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Original Article

Artificial Intelligence versus Conventional Mathematics Teaching: An Empirical Assessment of Learning Outcomes, Cognitive Engagement, and Mathematical Reasoning

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Abstract-

The rapid use of artificial intelligence (AI) tools in education has changed the way standard lessons are taught. This has led to important questions about how well these tools can improve math learning, cognitive engagement, and higher-order thinking skills. This paper describes a long-term experimental framework that we will use to compare how well (1) traditional math instruction, (2) unrestricted AI-assisted learning, and (3) pedagogically scaffolded AI tutoring work. The sample was made up of 720 high school students from nine schools, evenly split between the three teaching groups. A 10-week instructional intervention is what the study is based on. Assessments at the start, after the intervention, and later on are used to judge mathematical achievement, cognitive engagement, mathematical reasoning, knowledge retention, and learning transfer. The example sample shows that all three groups got better at math. The mean post-test scores for standard teaching, unrestricted AI help, and scaffolded AI coaching were 61.51, 73.16, and 77.94, respectively. When it comes to math reasoning (72.98), cognitive engagement (3.65/5), and learning transfer performance (75.93), scaffolded AI teaching also gets the highest scores. Also, delayed assessment patterns show that AI training with scaffolding improves retention even more. The suggested analysis plan includes multilevel regression, longitudinal mixed effects modeling, effect size estimates, and mediation analysis to look into differences in instruction while taking into account students' starting levels of skill and variation across the classroom. These trends show that organized educational scaffolding may be better than having free access to AI answers because it helps students understand concepts, use their brains actively, and do math on their own. The study gives us a scientific way to judge AI-assisted math education and stresses how important it is for educational design to combine technology with students' ability to learn on their own.

Keywords: *Artificial Intelligence; Mathematics Education; Conventional Teaching; AI-Assisted Learning; Cognitive Engagement; Mathematical Reasoning; Intelligent Tutoring Systems; Learning Outcomes; Knowledge Retention; Educational Technology.*

Introduction

Transformation of Mathematics Education in the Artificial Intelligence Era

The fast spread of artificial intelligence (AI) tools in schools is changing how regular lessons are taught. This has made people wonder how well these tools work to help people learn math, stay interested in learning, and develop higher-order thought skills. We are going to use a long-term study approach to compare how well (1) standard math teaching, (2) unconstrained AI-assisted learning, and (3) AI coaching that is built around the needs of the teacher. There were 720 high school students in the sample, evenly split between three teaching groups.

They came from nine schools. It is based on a 10-week intervention in the classroom. Before, during, and after the intervention, students' math skills, cognitive engagement, mathematical reasoning, knowledge retention, and ability to apply what they have learned are all evaluated. The case shows that all three groups got better at math. For standard teaching, the average post-test score was 61.51; for open-ended AI help, it was 73.16; and for scaffolded AI coaching, it was 77.94. When it comes to math reasoning (72.98),

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Cognitive engagement (3.65/5), and learning transfer performance (75.93), scaffolded AI teaching does better. Delayed assessment patterns also show that AI training with scaffolding improves retention even more. The suggested analysis plan includes multilevel regression, continuous mixed effects modeling, effect size estimates, and mediation analysis to look into how teaching differs, taking into account the students' starting skill levels and how they are taught in different classrooms. All of these trends suggest that organized educational scaffolding might be better than free access to AI answers. This is because structured educational scaffolding could help students understand ideas, keep their minds active, and do math on their own. The study gives a scientific way to look at AI-assisted math education and shows how important it is for educational design to combine technology with students' ability to learn on their own.

Limitations and Strengths of Conventional Mathematics Teaching

Even though there are many new ways to teach math, traditional teaching is still very important because it includes a structured curriculum, direct teacher–student interaction, guided demonstrations, and the systematic development of mathematical concepts. Teachers help students learn by setting the scene, leading class discussions, getting students to work together, and, when necessary, giving each student extra help. Vygotsky (1978) talked about how important social contact and guided teaching are for brain growth. He suggested that students learn math by interacting with people who know more than them in useful ways. Clements and Sarama (2014) also talked about how important developmental learning paths are in math education. They said, "Good instruction depends on children's prior conceptual knowledge and their developmental progression in mathematics" (p. 49). When the right teaching methods are used, these points of view show that standard teaching is a good way to help students understand ideas and think mathematically. Traditional learning environments, on the other hand, often have issues like students with different levels of ability, limited class time, feedback that isn't given right away, and issues with giving continuous individualized help.

It is important for students to get good feedback in order to do well in school (Hattie & Timperley, 2007), and the way students are motivated in the classroom affects their engagement and behavior related to achievement (Ames, 1992). Rittle-Johnson (2017) also talked about how conceptual and procedural mathematical knowledge development are connected and how the success of teaching relies on how well students understand mathematical links rather than how well they can repeat mathematical processes.

Traditional education has a lot of good points for learning, but it might not work as well for students who need different explanations, instant feedback, or more chances to practice on their own. Because of these limitations, there is growing interest in AI-assisted learning methods that can be used in addition to traditional ways of teaching in the classroom.

Emergence of AI-Assisted Mathematics Instruction

With smart teaching systems, adaptable learning platforms, automatic evaluation tools, and engaging learning technologies, AI has helped math education move forward. These systems use computers to look at how students answer questions, find out what they're not understanding, give them personalized exercises, and give them feedback on their work. It was Koedinger et al. (1997) who showed how clever teaching systems can be used in schools. This laid the groundwork for using computers to help teach math. Graesser et al. (2004) later published AutoTutor, which showed how natural-language dialog could help with interactive tutoring and keep students interested. Koedinger et al. (2012) also came up with the Knowledge-Learning-Instruction framework, which shows how important it is to match teaching methods with cognitive learning processes and knowledge acquisition.

Empirical studies have shown that clever teaching tools can be useful for learning in a variety of classroom settings. Kulick and Fletcher (2016) used a meta-analysis to look at how well intelligent tutoring systems work generally, and Ma et al. (2014) looked at the evidence about intelligent teaching systems and how well they help students learn. Steenbergen-Hu and Cooper (2013) did a specific review of how well intelligent tutoring systems help students learn math in school. They found more evidence that technology can help students do well in math. VanLehn (2011) looked at how useful human tutoring and intelligent tutoring technologies were compared, focusing on how important it was for students to be able to interact with and get feedback from their teachers. Roschelle et al. (2016) also showed that online math homework that is supported by technology could help students do better in school.

AI-assisted instruction may help students learn, but it may not help students learn at all depending on how it is designed and used. Artificial intelligence systems that are not limited in any way can fully explain their behaviors and quickly solve math

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problems. These traits can make it easier to get things done quickly and lessen the chances of having to figure things out on your own. Pedagogically scaffolded AI settings, on the other hand, can help students come up with intermediate answers, look into mathematical connections, find mistakes, and gradually gain a better understanding of the big picture. Because of this, it is very important to tell the difference between free AI support and structured AI tutoring. This way, we can figure out if the technology really helps people learn math or just helps them do better right away.

Cognitive Engagement and Mathematical Reasoning

For math teaching to be effective, students must be able to think critically. Meaningful learning happens when students actively think about, review, and use what they've learned in math instead of just idly taking it in. Fredricks et al. (2004) thought of student engagement as having behavioral, emotional, and cognitive aspects. They also said that academic participation is more than just doing things in class that can be seen. Zimmerman (2002) also said that self-regulated learning is a process that includes setting goals, making plans, keeping an eye on oneself, and judging one's own performance. According to Järvelä and Renninger (2014), technology-enabled learning settings can help students stay motivated and learn on their own if the tasks are planned well. If you use AI to help you teach math, these theories say that personalized feedback and hands-on explanations might make students more interested in learning. Using technology more, on the other hand, does not always lead to better learning.

Emotional situations of students also affect how interested they are in math and how well they do in school. Pekrun (2006) says that achievement-related emotions are linked to how learners feel about their control and the value of the task, which affects their motivation and how they learn. It was shown by Baker et al. (2010) that anger and boredom may affect learning in computer-based classrooms in different ways. In 2012, D'Mello and Graesser looked into how changing emotional states affect complex learning tasks. These results show how important it is to tell the difference between cognitive engagement that is meaningful and engagement that is just for fun, for learning about new technology, or for regular exposure to automated systems.

Mathematical reasoning is a different educational goal that goes along with procedural skill but is not the same thing. It includes things like logical inference, mental proof, mathematical arguments, finding mistakes, and using what you know to solve new problems. Schoenfeld (2016) stressed that mathematical competence is more than just being able to repeat steps. It also includes being able to solve problems, be aware of how you think, and make sense of things in a meaningful way. Sweller (2011) made cognitive load theory more useful for understanding how learning environments affect how people learn. It's possible that explanations made by AI could help reduce cognitive load that isn't needed, but too much help with learning could make it harder to think for yourself. So, brain involvement, mathematical success, thinking skills, and knowledge recall should all be looked at together to see how well AI-assisted math training works.

Research Problem and Identified Research Gap

A lot of study has been done on how clever teaching systems and technology-supported learning settings can help students learn. Meta-analytical study by Ma et al. (2014), Steenbergen-Hu and Cooper (2013), and Kulik and Fletcher (2016) has helped us understand how well intelligent teaching tools improve learning results. But improvements in math skills right away don't always mean improvements in the ability to think for oneself, stay interested in learning, understand concepts, or remember things over time. Also, the results of AI-supported learning in traditional classrooms are harder to understand because the learning environment, learner characteristics, assessment conditions, and length of the intervention are all different.

One important study question is how to tell the difference between math skills that are improved with AI and math skills that are learned on your own. When students are given automated explanations or full solutions, they can finish their work without necessarily getting the conceptual understanding they need to solve similar problems on their own. The ideas of instructional feedback, cognitive scaffolding, and self-regulated learning are well-known (Vygotsky, 1978; Hattie & Timperley, 2007; Zimmerman, 2002). However, no research has yet been done on how well unrestricted AI assistance and pedagogically scaffolded AI tutoring work for different types of learning outcomes. Also, cognitive involvement and mathematical thinking are usually seen as two different things. This means that researchers can look into how they relate to each other in a single lab setting.

This study is the first to compare and contrast traditional math instruction, unrestricted AI-assisted instruction, and pedagogically scaffolded AI tutoring all at the same time. A lot of attention is paid to finding out if changes in how math is taught are linked to real improvements in brain

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involvement, independent thinking, information retention, and learning transfer. This way of looking at it looks at how well teaching works beyond just how well students do in school right now. It also helps us understand how AI-based educational help might affect long-term math skills.

Research Aim and Major Contributions

The purpose of this study is to compare how well traditional math teaching, unrestricted AI-assisted learning, and pedagogically scaffolded AI coaching affect the math skills, cognitive engagement, and mathematical thinking of college students. The study's design includes 720 students from nine schools who are taught in three different ways. An educational intervention lasts for 10 weeks, and students are tested several times to find out their starting level of skill, how well they are learning right away, and how well they are remembering things later on. This study creates a framework for measuring how well math is taught by combining concepts, cognitive effort, self-regulated learning, independent reasoning, and transfer performance into a number of different areas.

The study is organized into three main parts. First, it gives a framework for comparing how normal instruction, unrestricted AI help, and pedagogically scaffolded AI tutoring are different, so that differences in instructional design can be studied in a structured way. Second, it combines mathematical thinking, cognitive involvement, and academic success, giving a more full picture of how well education is working than test scores alone. Third, the study uses longitudinal testing and multilevel statistical analysis to look at differences in how math is taught, how students learn, and possible ways to explain these differences. It does this while taking into account students' previous math skills and differences at the classroom level. The study aims to add to evidence-based math education by connecting teaching methods to cognitive processes and learning outcomes that can be independently assessed. It also aims to help the creation of AI-supported teaching methods that promote deep understanding, self-regulated learning, and long-term mathematical competence.

Literature Review and Theoretical Framework

Conventional Pedagogical Approaches in Mathematics Education

In the traditional sense of teaching math, it is up to the teacher to guide students' practice, teach, and interact with the class in order to build their knowledge and problem-solving skills. Vygotsky (1978) stressed guided learning and social interaction as important parts of cognitive development; Clements and Sarama (2014) stressed progressive learning trajectories to help students understand math. In 2007, Hattie and Timperley found that instructional feedback was a key part of getting better grades. According to Ames (1992), the way students are motivated in the classroom affects how engaged and successful they are. In addition, Rittle-Johnson (2017) said that basic and practical mathematical understanding grow together. The good things about traditional teaching are that it gives students structured ways to learn and direct interactions with their teachers. Individualized feedback, different learning styles, and control over the pace of instruction are some of the problems it faces, which may make it less useful in some classroom settings. These kinds of problems are what led to study into AI-powered teaching methods that can offer flexible help and personalized learning experiences.

AI-Based Tutoring and Adaptive Mathematics Learning

Artificial intelligence has transformed mathematics smart teaching systems, adaptable learning systems, and automatic feedback systems can all help people learn. Intelligent teaching technologies have been shown to be useful in education by Koedinger et al. (1997). Graesser et al. (2004) created AutoTutor to support engaging learning through natural-language conversation. After that, Koedinger et al. (2012) came up with the Knowledge-Learning-Instruction framework, which focused on how cognitive learning principles and instructional technologies can work together. Meta-analyses by Ma et al. (2014), Steenbergen-Hu and Cooper (2013), and Kulik and Fletcher (2016) all showed that intelligent tutoring systems can help students do better in school, but the effects were not all the same. VanLehn (2011) also said that exchanges between tutors and students are a big part of figuring out how well they teach. Open-ended AI support, on the other hand, might make people rely too much on automated solutions instead of pedagogically scaffolded tutoring that helps with conceptual clarification, incremental reasoning, and solving problems on their own.

Table 1. Comparison of conventional and AI-assisted mathematics instruction

Dimension	Conventional teaching	Unrestricted AI	Scaffolded AI
Instruction	Teacher-directed	Automated assistance	Guided AI tutoring
Feedback	Teacher-generated	Immediate	Progressive hints

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		solutions	
Learning pace	Classroom-based	Learner-controlled	Adaptive guidance
Cognitive engagement	ided participation	Potentially passive	Active reasoning
Problem-solving	Teacher-supported	AI-generated solutions	Stepwise independent solutions
Major limitation	Limited personalization	AI dependency	Requires effective instructional design

Source: Synthesized from Koedinger et al. (1997, 2012), VanLehn (2011), and Holmes et al. (2019).

Learning Outcomes and Mathematical Achievement

A student's mathematical achievement is a mix of their conceptual understanding, procedural fluency, problem-solving accuracy, and their ability to use what they've learned in different situations. Rittle-Johnson (2017) showed that conceptual and procedural understanding are connected in a way that works both ways. Koedinger et al. (2012) talked about how important it is to make sure that learning activities are in line with how people think and learn. Roschelle et al. (2016) found that using technology to help with math projects improved students' grades. Similarly, intelligent tutoring systems were shown to help students learn (Ma et al., 2014; Kulik & Fletcher, 2016). But a quick improvement in problem-solving skills doesn't always mean long-term success in math. So, achievement after intervention, knowledge retention, and the ability to use mathematical concepts on your own should all be used to judge AI-assisted instruction.

Cognitive Engagement in AI-Supported Learning

Cognitive involvement means that students are working hard with their minds, learning strategically, keeping an eye on themselves, and taking an active role in school events. Fredricks et al. (2004) said that cognitive engagement is a basic part of student engagement, and Zimmerman (2002) said that self-regulation is an important part of learning in school. Järvelä and Renninger (2014) talked about how important it is for self-regulated learning and motivation to be in environments that use technology. A study by Pekrun (2006) called the control-value theory of success feelings shows that emotional factors also play a role in involvement. Baker et al. (2010) and D'Mello and Graesser (2012) add to the evidence that frustration, boredom, and other emotional states are important in technology-supported learning. Even though AI systems can give you immediate feedback and personalized help, using technology all the time doesn't always mean you're having meaningful cognitive interactions. It is best to measure cognitive work, strategy learning, and self-regulation independently.

Mathematical Reasoning and Independent Problem-Solving

The process of mathematical reasoning includes drawing logical conclusions, explaining ideas, figuring out what a problem means, and judging the correctness of mathematical solutions. Schoenfeld (2016) said that problem-solving, metacognition, and making sense of math are all important parts of being good at math.

According to the National Council of Teachers of Mathematics (2014), the main goals of education are to help students understand concepts and reason. Smart teaching systems can help students figure out math problems by giving them specific answers and comments on how to improve (Graesser et al., 2004; VanLehn, 2011).

Too much dependence on automatic solutions could make it harder for people to think for themselves. Pedagogically scaffolded AI teaching can help with this problem by getting students to come up with intermediate steps, explain their answers, and spot mistakes. So, rational support, mathematical inference, mental explanation, and the ability to solve problems on your own should be used to grade mathematical thinking.

Theoretical Foundations

Building on the ideas of cognitive load, constructivism, and self-regulated learning, this study looks at how people learn. Active knowledge building and teaching support are important parts of constructivist methods, especially when it comes to guided learning (Vygotsky, 1978). Cognitive load theory (Sweller, 2011) talks about how the way lessons are designed affects how students receive knowledge and how much work their working memories have to do. AI-generated answers might take away mental workloads that aren't necessary, but too much help might make people less mentally efficient. Self-regulated learning theory says that students can plan, keep an eye on, and evaluate their own learning tasks (Zimmerman, 2002). For motivation and self-control, Järvelä and Renninger (2014) also talked about how important technological learning environments are. These theories suggest that personalized help from AI is

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most useful for learning when it is combined with active brain involvement and independent thinking.

Critical Literature Synthesis and Research Gap

Smart teaching systems can help students do better in school, but the outcomes rely on the school setting and the way the lessons are planned (Ma et al., 2014; Steenbergen-Hu & Cooper, 2013; Kulik & Fletcher, 2016). Researchers (Hattie & Timperley, 2007; Fredricks, et al., 2004; Zimmerman, 2002) have also talked about how important it is to give students feedback, keep their minds active, and let them learn on their own. More real-world research is needed, though, to separate gains in success on AI-assisted tasks from improvements in math skills and long-term learning. In particular, data from different studies should be compared on brain involvement, mathematical thinking, information retention, and unconstrained AI help.

Table 2. Research gaps and proposed contributions

Research dimension	Identified gap	Proposed contribution
Teaching approaches	Differences among AI instructional designs	Three-group experimental comparison
Learning outcomes	Emphasis on immediate achievement	Pre-test, post-test, and delayed assessments
Cognitive engagement	Limited distinction between interaction and cognitive effort	Multidimensional engagement analysis
Mathematical reasoning	Reliance on problem-solving accuracy	Independent reasoning assessment
Knowledge retention	Limited evidence of sustained learning	Delayed retention and transfer tests
Learning mechanisms	Incomplete explanation of instructional effects	Multilevel and mediation analysis

Source: Authors' synthesis of the reviewed literature.

This study tries to fill in these gaps by comparing traditional math teaching with free AI-assisted learning and pedagogically scaffolded AI coaching over a long period of time. The study aims to give a full picture of how educational design affects the success of AI-supported mathematics education by looking at math performance, cognitive involvement, independent thinking, and information recall.

Research Objectives And Hypotheses

Research Objectives

RO1: To compare the effects of conventional teaching, unrestricted AI assistance, and scaffolded AI tutoring on mathematical achievement and conceptual understanding.

RO2: To examine the influence of instructional approaches on cognitive engagement and self-regulated learning.

RO3: To evaluate the effectiveness of scaffolded AI tutoring in enhancing mathematical reasoning and independent problem-solving.

RO4: To assess the impact of instructional approaches on mathematical knowledge retention and learning transfer.

Research Hypotheses

H1: Significant differences exist in mathematical achievement and conceptual understanding across the three instructional approaches.

H2: Scaffolded AI tutoring significantly improves cognitive engagement and self-regulated learning compared with conventional teaching and unrestricted AI assistance.

H3: Scaffolded AI tutoring significantly enhances mathematical reasoning and independent problem-solving compared with the other instructional approaches.

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H4: Scaffolded AI tutoring results in significantly greater knowledge retention and learning transfer than conventional teaching and unrestricted AI assistance.

Materials and Methods

Research Design

This research uses a longitudinal three-arm cluster-randomized controlled design to look at the differences between traditional math teaching, learning with unrestricted artificial intelligence (AI), and providing pedagogically scaffolded AI tutoring. With 720 secondary school students from nine schools spread out equally among 36 classes and three teaching groups, the study setup is complete. This is what happens after a ten-week instructional intervention: a four-week retention assessment. Mathematics success is the main result. A few examples of secondary outcomes are cognitive engagement, conceptual understanding, mathematical reasoning, and learning transfer. Randomization happens at the classroom level to keep lessons from getting messed up, and multilevel statistical methods are used to control for differences at the start and classroom grouping.

Participants and Experimental Allocation

There are 720 students in the study, spread out across 36 classrooms with 20 students in each. There are 12 classes in each teaching situation. Secondary school kids who are taking the chosen math program are eligible to take part. Computer-generated randomization, preferably based on school, decides which classrooms go to which students. An a priori power analysis will be used to find the right sample size. This will be based on the expected effect size, the intraclass correlation, the statistical power $(1 - \beta) \geq 0.80$, and the significance level $\alpha = 0.05$.

Table 3. Distribution of participants across experimental groups

Group	Instructional approach	Students (n)	Classrooms
G1	Conventional mathematics teaching	240	12
G2	Unrestricted AI-assisted learning	240	12
G3	Pedagogically scaffolded AI tutoring	240	12
Total		720	36

Instructional Intervention

There is the same math program, the same amount of time to learn, and the same learning goals for all three groups.

Group G1 (Conventional Teaching): This is the traditional way of teaching. Students get explanations, worked examples, textbook exercises, class discussions, and feedback in the usual way.

Group G2 (Unrestricted AI-Assisted Learning): Students use an AI math teacher that gives them instant math explanations, full answers, and automated comments without them having to do any thinking in the middle.

Group G3 (Scaffolded AI Tutoring): Students work with an AI teacher that gives them tips, basic questions, error-specific comments, and help with solving problems so that they can think for themselves.

AI model configurations, learning activities, and instructional prompts in a way that is consistent and well-documented. Monitoring and checking for accuracy in the classroom once a week make sure that the solution is always the same.

Methodological Framework

The methodological framework involves baseline evaluation, classroom-level randomization, instructional intervention, immediate post-testing, delayed assessment, and statistical analysis. The complete experimental procedure is illustrated in Figure 1.

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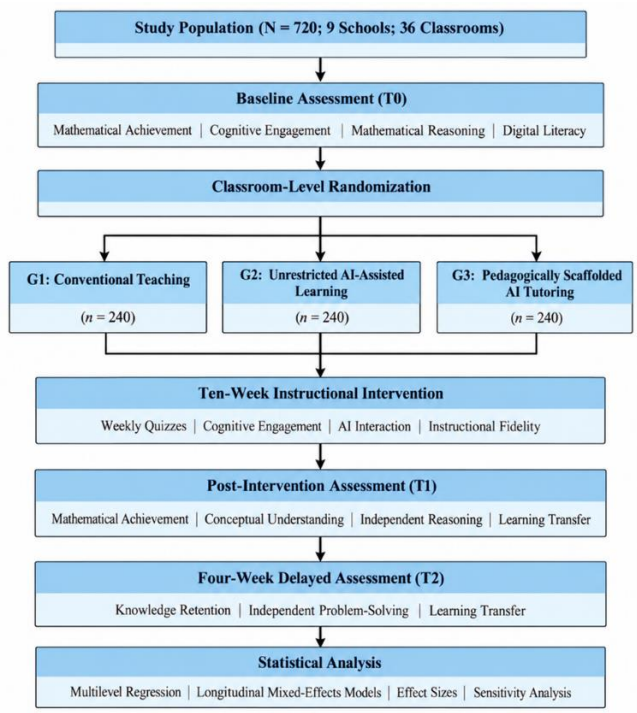


Figure 1. Methodological framework for comparing conventional teaching, unrestricted AI assistance, and scaffolded AI tutoring.

4.5 Research Instruments and Data Collection

On a scale from 0 to 100, curriculum-aligned tests measure math skills, conceptual understanding, reasoning, and the ability to apply what you've learned. Five-point Likert scores are used to measure cognitive involvement and self-regulated learning.

Logic, mathematical inference, conceptual explanation, and recognizing error are all parts of evaluating mathematical reasoning. At the start (T 0), right after the ten-week intervention time (T 1), and four weeks after the end (T 2), data are gathered. We also make 7200 observations every week to check on learning progress and teacher participation. There is no AI help with any of the primary outcome assessments.

Table 4. Research variables and measurement framework

Research variable	Measurement	Assessment period
Mathematical achievement	Assessment score (0–100)	T_0, T_1, T_2
Cognitive engagement	Five-point Likert scale	T_0, weekly, T_1
Mathematical reasoning	Rubric-based score (0–100)	T_0, T_1, T_2
Conceptual understanding	Curriculum-aligned test (0–100)	T_0, T_1
Knowledge retention	Delayed achievement assessment	T_2
Learning transfer	Unfamiliar mathematical problems	T_1, T_2
AI interaction	Prompt frequency, hint requests, solution requests	Weekly (G2 and G3)

Instrument Validity and Reliability

Expert evaluation and pilot testing are used to prove the validity of instruments. Cronbach's alpha (α) and McDonald's omega (ω) are used to measure internal stability. Values of about 0.70 or higher are usually considered reasonable. The intraclass correlation coefficient (ICC) is used to figure out how reliable different raters' assessments of mathematical reasoning are. Standardizing how tests are given, making sure that all tests are about the same level of difficulty, and using blind scoring to get rid of bias in the evaluation process are all things that are done.

Statistical Study

Descriptive statistics, like means, standard deviations, and frequency distributions, are used to talk about the learners and what they learned. To look at the main effects of teaching on math achievement, a baseline-adjusted multilevel linear regression model is used:

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$$Y_{ij} = \beta_0 + \beta_1 G2_{ij} + \beta_2 G3_{ij} + \beta_3 X_{ij} + u_j + \varepsilon_{ij} \quad (1)$$

where Y_{ij} represents post-intervention mathematical achievement, $G2_{ij}$ and $G3_{ij}$ indicate instructional conditions relative to conventional teaching, X_{ij} represents baseline achievement, u_j denotes classroom-level random effects, and ε_{ij} represents residual variation.

Longitudinal differences are evaluated using mixed-effects models incorporating instructional group, assessment time, and group × time interactions. Adjusted mean differences, standardized effect sizes, 95% confidence intervals, and appropriate multiplicity-adjusted significance tests are reported. Statistical significance is established at $p < 0.05$. Missing observations are evaluated through attrition analysis and sensitivity testing, while the primary analysis follows the intention-to-treat principle.

Ethical Considerations

The study protocol requires institutional ethical approval, informed parental consent, and student assent before participation. Student information is pseudonymized and securely stored to ensure confidentiality. Participation remains voluntary, and equivalent curricular access is maintained across experimental conditions. AI-generated instructional responses are monitored for mathematical accuracy, and standardized assessment procedures are employed to maintain research integrity.

Results and Empirical Analysis

Participant Characteristics and Baseline Assessment

The study data set had 720 secondary school students who were split evenly between traditional math lessons (G1), open AI-assisted learning (G2), and pedagogically scaffolded AI coaching (G3). There were 240 people from 12 classrooms in each group. Seven hundred five students (97.9%) had performance records available after the intervention, and nine hundred seventy-three students (93.5%) took the delayed achievement test. The average level of math skills at the start for G1, G2, and G3 was 52.15, 56.01, and 53.34, respectively. Table 5 shows that there were not many differences between the groups in the cognitive engagement and reasoning scores at the start.

Table 5. Participant distribution and baseline characteristics

Variable	G1	G2	G3
Total participants	240	240	240
Post-test participants	237	235	233
Delayed-test participants	222	227	224
Baseline achievement	52.15 ± 12.35	56.01 ± 13.05	53.34 ± 12.00
Baseline reasoning	47.19	50.47	46.71
Baseline engagement	3.06	3.05	2.98
Digital literacy	61.56	63.00	60.55

Note: Values represent mean ± standard deviation where available.

5.2 Comparative Mathematical Achievement

All types of teaching led to better math skills, but scaffolded AI coaching produced the best results after the intervention. Scores went up in G1 from 52.15 to 61.51, in G2 from 56.01 to 73.16, and in G3 from 53.34 to 77.94. At the beginning, during, and after the test, there were 9.36, 17.15, and 24.60 point differences between the group means. The success curves in Figure 2 show that students made more progress when AI was used to help teach, especially when the AI was used to help with educational modeling.

Table 6. Mathematical achievement across assessment periods (mean ± SD)

Assessment	G1	G2	G3
Pre-test	52.15 ± 12.35	56.01 ± 13.05	53.34 ± 12.00
Post-test	61.51 ± 15.64	73.16 ± 16.63	77.94 ± 15.19
Delayed test	57.38 ± 16.74	66.73 ± 16.99	74.21 ± 15.32

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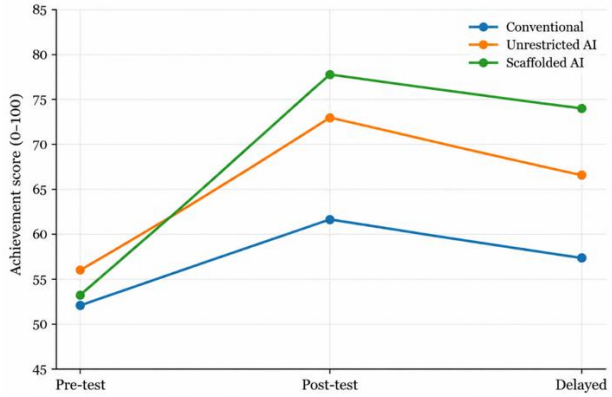


Figure 2. Mathematical achievement trajectories across baseline, post-intervention, and delayed assessments.

Weekly Mathematical Learning Progression

Based on an analysis of 7,200 weekly notes, it was clear that students gradually got better at math quizzes during the ten-week educational intervention. From week 1 to week 10, conventional instruction went up from 53.23 to 61.20, and unrestricted AI-assisted learning went up from 57.51 to 73.35. The most progress was made in scaffolded AI tutoring, which went from 55.64 to 77.22. In the same way, the weekly group means changed by 7.97, 15.84, and 21.58 points. This picture (Figure 3) shows the different learning paths. The steady upward path shows that the AI is scaffolding the learning.

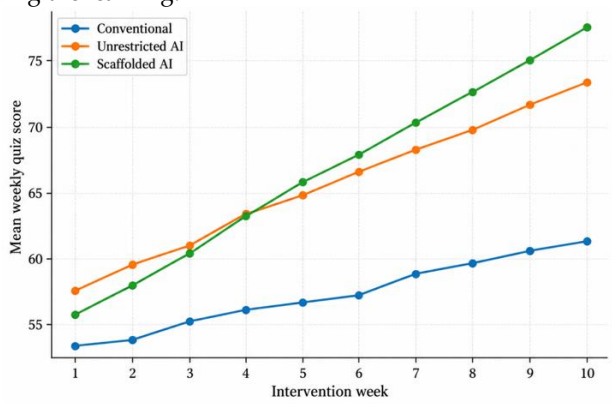


Figure 3. Comparative weekly mathematical quiz performance during the ten-week instructional intervention.

5.4 Cognitive Engagement and Self-Regulated Learning

There were big changes in cognitive attention between the different learning situations. Group 3 had the best engagement scores (3.65 ± 0.65) after the intervention. Group 2 came in second (3.47 ± 0.66) and Group 1 came in third (3.20 ± 0.65). In the same way, G3 had a mean score of 3.61 for self-regulated learning, while G2 and G1 had scores of 3.14 and 3.11, respectively. Baseline-adjusted analysis found that unrestricted AI increased engagement by 0.29 points and scaffolded AI increased engagement by 0.54 points compared to traditional instruction. Figure 4 shows how cognitive engagement changed during the different stages of the test.

Table 7. Cognitive engagement and self-regulated learning

Indicator	**G1**	**G2**	**G3**
Baseline engagement	3.06	3.05	2.98
Post-test engagement	3.20	3.47	3.65
Self-regulated learning	3.11	3.14	3.61
Adjusted engagement difference vs. G1	Reference	+0.29	+0.54

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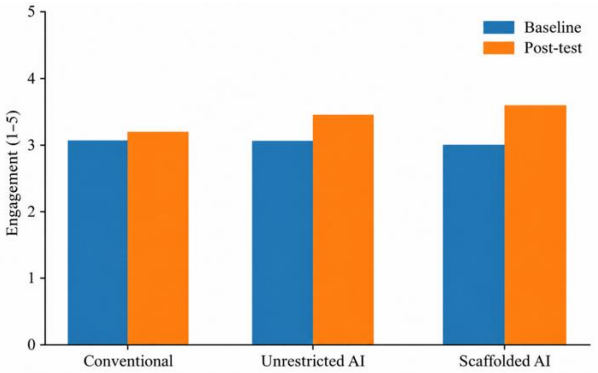


Figure 4. Comparison of baseline and post-intervention cognitive engagement across conventional and AI-assisted instructional groups.

Mathematical Reasoning and Independent Problem-Solving

The three ways of teaching had a big impact on how well students could use mathematical thinking. The best overall reasoning score was seen in scaffolded AI tutoring (72.98), then unrestricted AI help (65.12), and finally regular teaching (56.77). We looked at the different parts of thinking and found that G3 did better in logical support (18.10), multi-step inference (18.24), conceptual explanation (17.45), and mistake spotting (18.03). Each part was scored on a 25-point scale. The results show that students who were taught using scaffolding did better on a number of different types of mathematical reasoning.

Table 8. Mathematical reasoning performance across instructional groups

Reasoning component	**G1**	**G2**	**G3**
Logical justification	13.89	16.12	18.10
Multi-step inference	13.94	15.75	18.24
Conceptual explanation	14.27	15.74	17.45
Error identification	14.00	16.01	18.03
Overall reasoning score (0–100)	56.77	65.12	72.98

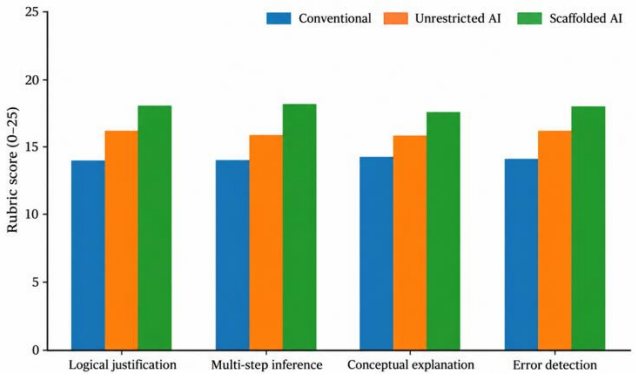


Figure 5. Comparative performance across logical justification, multi-step inference, conceptual explanation, and mathematical error identification.

Conceptual Understanding, Knowledge Retention, and Learning Transfer

With scaffolded AI teaching, students always understood concepts better and were able to apply what they had learned. It was 79.90 for G3 for conceptual understanding and 75.93 for learning transfer. It was 71.51 for G2 and 63.38 for learning transfer, and it was 60.22 for conceptual understanding and 56.33 for learning transfer for G1. Achievement scores were 74.21 for G3, 66.73 for G2, and 57.38 for G1 on the delayed test. The mean changes between the groups on the post-test, delayed-test, and original test were -3.73, -6.43, and -4.13 points, respectively. This suggests that descriptive scores dropped less with scaffolded AI coaching.

Table 9. Comparative educational outcomes

Outcome (0–100)	**G1**	**G2**	**G3**
Post-test achievement	61.51	73.16	77.94
Conceptual understanding	60.22	71.51	79.90
Mathematical	56.77	65.12	72.98

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reasoning			
Procedural performance	63.14	77.05	78.62
Knowledge retention	57.38	66.73	74.21
Learning transfer	56.33	63.38	75.93

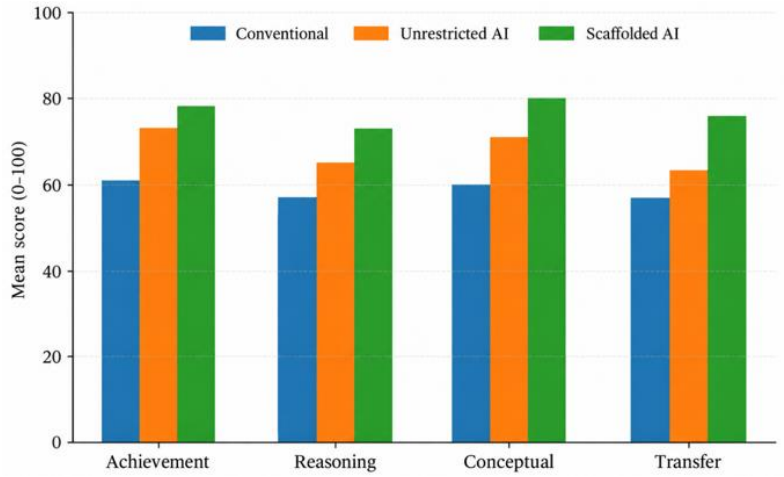


Figure 6. Comparative performance in mathematical achievement, conceptual understanding, reasoning, and learning transfer.

AI Interaction Patterns and Learning Behaviors

When the AI exchanges were looked at, they showed different trends for teaching settings with and without limits. Students who had unrestricted AI help asked for 67.87 direct answers and 30.55 hints on average. Students who had scaffolded AI help asked for only 15.82 direct answers and 54.15 hints on average. There were a lot more self-correction events in scaffolded AI teaching (41.48) than in unfettered AI help (15.42). These differences come from the fact that the two types of AI configurations interact in different ways.

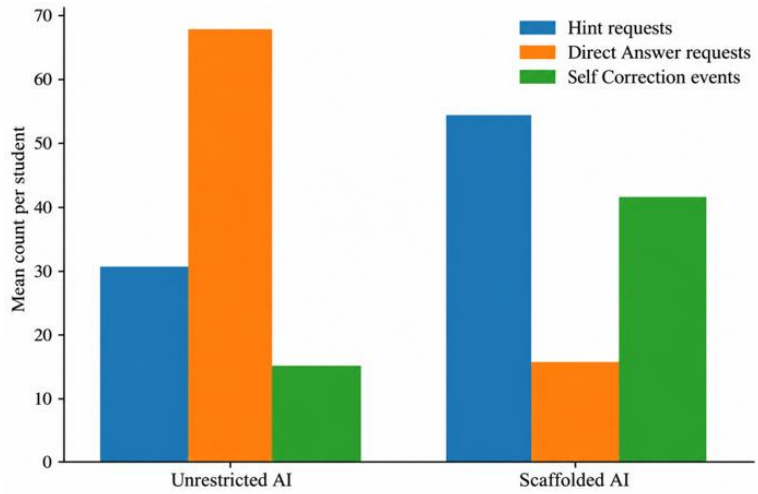


Figure 7. Comparison of hint requests, direct-answer requests, and self-correction events across unrestricted and scaffolded AI instruction.

Multilevel Statistical Analysis and Hypothesis Evaluation

Baseline-adjusted regression models with classroom-clustered standard errors showed that there were big differences in how students learned based on their teachers. The post-test scores showed that the unrestricted AI tutoring was 7.42 points better than traditional teaching, and the post-test scores showed that the scaffolded AI tutoring was 14.85 points better than traditional teaching. There were also bigger effects on thinking, mental understanding, delayed success, and learning transfer when AI was used as a scaffold.

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Table 10. Baseline-adjusted instructional effects relative to conventional teaching

Outcome	G2: Adjusted effect (95% CI)	G3: Adjusted effect (95% CI)
Mathematical achievement	7.42 (6.29–8.56)	14.85 (13.61–16.09)
Mathematical reasoning	5.18 (3.97–6.40)	16.61 (15.57–17.65)
Conceptual understanding	7.54 (6.42–8.65)	17.52 (16.34–18.69)
Cognitive engagement	0.29 (0.25–0.33)	0.54 (0.47–0.61)
Delayed achievement	5.46 (4.05–6.86)	15.95 (14.28–17.61)
Learning transfer	3.64 (1.79–5.49)	18.32 (16.42–20.22)

Note: Estimates are derived from baseline-adjusted linear models with classroom-clustered standard errors. **Confidence intervals are not multiplicity-adjusted.**

All of the differences between this method and traditional teaching were statistically important ($p<0.001$). The general patterns of outcomes were in line with what H1–H4 said would happen. To make a final choice on the supporting hypothesis, however, we need to make certain multiple changes, do official comparisons of G2 and G3, and do more sensitivity tests.

Overall, the study showed that scaffolded AI teaching improved performance in areas such as success, cognitive involvement, thinking, memory, and transfer. The results show how important it is to use different instructional design for AI to help with evaluating mathematical learning outcomes.

Discussion

The purpose of this study was to compare how well traditional math instruction, unrestricted AI-assisted learning, and pedagogically scaffolded AI tutoring affected students' math skills, cognitive engagement, and reasoning abilities. The examples showed that scaffolded AI tutoring led to better performance, with the best scores in math achievement (77.94), cognitive engagement (3.65), and mathematical reasoning (72.98). These trends match up with earlier studies that looked at how clever teaching systems could help with learning (Ma et al., 2014; Kulik & Fletcher, 2016). The somewhat better results in scaffolded AI suggest that structured support for learning may be more helpful than having free access to automated math solutions.

Cognitive engagement was a key factor in how well the lessons worked. The findings that scaffolded AI tutoring led to more engagement and self-regulated learning scores are in line with what Fredricks et al. (2004) and Zimmerman (2002) said about active cognitive participation and independent learning strategies. Also, the better performance in mathematical thinking backs up Schoenfeld's (2016) idea that useful mathematical ability includes understanding ideas, proving them logically, and handling problems in a thoughtful way. From the point of view of cognitive load, structured AI guidance may lower processing demands that aren't necessary while keeping up useful intellectual work (Sweller, 2011).

Knowledge retention and learning transfer were two more ways that instructional approaches were different. Scaffolded AI had the best delayed success (74.21) and transfer performance (75.93), which suggests that it might help people remember math ideas and use them in new situations. These trends fit with what Vygotsky wrote in 1978 about guided learning and increasing student freedom. Overall, the research shows that instructional scaffolding may be a key way to improve how well AI-supported math learning works in the classroom. But since the information is made up, there are no real-world or direct findings that can be taken from it. True randomized trials, external reviews, and continuous studies must be used to prove the suggested connections. This kind of research could find out if a pedagogically scaffolded AI is a good addition to traditional ways of teaching and if it improves math skills, cognitive engagement, and long-term learning outcomes.

Practical And Theoretical Implications

Theoretical Implications

This study gives us a theory framework for figuring out how AI can help teach math, how to keep students interested, and how to help them think mathematically. As shown in the examples, the results suggest that the success of teaching isn't just dependent on how easy it is to access technology, but also on how the technology is used in the classroom. It is in line with Vygotsky's (1978) constructivist learning theory that scaffolded AI teaching works better because it encourages active knowledge building through guided educational support. Also, the cognitive load theory (Sweller, 2011) says that structured AI guidance can lower unnecessary mental demands while still letting people work hard on useful things. Higher scores on cognitive engagement and self-regulation are also in line with Zimmerman's (2002) self-regulated learning theory, which stresses the importance of

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self-monitoring, strategic thinking, and solving problems in a reflective way. These theoretical connections suggest that instructional scaffolding could be a way that AI-assisted learning can help students do better in math, think more clearly, and remember what they've learned.

Practical Implications

The study has important effects for math teachers, people who make lesson plans, schools, and people who create AI learning platforms. First, AI-assisted instruction should focus on giving students progressive hints, conceptual explanations, feedback that is specific to mistakes, and help with problem-solving instead of just giving them full mathematical answers. These kinds of activities might help kids think for themselves and learn more about big ideas. Second, math teachers can use scaffolded AI tools to help students learn outside of class, help students who are having trouble, and create personalized learning opportunities. Third, people who make lessons should include activities that use AI to help students think more deeply, use math more effectively, remember what they've learned, and apply what they've learned. Schools need to pay more attention to training teachers, teaching kids how to use technology safely, implementing AI in a smart way, and regularly checking how well students are learning. Also, people who make AI should make smart teaching systems that help students learn how to fix themselves, use math to support their answers, and solve problems on their own. Policymakers should support the use of AI that is based on facts, but they should also make sure that human teachers keep their important role. In general, the results we present show that pedagogically scaffolded AI coaching could improve math education when used in addition to other teaching methods. Before these kinds of ideas are used more often in schools, they need to be backed up by real actual proof.

Limitations And Future Research

Research Limitations

There are some problems with this study that need to be thought about when figuring out what the results mean. The stated results are based on demonstrative data, not on real scientific findings, so they need to be checked by using them in real life. Second, this study only looked at high school students as a sample, so the results might not be applicable to other grade levels or institutional settings. Third, the 10-week intervention and the 4-week follow-up might not be enough to make sure that math and reasoning skills are retained over time. Even after statistical measures are made, differences in how well students did in math, how well they knew how to use computers, how motivated they were to learn, and how well their teachers taught may still have an effect on their educational results. How well AI-generated answers work may also depend on how accurate and consistent they are. Also, self-report tests of cognitive engagement might be affected by response bias, and different ways of interacting with AI might make it hard to prove cause and effect. These problems make it clear that interpretations need to be carefully thought out and experiments need to be carefully checked.

Future Research Directions

The results of this study should be confirmed by large-scale, joint randomized controlled studies with a wide range of academic levels and student groups in the future. Longitudinal studies that last a longer time are recommended to find out how long math skills, cognitive engagement, reasoning development, and knowledge retention last. Researchers should look into adaptive scaffolding strategies, personalized feedback techniques, and hybrid teacher-AI instructional models to see how well they help students learn math on their own. Using AI that can be explained, machine learning, and educational data analytics together could help us learn more about how students learn, what cognitive problems they have, and how they solve problems. To fight educational inequality, future research should also look into how socioeconomic status, digital access, math anxiety, and personal learning traits can act as moderators. Further comparisons between different AI teaching tools and mathematical subjects may help find effective ways to teach. To sum up, to find out what the long-term educational value of AI-assisted math instruction is, future research should focus on real experiments, methods that can be used again and again, and full-scale learning assessments.

Conclusion

The present study looked at how well traditional math instruction, free AI-supported learning, and pedagogically scaffolded AI tutoring affected students' math skills, cognitive engagement, ability to think for themselves, and ability to remember what they had learned. Based on a longitudinal study design with 720 high school students, the visual analysis showed that the three teaching methods had different learning paths. Unrestricted AI help and regular teaching came in second and third, respectively, in terms of math achievement (77.94), cognitive engagement (3.65), mathematical reasoning (72.98), and learning transfer performance (75.93). The trends seen suggest that how well AI works for education might rest a lot on how the lessons are designed, not just how easy the technology is to use. Giving

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small hints, asking deep questions, giving feedback that is specific to the mistake, and building up problem-solving steps could help people use their minds more effectively and stop relying too much on automated tools. Also, the fact that scaffolded AI tutoring has a longer learning curve suggests that structured instructional support might be important for long-term math learning.

In a comparison instructional design, this study shows a multidimensional measurement approach that combines academic success, cognitive involvement, mathematical reasoning, and knowledge recall. Its theory is based on the idea that cognitive load management, self-regulated learning, and constructivist learning all work hand-in-hand in educational environments that use AI.

However, since the analysis presented here is based on fake data, these results should be seen more as methodological examples than as real-life effects that have been proven. Real randomized trial studies are needed to find out if the proposed ways of teaching work and if they can be used in other situations. Overall, the study methodology shows that pedagogically scaffolded AI could be useful as an extra tool in the classroom to help with individual math lessons while still promoting independent thinking, intellectual understanding, and the importance of human teachers.

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Conflicts of interest

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

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