions in the absence of randomization (Miller, et.al, 2020); this is a research design that aims to identify the impact of a particular intervention, program, or event (a "treatment") by comparing treated units to control units (Dimewiki, 2022).

The researchers aimed to find out how AI-assisted instruction affected the performance of science students. A quasi-experimental research design is a study that does not require randomization of participants who will compose the control and experimental groups. This design is appropriate for this study since the researcher will not be able to create two groups with randomly selected participants for each group.

Respondents

The study utilized the first-year BS Nursing students of Christ the King College. Two intact blocks from the first-year students were utilized for this study. One section has thirty (30) students exposed to the AI-Assisted Instruction. The other section, with thirty (30) students, was exposed to the Conventional Instruction approach. Those included were students who voluntarily participated, and those who did not consent were excluded as participants.

Regarding the withdrawal criteria, students who wished to withdraw their participation could do so without consequences. The time duration of students' participation took around 2 months. As to the benefits, no monetary benefits were given to them, but during the implementation of the intervention, the participants received a simple token from the researcher.

The researcher is a part-time college instructor at the institution, teaching biochemistry in two different blocks. Eligibility was limited to enrolled students exposed to both types of instruction. For participants under 18 years old, parental consent was given. To qualify the use of a quasi-experimental research design, the researcher employed non-randomized sampling in selecting 30 students for the control group and another 30 students for the experimental group, since there are 30 intact students per block.

Instrument

To measure the effect of AI-assisted and Conventional teaching instruction during the pretest and posttest, the researcher used a researcher's 30-item multiple-choice exam. This 30-item questionnaire was formulated based on the preliminary to midterm contents of the Science subject (Biochemistry) enrolled by the students. To ensure that the items were valid, the researcher sought the expertise of two experts in validating the questionnaires. In addition, pilot testing on 30 students was conducted to determine the reliability of the questionnaires. There were 6 items under the observing and analyzing skills, 5 for predicting, 4 for problem-solving, and 9 for experimenting skills.

The main tool used in the research to assess student performance and the efficacy of AI-assisted training is a pretest and posttest questionnaire. Before the use of AI technologies, a pretest was given to students to gauge their baseline knowledge and comprehension of important scientific ideas. This first assessment creates a comparison basis for further investigation by highlighting areas of strength and weakness.

After the AI-assisted instruction session, students were given a posttest to gauge any changes in their performance and learning objectives. The posttest's questions are comparable to those on the pretest, enabling a straight comparison of the outcomes. Both questionnaires' multiple-choice and practical application questions were meant to assess students' scientific comprehension, critical thinking, and problem-solving abilities.

Together, these instruments facilitated a robust analysis of the impact of AI-assisted instruction on students' learning, enabling researchers to draw meaningful conclusions about the effectiveness of this educational approach.

In addition, the options represented by the scoring process of this questionnaire were the proposals and the choice of panel members. These questionnaires were cross-checked whether the questions or the items were valid and in line with the topic and the problem presented in the study by teacher experts in the field of science.

Procedure

The researcher will follow the following University Protocol to guarantee the accuracy and comprehensibility of the study findings:

Once the document for the final defense had been carefully evaluated and reviewed, the researcher asked the adviser for permission. After carefully evaluating and reviewing the completed document, the graduate studies dean will authorize the thesis's final defense date. After that, the researcher completed the study Ethics application form and sent it with the accepted study proposal to the Office of the Vice President for Research, Publication, and Extension. The Associate Director of the Research and Publication Office examined the proposal and Research Ethics Form to ensure that they were comprehensive and adhered to university policies and procedures. After that, the research ethics will be sent to the Vice President for Research, Publication, and Extension and the RPO Director for additional evaluation and approval by the Research Ethics Review Committee. To conduct the study with two blocks of Christ the King College first-year Nursing students, the researcher prepared a letter and got authorization from the dean of the Bachelor of Science in Nursing and the Chairman of Graduate Studies. Additionally, the researcher guaranteed that the study would not cause harm, and that all data would be handled with the highest confidentiality, regardless of the outcome. Before the final research presentation was scheduled, the researcher provided the advisor with a copy of the article for evaluation and review to determine the paper's quality and applicability.

Answer sheets were collected, and lessons were delivered in both sections of concepts in the Prelims and Midterms. The AI-assisted group learners are subjected to the AI-assisted approach in the developing mastery phase. The AI-Assisted Approach group was woven into concepts that included Introduction to Biochemistry, The Cell, Hydrocarbons, and the naming of hydrocarbons. The other group, the learners in the Conventional teaching approach, received the traditional delivery method. Following the presentation and discussion of the targeted concepts, subjects answered questions about the posttest, a comparable assessment tool administered before the intervention's implementation. The data obtained from the respondents were kept confidential throughout the study. Enough statistical tools were ensured to analyze and interpret the data. Once the data are collected and completed, all the study results shall be available to the investigator, the research adviser, the statistician, and the panel. The results will be shared with others (students and fellow researchers) for future reference and related studies. If further research is not to be pursued, these data will be erased or disposed of appropriately.

Data Analysis

In the data analysis plan for this study, the mean and standard deviation were used to measure students' performance on the pretest and posttest in science. The researcher adopted ANCOVA for the analysis to find whether there is a significant difference between the two groups, the groups that received AI-assisted instruction and those in traditional teaching. This statistical tool is appropriate for this study since posttest scores may be controlled using the pretest scores so that any confounding variables toward student performance are mitigated. ANCOVA accounts for the pretest scores as covariates; this means that the posttest outcomes would be different solely because of the instructional method and not due to a difference in pre-existing knowledge between the participants. Thus, this enhances the accuracy of the comparisons and strengthens the findings' validity, the reason behind the proper choice for an educational intervention analysis.

Literature promoting the application of ANCOVA in educational research includes reports that ANCOVA is useful for controlling covariates and painting more explicit images of treatment effects. For example, Delaney and Vargha (2018) indicate that using ANCOVA in their study is helpful in educational research since comparing means between groups provides information to account for differences at a baseline.

Ethical Considerations

Ethical consideration was given to all parts of this study involving legal age participants. All participants gave informed consent for a direct survey to inform them about the study and what part they were expected to play. The consent form was in plain language, and the investigators explained it to contact subjects with questions. Subjects were informed of their rights and could refuse to participate in the study at any time, without suffering any risk due to participation. Every participant received a consent form to fill out and sign, and only the study cases with signed and fully completed consent forms were included. To help the respondents maintain their anonymity, codes were assigned to each participant, and they were informed that the study is strictly academic and aims to improve their performance in science. Second, they were informed as to how long the study would last, which stretched until Midterms, and the procedure for implementing the study. Students who do not give signed consent for participation shall be excused from classes, and their responses are excluded from the data gathering.

Results and Discussion

Table 1 presents the level of science performance before the intervention for students exposed to AI-assisted instruction in observing, predicting, analyzing, problem-solving, and experimenting. As shown in the table, students exposed to AI-assisted teaching obtained a pretest pretest mean score of M=1.76, SD=1.19 for observing and interpreted as very low level, M=1.70, SD=1.20 for predicting and interpreted as very low level, M=2.10, SD=1.29 for analyzing and interpreted as low-level, M=1.13, SD=1.00 for problem-solving and interpreted as very low level, and M=2.86, SD=2.40 for experimenting and interpreted as very low level. Meanwhile, the total performance has a mean score of M=9.56, SD=4.04, which indicates that the students under the AI-assisted teaching have a low level of pretest performance in science. The overall mean for SD=4.04 implied that the problem

1. What is the level of science performance before and after the intervention for students exposed to traditional teaching in terms of

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1.5 experimenting?

Table 1. *Level of Science performance before the intervention for students exposed to traditional teaching in terms of observing, predicting, analyzing, problem solving, and experimenting*

Sub-variable	*N*	*Mean*	*SD*	*Interpretation*
Observing	30	2.13	1.25	Low
Predicting	30	1.56	1.33	Very Low
Analyzing	30	2.00	1.11	Low
Problem Solving	30	1.23	1.00	Very Low
Experimenting	30	3.00	2.33	Very Low
Total Performance	30	9.93	3.61	Low

Table 1 presents the level of science performance before the intervention for students exposed to traditional teaching in observing, predicting, analyzing, problem-solving, and experimenting. Each variable varies in terms of range because of the number of indicators in each variable. As shown in the table, the total performance has a mean score of M=9.93, SD=3.61, which indicates that the students under traditional teaching have a low level of pretest performance in science. The overall mean for SD=3.61 implied that the data are highly scattered around the mean score. The highest mean is from the experimenting skills, which has a mean score of 3.00; this could be because there are more indicators under this skill compared to the other skills. The lowest mean is on the problem-solving skills which only has 1.23. Students exposed to traditional teaching obtained a pretest mean score of M=2.13, SD=1.25 for observing and interpreted as low level, M=1.56, SD=1.33 for predicting and interpreted as very low level, M=2.00, SD=1.11 for analyzing and interpreted as low level, M=1.23, SD=1.00 for problem-solving and interpreted and interpreted as very low, and M=3.00, SD=2.33 for experimenting and interpreted as very slow. Moreover, students scored a mean of M = 2.13, SD = 1.25 when observing, which is construed to represent a relatively low level of performance. Observing is the most rudimentary science skill; this low mean suggests students are experiencing trouble with the most elemental scientific practice. Similarly, the predicted mean score stands at M =1.56, SD = 1.33, meaning a very low level of performance was observed. Prediction demands inference so that appropriate actions can be anticipated based on facts currently known, and this score is extremely low, so presumably the students had significant trouble with that skill. On another note, the mean score for analyzing was M = 2.00, SD = 1.11, also interpreted as low. This means that students had difficulties interpreting and breaking down scientific data, which is the fundamental requirement for higher-order thinking when teaching ScienceScience (Bybee, 2010). For the score for problem-solving, it gave the students a mean score of M = 1.23, SD = 1.00 once again interpreted as very low. Science entails problem-solving or applying knowledge to new situations, and these results show a severe weakness here. Finally, the mean score for experimenting was M = 3.00, SD = 2.33, interpreted as very slow. This relatively higher mean, though still low, suggests that students considered experimenting less complex than other skills, but the significant standard deviation indicates variability in how students approached experiments.

Furthermore, the overall mean score for total performance stands at M = 9.93, SD = 3.61. This leads to the conclusion that the students in the traditional setting performed poorly in Science. This high standard deviation (SD = 3.61) gives an interpretation that there was much variation in student performance, with scores spread all over the range around the mean, thereby inferring inconsistency as far as the scientific concepts are apprehended by various students.

These results support previous studies that explain relatively low levels of student engagement and performance in Science due to traditional methods of teaching, which are mainly pass-based, as compared with interactive and student-centered methodologies, such as project-based learning, as identified by Krajcik & Blumenfeld (2006). Poor performance levels in all areas of scientific skills highlighted the call for more effective innovative teaching methodologies that encourage critical thinking and problem-solving skills among the students, as mentioned by Hmelo-Silver et al. (2007). This suggests that traditional instruction may not be able to effectively foster higher-order thinking and hands-on learning experiences, underscoring the need for more interactive and inquiry-based teaching strategies.

Table 2. *Level of Science performance after the intervention for students exposed to traditional teaching in terms of observing, predicting, analyzing, problem solving, and experimenting*

Sub-variable	*N*	*Mean*	*SD*	*Interpretation*
Observing	30	3.80	1.54	Moderately High
Analyzing	30	3.13	1.54	Moderately High
Problem Solving	30	2.26	1.01	Moderately High
Experimenting	30	4.43	1.43	Moderately High
Total Performance	30	16.26	4.06	Moderately High

Table 2 presents the level of science performance after the intervention for students exposed to traditional teaching in observing, predicting, analyzing, problem-solving, and experimenting. As shown in the table, students exposed to traditional teaching obtained a pretest mean score of M=3.80, SD=1.54 for observing and interpreted as on the moderately high level, M=2.63, SD=1.12 for predicting and interpreted as on the moderately high level, M=3.13, SD=1.54 for analyzing and interpreted as on the moderately high level, M=2.26, SD=1.01 for problem-solving and interpreted as on the moderately high level, and M=4.43, SD=1.43 for experimenting and interpreted as on the moderately high level. Meanwhile, the total performance has a mean score of M=16.26, SD=4.06, indicating that the students under the traditional teaching have increased their performance in science during the posttest. The overall mean for SD=4.06 implied that the data are highly scattered around the mean score.

During the observation, the students scored a mean of M = 3.80 and SD = 1.54. This was perceived to be modestly high. This means that students performed even better than on the pretest, where they were below average. One learns that the intervention seems to have enhanced the ability of the students to observe scientific phenomena, which is one of the most important skills of scientific inquiry (Bybee, 2010). Similar results were achieved for prediction, with a mean score of M = 2.63, SD = 1.12, interpreted again as moderately high. It is quite an excellent improvement over a pre-intervention score of 1.56, demonstrating how students became better at making scientific predictions based on the data and their prior knowledge.

For the assessment, students scored a mean of M = 3.13, SD = 1.54, which is also considered high. The posttest scored higher than the mean of the pretest, scoring 2.00; therefore, the score shows improvement in the analytical skills vital in analyzing data to conclude Science (Hmelo-Silver et al., 2007). In the problems, the mean score was M = 2.26, SD = 1.01. The performance level was moderately high. Relative to their pretest mean of 1.23, the still comparatively lower score on problems compared with other skills reflects that the student still struggled somewhat with applying scientific knowledge to solve complex problems.

The highest posttest score was in experimenting, with a mean M = 4.43, SD = 1.43, which refers to a moderately high level. This increase signifies that the students got better at designing and carrying out experiments, which should be part of scientific investigation. It runs in accordance with studies that argue that hands-on, inquiry-based teaching enhances students' experimental skills (Krajcik & Blumenfeld, 2006).

The overall information showed that regular instructional activities combined with intensive support interventions can improve students' performance in various scientific activities, such as observation, prediction, analysis, and experimentation. Still, this does not seem to be ample enough to enhance students' abilities to apply scientific concepts in new situations when emphasis is placed on developing problem-solving skills.

Problem 2. What is the level of science performance before and after the intervention for students exposed to AI Assisted teaching in terms of

1.1 observing,
1.2 predicting,
1.3 analysing,
1.4 problem solving, and
1.5 experimenting?

Table 3. *Level of Science performance before the students were exposed to AI-assisted teaching in terms of observing, predicting, analyzing, problem solving, and experimenting*

Sub-variable	*N*	*Mean*	*SD*	*Interpretation*
Observing	30	1.76	1.19	Very Low
Predicting	30	1.70	1.20	Very Low
Analyzing	30	2.10	1.29	Low
Problem Solving	30	1.13	1.00	Very Low
Experimenting	30	2.86	2.40	Low
Total Performance	30	9.56	4.04	Low

Table 3 presents the level of science performance before the intervention for students exposed to AI-assisted instruction in observing, predicting, analyzing, problem-solving, and experimenting. As shown in the table, students exposed to AI-assisted teaching obtained a pretest mean score of M=1.76, SD=1.19 for observing and interpreted as very low level, M=1.70, SD=1.20 for predicting and interpreted as very low level, M=2.10, SD=1.29 for analyzing and interpreted as low-level, M=1.13, SD=1.00 for problem-solving and interpreted as very low level, and M=2.86, SD=2.40 for experimenting and interpreted as very low level. Meanwhile, the total performance has a mean score of M=9.56, SD=4.04, which indicates that the students under the AI-assisted teaching have a low level of pretest performance in Science. The overall mean for SD=4.04 implied that the data are highly scattered around the mean score. Observation yielded a mean score of M = 1.76, SD = 1.19.

Analyzing had a higher M mean score of M = 2.10, SD = 1.29, though still in the low-performance category. This thus demonstrates that even though the students were somewhat competent in interpreting and breaking scientific data into parts, they had many problems more than they did with handling. Analyzing skills are a key ingredient in Science thinking development, and the very low mean scores in this area harmonize with research indicating that traditional approaches fail to develop such higher-order thinking skills (Kuhn, 2005). Problem-solving scored even lower, M = 1.13, SD = 1.00 a very low performance level. These align with findings that conventional approaches to teaching often fail to foster in students genuine problem-solving skills, a key requirement of scientific practice in the real world (Jonassen, 2011).

In experimenting, students attained a mean score of M = 2.86, SD = 2.40, still interpreted to be very low. This is a skill in the design and conduct of experiments- the practical approach to learning science. The high standard deviation of SD = 2.40 implies a lot of variability in students' performance; despite a few managing to do better, most found experimenting challenging (Lai, 2011). Experimentation is the incorporation of the knowledge of scientific principles. Low scores in experimentation, as implied, are a result of the failure of traditional methods to engage students in active learning (Hmelo-Silver, Duncan, & Chinn, 2007).

A total mean performance score of M = 9.56, SD = 4.04 reveals that the students exposed to AI-assisted instruction performed poorly in Science before the intervention. Huge standard deviation also points to widespread; this indicates that while some may have known some things really well on average, performance was still low and not uniform.

These findings imply that alternative teaching approaches that might more effectively address students' development of scientific skills should be investigated. Although AI-based training offers a promising way to develop more contextualized learning experiences, additional research is needed to determine how well it can enhance scientific competencies. According to research, AI systems can offer more immediate feedback and adaptable learning paths, which could affect students' comprehension and engagement (Zawacki-Richter et al., 2019). The results of the pretest suggest that the development of important scientific skills may not be adequately supported by the existing standard teaching techniques, underscoring the necessity to investigate creative teaching strategies.

Table 4. *Level of Science performance after the intervention for students exposed to AI-assisted teaching in terms of observing, predicting, analyzing, problem-solving, and experimenting*

Sub-variable	*N*	*Mean*	*SD*	*Interpretation*
Observing	30	4.36	1.15	Moderately High
Predicting	30	2.80	1.09	Moderately High
Analyzing	30	3.13	1.19	Moderately High
Problem Solving	30	2.20	.805	Moderately High
Experimenting	30	4.66	2.00	Moderately High
Total Performance	30	17.16	3.97	Moderately High

Table 4 presents the level of science performance after the intervention for students exposed to AI-assisted teaching in observing, predicting, analyzing, problem-solving, and experimenting. As shown in the table, students exposed to AI-assisted teaching obtained a posttest mean score of M=4.36, SD=1.15 for observing and interpreted as on the moderately high level, M=2.80, SD=1.09 for predicting and interpreted as on the moderately high level, M=3.13, SD=1.19 for analyzing and interpreted as on the moderately high level, M=2.20, SD=.805 for problem-solving and interpreted as on the moderately high level, and M=4.66, SD=2.0 for experimenting and interpreted as on the moderately high level. Meanwhile, the total performance has a mean score of M=17.16, SD=3.97, interpreted that the students under the AI-assisted teaching have increased their performance in science during the posttest. The overall mean for SD=3.97 implied that the data are highly scattered around the mean score.

In observation, the mean score for students was M = 4.36, SD = 1.15, which is interpreted as moderately high. This score manifests excellent improvement in the ability of the students to observe and describe scientific phenomena that would act as a way to form the foundation of scientific inquiry (Bybee, 2010; Krajcik & Schneider, 2009). This can be attributed to the interactive nature of AI tools, which, more often than not, provide feedback in real-time and the chance to learn practically (Luckin et al., 2016; Lee et al., 2020).

Similarly, the mean score of M = 2.80, SD = 1.09 for prediction is also in the moderately high category. This improvement means that students are now becoming better at being discriminative while inferring by making educated predictions as they go through their observations; this is one important skill in developing scientific reasoning (National Research Council, 2012; Chen et al., 2020). Adaptive learning features of AI may contribute to enhanced predicting skills as it personalizes its learning experiences based on a student's performance (Zawacki-Richter et al., 2019).

The mean score, M = 3.13, SD = 1.19, on the analytical skills dimension shows a moderately high level of performance. Thus, it has been gathered that students have improved analytical skills to examine and critically assess data considerably more effectively. Thus, Scientific literacy requires these skills, often encouraged through active engagement and inquiry-based learning facilitated by AI technologies, Kuhn (2005), and Hmelo-Silver et al. (2007).

The mean score for problem-solving skills was M = 2.20, SD = 0.805, which is a moderately high score. This may signify that even though AI-based teaching has been instrumental, more strategies need to be implemented so that students can really develop problem-solving skills, which are essentially needed to adopt scientific knowledge into practicality (Jonassen, 2011; van Merriënboer & Kirschner, 2007).

Finally, for experimentation, the mean score of M = 4.66, SD = 2.0 points to a moderately high level of performance. This reasonably significant improvement also proves how effectively AI-assisted teaching provides hands-on experience in experimenting, an indispensable aspect of developing realistic scientific skills. The extensive range according to standard deviation indicated a large variation in students' engagement and proficiency in experimenting. Some students indicated significant benefits from AI tools (Hmelo-Silver, Duncan, & Chinn, 2007; Miao et al., 2020).

The overall mean score of M = 17.16, SD = 3.97 indicates a significant increase in the overall score about science performance among students who had been taught assisted by AI. A wide range of performance outcomes, as indicated by the large standard deviation, indicates that while the majority benefit from the intervention, more support is likely required to reach optimal performance levels.

This finding highlights the value of diverse assistance tactics in AI-integrated learning settings. It's possible that elements like past knowledge, technology accessibility, and student preparedness affected each person's performance.

Problem 3. Is there a significant difference between the pretest and posttest performance of students exposed to traditional teaching?

Table 5. *Results of T-Test for Paired Samples Analysis for significant difference between the pretest and posttest performance of students exposed to traditional teaching*

Paired Variables		*Mean*	*SD*	*t*	*p*	*Interpretation*
Observing	Pretest	2.13	1.25	-4.51	.000	Significant
	Posttest	3.80	1.54			
Predicting	Pretest	1.56	1.33	-3.35	.002	Significant
	Posttest	2.63	1.12			
Analyzing	Pretest	2.00	1.11	-3.08	.004	Significant
	Posttest	3.13	1.54			
Problem Solving	Pretest	1.23	1.00	-4.26	.000	Significant
	Posttest	2.26	1.01			
Experimenting	Pretest	3.00	2.33	-2.53	.017	Significant
	Posttest	4.43	1.43			
Total Performance	Pretest	9.93	3.61	-6.46	.000	Significant
	Posttest	16.26	4.06			

Table 5 presents the Results of the T-test for Paired Samples Analysis for the significant difference between the pretest and posttest performance of students exposed to traditional teaching. As shown in the table there is a significant difference in students' pretest and posttest performance exposed to traditional teaching in observing ($p<.05$), predicting ($p<.05$), analyzing ($p<.05$), problem-solving ($p<.05$), experimenting ($p<.05$), and in total performance ($p<.05$). This means that there is strong evidence to claim that students exposed to traditional teaching significantly improved their performance in observing, predicting, analyzing, problem-solving, experimenting, and total performance during the posttest.

Strong evidence comes from the mean differences of the paired samples t-test that students who received traditional teaching methods had improved performance on several scientific competencies. Observe, first, shows a significant difference at $p < .05$: Now, students notice scientific phenomena more clearly and can better describe them-a prime skill in scientific inquiry (Wang et al., 2017; Taber, 2018). This is made even better because even the stiffest conventional teaching methods, given that they are done correctly, could help put into students' minds their observational skills.

In predicting, an increase reveals a significant improvement and indicates that the students can now make better predictions, informed by their observations. Such skills are fundamental to scientific reasoning and inquiry (Kahveci et al., 2016; Gormally et al., 2016). Increased opportunities for students to apply knowledge could be why there are gains in predictive skills.

The significant difference in analyzing ($p < .05$) further supported the idea that students enriched their scientific literacy capability of making interpretations and assessments of scientific data. These kinds of abilities for critical analysis are also crucial for being scientifically literate, and the positive results indicate the fact that the instructional strategy used by traditional teaching effectively supports this kind of learning (Krajcik et al., 2017; Manz et al., 2016).

It is found that the difference in ability to cope better with scientific challenges is significant in terms of problem-solving, at a $p < .05$ level. It shows that traditional teaching improves critical thinking and knowledge application to real-life situations (Boer et al., 2021; Cottam & Fawkes, 2014).

Finally, the analysis reveals a significant improvement in experimentation ($p < .05$), indicating that the students have even improved. Therefore, an improvement in this experimental practice with science in students through blended traditional teaching and hands-on activities can be viewed through the application of traditional methods (Hmelo-Silver et al., 2007; Adams et al., 2014).

Thus, the net significance in total performance ($p < .05$) suggests a generalized positive effect of traditional teaching methods on students' scientific competencies. The latter, naturally, means not only that the students improved in specific areas but also that they realized general improvement in the learning process of science.

Problem 4. Is there a significant difference between the pretest and posttest performance of students exposed to AI-assisted teaching?

Table 6. *Results of T-Test for Paired Samples Analysis for significant difference between the pretest and posttest performance of students exposed to AI-assisted teaching*

Paired Variables		*Mean*	*SD*	*t*	*p*	*Interpretation*
Observing	Pretest	1.76	1.19	-8.40	.000	Significant
	Posttest	4.36	1.15			
Predicting	Pretest	1.70	1.20	-3.97	.000	Significant
	Posttest	2.80	1.09			
Analyzing	Pretest	2.10	1.29	-3.26	.003	Significant
	Posttest	3.13	1.19			
Problem Solving	Pretest	1.13	1.00	-4.86	.000	Significant
	Posttest	2.20	.805			
Experimenting	Pretest	1.76	1.19	-3.11	.004	Significant
	Posttest	4.36	1.15			
Total Performance	Pretest	1.70	1.20	-7.50	.000	Significant
	Posttest	2.80	1.095			

Table 6 presents the Results of the T-test for Paired Samples Analysis for the significant differences between the pretest and posttest performance of students exposed to AI-assisted teaching. As shown in the table there is a significant difference in students' pretest and posttest performance exposed to AI-assisted teaching in observing ($p<.05$), predicting ($p<.05$), analyzing ($p<.05$), problem-solving ($p<.05$), experimenting ($p<.05$), and in total performance ($p<.05$). This means that there is strong evidence to claim that students exposed to AI-assisted teaching significantly improved their performance in observing, predicting, analyzing, problem-solving, experimenting, and total performance during the posttest.

All competencies show overall significant improvements. Therefore, there is strong evidence that AI-assisted teaching has performance-enhancing effects on students. Specifically in the competencies of observing, the statistically significant difference was that, indeed, with $p < .05$, students had developed more excellent observational skills. Improved observation skills are key in scientific inquiry to enable them to collect accurate data and formulate hypotheses based on empirical evidence (Meyer et al., 2018; Ke et al., 2020).

In predicting, a significant growth rate ($p < .05$) suggests that, at this stage, students could make more reliable predictions of what might happen in a scientific context. This skill is essential for developing scientific thought and enables them to use theoretical knowledge in practical contexts (Hsu et al., 2019; Hmelo-Silver et al., 2020). Perhaps the AI tools gave the students more contextual information and feedback that helped them make accurate predictions about what they witnessed.

Such an analysis at ($p < .05$) shows that AI instruction has significantly affected the students' enhancement of critical thinking skills. Such support is a requirement for critical scientific data evaluation as part of scientific literacy (Huang et al., 2020; Gormally et al., 2016). The process can then be supported by AI technologies providing real-time data analysis tools and other resources that allow more profound engagement with scientific concepts.

There was a significant difference in this case ($p < .05$), indicating that students had better skills in solving scientific problems. This AI-assisted environment most probably triggered collaboration for problem-solving strategies and offered simulated conditions to practice their skills (Lu et al., 2021; Yilmaz et al., 2020). Such an environment will spur the development of critical thinking by the pupils because it develops the ability to analyze problems from more than one angle.

In experiments, a significant increase ($p < .05$) shows that students have developed better skills in conducting experiments. The AI tool may interactively give space for a virtual lab experience or simulation, enabling students to do experiments that are otherwise impossible to execute within a physical lab situation (Blasco et al., 2019; Liu et al., 2021). Hands-on experience is essential to cement the concepts of science and methods.

This is the comprehensive significant difference in total performance that justifies the conclusion: AI-assisted teaching and learning have a significant positive effect on the learning experiences of students in science. Improved educational performances of students in diverse scientific competencies, then summarize the success of having AI technologies implemented in education systems. According to Simens and Downes (2005) in their Connectivism theory, learning is not just an individual cognitive process but also a product of interactions within a digital and social environment. Connectivism emphasizes how the digital-native age of today learns via networks, technology, and teamwork. Students are now active participants in their Education rather than passive learners, thanks to continual access to social media, interactive platforms, and AI tools. AI-assisted learning improves engagement by offering individualized experiences, instant feedback, and practical problem-solving opportunities. This method prepares students for self-directed learning, digital literacy, and flexibility—all critical abilities for success in the twenty-first century—and aligns with the fast-paced, information-driven world.

Problem 5. Is there a significant difference in science performance between students exposed to traditional teaching and those exposed to AI-assisted teaching?

Table 7. *Results of ANCOVA Analysis for the significant difference in science performance between students exposed to traditional teaching and those exposed to AI-assisted teaching*

Source	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	*Partial Eta Squared*
Corrected Model	13.40	2	6.70	.408	.667	.014
Intercept	2085.3	1	2085.3	126.8	.000	.690
Pretest	1.25	1	1.2	.076	.783	.001
Group	12.50	1	12.5	.761	.387	.013
Error	936.78	57	16.4			
Total	17717.0	60				
Corrected Total	950.183	59				

Estimated Marginal Means of Traditional Teaching Mean = 16.26
Estimated Marginal Means of AI Assisted Teaching Mean = 17.17

Table 7 presents the Results of ANCOVA Analysis for the significant difference in science performance between students exposed to traditional teaching and those exposed to AI-assisted teaching. As shown in the table, students exposed to AI-assisted teaching obtained a higher mean score of M=17.17 than those exposed to traditional teaching, who only obtained a mean score of M=16.26. However, the results of the ANCOVA analysis showed that there is no significant difference in the science performance since the probability value is higher than the alpha level (p (.387) >.05). This means that while those students exposed to AI-assisted teaching obtained a higher mean score of M=17.17, there is no substantial evidence to believe that their performance is significantly higher compared to other students exposed to traditional teaching. The results of this data analysis implied that AI-assisted teaching can be considered equally effective compared to traditional teaching.

From these results, it can be clearly understood that although the student recipients of AI-assisted teaching had a higher mean score in science, the difference did not come out to be statistically significant. As this result is not significant, the implication is that the higher mean of 17.17 does not provide strong evidence to go with the claim that AI-assisted teaching delivers much better performance than traditional teaching (Cohen et al., 2020). Accordingly, this finding is well aligned with previous studies that stressed the importance of contextual factors and individual differences in educational outcomes; these studies concluded that teaching methodologies may not uniformly affect the students.

This could also mean that the old approaches to teaching science remain efficacious, thus alluding to the notion that traditional pedagogies can still offer excellent learning outcomes. It remains an open possibility that AI-based instruction offers benefits whose capture is not easy with standardized measures, such as increased engagement, personalized experience, or the acquisition of higher-order thinking skills (Hwang et al., 2020; Chen et al., 2021).

Although the AI-assisted teaching group averaged a score higher than the traditionally instructed group, the results of ANCOVA indicate that the science-performance gap is not statistically significant. Thus, AI-assisted teaching could be regarded as having equivalent effectiveness to conventional teaching in improving students' scores in science. Future research would be worthwhile to dig deeper into the nuances of AI-assisted teaching, such as potential benefits other than conventional performance metrics.

The results show that students exposed to traditional and AI-assisted teaching techniques do not significantly differ in their performance in science. This implies that, unlike traditional teaching methods, integrating AI may provide creative learning opportunities but does not always result in improved academic achievement. This result could be explained by several factors, including learning styles, teacher efficacy, students' capacity to adjust to AI technologies, and technology accessibility.

Conclusions

This study examined the effectiveness of AI-assisted instruction compared to conventional teaching methods in science education. It addressed critical concerns such as low baseline performance, limited student engagement, and the pressing need for innovative pedagogies. Findings revealed that AI-enhanced instruction offers notable advantages, such as personalized learning and increased interactivity, but traditional methods remain effective and relevant. The study underscores the importance of blending both approaches to create a more inclusive and effective learning environment. A hybrid teaching model can better accommodate diverse learner needs, enhance engagement, and foster critical thinking and collaboration.

In light of these findings, several recommendations are proposed. School administrators should prioritize investment in technological infrastructure, including reliable internet and appropriate hardware, and support continuous professional development to equip teachers for AI integration. Encouraging a culture of collaboration and regularly updating curricula to reflect current educational technologies are also essential. Teachers are advised to combine traditional and AI-based strategies, pursue ongoing training in educational technology, diversify assessment methods such as project-based evaluations, and create student-centered classrooms. Students should take a more active role in their learning by engaging with educational technologies, participating in collaborative activities, and providing feedback on instructional practices. Researchers are encouraged to further explore the impact of AI-assisted instruction across different contexts and student demographics. Incorporating qualitative methods such as interviews and focus groups can yield deeper insights into learner experiences and inform strategies to overcome challenges in AI adoption. Overall, this study contributes to the evolving discourse on effective teaching strategies in science education by advocating for a balanced and adaptive approach to instruction.

References

Abah, J. A. (2020). An appeal in the case involving conventional teaching: Emphasizing the transformation to enhanced conventional teaching in mathematics education. HAL (Le Centre Pour La Communication Scientifique Directe). https://doi.org/10.5281/zenodo.3860320

AIAL Lab. (n.d.). https://research.csc.ncsu.edu/aial/home/

Anohina, A., & Ijasan, A. (2021). The impact of virtual labs on students' engagement and predictive skills in science. *Journal of Science Education and Technology, 30*(2), 110–123. https://doi.org/10.1007/s10956-021-09875-0

Application of artificial intelligence in computer-aided instruction. (2009, December 1). *IEEE Conference Publication | IEEE Xplore*. https://ieeexplore.ieee.org/document/5413068/citations#citations

Artificial intelligence. (n.d.-a). *Caltech Science Exchange*. https://scienceexchange.caltech.edu/topics/artificial-intelligence-research

Artificial intelligence. (n.d.-b). *Google Books*. https://books.google.com.ph/books?hl=en&lr=&id=_ixmRlL9jcIC&oi=fnd&pg=PP1&dq=artificial+intelligence&ots=JRKGWUrDOR&sig=HThmiG915NpMeJ9cP9KmGpDWgDs&redir_esc=y#v=onepage&q=artificial%20intelligence&f=false

Artificial Intelligence - Office of Educational Technology. (2023, July 7). *Office of Educational Technology*. https://tech.ed.gov/ai/

Artificial intelligence in education. (2023, November 29). *UNESCO*. https://www.unesco.org/en/digital-education/artificial-intelligence

Artificial Intelligence in Education: A review. (2020). *IEEE Journals & Magazine | IEEE Xplore*. https://ieeexplore.ieee.org/document/9069875

Asma, H., & Sarnou, D. (2020). Cognitive load theory and its relation to instructional design: Perspectives of some Algerian university teachers of English. Arab World English Journal, 11(4), 110–127. https://doi.org/10.24093/awej/vol11no4.8

Blasco, J., Hoz, M. S., & Villegas, M. (2019). The use of virtual labs in science education: A review of recent literature. *Education Sciences, 9*(1), 33. https://doi.org/10.3390/educsci9010033

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think. *Proceedings of the ACM on Human-Computer Interaction, 5*(CSCW1), 1–21. https://doi.org/10.1145/3449287

Bumbaca, F. (1988). Intelligent computer-assisted instruction: A theoretical framework. *International Journal of Man-Machine Studies, 29*(3), 227–255. https://doi.org/10.1016/s0020-7373(88)80022-1

Bybee, R. W. (2010). The teaching of science: 21st-century perspectives. NSTA Press.

Chan, K. S., & Zary, N. (2019). Applications and challenges of implementing artificial intelligence in medical education: Integrative review. *JMIR Medical Education, 5*(1), e13930. https://doi.org/10.2196/13930

Chen, C. H., Chen, H. C., & Chang, Y. (2021). The effectiveness of artificial intelligence-assisted teaching on learning performance: A meta-analysis. *Educational Technology & Society, 24*(1), 102-115. https://www.jstor.org/stable/10.2307/26901345

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/access.2020.2988510

Chen, L., Huang, Y. M., & Liu, C. C. (2020). The effect of gamification on students' learning performance: A meta-analysis. *Computers & Education, 147*, 103778. https://doi.org/10.1016/j.compedu.2019.103778

Chen, X., Xie, H., Zou, D., & Hwang, G. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education. Artificial Intelligence, 1*, 100002. https://doi.org/10.1016/j.caeai.2020.100002

Chiang, I. A., Jhangiani, R. S., & Price, P. C. (2015, October 13). Quasi-experimental research. *Pressbooks*. https://opentextbc.ca/researchmethods/chapter/quasi-experimental-research/#:~:text=Quasi%2Dexperimental%20research%20involves%20the,and%20interrupted%20time%2Dseries%20designs

Cielo, A., Lopez, M. P., Torres, J., Tenio, A., & Fuente, A. L. D. (2019, April 1). Effectiveness of traditional method of teaching in academic performance of general academic strand students at Bestlink College of the Philippines. *AA Research Index*. https://ojs.aaresearchindex.com/index.php/aasgbcpjmra/article/view/1245

Clark, D. B., & Nelson, B. (2022). Virtual simulations in science education: Promoting experimental skills and cognitive engagement. Computers & Education, 177, 104349. https://doi.org/10.1016/j.compedu.2021.104349

Cohen, A. J., Rosenberg, M., & Riedel, B. (2020). Using ANCOVA to examine the impact of teaching strategies on students' performance: A practical guide. *Journal of Educational Psychology, 112*(1), 61-77. https://doi.org/10.1037/edu0000348

Cooper, G. (2023). Examining science education in ChatGPT: An exploratory study of generative artificial intelligence. *Journal of Science Education and Technology, 32*(3), 444–452. https://doi.org/10.1007/s10956-023-10039-y

Darayseh, A. A. (2023a). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education. Artificial Intelligence, 4*, 100132. https://doi.org/10.1016/j.caeai.2023.100132

Darayseh, A. A. (2023b). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education. Artificial Intelligence, 4*, 100132. https://doi.org/10.1016/j.caeai.2023.100132

Dede, C. J., & Others, A. (n.d.). Intelligent computer-assisted instruction: A review and assessment of ICAI research and its potential for education. *ERIC*. https://eric.ed.gov/?id=ED296701

Delaney, H. D., & Vargha, A. (2018). Analysis of covariance. In N. J. Salkind (Ed.), *Encyclopedia of research design* (pp. 23-30). SAGE Publications.

Desk, I. T. W. (2020, May 8). Traditional learning will always have a place in our classrooms. *India Today*. https://www.indiatoday.in/education-today/featurephilia/story/traditional-learning-will-always-have-a-place-in-our-classrooms-1675692-2020-05-08

Dhanapal, C., Asharudeen, N., & Alfaruque, S. Y. (2024). Impact of artificial intelligence versus traditional instruction for language learning: A survey. *World Journal of English Language, 14*(2), 182. https://doi.org/10.5430/wjel.v14n2p182

DiPerna, J. C., Volpe, R. J., & Elliott, S. N. (2001). A model of academic enablers and achievement. *ResearchGate*. https://www.researchgate.net/publication/232322367_A_model_of_academic_enablers_and_academic_achievement

Dunaway, M. K. (2011). Connectivism. *Reference Services Review, 39*(4), 675–685. https://doi.org/10.1108/00907321111186686

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jo

Affiliations and Corresponding Information

Genna Maro G. Dapiroc
Liceo de Cagayan University - Philippines