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Research Article

AI-Supported Digital Tools for Enhancing Learning Outcomes in Science and Mathematics Education

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Abstract
Particularly in science and math classes where students struggle with abstract thinking, conceptual comprehension, problem-solving, and sustained academic engagement, Artificial Intelligence (AI) has grown in importance as a component of instructional technology. As a result, AI-enabled digital solutions provide chances for data-driven teaching support, adaptive feedback, and personalized learning pathways. With a focus on conceptual comprehension, problem-solving skills, academic engagement, and self-directed learning, this research sought to determine the degree to which AI-powered digital tools improve students' learning outcomes in science and mathematics. The study used a mixed-methods approach, combining qualitative information from student comments and classroom observations with quantitative assessments of academic progress. The research was conducted in upper secondary and postsecondary educational environments. Science and math classrooms are using AI-supported technology like data-driven instructional dashboards, intelligent feedback mechanisms, and adaptive learning systems. While qualitative data offered insight into student participation, classroom interaction, and perceived learning assistance, quantitative data were used to evaluate students' learning performance before and after the intervention. The results show that using AI-supported digital tools enhanced learning outcomes, especially in courses that call for gradual conceptual expansion, abstract cognition, and iterative reasoning. Additionally, qualitative data indicated that students benefited from increased autonomy during learning activities, timely feedback, ongoing observation, and personalized learning paths. The research comes to the conclusion that, when paired with curriculum goals and efficient instructional design, AI-supported digital tools should be seen as cognitive and pedagogical support systems rather than just technical advancements that might enhance science and math teaching.

Keywords: Artificial Intelligence, Digital Learning Tool, Learning Outcome, Mathematics Education, Science Education

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1. INTRODUCTION

Artificial Intelligence (AI) has become an essential part of modern educational reform in learning settings that need data-driven instructional decision-making, personalized assistance, and adaptive feedback (Acuña Acuña, 2023). These technologies have become more important in science and math education because they may help students who have trouble with symbolic representation, cumulative conceptual frameworks, abstract thinking, and iterative problem-solving techniques. Scholarly interest in AI's potential, its ability to carry out pedagogical tasks, and how these tools function in formal educational contexts where curriculum alignment, teacher mediation, and instructional design are still crucial to learning outcomes has increased as a result of these breakthroughs.

Even with the growing availability of digital tools, there are still pedagogical issues in science and math instruction. Pupils often find it difficult to stay engaged in mentally taxing tasks, adapt problem-solving strategies to new situations, and relate abstract concepts to real-world knowledge. These challenges are particularly relevant in educational environments where conventional digital technologies provide access to content but provide no adaptive support, immediate feedback, or personalized learning paths.

Science and math education have historically included complex pedagogical criteria, including the development of abstract conceptualization, the transfer of problem-solving strategies, and the fostering of ongoing student engagement. Previous research indicates that conventional digital tools and teaching techniques often provide limited opportunities for multiple learning routes, adaptive feedback, and continuous student progress monitoring (Hattie, 2009). Therefore, via data-driven customization, intelligent feedback, and continuous student progress monitoring, AI-powered digital technologies provide chances to enhance instructional design.

According to earlier research, AI applications with strong pedagogical underpinnings, such as learning analytics dashboards, intelligent tutoring systems, and adaptive learning systems, may improve student performance and motivation (Luckin et al., 2016; Holmes et al., 2019). However, the empirical study still has a number of shortcomings. While many studies on AI in education focus on technological functionality, platform design, or general perceptions of innovation, fewer examine how AI-supported tools impact quantifiable learning outcomes and classroom engagement in science and math using an integrated quantitative and qualitative approach. Particularly required are studies that connect academic success data with classroom-based data about learner autonomy, feedback usage, and teacher-mediated instructional support.

This study examines how AI-supported digital tools impact students' learning outcomes and academic engagement in science and math classrooms in an effort to bridge this gap. It specifically investigates whether the integration of learning analytics dashboards, intelligent feedback mechanisms, and adaptive learning systems improves self-directed learning, problem-solving abilities, and conceptual understanding. The project intends to improve our understanding of how AI may support significant learning beyond fundamental technological advancements by combining the findings of earlier research and offering actual data from educational contexts. The research examines contemporary calls for the evidence-based integration of AI in education at the nexus of instructional design, learning sciences, and educational technology (OECD, 2021). This research makes two contributions. First, it offers actual data about how AI-powered digital tools affect students' participation and academic achievement in science and math classes. Second, it provides a pedagogical perspective on AI as a cognitive and instructional support system, highlighting its function in data-driven teaching choices, adaptive feedback, and personalized learning progression. This perspective is essential for educators, researchers, policymakers, and curriculum designers who want to appropriately and pedagogically integrate AI into formal education.

1.1. Literature Review

1.1.1. Artificial Intelligence in Educational Contexts

Artificial intelligence in education refers to the use of computer systems that can perform human-like tasks, such as reasoning, pattern recognition, prediction, adaptive decision-making, and the generation of tailored feedback. The first implementations were intelligent tutoring systems that used rule-based models and domain-specific knowledge representations to provide individualized instructional assistance and flexible learning opportunities (VanLehn 2011). These days, AI-powered systems go beyond these limits by using data and machine learning to adjust courses and feedback as they happen.

According to Holmes et al. (2019), AI is beneficial in education because technology may enhance human learning by providing insights that traditional teaching techniques cannot, rather than just making automation simpler. AI systems are capable of analyzing massive volumes of learner interaction data, identifying performance patterns, identifying recurring problems, and offering teachers and students customized guidance. In math and science classes, where learning requires organizing data and drawing connections between ideas, these attributes are especially important.

From a pedagogical perspective, rather than taking the place of teacher competence, AI should be seen as a support system that might improve the teacher's capacity to recognize learning needs, adapt lessons, and provide timely interventions. In formal educational settings, where technology innovation must continue to be in line with curriculum design, assessment standards, and instructors' professional judgment, this difference is especially crucial.

However, integrating AI into education also brings up significant institutional, ethical, and pedagogical issues, especially with regard to data security, algorithmic transparency, teacher autonomy, and the appropriate use of student data. Selwyn (2019) asserts that thorough data consumption analysis, instructor autonomy, and clear design principles are necessary for the effectiveness of AI-powered gadgets. As a result, empirical research must both show performance gains and situate AI within the framework of current educational ideas and practices.

1.1.2. AI-Supported Digital Tools in Science Education

The use of AI in scientific education has benefited formative assessment, conceptual modeling, and inquiry-based learning. Intelligent feedback systems and adaptive simulations may help students grasp challenging scientific subjects by allowing them to investigate and get immediate feedback (Chen et al., 2020). With the help of these tools, students may experiment with abstract processes, alter variables, and get customized feedback on their work.

When students are required to assess variables, test hypotheses, model phenomena, and make connections between empirical data and theoretical interpretations, the need for AI-supported tools in scientific training becomes more apparent. By promoting inquiry, experimentation, and reflective mistake correction, adaptive simulations and feedback systems may assist students in moving beyond passive material reception.

AI-enhanced settings may improve students' comprehension of physics, chemistry, biology, and other scientific subjects when combined with organized teaching approaches, according to earlier research. By offering a range of learning sequences, instant feedback, and task difficulty adjustments, AI-supported systems may make it easier to integrate new scientific ideas with existing knowledge. More sophisticated technology does not, however, always result in better learning outcomes, according to a study. Successful integration unquestionably supports student learning and is in line with academic goals.

To guarantee the pedagogical quality, ethical orientation, and curriculum relevance of AI-assisted learning, teacher participation is still crucial. Teachers gain more from AI technology when it works with them to make better decisions rather than taking the place of their expertise. This method emphasizes how crucial it is to assess educational resources with AI support in real classrooms.

1.1.3. AI Applications in Mathematics Learning

Digital technologies have gradually been included in mathematics education to help the development of procedural fluency, conceptual comprehension, symbolic representation, and problem-solving skills. By offering personalized workouts, comprehensive feedback, and quick student problem detection, AI-supported solutions expand these prospects. Research on intelligent tutoring systems in mathematics suggests that adaptive feedback may improve conceptual comprehension and problem-solving abilities (Ma et al., 2014).

The use of machine learning algorithms to enhance adaptive learning pathways in mathematics education was the subject of recent research. In order to detect mistakes and modify the training sequence, these systems monitor the learner's progress (Ritter et al., 2016). According to research, these adaptive techniques may lessen cognitive load and boost student participation in classes that call for symbolic manipulation and abstract cognition.

However, students' ability to think critically, defend tactics, and comprehend the rationale behind remedial suggestions determines how successful adaptive mathematical tools are. Adaptive feedback may help students, but if they do not have enough time to think about it, they can forget what they learned or why. Therefore, recent research supports the evaluation of AI-driven mathematical tools using conceptual comprehension, learner autonomy, and metacognitive growth in addition to performance indicators.

1.1.4. Learning Outcomes and Pedagogical Effectiveness

Learning outcomes are intricate measures of an educational intervention's efficacy that include cognitive, emotional, and metacognitive components. Academic success, conceptual comprehension, engagement, and students' ability to manage their own learning are often used to evaluate the efficacy of AI-supported digital technologies. A meta-analysis found that if technology-enhanced training is based on effective teaching methods and is used often, it may provide modest learning increases (Schindler et al., 2017).

Artificial intelligence allows students to make changes and get ongoing feedback in the classroom. By empowering students to identify mistakes, modify tactics, and gradually change their knowledge, this method may improve learning. The OECD (2021) states that curriculum, the caliber of teachers, and school assistance continue to have an effect on how AI affects education. Therefore, to comprehend the various impacts of AI-enhanced learning settings, empirical research combining quantitative performance indicators with qualitative insights is essential.

This adaptability is especially important while studying mathematics, since many issues are the result of cumulative gaps in prior knowledge. Subsequent subjects often become more challenging when pupils do not grasp a previous idea. AI-assisted solutions may be able to detect these gaps earlier and provide tailored practice before misunderstandings get deeply entrenched.

This study will add to the body of knowledge regarding how AI-powered smart devices affect students' performance on math and science exams. By combining performance metrics with qualitative information on student engagement and perceived instructional assistance, this study builds on previous research on the effects of AI-supported digital tools on science and math learning.

Because of this, assessing AI-supported learning environments needs more than just looking at test results. Examining how students respond to feedback, how they see instructional support, and how teachers use learning data to inform pedagogical choices are all crucial. This integrated viewpoint supports the current study's mixed-methods methodology.

2. METHODOLOGY

This research assessed the pedagogical efficacy of AI-supported digital tools in science and math teaching using a mixed-methods methodological approach. The relationship between AI-mediated instruction, academic performance, student engagement, and classroom experience can be examined from complementary quantitative and qualitative perspectives thanks to the methodological design, which was organized to guarantee clarity, replicability, and analytical coherence. In accordance with the highest standards in educational research and technology-enhanced learning, the approach was created to be clear, reproducible, and methodologically sound. In order for future researchers to replicate the study under the identical circumstances, every methodological step was meticulously specified.

2.1. Research Design

The study used a mixed-methods quasi-experimental technique to integrate quantitative and qualitative approaches into a unified framework. This approach was used to evaluate how AI-powered digital tools affect learning and to clarify the contextual factors that affect their impact on academic results. Because cognitive, behavioral, and environmental factors have a substantial impact on learning outcomes, mixed-methods techniques are appropriate for educational research.

The quantitative component uses a pre-test-post-test design in conjunction with a non-equivalent control group in educational settings where random assignment is impractical or unethical (Shadish et al., 2002). Students may compare their learning progress to that of their classmates who get traditional technology-enhanced education by using AI-powered digital tools.

A qualitative component was included to provide a more comprehensive explanation. This research looked at students' perceptions of their education in terms of involvement, support, and interaction. Convergent parallel architecture allowed for the simultaneous collection and analysis of both quantitative and qualitative data. Our method improved internal validity and allowed us to completely comprehend the data by using triangulation.

The quantitative component measured changes in academic performance and student engagement before and after the intervention, while the qualitative component examined how students interacted with AI-supported tools, how they interpreted feedback, and how the use of adaptive digital resources affected classroom dynamics. By integrating the two components, the study was able to examine the pedagogical processes via which AI-supported tools impacted learning, going beyond performance comparison.

2.2. Participants

Eighty-four Costa Rican university students enrolled in science and math courses participated in the research. There were 84 students in the final sample, 48 of whom were female and 36 of whom were male. There were 42 students in the experimental group, 24 female and 18 male, and 42 students in the control group, 24 female and 18 male. Each of the two complete instructional groups, experimental (n = 42) and control (n = 42), was allocated at random. In line with quasi-experimental research methods in education, using intact groups preserved the teaching flow and decreased the possibility of disturbances to school operations.

The participants were enrolled in science and math classes throughout the academic term when the intervention was carried out, and their ages varied from 17 to 23. Everyone was using learning objects and typical learning management systems before the intervention. However, they all started at the same position, as none of them had used AI-powered adaptive learning systems before.

Procedures for obtaining informed consent, safeguarding privacy, and promoting voluntary involvement were created in order to resolve ethical issues. The study complied with the university's ethical guidelines for educational research as well as the requirements for data management and participant privacy protection.

2.3. Research Instruments

A variety of research instruments were used and validated in line with the objectives of the study in order to fully collect the data and learning experiences.

2.3.1. Academic Performance Tests

The purpose of the Academic Performance Test is to assess students' conceptual knowledge and problem-solving abilities in mathematics and science. Short-answer questions, multiple-choice questions, and applied problem-solving exercises made up the 30 items in the test. While the short-answer and problem-solving questions tested procedural correctness, reasoning, justification, and the capacity to apply knowledge to novel circumstances, the multiple-choice questions evaluated the identification, interpretation, and application of important ideas. Exam scores ranged from 0 to 100 points. For multiple-choice questions, dichotomous scoring was used, awarding one point for each correct answer and zero points for incorrect answers. Short-answer and problem-solving exercises were assessed using an analytical rubric that considered conceptual accuracy, procedural development, consistency of reasoning, and final response correctness. Students had sixty minutes to complete the test. The pre-test and post-test used the same format to ensure comparability between the two measurement occasions. Three experts in math and science education assessed the instrument to ascertain its content validity. Internal consistency was assessed using Cronbach's alpha; values higher than 0.80 indicated adequate reliability (DeVellis, 2017).

2.3.2. Student Participation Questionnaire

Student involvement was measured using a modified Student Involvement Questionnaire based on the behavioral, cognitive, and emotional engagement components recommended by Fredricks et al. (2004). The questionnaire had eighteen items that represented the three components of behavioral engagement, cognitive engagement, and emotional involvement. A five-point Likert scale, with 1 denoting strongly disagree and 5 denoting strongly agree, was used to gather responses. Better scores indicate better levels of student involvement and engagement. The lowest possible score was 18 points, and the greatest possible score was 90 points. It took participants around 10 minutes to complete the questionnaire. Items pertaining to perceived feedback usefulness, engagement with digital resources, self-directed learning, and perceived instructional assistance were added to the instrument in order to adapt it to the setting of AI-mediated learning. With a Cronbach's alpha of 0.87, the reliability analysis demonstrated sufficient internal consistency.

2.3.3. Qualitative Observation And Reflection Tools

Qualitative data were collected using student reflection tasks and a methodical approach to classroom observation. The observation technique combined a checklist-based approach with field notes. The checklist focused on four areas: how students used adaptive feedback, how they engaged with AI-supported digital tools, how persistent they were throughout learning activities, and how instructors mediated AI-supported education. Field notes were used to record relevant classroom situations, trends in student participation, difficulties faced during problem-solving activities, and students' responses to customized feedback. An independent academic observer assessed the course instructor's observations in order to increase consistency in the interpretation of classroom evidence. Short written responses were employed to collect student reflections at certain intervals throughout the intervention. Students were asked to describe in these remarks how adaptive feedback, personalized learning routes, progress indicators, and digital support affected their understanding, engagement, and autonomy throughout scientific and math learning activities.

2.4. Procedures

The intervention lasted for ten weeks, or a school semester. It used a systematic approach to ensure that each group received an equal degree of education. Both groups completed the participation questionnaire and pre-test within the first week. From the second to the ninth week, there was an intervention. As part of the school's LMS, the experimental group made use of AI-powered tools, including learning analytics dashboards, intelligent feedback engines, and adaptive learning modules. There were three primary digital components to the AI-supported intervention. Initially, adaptive learning modules modified the order and degree of difficulty of tasks based on how well students performed. Second, after providing inaccurate, partial, or incomplete answers, intelligent feedback systems provided prompt help, enabling students to modify their processes and spot conceptual flaws. Third, the teacher was able to track students' progress, spot recurring issues, and provide tailored assistance during the intervention thanks to learning analytics dashboards. Instead of being utilized as stand-alone or isolated technical tasks, these technologies were included in routine classroom activities as supplementary teaching resources. Based on the student's performance and level of engagement, these technologies updated the learning material in real time.

The control group utilized regular digital materials instead of AI-adapted ones, but they adhered to the identical curriculum, learning goals, and teaching schedule. They all employed the identical lesson plan, with the exception of the digital tools available to their groups, in order to remove differences between instructors. Throughout the intervention, the teacher recorded the session and conducted recurring inspections to make sure it was completed correctly. Every participant in the study completed the participation questionnaire and post-test in week 10. Students' observations and insights were the final product of the qualitative data gathering.

2.5. Data Analysis

Inferential statistics suitable for quasi-experimental designs were used to analyze quantitative data. The Shapiro-Wilk test validated the normality assumptions. We examined intra-group learning improvements using paired-samples *t*-tests and inter-group differences in post-test outcomes using independent-samples *t*-tests. To determine the practical magnitude of the observed differences, effect sizes were computed using Cohen's *d*. SPSS version 27 was used for all statistical analyses, with a significance threshold of $p < 0.05$. Confidence intervals may enhance interpretation validity, according to some studies.

We performed reflective thematic analysis on qualitative data using Braun and Clarke's (2006) six-phase method. To find patterns in customization, engagement, feedback effectiveness, and perceived learning assistance, we used iterative coding. To improve reliability, an impartial coder examined the coding procedure, and disagreements were settled via critical conversation.

Throughout the interpretation process, we examined both quantitative and qualitative data to observe their interactions, collaborations, and divergences. This integrated approach reinforced the research's claims and offered proof to back up beliefs on how AI-supported digital tools can impact students' learning processes.

The process of interpretation included the integration of both quantitative and qualitative data. While qualitative data explained how students received adaptive feedback, customized learning paths, and instructional assistance, quantitative findings demonstrated increases in performance and engagement. In addition to statistical data, this integration expanded the study's explanatory scope and made it possible to analyze how AI-supported technology affects classroom practices and students' perceptions of their educational experiences.

3. RESULTS

The quantitative and qualitative results from the examination of student involvement, academic performance, classroom observations, and student comments are presented in this section. Baseline equality across groups, within-group learning gains, between-group post-test comparisons, engagement outcomes, and qualitative data supporting the interpretation of the quantitative findings are presented in the order of the results in accordance with the objectives of the study.

3.1. Baseline Equivalence Between Groups

Before the AI-assisted educational intervention was implemented, pre-test data were utilized to assess baseline comparability between the experimental and control groups. The initial learning results did not vary statistically significantly, according to an independent-samples *t*-test, indicating that both groups started the intervention in similar educational settings. Table 1 presents the descriptive statistics for pre-test performance.

Table 1. Pre-Test Descriptive Statistics for Experimental and Comparison Groups

Group	N	Mean	Standard Deviation
Experimental (AI-supported)	42	62.48	8.21
Comparison (Non-AI)	42	61.93	7.89

The mean scores of the comparison group (M = 61.93, SD = 7.89) and the experimental group (M = 62.48, SD = 8.21) were comparable prior to the intervention. Because the observed increases may be more plausibly linked to the instructional intervention rather than significant pre-existing inequalities among groups, this baseline equality helps explain future post-test discrepancies.

3.2. Within-Group Learning Gains

By comparing the pre-test and post-test findings, paired-samples *t*-tests were used to investigate learning improvements within each group. After using digital tools with AI assistance, the experimental group's learning results significantly improved. Conversely, the comparison group's advantages were fewer but statistically significant. Table 2 summarizes the pre-test and post-test results for both groups.

From a pre-test mean of 62.48 to a post-test mean of 78.36, the experimental group improved by 15.88 points. The comparison group, on the other hand, increased by 7.21 points from 61.93 to 69.14. Although both groups showed statistically significant improvement, the experimental group's rise was more than double that of the comparison group. This pattern suggests that AI-assisted digital tools might have provided more learning support than conventional digital resources.

Table 2. Pre-Test and Post-Test Learning Outcomes by Group

Group	Test	Mean	Standard Deviation	t	p
Experimental	Pre-test	62.48	8.21	11.92	< .001
	Post-test	78.36	7.45		
Comparison	Pre-test	61.93	7.89	5.03	< .001
	Post-test	69.14	8.02		

The experimental group significantly improved because the intervention focused on learning tasks demanding conceptual understanding, procedural accuracy, and iterative problem solving. According to studies, students who utilized AI-supported technology in the classroom were able to assess errors, get timely feedback, and change their responses more often as they gained new knowledge. Consequently, the numerical growth seems to be consistent with patterns of concentrated practice, more active correction, and incremental conceptual refinement.

3.3. Between-Group Comparison of Post-Test Performance

The impact of the various teaching strategies on the students was assessed by comparing the post-test outcomes between groups using an independent-samples *t*-test. The research found a statistically significant difference that favored the experimental group. Table 3 presents the post-test descriptive statistics for both groups.

Table 3. Post-Test Learning Outcomes by Group

Group	N	Mean	Standard Deviation
Experimental (AI-supported)	42	78.36	7.45
Comparison (Non-AI)	42	69.14	8.02

There is an average difference of 9.22 points in favor of the AI-supported condition between the experimental group (M = 78.36, SD = 7.45) and the comparison group (M = 69.14, SD = 8.02). Because research indicates that students exposed to AI-supported technology performed better after getting adaptive feedback, individualized task sequencing, and ongoing progress monitoring throughout the intervention, this difference is both statistically significant and educationally important.

3.4. Student Engagement Outcomes

To get a better understanding of the behavioral and emotional aspects of learning related to the educational intervention, we looked at student involvement. Students in the experimental group engaged at much higher levels, according to an analysis of engagement questionnaire data. Table 4 reports overall engagement scores by group.

Table 4. Student Engagement Scores by Group

Group	N	Mean	Standard Deviation
Experimental (AI-supported)	42	4.21	0.46
Comparison (Non-AI)	42	3.67	0.51

The engagement results showed that the experimental group had a higher mean score (M = 4.21, SD = 0.46) than the comparison group (M = 3.67, SD = 0.51). This disparity suggests that learning environments with AI support might raise students' academic performance and motivation to continue their studies. The qualitative results highlighted this pattern, demonstrating that students often connected their participation to explicit success indicators, timely feedback, and the chance to follow learning pathways customized to their needs.

Throughout the intervention, observers saw that when given difficult tasks, pupils in the experimental group showed more persistence. Students tended to examine the system's feedback, adjust their strategies, and try other strategies rather than giving up on a task after providing an incorrect response. This tendency was less evident when students in the comparison group relied more on teacher support or waited for group explanations before making changes to their work.

3.5. Qualitative Evidence Supporting Quantitative Findings

Additional understanding of the processes behind the experimental group's quantitative gains came from the qualitative study of student comments and classroom observations. The research revealed three main trends: the role of tailored learning paths in learner autonomy; the impact of AI-supported technology on teacher mediation and classroom engagement; and the significance of adaptive feedback in mistake correction.

3.5.1. Adaptive Feedback and Error Correction

Based on observations made in the classroom, students in the experimental group recognized conceptual or procedural problems and utilized adaptive feedback as a guide to correct their answers. Students received timely guidance that enabled them to reconsider the methods used in an assignment, rather than only receiving a final indication of whether a solution was right or not. This was especially evident in scientific assignments requiring the interpretation of variables or conceptual connections, as well as in math activities requiring sequential thinking. Furthermore, student replies showed that getting feedback immediately dispelled any uncertainty and allowed them to correct mistakes before continuing on to more challenging assignments.

3.5.2. Personalized Learning Pathways and Autonomy

A second qualitative trend was linked to the perceived value of individualized learning routes. Because of the activities' adaptive sequencing, students in the experimental group reported being able to work at a pace more in accordance with their understanding level. This feature seemed to improve self-directed learning since it allowed students to study specific content, reinforce previously learned concepts, and advance once they felt more at ease. Furthermore, observational data showed that students engaged with the content more often when exercises were adjusted depending on their performance, suggesting a stronger sense of control over the learning process.

3.5.3. Classroom Engagement and Teacher Mediation

The third pattern was associated with classroom involvement and teacher mediation. Students who utilized AI-supported tools showed more task endurance, especially when it came to challenging problem-solving or abstract thinking. The teacher's participation was still essential since the learning analytics dashboard provided information on students' development and ongoing difficulties. This allowed the instructor to provide more targeted explanations and support students who needed additional assistance. Therefore, rather than acting as pedagogical mediation, the qualitative findings suggest that AI-supported tools improved the teacher's ability to identify learning needs and respond more correctly during instruction.

Overall, the qualitative results corroborate the quantitative findings by demonstrating that the benefits of AI-supported tools extended beyond final performance ratings. According to the research, these technologies have an impact on learning via improved feedback, autonomy, teacher-student engagement, and customisation. When coupled pedagogically with instructional goals, AI-assisted digital tools may improve science and math learning, according to this mix of quantitative and qualitative research.

4. DISCUSSION

This research looked at how AI-supported digital tools affected learning results and student engagement in math and science classes. The results provide empirical proof that, when these technologies are in line with curricular goals, instructional design, and teacher mediation, integrating AI into formal educational settings may lead to statistically significant and pedagogically important advancements. This part addresses the practical implications for teaching science and math, the cognitive and pedagogical function of AI-supported tools, and the results' applicability in light of earlier studies.

4.1. Interpretation of Improvements in Learning Outcomes

When compared to traditional technology-enhanced training, the experimental group's learning gains reveal that AI-supported digital tools produced deeper and more organized learning experiences. The post-test findings showed that students who had access to learning analytics dashboards, intelligent feedback systems, and adaptive learning modules outperformed the comparison group in terms of academic performance. These results are in line with earlier studies that demonstrate how intelligent tutoring programs and adaptive learning may enhance students' conceptual knowledge and problem-solving abilities in science and math classes (Ma et al., 2014; Zhai et al., 2022).

The flexibility of the intervention may have helped the experimental group. Unlike static digital resources, AI-supported technology offered instant feedback, modified learning activities based on student performance, and let students work through unsolved issues before advancing to more challenging assignments. In the fields of science and mathematics, where learning is cumulative and conceptual gaps might impede future comprehension, this flexibility is especially important. Thus, by assisting students in identifying mistakes, improving processes, and gradually strengthening conceptual links, AI-supported tools served as cognitive scaffolding.

These results also emphasize how crucial formative feedback and other forms of instructional assistance are. Students in the experimental group engaged with technology that reacted to their performance and offered advice throughout the learning process, as opposed to just receiving more digital material. This implies that AI's instructional usefulness stems from its ability to provide timely correction, conceptual clarification, and personalized learning progression in addition to automation. Thus, the findings support the notion that guided scaffolding and adaptive feedback are essential tactics for enhancing learning outcomes in cognitively demanding topics (Hattie, 2009).

4.2. Output: Student Participation as a Mediating Agent

Higher levels of student participation in the experimental group may have acted as a mediator between improved learning outcomes and AI-supported teaching. The findings showed that when students utilized AI-supported resources, their sustained attention, cognitive engagement, and sense of instructional assistance all increased. These results are consistent with engagement theory, which highlights how behavioral, cognitive, and emotional involvement affect academic achievement (Fredricks et al., 2004).

The engagement effect may be associated with many aspects of AI-supported learning settings. Adaptive assignments enabled students to work at a level of difficulty closer to their past competence, progress indicators made learning progress more evident, and immediate feedback decreased uncertainty during task completion. These components may encourage students to keep up with learning activities while lowering discontent with conceptually or numerically challenging subjects. AI-supported technology may encourage self-regulated learning by assisting students in identifying areas for growth, assessing their success, and choosing how to pursue further education.

But being more focused or attentive is just one aspect of engagement. Participation in this research also seems to increase learning autonomy, mistake correction, and feedback. In addition to completing digital assignments, students who used AI-supported tools modified their learning approaches and reassessed their concepts in response to system feedback. This implies that AI-assisted settings may encourage cognitive and metacognitive kinds of involvement in addition to behavioral ones.

4.3. Complementarity of Quantitative and Qualitative Results

The results' main consequence is that digital tools with AI assistance should not be seen as passive technology additions to traditional educational methods. Instead, the findings imply that AI might serve as a pedagogical, metacognitive, and cognitive support system when included in a thoughtful educational design.

From a cognitive standpoint, AI-supported technology assisted students in assimilating information, identifying mistakes, receiving prompt assistance, and making connections between previously taught material and novel ideas. For mathematical and scientific tasks involving abstract cognition, sequential processes, and conceptual transfer, this quality was essential. The tools helped students identify if a solution was flawed and where a problem arose throughout the reasoning process by offering adaptive feedback.

AI-supported technology allowed students to monitor their development and take more control over their education from a metacognitive perspective. Thanks to individualized learning pathways and success indicators, students were able to become more aware of their strengths, weaknesses, and progress during the intervention. This position is essential because, in order for students to study science and math effectively, they must not only finish tasks but also evaluate their own understanding and choose whether to go on, go back, or make changes.

From a pedagogical perspective, AI-supported technology improved the teacher's capacity to make data-driven instructional decisions. Learning analytics dashboards included information on student growth, recurring misconceptions, and engagement levels. This made it possible for the teacher to modify explanations, provide specific assistance, and determine which pupils needed more help. Therefore, by providing additional evidence for instructional decision-making, AI enhanced pedagogical mediation rather than replacing teachers.

4.4. Implications for Science and Mathematics Teaching

The results become easier to grasp by combining quantitative and qualitative data. While qualitative data showed the instructional strategies that brought about these improvements, quantitative statistics showed significant gains in academic achievement and engagement. The significance of adaptive feedback, individualized learning paths, transparent progress tracking, and instructor mediation was emphasized by student remarks and classroom observations.

This complementarity demonstrates the value of mixed-methods approaches in educational technology research. While quantitative statistics may show if there is a change, qualitative evidence explains how and why the intervention affects learning. The study's qualitative findings demonstrated how AI-supported tools influenced learning by promoting independence, perseverance, active correction, and more targeted teaching support. This supports the idea that increased exposure to digital materials alone was not the cause of the observed performance gains, but rather a more responsive learning environment.

The results also suggest that there are other factors to take into account when assessing AI-assisted learning. Academic achievement is crucial, but it does not completely capture the benefits of AI-mediated learning for education. Understanding student autonomy, engagement, feedback utilization, and teacher decision-making is also necessary to comprehend the educational effect of AI-supported technology. This viewpoint encourages the use of mixed-methods designs to investigate complex educational interventions (Creswell & Plano Clark, 2018).

4.5. Limitations and Future Lines of Research

These results have a number of useful ramifications for science and math instruction. According to the report, teachers may recognize student problems faster and provide more targeted instructional assistance by using AI-supported technologies. By using learning analytics, teachers may keep an eye on their students' progress, identify recurrent misunderstandings, and take action before it becomes more difficult to bridge learning gaps. However, the teacher's capacity to pedagogically assess data and link digital feedback with relevant classroom teaching is what determines how successful AI is.

The results emphasize how crucial it is that curriculum designers include AI-supported technologies in lesson plans rather than seeing them as separate technology resources. Learning goals, assessment standards, and the conceptual development of scientific and mathematical material should all be in line with adaptive activities, feedback systems, and learning analytics. Therefore, curriculum design should take into account not just the technical tools that are accessible but also how they facilitate problem solving, reasoning, and conceptual growth.

According to the results, professional development programs should prepare teachers to employ AI in the classroom. Training should include learning analytics interpretation, adaptive activity design, assessing AI-generated feedback, and ethical issues with student data, in addition to technical operation. To utilize AI critically, morally, and in ways that maintain their pedagogical autonomy, educators must get professional training.

The study demonstrates that researchers should use both quantitative and qualitative techniques when examining AI-supported learning environments. Future research should concentrate on how AI influences teacher decision-making, self-regulated learning, student achievement, and engagement across a range of disciplines and educational levels. Researchers must examine how AI-assisted technologies improve learning over time.

The findings suggest that educational authorities and institutional leaders should use AI in conjunction with curriculum alignment, infrastructural support, teacher development, and ethical standards. Using AI in the classroom should include more than simply purchasing devices. Data security laws, institutional readiness, and a clear pedagogical framework describing how AI will improve teaching, learning, and assessment are all essential.

4.6. Limitations and Future Research Directions

It is crucial to acknowledge the limitations of this research. First, the application of causal inferences outside of the specific educational context where the intervention occurred is limited by the use of intact groups. Even if the quasi-experimental design allowed comparison between an experimental and a control group, the absence of full random assignment requires caution when interpreting causal relationships.

Second, since the intervention was only implemented for one academic term, assessments of long-term retention, learning transfer, and sustained engagement are constrained. In order to determine if students use their newly acquired skills in other learning situations and whether the benefits of AI-supported digital tools last over time, future research should include longitudinal designs. Third, the study focused on math and science courses in specific educational settings. Future research should involve more institutional settings, larger and more diverse populations, and cross-level comparative investigations. Future research should primarily concentrate on the ethical, cognitive, and pedagogical implications of AI-supported decision-making in education, particularly with regard to algorithmic transparency, data privacy, equality, and student autonomy.

5. CONCLUSION

This study examined the effects of AI-supported digital technologies on students' learning outcomes and engagement with science and math courses. The results provide empirical proof that integrating AI into pedagogically structured learning environments may lead to significant gains in academic performance, especially when these technologies are in line with curriculum objectives, teacher mediation, and instructional design.

The results showed that students who utilized AI-supported digital tools reported higher levels of engagement and learning gains than those who received conventional technology-enhanced training. These findings provide credence to the notion that AI may enhance conceptual understanding, problem-solving skills, and self-directed learning when it provides adaptive feedback, personalized learning routes, and continuous progress monitoring.

The primary conclusion of this research is that the effectiveness of AI-supported learning environments is not only determined by technological complexity. Rather, the educational value of these tools lies in their capacity to function as pedagogical, metacognitive, and cognitive support systems. According to this viewpoint, AI helps students recognize mistakes, take control of their education, and progress through a range of learning sequences while also assisting teachers in making data-driven educational decisions. Therefore, rather than being a replacement for human instruction, AI should be seen as an additional instrument that might enhance pedagogical mediation. It is also critical to acknowledge the limits of research. The use of intact groups in the quasi-experimental paradigm limits the generalizability of causal results outside the specific educational context under investigation. Results concerning long-term retention, learning transfer, and sustained engagement are also limited since the intervention was only used for one academic term. Future research should use longitudinal designs, bigger and more varied samples, and comparative studies across various educational levels and institutional settings in order to overcome these problems. For educators, curriculum designers, academics, professional development programs, and legislators interested in the appropriate integration of AI in science and math teaching, this study provides theoretical and practical insights. The findings emphasize the need to use AI in ethical, empirically supported, and pedagogically meaningful ways, particularly in learning situations that require conceptual abstraction, iterative reasoning, and continuous instructional support.

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Data Availability Statement. The datasets produced and examined in this work are not accessible to the public because of institutional data protection regulations and confidentiality agreements with participants. However, the corresponding author may provide anonymised data upon reasonable request for academic and research reasons.

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REFERENCES

Acuña Acuña, E. G. (2023). Estrategias para promover la investigación en estudiantes de ingeniería en universidades latinoamericanas. *New Trends in Qualitative Research, 17*, Article e867. https://doi.org/10.36367/ntqr.17.2023.e867

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

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

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203771587

Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications. https://books.google.com/books?id=-LvwjwEACAAJ

DeVellis, R. F. (2017). *Scale development: Theory and applications* (4th ed.). SAGE Publications. https://books.google.com/books?id=48ACCwAAQBAJ

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Hattie, J. (2009). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*. Routledge. https://doi.org/10.4324/9780203887332

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. https://curriculumredesign.org/wp-content/uploads/AIED-Book-Excerpt-CCR.pdf

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson. Retrieved from https://www.pearson.com/content/dam/one-dot-com/one-dot-com/global/Files/about-pearson/innovation/Intelligence-Unleashed-Publication.pdf

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology, 106*(4), 901–918. https://doi.org/10.1037/a0037123

OECD. (2021). *OECD Digital Education Outlook 2021: Pushing the frontiers with artificial intelligence, blockchain and robots*. OECD Publishing. https://doi.org/10.1787/589b283f-en

Ritter, S., Anderson, J. R., Koedinger, K. R., & Corbett, A. (2007). Cognitive Tutor: Applied research in mathematics education. *Psychonomic Bulletin & Review, 14*(2), 249–255. https://doi.org/10.3758/BF03194060

Schindler, L. A., Burkholder, G. J., Morad, O. A., & Marsh, C. (2017). Computer-based technology and student engagement: A critical review of the literature. *International Journal of Educational Technology in Higher Education, 14*, Article 25. https://doi.org/10.1186/s41239-017-0063-0

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press. https://www.wiley.com/en-se/Should%2BRobots%2BReplace%2BTeachers%3F%3A%2BAI%2Band%2Bthe%2BFuture%2Bof%2BEducation-p-9781509528967

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin. https://books.google.com/books?id=o7jaAAAAMAAJ

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist, 46*(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Zhai, X., He, P., & Krajcik, J. (2022). Applying machine learning to automatically assess scientific models. *Journal of Research in Science Teaching, 59*(10), 1765–1794. https://doi.org/10.1002/tea.21773