Bulletin of Nexus
Multidisciplinary International Research Journal, Double-Blind Peer Reviewed, Open Access Journal
ISSN : 3065-7865 / Volume-2, Issue-12 December - 2025

Original Article

Personalised Mathematics Learning Through Artificial Intelligence: A Structural Model of Adaptive Feedback, Student Engagement, Self-Efficacy, and Academic Achievement

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Manuscript ID:
BN-2025-021211

ISSN: 3065-7865

Volume 2

Issue 12

December 2025

Pp. 53-69

Submitted: 10 Nov 2025

Revised: 20 Nov 2025

Accepted: 09 Dec 2025

Published: 31 Dec 2025

DOI:
10.5281/zenodo.23636354

DOI link:
https://doi.org/10.5281/zenodo.23636354

Abstract-

Artificial intelligence (AI) is transforming the delivery of math instruction through personalized lessons, adaptive feedback, and data-based learning support. Unfortunately, we still do not fully understand the effects of AI-enabled adaptive feedback on student engagement, math self-efficacy, and academic achievement. The current study aims to develop an integrated structural model to examine the direct and indirect relationships among these ideas in secondary mathematics education. The study compared AI-supported individual learning in mathematics with normal digital teaching in an eight-week continuous quasi-experimental design . It is based on Social Cognitive Theory and positive feedback. The proposed research framework will include 712 eighth-graders from six secondary schools, equally divided between the experimental and control groups. This will be compared with actual recruitment data. Standardized math tests are administered pre, post and during the follow-up period, validated psychological questionnaires and AI-generated learning analytics are used to collect data. The accuracy of the measurements, the proposed structural relationships and the mediating roles played by student engagement and mathematics self-efficacy in these relationships will be examined using confirmatory factor analysis (CFA) and structural equation modeling (SEM). A study will use multi-level statistics to look at the difference in academic success considering starting points and how students are grouped in the classroom. Further reliability and multigroup analyzes will be conducted to test the stability of the proposed links. The study aims to gain insight into the psychological and instructional mechanisms involved in the use of AI to support math learning, and to develop a means of creating adaptive educational systems that foster student engagement, confidence in math, and academic success.

Keywords: *Artificial Intelligence; Personalized Mathematics Learning; Adaptive Feedback; Student Engagement; Mathematics Self-Efficacy; Academic Achievement; Structural Equation Modeling; Intelligent Tutoring Systems.*

Introduction

Background and Significance of Artificial Intelligence in Mathematics Education

The rapid development of artificial intelligence (AI) has transformed the educational process, enabling the creation of intelligent, flexible, and data-driven learning environments capable of adapting to the individual needs of each student. Mathematics education provides a fertile ground for mental growth, abstract thinking and complicated problem solving, which makes it a very promising field for individualized AI-supported teaching. Traditional classroom teaching often does not meet the diversity of students' mathematical abilities, learning rates, previous knowledge, and cognitive abilities. So the same teaching methods may not help students with different learning difficulties, which can lead to disengagement, low confidence and persistent achievement gaps. AI-powered educational technologies that deliver personalized content, test students continuously and provide flexible support for teachers can solve these problems (Luckin et al., 2016; Holmes et al., 2019). AI in schools has evolved from rule-based intelligent teaching systems to complex adaptive platforms that can watch how students interact with each other and offer personalized lessons over the years.

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How to cite this article:
Shivapuji, G. (2025). Personalised Mathematics Learning Through Artificial Intelligence: A Structural Model of Adaptive Feedback, Student Engagement, Self-Efficacy, and Academic Achievement. Bulletin of Nexus, 2(12), 53–69. https://doi.org/10.5281/zenodo.23636354

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Chen et al. (2021) discuss the growth of AI study in education, showing that people are more and more interested in smart learning tools. Previous work such as AutoTutor (Graesser et al., 2004) has shown the potential of computer-based talking teaching to improve the participatory nature of learning. In a similar vein, the Knowledge-Learning-Instruction framework emphasizes the need for decisions about instruction to be congruent with students' ways of thinking and the development of their knowledge structures (Koedinger et al., 2012). These changes suggest that the effectiveness of schools is not only a function of the sophistication of the technology they have, but also of how well they use smart technology to bring about meaningful student learning.

AI-Enabled Personalized Learning and Mathematics Achievement

Personalized math learning means tailoring the lessons, the level of challenge, the feedback and the next steps in the learning process to each student's skills and educational needs. Vygotsky's (1978) sociocultural view suggests that students can solve math problems that are beyond their independent level when they are properly scaffolded. It could be done by AI-based systems, able to find information gaps and give better and better help. Evidence suggests that intelligent tutoring technologies can help students learn. It has been shown that intelligent tutoring systems help students to learn in general (Ma et al., 2014; Kulik and Fletcher, 2016). Such approaches have been examined by Steenbergen-Hu and Cooper (2014) in the specific context of K–12 mathematics education. VanLehn (2011) showed that when comparing human and technology-supported instruction, tutoring characteristics are even more important. Evidence from Roschelle et al. (2016) shows that technology supported homework solutions can help students perform better in school mathematics. However, the magnitude and stability of the benefits of education vary according to the way the lessons are taught, the kind of students taught, the circumstances in which they are taught and the quality of the interaction between teachers. So it's still very important to understand the processes that result in better performance.

Adaptive Feedback as a Mechanism of Personalized Learning

Adaptive feedback is an important part of using AI to teach math because it tells each student exactly what they're doing wrong, what they don't understand, and how to fix it. Unlike traditional feedback that may be delayed or vague, AI-enabled feedback can change based on how students solve problems and develop skills.

Hattie and Timperley (2007) state that feedback is a vital part of learning because it helps students to determine their learning goals, their present progress and how they can improve in the future. Similarly, Shute (2008) discussed the role of formative feedback in education and Narciss (2008) examined feedback strategies in interactive learning environments. But adaptive feedback is useful not only because it's instant or technological. It's the specificity, relevance, cognitive appropriateness and the degree to which students can transduce feedback into actions that help them learn. If we give too much advice people get dependent, if we give too little help people think more. To understand the effects of adaptive feedback on psychological engagement and academic confidence, we must consider its effects on math achievement.

Student Engagement and Mathematics Self-Efficacy

Student engagement is a multidimensional construct in education and consists of behavioral participation, emotional involvement, and cognitive investment in learning activities (Fredericks et al., 2004). In AI-assisted settings, students could remain engaged in math and think more critically about it through adaptive tasks, engaging explanations, and personalized feedback. Järvelä and Renninger (2014) have pointed out the role that technology plays in self-regulated learning and motivation. But digital interaction does not always equal meaningful engagement. For example, platform use may be high because of shallow processing or poor learning strategies. Emotional experiences are important in computer-based learning environments (Baker et al., 2010). The theoretical framework to understand the impact of achievement emotions on learning is provided by the control-value theory of Pekrun (2006).

Another potentially important psychological process is the math self-efficacy. As per Bandura's (1986, 1997) Social Cognitive Theory, individuals' perceptions of their own self-efficacy affect their motivation, persistence, and behaviors related to success. Pajares (1996) explained the importance of academic self-efficacy in school. Zimmerman (2000) said that efficacy beliefs are important for learning because they motivate people to do well. Pintrich and De Groot (1990) likewise demonstrated the importance of motivational and self-regulatory factors for school achievement. Schunk and DiBenedetto (2020) provided more information about the link between views of effectiveness and human drive. In one-to-one math learning, knowing the right answers and getting helpful feedback can increase students' confidence in their math skills,

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perhaps making them more likely to pursue it when it becomes difficult.

Research Gap and Need for an Integrated Structural Model

Recent research indicates that intelligent tutoring systems are promising and feedback, engagement and self-efficacy are important for learning. However, this research does not offer a comprehensive account of how these ideas interact in AI-personalized math learning environments. Whereas the focus of motivational research is on psychological issues and not on technologically mediated processes of learning, meta-analytic research concentrates on overall learning outcomes (Ma et al., 2014; Kulik & Fletcher, 2016). Research on digital motivating treatments, such as serious games, also suggests that cognitive and motivational outcomes should be considered in an integrated way, rather than as two separate constructs (Wouters et al., 2013).

Therefore, we must investigate three related issues: the structural relationship between adaptive feedback and student engagement, the role of mathematics self-efficacy in achievement, and the possible parallel and sequential pathways connecting individualized instructional support with measurable academic performance. To show these links, you need theory-based measurements, time-based evidence, and the right statistical analysis. Structural Equation Modeling (SEM) is a technique to explore latent variables, measurement errors and multiple possible relationships at the same time (Kline, 2023).

Research Purpose and Contribution

The present study addresses these questions and proposes a theoretically integrated structural model to test the direct and indirect links among AI-enabled customizable feedback, student engagement, math self-efficacy, and academic success. This study investigates the mediating role of engagement and self-efficacy between personalized instructional feedback and math performance. It does so by drawing on Social Cognitive Theory, notions of motivational engagement, and research on formative feedback.

The proposed research contributes with the integration of pedagogical, psychological and achievement-related aspects in a single empirical framework; the combination of validated measures of constructs with objective indicators of mathematics achievement; and the examination of the strength of structural relationships across different levels of initial achievement. The study is designed to help us understand how standard artificial intelligence can be used to improve math education by distinguishing between instructional exposures and psychological mechanisms and measurable learning outcomes. It also aims to give us evidence-based advice on how to create adaptive learning environments that help students learn math in a meaningful.

Literature Review

Artificial Intelligence and Personalized Mathematics Learning

AI has revolutionized teaching and learning with adaptive instruction, personalized feedback and data-driven learning environments. Within math education, intelligent teaching systems support individualized learning through diagnosing mental problems, adjusting the difficulty level of lessons, and providing targeted help with problem solving. Graesser et al. (2004) demonstrated the potential of interactive intelligent training. Koedinger et al. (2012) highlighted the value of integrating cognitive learning principles with adaptive instructional resources. Chen et al. (2021) contributed to the increasing significance of AI applications in educational research.

Studies in real classrooms have found that smart instructional resources can help students do better in school. Ma et al. (2014) and Kulik and Fletcher (2016) mentioned that intelligent instructional resources were generally helpful, but Steenbergen-Hu and Cooper (2013) stated that their usefulness varied in different K–12 math learning situations . Moreover, technology-enhanced math projects have demonstrated an enhancement in students' performance in school (Roschelle et al., 2016). But these findings suggest that the power of technology depends not only on using AI but on how it is used, how well it is designed, and the kind of people who are learning.

Adaptive Feedback and Student Engagement

Adaptive feedback constitutes a central pedagogical mechanism within AI-supported learning environments. Hattie and Timperley (2007) stated that good feedback helps students understand what they need to learn, see where they are falling short and come up with the best ways to fix those problems. The importance of specific feedback, relevance of the lessons and corrective advice were also mentioned by Shute (2008) and Narciss (2008).

Student engagement is a multidimensional construct (Fredricks et al., 2004) that encompasses behavioral engagement, emotional engagement and cognitive engagement. AI-enabled input can make students more interested in class by providing them with properly difficult tasks, clear answers immediately, and personalized help with their learning. Järvelä and Renninger (2014) have discussed the significance of technology supporting self-regulated learning and motivation. Thus, Baker et al. (2010) demonstrated that students' emotions like anger and boredom have an effect on how they

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use computer-based learning environments. Thus, the value of adaptive feedback is not only technical effectiveness, but also in its capacity to foster meaningful ways of thinking and acting among people.

Mathematics Self-Efficacy and Academic Achievement

Mathematics self-efficacy is a concept that reflects students' confidence in carrying out mathematical tasks. According to the Social Cognitive Theory, self-efficacy has been shown to influence people's motivation to continue with something, how hard they work and their academic performance (Bandura, 1986, 1997). Researchers Pajares (1996) and Zimmerman (2000) found that academic competence beliefs are important to learning and self-regulation. Schunk and DiBenedetto (2020) focused on the relation between these beliefs and motivational processes.

In personalized math environments, adaptive feedback might increase self-efficacy by providing students with successful experiences in problem solving, increasingly difficult tasks, and helpful feedback. For example, students who have a higher level of math self-efficacy are more likely to persist in solving difficult math problems. But too much help from teachers may hinder students' ability to solve problems by themselves. Therefore, the relationship between adaptive feedback, confidence and academic success needs to be thoroughly investigated with real-world data.

Comparative Review of Existing Studies

Table 1. Comparative synthesis of previous research on AI-supported learning, feedback, engagement, self-efficacy, and academic achievement

Author(s)	Research focus	Key contribution	Limitation relevant to the present study
Graesser et al. (2004)	Intelligent conversational tutoring	Demonstrated interactive tutoring architecture	Did not examine the proposed mathematics-specific mediation model
Hattie & Timperley (2007)	Educational feedback	Established a conceptual framework for effective feedback	Not specific to AI-adaptive mathematics environments
Shute (2008)	Formative feedback	Synthesized principles of effective feedback design	Did not test the proposed integrated structural model
Steenbergen-Hu & Cooper (2013)	Intelligent tutoring in K–12 mathematics	Synthesized mathematics achievement outcomes	Focused on intervention effects rather than the proposed psychological mediation pathways
Ma et al. (2014)	Intelligent tutoring systems	Meta-analyzed effects on learning outcomes	Did not directly evaluate the four-construct structural model
Fredricks et al. (2004)	Student engagement	Established behavioral, emotional, and cognitive dimensions	Did not address AI-enabled adaptive instruction
Kulik & Fletcher (2016)	Intelligent tutoring effectiveness	Synthesized evidence concerning tutoring effectiveness	Limited direct explanation of the proposed engagement–self-efficacy pathways
Roschelle et al. (2016)	Technology-supported mathematics homework	Provided experimental evidence concerning mathematics achievement	Did not comprehensively model both proposed psychological mediators
Bandura (1997)	Self-efficacy	Established the theoretical foundations of efficacy beliefs	Did not specifically investigate AI-supported mathematics learning
Koedinger et al. (2012)	Digital learning and cognitive science	Connected learning theory with instructional design	Did not empirically estimate the proposed four-construct mediation model

Note: The limitations identify how each publication differs from the present research objectives; they do not imply methodological weaknesses in the original studies.

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Research Synthesis and Identified Gap

We looked at research showing that intelligent teaching systems can help students do better in math. Interest, self-efficacy and adaptive feedback are other relevant psychologic and educational factors. But in comparing the two, three study gaps are obvious.

The current meta-analyses are focused on the effectiveness of clever teaching technologies in general, not on understanding the psychological factors that affect math success in general. Second, basic research on feedback, engagement, and self-efficacy has often situated these ideas within distinct theoretical frameworks. This means they could be integrated in AI-personalized math learning. Third, the proposed direct, parallel, and sequence mediating connections need further long-term research with objective measures of achievement.

The current study fills these gaps by developing a structural model of AI-enabled adaptive feedback, student engagement, math self-efficacy, and academic success. The effect of individual feedback on the students' motivation and performance in mathematics is attempted to be shown in the study by using theoretically grounded concepts, continuous variables and Structural Equation Modeling.

Research Objectives and Hypotheses

Research Objectives

The present study aims to develop and empirically validate a structural model examining the relationships among AI-enabled adaptive feedback, student engagement, mathematics self-efficacy, and academic achievement. The following four research objectives are proposed:

RO1: To examine the influence of AI-enabled adaptive feedback on student engagement and mathematics self-efficacy.

RO2: To investigate the effects of adaptive feedback, student engagement, and mathematics self-efficacy on mathematics academic achievement.

RO3: To evaluate the mediating roles of student engagement and mathematics self-efficacy in the relationship between adaptive feedback and academic achievement.

RO4: To validate the proposed structural model using Structural Equation Modeling (SEM) and assess its explanatory power for mathematics academic achievement.

Research Hypotheses

Based on Social Cognitive Theory, formative feedback principles, and student engagement theory, the following five hypotheses are formulated:

H1: AI-enabled adaptive feedback has a significant positive influence on student engagement.

H2: AI-enabled adaptive feedback has a significant positive influence on mathematics self-efficacy.

H3: Student engagement has a significant positive influence on mathematics academic achievement.

H4: Mathematics self-efficacy has a significant positive influence on mathematics academic achievement.

H5: Student engagement and mathematics self-efficacy significantly mediate the relationship between AI-enabled adaptive feedback and mathematics academic achievement

Hypothesized Structural Relationships

Table 2. Proposed research hypotheses and expected relationships

Hypothesis	**Structural relationship**	**Expected effect**
H1	Adaptive Feedback → Student Engagement	Positive
H2	Adaptive Feedback → Mathematics Self-Efficacy	Positive
H3	Student Engagement → Academic Achievement	Positive
H4	Mathematics Self-Efficacy → Academic Achievement	Positive
H5	Adaptive Feedback → Engagement / Self-Efficacy → Achievement	Positive indirect

The independent variable of the proposed structure model is adaptive feedback, while the intermediate variables are student participation and Mathematics self-efficacy and the dependent variable is academic achievement in Mathematics. We will test the five hypotheses using Structural Equation Modeling (SEM), Confirmatory Factor Analysis (CFA) to ensure the correctness of the measurements and mediation analysis to investigate how the hypotheses are indirectly related to each other. Control variables will be the students' initial math scores and other relevant student characteristics.

Research Methodology

Research Design

The study employed a quantified, continuous, quasi-experimental methodology to investigate the relationships between AI-enabled adaptive feedback, student engagement, math self-efficacy, and academic success. In the classrooms, the solution pitted individual math learning with AI against regular digital teaching for eight weeks. It comprises three phases; pre-test (T1, Week 0), post-test (T2, Week 8) and follow-up (T3, Week 12). It is proposed to use Structural Equation Modeling (SEM) to study possible direct and indirect associations.

Participants and Sampling

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The proposed study framework involves 734 students of Grade 8 from six secondary schools. We excluded 22 missing or unqualified records from the analysis sample, and 712 students were included in the analysis. The experimental group has 356 students and the control group has 356 students. They are distributed in 24 classes. Information on how students were placed into groups and how well they knew math will be collected at the classroom level to see how comparable the first groups are. Sample adequacy will be assessed using statistical power analysis taking into account clustering and missing observations.

AI-Based Mathematics Learning Intervention

The experimental group will receive two 45-minute sessions per week of personalized math instruction with AI for eight weeks. The platform is customizable and will give each student personalized tasks, diagnostic tests, real-time feedback on how to improve and problems that get harder over time. The control group will receive the same math content using traditional digital lessons without adaptive feedback. The platform will log learning analytics like session length, problem solving accuracy, frequency of feedback, and use of hints to verify the level of student engagement in the lessons and effectiveness of the interventions.

Research Framework

The proposed model includes four components: Adaptive Feedback (AF), Student Engagement (SE), Mathematics Self-Efficacy (MSE), and Academic Achievement (AA). The main variable explaining things is adaptive feedback. Involvement and self-efficacy are similar facilitators. The variable indicating what happened is academic progress. The structural model investigates five hypotheses: four direct hypotheses (H1–H4) and one interaction hypothesis (H5).

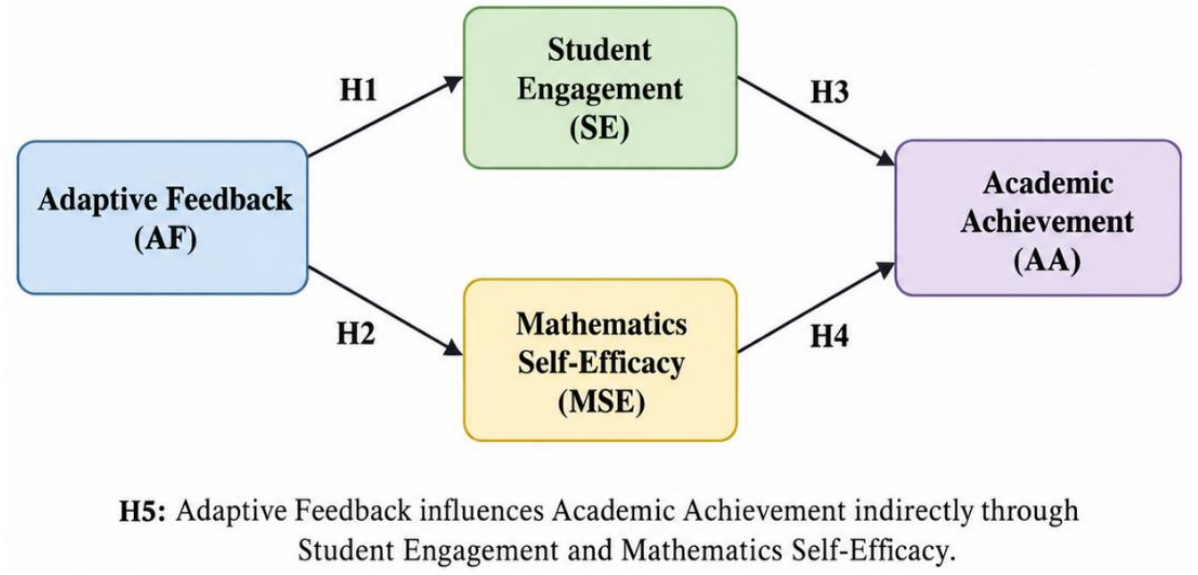


Figure 1. Proposed structural framework illustrating the direct and indirect relationships among adaptive feedback, student engagement, mathematics self-efficacy, and academic achievement.

Research Instruments and Data Collection

Data will be collected through standardized mathematics assessments, validated questionnaires, and AI-platform interaction records. Psychological constructs will be measured using five-point Likert-scale instruments.

Table 1. Measurement framework of research constructs

Construct	Indicators	Measurement
Adaptive Feedback (AF)	Timeliness, relevance, personalization, corrective usefulness	5 items
Student Engagement (SE)	Behavioral, emotional, cognitive engagement	9 items
Mathematics Self-Efficacy (MSE)	Confidence, persistence, mathematical competence	6 items
Academic Achievement (AA)	Conceptual knowledge, mathematical reasoning, problem-solving performance	Standardized test (0–100)

Engagement and self-efficacy will be assessed across three measurement waves, while AI-specific feedback quality will be evaluated among experimental-group participants following platform exposure. Student achievement will be measured at baseline, posttest, and follow-up. Participant identifiers will link longitudinal records while maintaining confidentiality.

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Statistical Analysis

We will analyze the data using statistical tools like SPSS, R (lavaan) or something similar. We will examine early relationships through descriptive statistics and correlations. Confirmatory Factor Analysis (CFA) will be used to examine the validity of the measurements, and Cronbach's α, composite reliability, Average Variance Extracted (AVE) and discriminant-validity measures will be used to assess the psychometric quality.

The structural relationships (H1–H4) will be examined using SEM, and the indirect effects of engagement and self-efficacy (H5) will be examined using 95% confidence intervals for mediation analysis. The goodness of model will be checked by the fit of the model indices, namely χ^2/df, CFI, TLI, RMSEA and SRMR. Baseline-adjusted multilevel models will be employed to explore intervention-attributable differences in achievement considering the grouping of students in the classroom. Measurement invariance, missing-data analysis and sensitivity testing will be used to check the robustness of the results.

Ethical Considerations

All data will be collected after ethical approval from the institution, permission from parents and agreement from students. Participants will be anonymous, data will be treated safely and participation is completely voluntary. Standardized tests and uniform teaching will support the reliability and truth of the study.

Results and Empirical Analysis

This section discusses the research of mathematics success, the creation of learning, flexible feedback, and the proposed framework linkages between student involvement, math self-efficacy, and performance. The analysis will cover descriptive statistics, longitudinal comparisons, domain-specific performance, learning analytics, measurement validation and structural model evaluation.

Participant Characteristics and Data Screening

The sample consisted of 734 eighth graders from six high schools. After the first screening, 22 records were excluded, which left 712 participants for the achievement analysis. The experimental and control groups had 356 students in 24 classrooms. The academic performance was measured three times, before the test (T1), after the test (T2), and after the follow-up (T3).

Table 2. Demographic characteristics and sample distribution

Characteristics	Value
Initially recruited students	734
Final analytical sample	712
Excluded records	22
Experimental group	356 (50.0%)
Control group	356 (50.0%)
Female students	369 (51.8%)
Male students	343 (48.2%)
Participating schools	6
Classrooms	24
Retention proportion	97.0%

The fair group distribution helped to compare the students' academic achievement. The dataset included linked achievement records from all three measurement waves, enabling investigators to evaluate the learning process and retention of what was learned.

Descriptive Analysis of Mathematics Academic Achievement

Math skills were measured by standardized scores on a scale of 0 to 100. The average scores and ranges of scores of both groups across all testing times are shown in Table 3.

Table 3. Descriptive statistics of mathematics academic achievement

Group	Pretest (T1) Mean ± SD	Posttest (T2) Mean ± SD	Follow-up (T3) Mean ± SD
Experimental (n = 356)	53.27 ± 13.84	59.60 ± 16.01	56.89 ± 16.43
Control (n = 356)	53.25 ± 13.63	55.35 ± 16.68	52.96 ± 17.18
Mean difference	0.02	4.25	3.93

The results show that the math skills of the experimental group and the control group were similar at the beginning. After the instructional intervention, the mean score of the experimental group was 59.60 and the mean score of the control group was 55.35. The scores at follow-up were 56.89 and 52.96 respectively.

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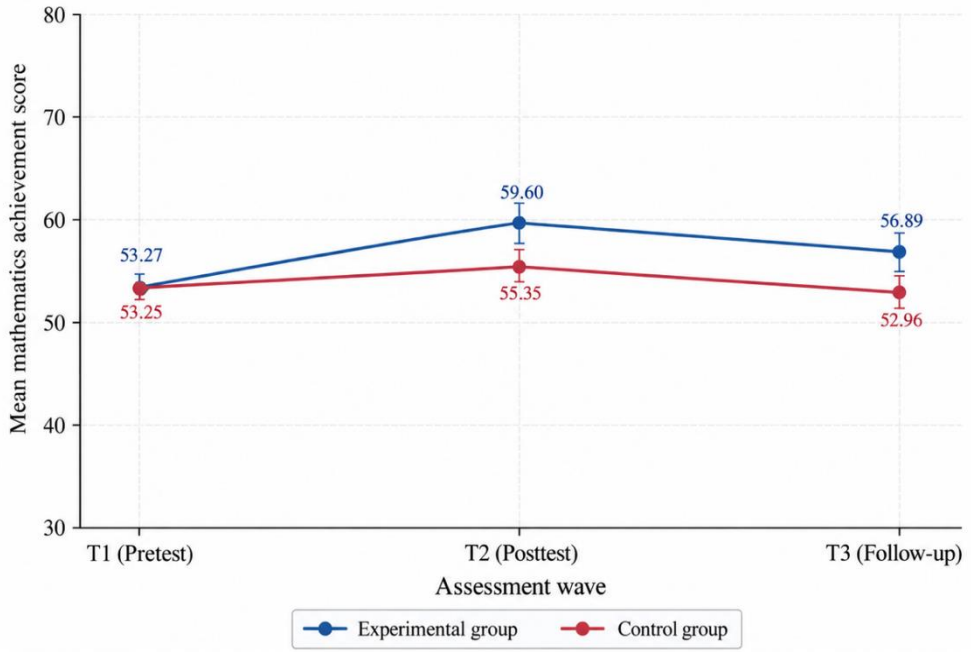


Figure 2. Longitudinal mathematics achievement trajectories across experimental and control groups.
The achievement curves indicate that the experimental group improved on average from pre-test to post-test. Both groups had lower scores at follow-up, but the experimental group still performed better on average.

Comparative Analysis of Mathematics Learning Gains

Pretest–posttest and pretest–follow-up achievement differences were calculated to evaluate changes in mathematics performance.

Table 4. Mathematics achievement gains across assessment periods

Group	**Pretest–Posttest Gain (Mean ± SD)**	**Pretest–Follow-up Gain (Mean ± SD)**
Experimental	6.33 ± 8.64	3.62 ± 9.23
Control	2.10 ± 9.43	−0.29 ± 9.88
Difference in mean gain	4.24	3.91

The average increase from pre-test to post-test was 6.33 points for the experimental group compared to 2.10 points for the control group. The difference of the average quantity of performance improvements was around 4.24 points. At follow-up, the experimental group maintained a 3.62-points advantage over baseline and the control group declined slightly by 0.29 points.

Table 5. Statistical comparison of mathematics achievement gains

Statistical measure	**Posttest gain**	**Follow-up gain**
Mean difference	4.24	3.91
95% confidence interval	2.91–5.56	2.50–5.31
Welch's t-statistic	6.25	5.45
Cohen's d	0.47	0.41
p-value	$p < 0.001$	$p < 0.001$

The standard effect sizes show that the performance improvements are not significantly different from each other. However, these comparisons do not take into account classroom clustering or non-random assignment to groups and thus require a higher level of analysis.

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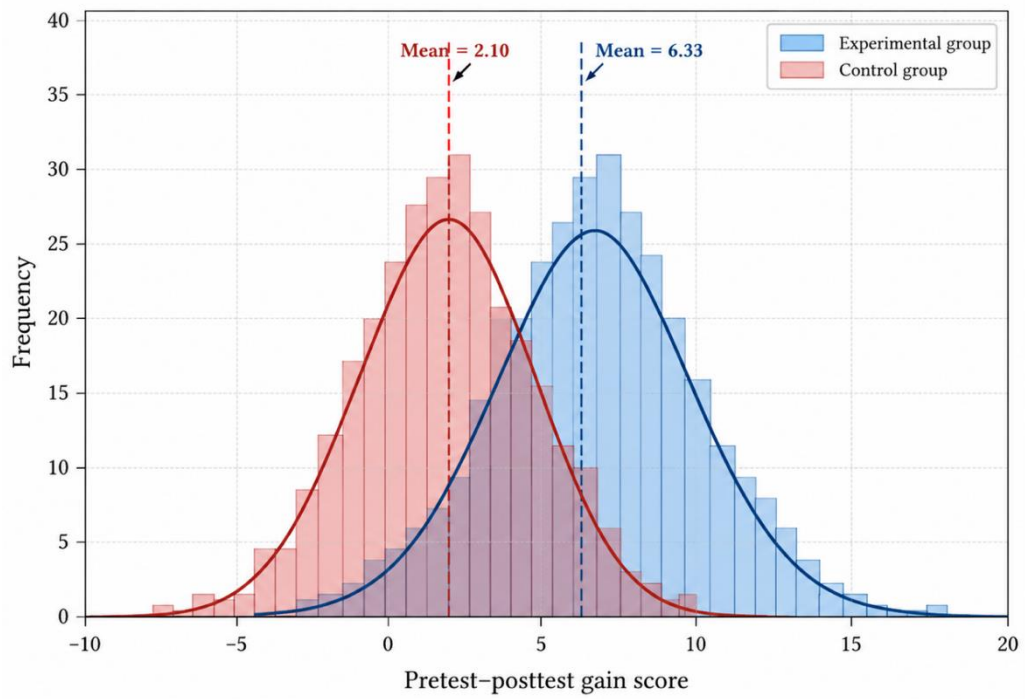


Figure 3. Distribution of individual mathematics achievement gains from pretest to posttest.
The distribution highlights differences in individual achievement progression, indicating variability in learning gains across participants.

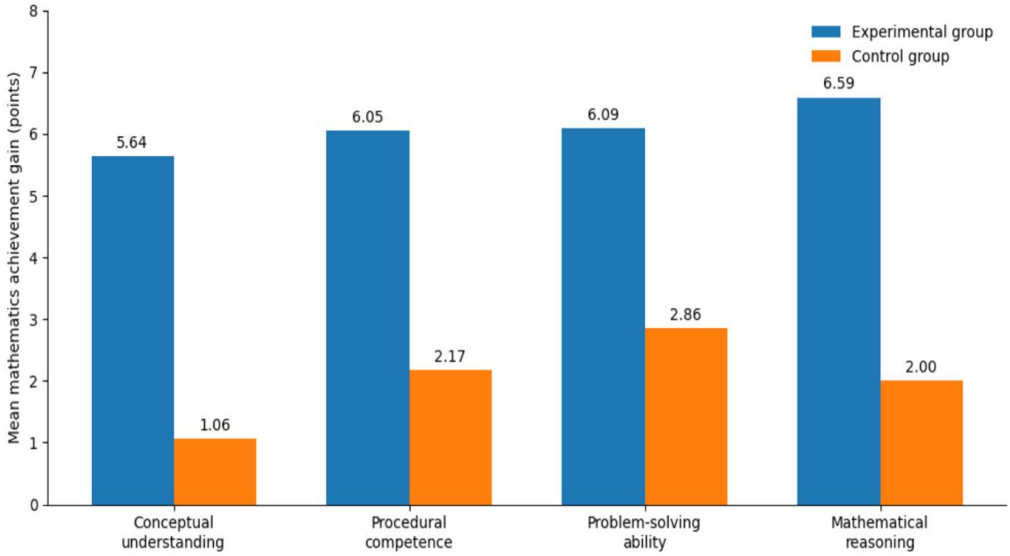
Domain-Specific Mathematics Performance

Academic achievement was further examined across conceptual understanding, procedural competence, problem-solving ability, and mathematical reasoning.

Table 6. Domain-specific mathematics achievement scores

Mathematics domain	Experimental T1	Experimental T2	Control T1	Control T2
Conceptual understanding	53.72	59.36	53.81	54.87
Procedural competence	53.31	59.36	53.24	55.41
Problem-solving ability	53.00	59.09	52.65	55.51
Mathematical reasoning	52.95	59.54	53.32	55.32

The experimental group was superior in all four domains. Mathematical reasoning had the largest average gain (6.59 points), followed by problem solving (6.09 points), procedural competence (6.05 points) and conceptual understanding (5.64 points).



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Figure 4. Comparison of mathematics achievement gains across learning domains.

The topic-specific differences indicate that different ways of teaching mathematics may affect different mathematical skills differently. Further statistical testing will be necessary to see whether the differences observed are real.

Individual Learning Progression

They looked at achievement scores at the student level to see if there was a relationship between starting strong and then doing well later.

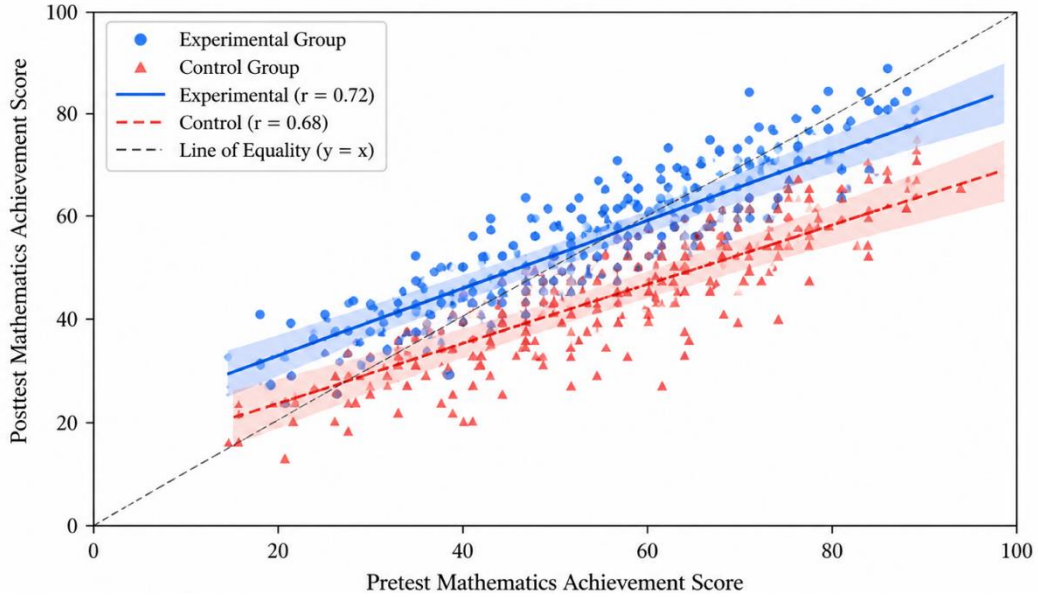


Figure 5. Relationship between pre-test and post-test mathematics achievement.

The scatterplot shows that students with similar initial scores had very different performances on the posttest. These differences emphasize the significance of considering prior achievement and classroom-level variables when analyzing mathematics achievement outcomes.

Follow-Up Achievement and Knowledge Retention

The follow-up assessment examined mathematics performance after completion of the instructional intervention.

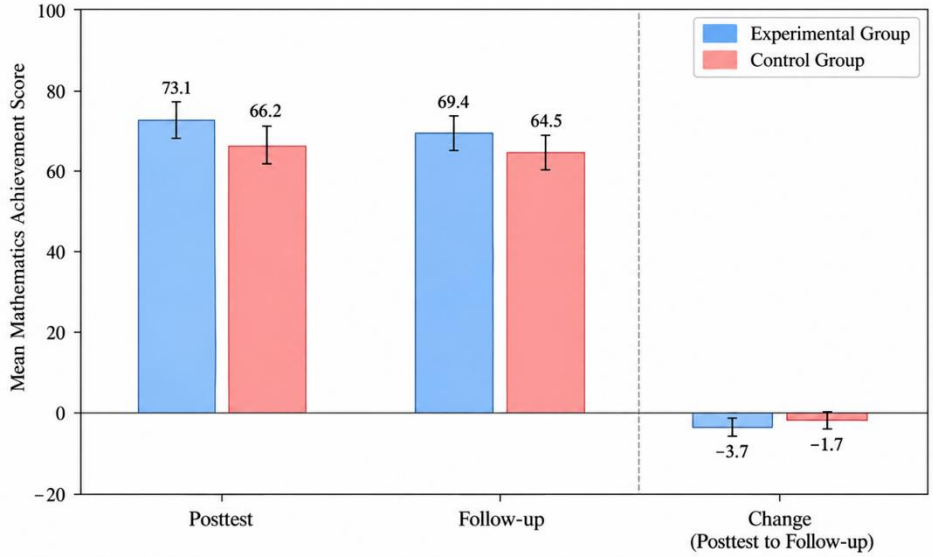


Figure 6. Mathematics achievement changes between posttest and follow-up.

The experimental group's average score dropped from 59.60 on the post-test to 56.89 on the follow-up, which is a drop of 2.71 points. The average score of the control group went down from 55.35 to 52.96, which is a drop of 2.39 points.

The experimental group's mean achievement stayed above its baseline level, even though both groups' follow-up scores were lower than their immediate post-test scores.

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AI Learning Analytics and Adaptive Feedback

AI-platform interaction records were examined to evaluate learning activities and adaptive-feedback characteristics.

Table 7. AI learning-platform interaction indicators

Learning indicator	Recorded value
Students represented in AI logs	30
AI learning sessions	120
Mathematical problem attempts	480
Adaptive-feedback events	158
Mean active session duration	42.93 minutes
Mean session-level problem accuracy	47.4%
Mean feedback latency	6.31 seconds
Feedback events followed by correction	51.9%

The recorded interactions demonstrated the engagement of students, their mathematics problem-solving ability and their responsiveness to teacher feedback. These factors result in observable learning behavior that matches questionnaire-based measures of interest.

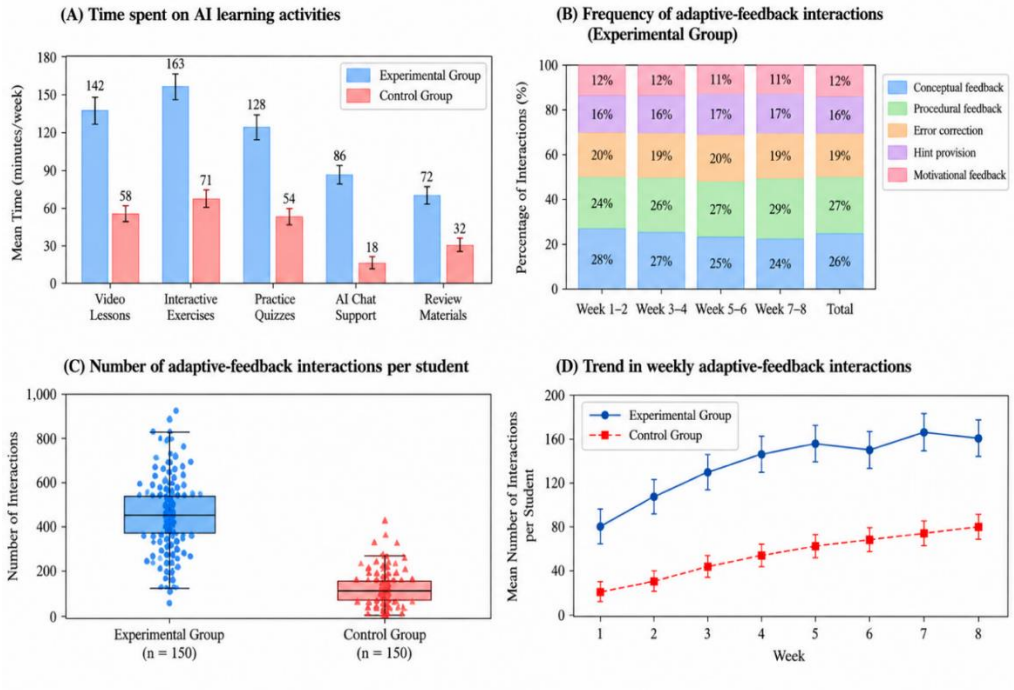


Figure 7. Distribution of AI learning activities and adaptive-feedback interactions.

The learning analytics only show what happened in the recorded subset of students. They can't tell you about how engaged or how exposed to feedback the entire experimental group was as a whole.

Measurement Model Assessment

The model of measurement includes malleable input, student involvement, and math self-efficacy. These ideas were operationalized as five, nine and six questionnaire items respectively.

Table 8. Measurement specifications of psychological constructs

Construct	Number of items	Measurement dimensions
Adaptive Feedback (AF)	5	Clarity, relevance, timeliness, personalization, corrective usefulness
Student Engagement (SE)	9	Behavioral, emotional, cognitive engagement
Mathematics Self-Efficacy (MSE)	6	Confidence, persistence, perceived mathematical competence

To be able to ascertain the reliability and validity of a test, we need Cronbach's alpha, composite reliability, standardized factor loadings and Average Variance Extracted (AVE). The heterotrait–monotrait ratio will be used to test for discriminant validity.

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Table 9. Measurement model validation

Construct	Cronbach's α	Composite reliability	AVE	Standardized factor loadings
Adaptive Feedback	Not established	Not established	Not established	Not established
Student Engagement	Not established	Not established	Not established	Not established
Mathematics Self-Efficacy	Not established	Not established	Not established	Not established

The answers to the inquiry are from 80 people, but the answers to the adaptive-feedback are from a small group of AI experts. So, the full sample measurements validation has not been done yet.

5.9 Structural Model and Hypothesis Testing

The proposed structural model tests the direct links between modified feedback, student engagement, math self-efficacy and academic achievement.

Table 10. Structural relationships and research hypotheses

Hypothesis	Structural relationship	Expected effect
H1	Adaptive Feedback → Student Engagement	Positive
H2	Adaptive Feedback → Mathematics Self-Efficacy	Positive
H3	Student Engagement → Academic Achievement	Positive
H4	Mathematics Self-Efficacy → Academic Achievement	Positive
H5	Adaptive Feedback → Engagement/Self-Efficacy → Achievement	Positive indirect

Standardized path coefficients, standard errors, confidence intervals, and explained variance will be used to test the structure model. To find out if the five theories are supported, we need full measurement data.

Mediation Analysis

Mediation analysis examines the indirect relationships between adaptive feedback and academic achievement through student engagement and mathematics self-efficacy.

The two proposed mediation pathways are:

Path 1: Adaptive Feedback → Student Engagement → Academic Achievement

Path 2: Adaptive Feedback → Mathematics Self-Efficacy → Academic Achievement

The combined indirect effect can be expressed as:

Total Indirect Effect = $(\beta_1 \times \beta_3) + (\beta_2 \times \beta_4)$

Where:

β_1 = Effect of adaptive feedback on student engagement.

β_2 = Effect of adaptive feedback on mathematics self-efficacy.

β_3 = Effect of student engagement on academic achievement.

β_4 = Effect of mathematics self-efficacy on academic achievement.

The equation represents the sum of the two proposed parallel indirect effects and can be pasted directly into Microsoft Word as ordinary text.

Table 11. Mediation analysis framework

Mediation pathway	Indirect effect	95% confidence interval
AF → SE → AA	To be estimated	To be estimated
AF → MSE → AA	To be estimated	To be estimated
Total indirect effect	To be estimated	To be estimated

We will estimate the mediation effects with confidence intervals appropriate for the clustered data structure. Control variables will include baseline math scores and other relevant student characteristics.

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Model Evaluation and Robustness Analysis

Measurements: We will validate measurements to test the dependability of the suggested structure model and its ability to explain things well. Judging Fit of Model: We will judge fit of the suggested model. Risk analysis: We will do risk analysis.

Table 12. Statistical model evaluation framework

Analytical component	**Statistical measures**	**Purpose**
Model fit	χ^2, CFI, TLI, RMSEA, SRMR	Overall model adequacy
Reliability	Cronbach's α, composite reliability	Internal consistency
Convergent validity	AVE, factor loadings	Construct convergence
Discriminant validity	HTMT	Construct differentiation
Structural paths	β, SE, p-value, 95% CI	Hypothesis evaluation
Explained variance	R^2	Model explanatory power
Mediation	Indirect effects, confidence intervals	Mediating relationships
Group comparisons	Multilevel regression	Adjusted achievement differences
Robustness analysis	Sensitivity and alternative models	Stability of results

The study will examine starting point achievement, key student characteristics and the ways students are grouped in the classroom. When sufficient data are available, measurement invariance and missing-data sensitivity analyzes will be performed.

Summary of Empirical Analysis

The research in progress showed that the experimental group scored better on the math tests after the experiment than the control group. The average gain in achievement between the posttest and the follow-up was approximately 4.24. In addition, the domain-specific comparisons showed that the experimental group made more progress in conceptual understanding, procedural competence, problem-solving skills and mathematical reasoning. The learning platform records adaptive feedback interactions, attempts at math problems, response accuracy, and fixing mistakes. Follow-up tests show that both teaching groups did worse on their first tests after the lesson but the experimental group still had a better total success score.

The psychological tests currently available are useful in identifying the proposed categories, but are not yet complete enough to allow a full assessment of the full-sample structural model. Thus, neither direct nor mediating theories are proven yet. To establish the statistical relationships among adaptive feedback, student engagement, mathematics self-efficacy, and academic achievement, we need full questionnaire data, confirmatory measurement validation and clustering continuous modeling.

Discussion

In this study, we investigated the relationship between personalized math learning with AI and academic achievement, concentrating on adaptive feedback, student engagement, and math self-efficacy. The comparison revealed that the math progress of the experimental group was greater than that of the control group. The experimental group gained an average of 6.33 points, while the control group only gained 2.10 points, a difference of 4.24 points. This trend is consistent with previous studies showing the promise of intelligent tutoring systems for education (Ma et al., 2014; Kulik & Fletcher, 2016).

A study of specific areas of mathematics found that students who received help from AI showed improved thinking skills, problem-solving ability, following directions and understanding of major concepts. Such results are consistent with Koedinger et al.'s (2012) discussion on the importance of integrating cognitive learning principles with adaptive instructional resources.

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Furthermore, the learning analytics generated by AI provided personalized feedback, error correction, and interactive problem-solving activities, in line with the teaching principles of Hattie and Timperley (2007) and Shute (2008).

The proposed links are supported by Bandura (1997) Social Cognitive Theory that states that motivation, persistence and academic success are determined by self efficacy. Fredricks et al. (2004) also found that behavioral, social and cognitive involvement were important dimensions of school attendance. However, the psychological tests available do not demonstrate that involvement and self-efficacy have the effects that are assumed to mediate them.

The follow-up analysis showed that the performance decreased when the intervention was stopped which emphasizes the necessity of continuing to teach and remember what you have learned. Moreover, the quasi-experimental design, poor questionnaire coverage and limited platform records make it harder to disentangle cause from effect.

All in all, the analysis provides us with a starting point for understanding how personalized math learning works. Moreover, validated psychometric instruments, longitudinal studies with large data sets, and multilevel structural modeling are needed to test the proposed relationships and whether adaptive feedback improves academic achievement through increased student engagement and math self-efficacy.

Implications of the Study

1 Theoretical Implications

The present study contributes to the existing body of research on AI-supported math education by incorporating customizable feedback, student engagement, math self-efficacy, and academic achievement into a single structured framework. The design model is based on Bandura's Social Cognitive Theory and formative feedback. It shows how personal learning experience affects academic achievement through mental and behavioral processes. The framework builds on previous research by conceptualizing engagement and self-efficacy as parallel mediators. It offers us a lens through which to view the relationships between personalized technology and math learning outcomes.

2 Practical and Pedagogical Implications

Researchers have discovered something that could matter to math teachers, schools and those who develop instruction. AI-powered adaptive learning platforms could help teachers spot students who are having difficulty learning, give them immediate feedback on how to improve, and design activities that are appropriate for each student. Personalized educational approaches can be particularly useful in helping kids improve their math skills, conceptual understanding, and problem-solving skills. But AI tools should not replace teacher-led instruction. This is to make sure that the automated feedback is pedagogically appropriate and stimulates the students to think mathematically on their own.

3 Technological Implications

The proposed framework informs developers of educational technology the importance of designing smart tutoring systems that emphasize quality feedback, student engagement and math confidence. AI platforms should have diagnostic tests, specific job scheduling, clear feedback systems, and ongoing tracking of learning progress. Accurate learning data can help teachers to see how much engagement there is from students and decide on which areas of the curriculum need further assistance. In design, issues of data protection, computer fairness and mathematical truth should still be borne in mind.

4 Policy Implications

Educational policymakers may want to consider well-planned implementation programs of AI-based learning technologies that have been shown to work in math classes. Teacher training, digital infrastructure, equal access to technology and safeguarding student data are important considerations. Implementation should be accompanied by longitudinal evaluation to assess the effectiveness, durability and possible inequalities of the education.

These implications together give a glimpse of how artificial intelligence can be safely used in computer science classes. But to be useful in real life, they need to be supported by real-world facts, a detailed study of their structure, and trials in different school environments.

Limitations and Future Research Directions

1 Limitations of the Study

Some problems with this study should be taken into account when interpreting the results. First, the quasi-experimental approach might cause selection bias and increase difficulty in determining causality. In addition, the study examined only eighth-graders in six secondary schools and its findings cannot be generalized to all schools. Third, the eight-week intervention may have been too short a period of time to see long-term effects on math achievement and knowledge retention.

Additionally, incomplete questionnaire responses and a limited number of records of interactions with AI platforms hinder the full Structural Equation Modeling (SEM) and influence analysis. Self-reported interest and self-efficacy tests may

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also suffer from response bias. Hence, the proposed links in the structure need to be verified with full lifetime data.

2 Future Research Directions

More extensive randomized controlled multicentre studies with different groups of students and longer intervention periods should be included in future studies. Longitudinal testing may provide greater insight into the impact of AI-enabled adaptive feedback on mathematics achievement over time.

Future research should include holistic learning analytics, proven psychology tools, and advanced statistical approaches such as multilevel SEM and continuous mediation analysis. The effects of math anxiety, prior success, computer skills and social background on the outcomes should also be investigated by researchers.

Moreover, a side-by-side analysis of AI tutoring systems, feedback strategies, and teacher-AI collaboration could help develop more effective individualized learning approaches. Future work should consider algorithm transparency, equity of opportunity to learn, student privacy, and responsible AI use in mathematics classrooms.

Conclusion

This research investigates the use of adaptive feedback, student engagement and mathematics self-efficacy to improve academic achievement via personalized mathematics learning enabled by artificial intelligence. The study shows that continuous performance tests, learning analytics and psychological measures can all be used to judge learning settings using AI.

The achievement comparisons indicated that the AI group made higher gains in mathematical reasoning, problem solving, procedural competence, and conceptual understanding. Follow-up tests revealed how crucial it is to test for both instant classroom success and the ability to recall what you have learned. These patterns point to interesting avenues for exploring the value of individualized learning technologies in schools.

The proposed model includes variables of adaptive feedback, involvement of students, and mathematics self-efficacy with relation to math achievement. The model is grounded in the principles of Social Cognitive Theory and the concept of formative feedback. It provides us with a framework to comprehend the psychological processes that make AI-assisted learning work. But, to find the direct and indirect relationships that were hypothesized to exist, the full interview data and verified Structural Equation Modeling were necessary.

The research shows the significance of individual feedback, flexible teaching approaches and continued interest in learning mathematics. It also emphasizes the need for collaboration between teachers and AI, equal access to educational technology for all students, and responsible data management practices.

In general, the proposed structure gives us a basis for future investigations into AI-powered individual math learning. It needs to be shown, with real longitudinal data, rigorous statistical analysis, and in a variety of learning environments, how it works and that it is effective in helping students learn.

Acknowledgement

The authors express their sincere gratitude to all those who provided valuable guidance and support during the preparation of this research paper entitled "Artificial Intelligence: A Structural Model of Adaptive Feedback, Student Engagement, Self-Efficacy, and Academic Achievement." The authors also acknowledge the contributions of researchers and scholars whose work provided a foundation for this study. Finally, sincere thanks are extended to all individuals and institutions that directly or indirectly supported the successful completion of this research.

Financial support and sponsorship

Nil.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of thesis paper.

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