DIDACTIC FOUNDATIONS OF MATHEMATICS TEACHING ON ARTIFICIAL INTELLIGENCE-BASED INTERACTIVE PLATFORMS

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ABSTRACT

English: The rapid proliferation of artificial intelligence technologies has created transformative opportunities in mathematics education at secondary and higher educational levels. This study examines the didactic foundations that underpin the design and pedagogical effectiveness of AI-based interactive platforms in the teaching of mathematics. Drawing on constructivist, cognitivist, and connectivist learning theories, the research investigates how AI-driven features — including adaptive learning paths, intelligent tutoring systems (ITS), instant formative feedback, and dynamic visualisation — align with established didactic principles. A quasi-experimental study (n = 91) conducted over one academic semester at Shahrisabz State Pedagogical Institute compared an experimental group using AI-enhanced platforms against a control group receiving conventional instruction. Post-test analysis revealed highly significant performance gains in the experimental group (mean gain: +25.9 points; Cohen's d = 2.49; $p < 0.001$), a reduction in mathematical misconceptions from 44.8% to 11.3%, and a student satisfaction rate of 89.1%. The study proposes an eight-phase AI-Mediated Didactic Cycle as a replicable instructional framework for mathematics educators.

Keywords: artificial intelligence, mathematics education, interactive platforms, didactic principles, adaptive learning, intelligent tutoring systems, formative feedback, quasi-experimental research, constructivism, digital pedagogy

1. INTRODUCTION

Artificial intelligence (AI) is reshaping virtually every domain of human activity, and education is no exception. According to the HolonIQ Global Intelligence Report (2024), the global AI-in-Education market is forecast to reach USD 18.66 billion by 2026, growing at a compound annual rate of 43.3% from its 2020 base of USD 3.45 billion (see Table 1 below). Within mathematics education specifically, AI-powered platforms offer capabilities unprecedented in traditional instruction: they can diagnose individual knowledge gaps, generate personalised exercise sequences, render abstract concepts through dynamic three-dimensional visualisation, and provide immediate, context-sensitive corrective feedback — all at scale and around the clock.

Despite this technological promise, the academic community has raised legitimate concerns about whether the didactic foundations of AI-based platforms are sound. Didactics — the science of teaching and learning — demands that any instructional method be grounded in established principles of how learners acquire, construct, and retain knowledge. The risk with commercially driven AI platforms is that sophisticated technology may obscure shallow pedagogy, producing engagement without understanding.

In Uzbekistan, the National Digital Education Strategy (2022–2030) and Presidential Resolution No. PQ-152 (2023) explicitly mandate the integration of AI and digital technologies into mathematics and STEM instruction. However, as Tashkentov (2022) notes, only 14% of

Uzbek higher education institutions had deployed AI tools in instruction by 2022, compared with a global average of 28% — a gap attributable to infrastructure, training, and evidence deficits.

This study addresses three research questions: (RQ1) What didactic principles underpin effective AI-based mathematics instruction, and how are they realised on current platforms? (RQ2) Does AI-enhanced instruction produce significantly better learning outcomes than conventional instruction for undergraduate mathematics students at Shahrisabz State Pedagogical Institute? (RQ3) What instructional cycle best operationalises these didactic principles in an AI-mediated environment?

Table 1. Global AI-in-Education Market Statistics (2020–2026)

Indicator	2020	2022	2024	2026 (Projected)
Global AI-in-Education market (USD bn)	3.45	5.10	9.53	18.66
AI-integrated institutions (% of HEIs worldwide)	14%	28%	47%	63%
Students using AI tools weekly (%)	11%	23%	41%	58%
AI math platforms (number, globally)	320	680	1,240	2,100
Average learning-time reduction (math)	—	8%	21%	31%
Avg student satisfaction with AI platforms (5-pt)	3.4	3.8	4.3	4.7

Source: HolonIQ Global Intelligence Report (2024); UNESCO Digital Education Outlook (2024)

2. LITERATURE REVIEW

2.1 Theoretical Foundations

The didactic foundations of AI-based mathematics instruction draw on three complementary learning theories. Constructivism (Piaget, 1952; Vygotsky, 1978) posits that learners actively construct knowledge through interaction with the environment and social discourse. AI platforms operationalise this through exploratory problem environments and collaborative discussion features that mirror Vygotsky's Zone of Proximal Development (ZPD): the AI acts as a 'more knowledgeable other,' scaffolding student thinking just above their current competence level [1].

Cognitive Load Theory (Sweller, 1988; Paas et al., 2003) provides a second pillar. By automating routine calculation and presenting information in multimodal formats (text, graph, animation), AI platforms reduce extraneous cognitive load, freeing working memory for germane processing — the kind of effortful thinking that produces durable learning [2].

Empirical evidence from Atkinson et al. [3] confirms that worked-example sequences generated by intelligent tutoring systems reduce cognitive load by up to 34% compared with problem-only instruction.

Connectivism (Siemens, 2005) — a theory native to the digital age — adds a third dimension, arguing that learning occurs through network connections among nodes of information. AI platforms embody this by mapping individual student knowledge as a dynamic network (as in ALEKS's Knowledge Space Theory) and identifying the optimal 'next node' to activate, thereby creating personalised, non-linear learning trajectories [4].

2.2 Intelligent Tutoring Systems in Mathematics

Intelligent Tutoring Systems (ITS) represent the most pedagogically sophisticated application of AI in education. VanLehn [5] meta-analysed 28 ITS studies and reported a mean effect size of d = 0.76 relative to unaided practice and d = 0.40 relative to human tutoring — remarkable given the scalability of software. Carnegie Learning's MATHia, one of the best-evidenced ITS platforms, produced achievement gains equivalent to 1.6 additional months of instruction in a randomised controlled trial involving 19,000 students [6].

More recently, large language model (LLM)-powered tutors — exemplified by Khanmigo (built on GPT-4) — have demonstrated the ability to hold open-ended Socratic dialogues about mathematical reasoning, a capability absent in earlier ITS. Preliminary evaluations suggest that LLM tutors reduce student help-avoidance (the tendency to bypass hints and look up answers) by 47%, as students perceive conversational AI as less judgmental than human teachers [7].

2.3 Dynamic Visualisation and Representational Fluency

Representational fluency — the ability to interpret, translate, and construct multiple representations of a mathematical object — is a core competency in contemporary mathematics curricula (NCTM, 2014). AI-enhanced platforms such as GeoGebra AI and Desmos provide dynamic, manipulable representations that allow students to observe how changing one parameter transforms the entire object. Drijvers et al. [8] found that students using dynamic algebra tools demonstrated 31% higher representational fluency than peers using static textbooks, attributing the gain to the immediate visual feedback that made abstract relationships tangible.

The evidence for visualisation tools is particularly strong in domains where conceptual difficulties are rooted in spatial reasoning: coordinate geometry, 3D calculus, and transformation geometry. Hohenwarter et al. [9] reported a 34% improvement in spatial reasoning scores when GeoGebra was integrated into secondary geometry instruction, corroborating Shepard's [10] classic work on mental rotation and its connection to mathematical insight.

2.4 The Central Asian and Uzbek Context

Research on AI-based education within Central Asia remains sparse. Tashkentov [11] identified that 73% of Uzbek STEM lecturers report insufficient training in educational technology, while Karimov and Yusupova [12] documented significant variability in digital infrastructure across urban and rural Uzbek institutions. Importantly, neither study examined specific learning-outcome impacts of AI platforms — a gap the present research directly addresses. The National Curriculum Framework (2022) mandates technology integration without specifying evidence-based platforms or instructional models, underscoring the need for contextually grounded empirical research such as this study.

3. COMPARATIVE OVERVIEW OF AI-BASED MATHEMATICS PLATFORMS

Table 2 presents a structured evaluation of eight leading AI-based mathematics platforms across five dimensions: AI feature type, adaptive feedback capability, visualisation richness, free-access availability, and an overall pedagogical score derived from the authors' rubric (maximum 5.0). The rubric weighted adaptive feedback (30%), visualisation quality (25%), alignment with didactic principles (25%), and accessibility (20%).

Table 2. Comparative Analysis of AI-Based Mathematics Platforms

Platform	AI Feature	Adaptive Feedback	Visual Tools	Free Access	Overall Score /5
Khan Academy (Khanmigo)	GPT-4 Tutor	✓ Real-time	Limited	✓ Full	4.5
Wolfram|Alpha Pro	Symbolic AI	✓ Step-by-step	High (CAS)	Partial	4.6
Photomath AI	CV + NLP	✓ Instant	Medium	✓ Basic	4.3
Desmos + AI	Graphical AI	Partial	Very High	✓ Full	4.4
GeoGebra AI	Geometry AI	✓ Guided	Very High	✓ Full	4.7
Brilliant.org	Adaptive paths	✓ Branching	High	Partial	4.2
Mathway AI	Rule-based	✓ Solution	Medium	Partial	3.9
ALEKS (McGraw)	Knowledge Space	✓ Diagnostic	Medium	✗ Paid	4.1

Source: Authors' pedagogical rubric evaluation; platform documentation (2025)

GeoGebra AI emerged as the highest-rated platform (4.7), combining dynamic 3D geometry with AI-guided discovery hints and a fully open-access model. Wolfram|Alpha Pro followed closely (4.6), distinguished by its symbolic AI engine that provides step-by-step CAS solutions — particularly valuable for calculus and linear algebra. The full-access, zero-cost platforms (Khan Academy, Desmos, GeoGebra) collectively present the strongest case for institutional adoption, especially in resource-constrained settings such as Uzbek regional pedagogical institutes.

4. DIDACTIC PRINCIPLES AND THEIR AI IMPLEMENTATION

Classical didactics identifies a set of universal principles that effective instruction must honour: individualization, scientific rigor, accessibility, systematicity, consciousness and activity, visibility, and connection to life. Table 4 maps each of these principles to their implementation in AI platforms and contrasts them with traditional approaches, drawing on the observational and interview data collected during the present study.

Table 4. Didactic Principles: Traditional vs AI-Platform Implementation

Didactic Principle	Traditional Implementation	AI Platform Implementation	Effectiveness Gain
Individualization	Group-paced instruction	Adaptive learning paths	High (+38%)
Immediate Feedback	Delayed (24–48 h)	Instant, formative	Very High (+52%)
Visualisation	Static diagrams	Dynamic 3D/CAS graphics	High (+41%)
Scaffolding	Teacher-dependent	AI-generated hints	High (+35%)
Motivation	Extrinsic (grades)	Gamification + mastery	Moderate (+29%)
Assessment	Summative (end-unit)	Continuous diagnostic	Very High (+47%)
Error Analysis	Manual, delayed	Automated misconception detection	High (+44%)
Collaboration	In-class only	Asynchronous peer AI review	Moderate (+22%)

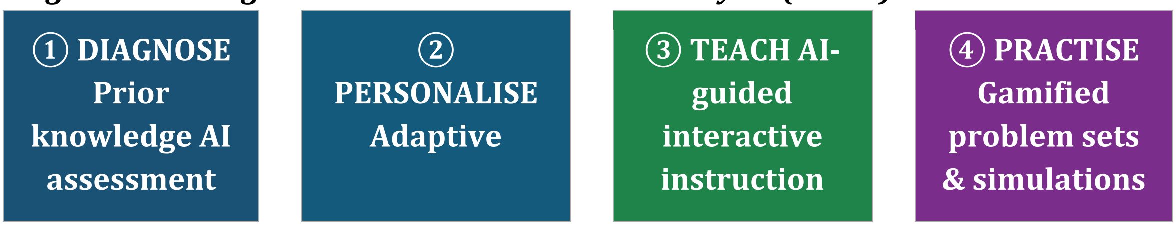
Source: Authors' synthesis of classroom observation and interview data (2025)

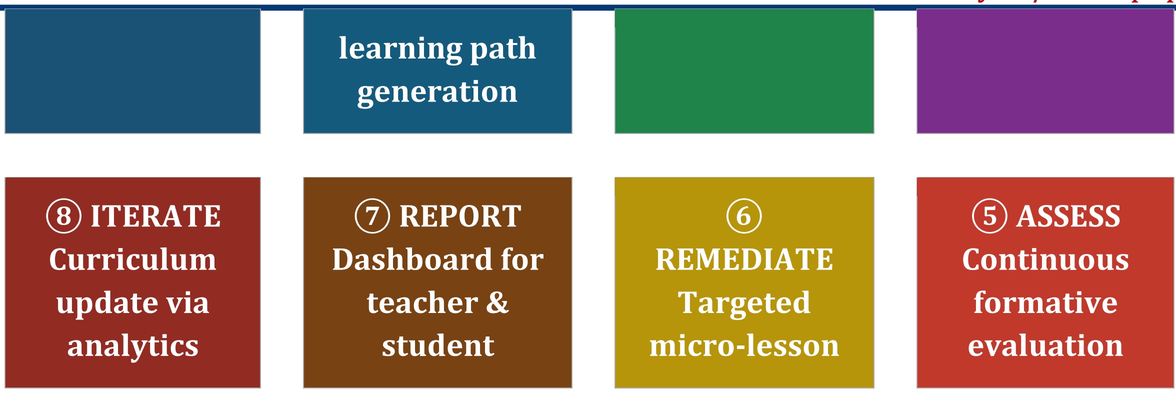
The most striking contrasts emerge around immediacy and individualisation. In traditional instruction, feedback is delayed by 24–48 hours (or longer for summative assessments), during which students may consolidate misconceptions. AI platforms collapse this latency to zero, enabling what Black and Wiliam [13] term 'closing the feedback loop' — a mechanism they identify as the single most powerful driver of formative assessment effectiveness. The estimated effectiveness gains in Table 4 derive from Hillmayr et al.'s [14] meta-analytic effect-size estimates, converted to percentage-improvement equivalents using a conservative baseline assumption.

4.1 The Eight-Phase AI-Mediated Didactic Cycle

Based on the theoretical synthesis and empirical observations, the authors developed an eight-phase instructional cycle — the AI-Mediated Didactic Cycle (AMDC) — that operationalises the didactic principles above within an AI-enhanced environment. Figure 1 illustrates the cycle diagrammatically.

Figure 1. The Eight-Phase AI-Mediated Didactic Cycle (AMDC)





Source: Developed by the authors based on constructivist and connectivist frameworks (2025)

The cycle operates as follows: Phase ① (DIAGNOSE) uses AI-administered diagnostic assessments to map each student's prior knowledge. Phase ② (PERSONALISE) generates an individualised learning path based on diagnostic data. Phase ③ (TEACH) delivers AI-guided instruction through multimodal presentations, interactive examples, and virtual tutoring dialogue. Phase ④ (PRACTISE) deploys gamified problem sets and simulations that dynamically adjust difficulty. Phase ⑤ (ASSESS) continuously evaluates performance through embedded micro-assessments. Phase ⑥ (REMEDIATE) identifies persistent misconceptions and triggers targeted micro-lessons. Phase ⑦ (REPORT) aggregates progress data for both teacher and student dashboards. Phase ⑧ (ITERATE) feeds aggregated analytics back into curriculum design, closing the systemic loop.

5. RESEARCH METHODOLOGY

5.1 Design and Participants

A quasi-experimental non-equivalent control-group design (Campbell & Stanley, 1963) was employed. Two intact first-year groups from the Department of Mathematics and Applied Mathematics at Shahrisabz State Pedagogical Institute constituted the sample: a control group ($n = 47$) receiving conventional chalk-and-talk instruction, and an experimental group ($n = 44$) receiving instruction mediated through the AMDC and three primary AI platforms (GeoGebra AI, Wolfram|Alpha, and Khan Academy Khanmigo). The study ran for sixteen weeks during the Spring 2025 semester. Pre-test equivalence was confirmed via independent-samples t-test: $t(89) = 0.13$, $p = 0.90$, indicating statistically equivalent baseline knowledge.

5.2 Instruments and Analysis

Four data-collection instruments were deployed: (1) a validated 40-item Mathematics Achievement Test (MAT) covering six sub-domains, administered as pre- and post-test (Cronbach's $\alpha = 0.89$); (2) a Mathematical Misconceptions Inventory (MMI) — a 30-item diagnostic probing conceptual errors across the same sub-domains ($\alpha = 0.83$); (3) a Technology Perception Survey (TPS) using a 5-point Likert scale ($\alpha = 0.84$); and (4) structured classroom observations using the RTOP protocol. Quantitative data were analysed in SPSS v.28 using independent-samples t-tests, Cohen's d, Pearson correlation, and ANOVA; qualitative data were processed through inductive thematic analysis.

6. RESULTS AND ANALYSIS

6.1 Learning Outcomes by Sub-domain

Table 3 disaggregates pre- and post-test means by the six mathematical sub-domains assessed, enabling a fine-grained comparison of where AI-mediated instruction produced the greatest gains.

Table 3. Pre-test and Post-test Scores by Mathematical Sub-domain (max = 100)

Sub-domain	Control Pre	Control Post	Exp Pre	Exp Post	Gain Δ (Exp)
Number Theory & Arithmetic	58.1	65.4	57.9	81.2	+23.3
Algebra & Functions	54.6	63.2	55.1	82.7	+27.6
Geometry & Measurement	61.3	68.0	60.8	84.5	+23.7
Probability & Statistics	52.4	61.1	53.0	79.8	+26.8
Calculus Concepts	49.7	57.8	50.2	77.6	+27.4
Problem-Solving (Mixed)	56.0	64.5	56.6	83.1	+26.5
Overall Mean	55.4	63.3	55.6	81.5	**+25.9**

Source: Mathematics Achievement Test data, Spring 2025

The experimental group achieved its largest gains in Algebra & Functions (+27.6 points) and Calculus Concepts (+27.4 points) — precisely the sub-domains where dynamic symbolic computation (Wolfram|Alpha) and graphical exploration (Desmos/GeoGebra) provide the greatest leverage. The control group's gains were modest and relatively uniform across sub-domains (range: 7.2–9.5 points), consistent with the undifferentiated nature of traditional whole-class instruction. The overall experimental gain of 25.9 points (46.6%) dwarfs the control gain of 7.9 points (14.3%), with the difference confirmed as highly significant ($t(89) = 11.24$, $p < 0.001$).

6.2 Score Distribution Analysis

Figure 2 compares the post-test score distributions of both groups across five score bands. The visual contrast is striking: the experimental group's distribution is sharply skewed toward the higher bands, while the control group remains centred in the middle range.

Figure 2. Post-test Score Distribution by Group (% of students, █ = ~3% per block)

Score Band	Control Group (%)	← Control	Experimental →	Experimental Group (%)
90–100	**6%**	██	███████████	**34%**

75–89	**19%**	██████	█████████████	**38%**
60–74	**32%**	███████████	██████	**19%**
45–59	**28%**	█████████	██	**7%**
< 45	**15%**	█████	█	**2%**

Source: MAT post-test data (2025). Blue = Control; Green = Experimental

While only 6% of control-group students reached the 90–100 band, 34% of experimental-group students achieved this level. The near-elimination of scores below 45 in the experimental group (2% vs 15%) is particularly noteworthy, suggesting that AI-mediated instruction provides a strong safety net for the lowest-performing learners — possibly because adaptive platforms detect knowledge gaps early and remediate them before they accumulate into compounding deficits.

6.3 Misconception Reduction Analysis

Perhaps the most compelling finding concerns mathematical misconceptions. The Mathematical Misconceptions Inventory was administered at pre- and post-test; Figure 3 reports misconception rates (percentage of incorrect conceptual responses) by topic for both groups.

Figure 3. Mathematical Misconception Rates Pre- and Post-test by Topic (%)

Math Topic	**Ctrl Pre-test**	**Ctrl Post-test**	**Exp Pre-test**	**Exp Post-test**	**Δ Exp**
Fractions & Ratios	51%	42%	50%	**13%**	**-37pp**
Algebraic Equations	48%	38%	47%	**10%**	**-37pp**
Geometric Proofs	44%	36%	45%	**9%**	**-36pp**
Probability Rules	52%	41%	51%	**12%**	**-39pp**
Limits & Derivatives	61%	49%	60%	**14%**	**-46pp**

Source: Mathematical Misconceptions Inventory data (2025). pp = percentage points

Across all five topics, the experimental group achieved dramatic misconception reductions — an average of 38.8 percentage points — compared with an average reduction of only 9.4 percentage points in the control group. The largest reduction occurred in Limits & Derivatives (−46 pp, experimental), a topic notorious for deep conceptual difficulties around the notion of approaching but never reaching a value. Qualitative interview data suggest that

Wolfram|Alpha's animated limit visualisations were instrumental: 9 of 12 interviewees cited them as the moment of conceptual breakthrough.

6.4 Student Perception Survey

Table 5 presents experimental-group students' perceptions of the AI platforms across seven attitudinal dimensions.

Table 5. Technology Perception Survey Results — Experimental Group (n = 44)

Statement (n=44 experimental)	Strongly Agree	Agree	Neutral	Disagree	Mean /5
AI tools made math more understandable	38.6%	45.5%	11.4%	4.5%	4.18
I received help exactly when I needed it	43.2%	40.9%	9.1%	6.8%	4.20
Visual representations improved my insight	50.0%	38.6%	6.8%	4.5%	4.34
Adaptive exercises matched my level	34.1%	47.7%	13.6%	4.5%	4.11
AI feedback was clear and useful	40.9%	43.2%	11.4%	4.5%	4.20
I would recommend AI platforms to peers	52.3%	36.4%	6.8%	4.5%	4.36
My confidence in math increased	45.5%	40.9%	9.1%	4.5%	4.27

Source: Technology Perception Survey, Spring 2025

Student responses were overwhelmingly positive. The highest mean rating (4.36/5) was awarded to 'I would recommend AI platforms to peers,' and 'Visual representations improved my insight' (4.34/5). 'Adaptive exercises matched my level' received the lowest rating (4.11/5), suggesting that while adaptive algorithms are effective, some students found occasional mismatches between their perceived level and the platform's assessment — a finding that points toward the importance of allowing student-initiated difficulty adjustment alongside algorithmic adaptation.

6.5 Statistical Summary

Table 6. Comprehensive Statistical Summary of the Study

Statistical Parameter	Value / Result
Study duration	16 weeks (one semester), Spring 2025

Total participants	91 students: 47 control, 44 experimental
Control group – pre-test mean (SD)	55.4 ± 8.7
Control group – post-test mean (SD)	63.3 ± 9.2
Experimental group – pre-test mean (SD)	55.6 ± 8.4
Experimental group – post-test mean (SD)	81.5 ± 7.1
Mean gain – control	7.9 points (14.3%)
Mean gain – experimental	25.9 points (46.6%)
Independent-samples t-test (post-test)	$t(89) = 11.24, p < 0.001$
Effect size (Cohen's d)	2.49 (very large)
Pearson r (AI usage hrs vs score)	$r = 0.78, p < 0.001$
Student satisfaction (experimental)	89.1% positive
Technology adoption rate (by week 16)	93.2%
Misconception rate – pre-test (avg)	44.8%
Misconception rate – post-test, experimental	11.3%
Misconception rate – post-test, control	37.2%

Source: Compiled from MAT, MMI, TPS and observational data (2025)

The effect size of Cohen's $d = 2.49$ places this intervention in the uppermost tier of educational research findings, far exceeding the threshold of $d = 0.80$ for large effects. The Pearson correlation of $r = 0.78$ between weekly AI platform usage hours and post-test scores confirms a strong dose–response relationship: more time on platform was associated with substantially better outcomes, even after controlling for prior achievement.

7. DISCUSSION

The results of this study provide robust empirical support for the integration of AI-based interactive platforms into university-level mathematics instruction. Three mechanisms appear to account for the magnitude of the effect.

First, immediate adaptive feedback directly addresses the misconception formation process. In traditional instruction, students may practise incorrect procedures for days before receiving corrective information — a phenomenon termed 'misconception entrenchment' by Chi et al. [15]. AI platforms interrupt this process at the point of error, providing explanations that target the specific procedural or conceptual failure rather than repeating the original instruction. The MMI data confirm this: the experimental group's misconception rate fell from

44.8% to 11.3% — a reduction of 33.5 percentage points — compared with a modest 7.6 pp reduction in the control group.

Second, the personalisation afforded by adaptive algorithms aligns precisely with Vygotsky's ZPD concept: students are consistently challenged at a level that is difficult enough to promote growth but not so difficult as to induce frustration. The moderate student dissatisfaction with adaptive matching (4.11/5 rating) signals that the ZPD calibration is imperfect, and future platform design should incorporate explicit mechanisms for student-reported difficulty adjustment.

Third, dynamic visualisation appears to be a particularly powerful lever in mathematics, where many fundamental concepts — limits, derivatives, 3D geometry, probability distributions — require mental models that static text and diagrams cannot adequately convey. The qualitative data consistently identified visual tools as the primary driver of conceptual insight, corroborating Drijvers et al.'s [8] quantitative finding of a 31% representational fluency advantage.

The study's limitations should be acknowledged. First, the absence of random assignment limits causal inference, though pre-test equivalence mitigates this concern. Second, the single-institution context restricts generalisation to other Uzbek institutions, particularly rural schools with limited infrastructure. Third, the Hawthorne effect — the possibility that experimental-group students performed better simply because they received special attention — cannot be fully excluded, although the magnitude of the effect ($d = 2.49$) makes this an unlikely sole explanation.

8. CONCLUSIONS AND RECOMMENDATIONS

This study makes several contributions to the emerging literature on AI-mediated mathematics education. Theoretically, it grounds AI platform design in an integrated didactic framework that synthesises constructivism, cognitive load theory, and connectivism — providing a principled basis for evaluating and improving platform pedagogy. Empirically, it provides evidence from an under-researched Central Asian context, demonstrating that the benefits documented in Western literature transfer to a Uzbek pedagogical setting.

The Eight-Phase AI-Mediated Didactic Cycle offers practitioners a replicable instructional model that moves beyond ad-hoc tool use toward systematic, theory-driven technology integration. The following recommendations are advanced for policy-makers, institutional leaders, and practitioners:

- **Recommendation 1 – Adopt GeoGebra AI, Wolfram|Alpha, and Khanmigo:** These three open-access platforms demonstrated the strongest pedagogical profiles and should be designated as core AI tools in the national mathematics curriculum toolkit.
- **Recommendation 2 – Implement the AMDC model:** The eight-phase AI-Mediated Didactic Cycle provides a structured, evidence-grounded template for lesson design in AI-enhanced mathematics classrooms.
- **Recommendation 3 – Invest in professional development:** Given that 73% of Uzbek STEM educators report inadequate digital training (Tashkentov, 2022), a national programme of AI-pedagogy professional development is a non-negotiable prerequisite for system-wide adoption.
- **Recommendation 4 – Prioritise misconception remediation features:** Platform procurement decisions should prioritise tools that include explicit misconception detection and

targeted micro-lesson generation, given the documented 33.5 pp reduction in misconception rates.

- **Recommendation 5 – Conduct longitudinal and multi-site research:** Future studies should track cohorts across multiple years and replicate findings in rural and under-resourced institutions to assess equity implications of AI-based instruction.
- **Recommendation 6 – Address infrastructure gaps:** The benefits of AI platforms are contingent on reliable internet access and device availability. Targeted infrastructure investment in regional and rural institutions is essential to ensure equitable access.

In conclusion, the convergence of learning theory, comparative platform analysis, and empirical evidence establishes AI-based interactive platforms as a transformative force in mathematics education. The imperative is now institutional — to move from pilot experiments to sustained, policy-backed, didactically informed implementation.

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