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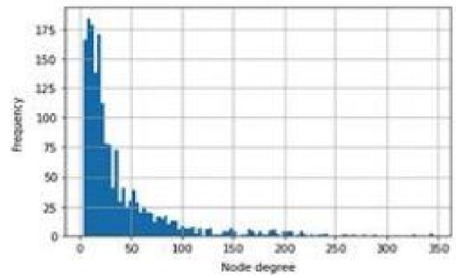

Educación Matemática Impulsada por la IA: Exploración de Vías Integradas desde una Perspectiva de la Educación STEM

AI-Driven Mathematics Education: Exploring Integrated Pathways from a STEM Education Perspective

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Artificial intelligence (AI) is transforming mathematics education by functioning as a cognitive mediator in STEM learning. This study proposes a three-layer model—diagnostic, regulatory, and generative—to integrate AI into teaching. The diagnostic layer profiles learners through knowledge tracing and error analysis; the regulatory layer offers real-time adaptive support; and the generative layer fosters conceptual transfer and higher-order reasoning through simulations and AI-generated tasks. A holistic framework incorporating cognitive, emotional, and social dimensions supports both self-regulated and co-regulated learning. Using a mixed-methods design, the study examines AI's impact through experiments, learning trajectory analysis, and classroom observations, supported by a multi-level evaluation system.

Keywords: Artificial Intelligence; Mathematics Education; STEM Education; Adaptive Learning; Learning Analytics; Human–AI Collaboration; Metacognition; Behavior Analysis; Intelligent Learning Environments

1. INTRODUCTION

The rapid development of artificial intelligence (AI) has opened new possibilities for transforming teaching and learning across disciplines. In the field of mathematics education, AI technologies—ranging from adaptive learning systems and intelligent tutoring platforms to automated assessment and learning analytics—offer unprecedented opportunities to enhance instructional effectiveness and support individualized learning pathways [1], [2]. These innovations coincide with the global push toward STEM education, which emphasizes interdisciplinary thinking, real-world problem solving, and the integration of science, technology, engineering, and mathematics into cohesive learning experiences [3].

Within the STEM education framework, mathematics serves as both a foundational discipline and a bridge that enables students to engage in higher-order reasoning, modeling, and computational thinking. However, traditional mathematics instruction often faces persistent challenges, including limited differentiation, insufficient student engagement, and the difficulty of connecting mathematical concepts to authentic applications [4]. AI-driven tools have the potential to address these limitations by providing personalized feedback, diagnosing learning gaps with higher precision, and creating interactive environments that foster deeper conceptual understanding [5], [6].

Despite the growing body of research on AI and STEM education, systematic pathways for integrating AI into mathematics teaching remain underexplored. Existing studies tend to focus either on technological development or on pedagogical reform, with limited attention to how the two can be effectively integrated [7]. Moreover, educators often lack practical frameworks that guide the adoption of AI tools in ways that align with STEM competencies and curricular goals [8]. Fig. 1 provides an overview of the key patterns that emerged from the analysis.

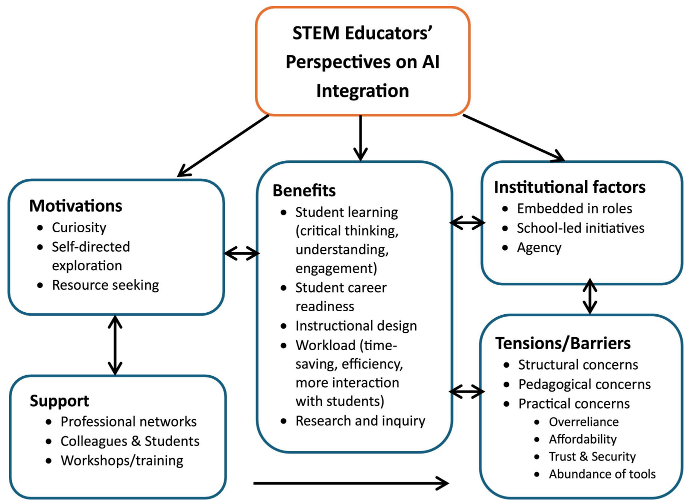

Fig. 1. Overview of key patterns emerging from the reflexive thematic analysis

This study aims to address these gaps by examining the integration of AI into mathematics education from a STEM perspective and proposing a structured pathway for its implementation. Through a review of theoretical foundations, analysis of current AI applications, and presentation of a multi-dimensional integration framework, this work seeks to provide educators, researchers, and policymakers with insights into how AI can meaningfully empower mathematics education and support STEM-oriented instructional practices.

2. Related Works

Research on artificial intelligence in education has evolved substantially over the past decades, forming several interconnected streams that collectively shape the understanding of how AI can enhance mathematics learning within STEM contexts. Early studies on intelligent tutoring systems established strong empirical evidence that well-designed AI-driven tutors can improve learning outcomes by offering individualized feedback and step-level guidance, enabling more precise diagnosis of students' misconceptions and knowledge states [1], [2]. Advances in knowledge tracing further deepened this diagnostic function, with Bayesian and neural approaches able to infer latent mastery patterns from student interactions; however, concerns regarding interpretability, model transferability, and pedagogical alignment continue to motivate subsequent refinements [3], [4]. These lines of work emphasize the foundational role of diagnostic precision in AI-mediated mathematics instruction and underline the need for models that can interface meaningfully with teacher decision-making.

As diagnostic technologies matured, adaptive learning research expanded the regulatory dimension of AI, demonstrating that dynamic difficulty adjustment and personalized learning pathways can enhance engagement and reduce the limitations associated with uniform instructional pacing. Empirical findings indicate that adaptive systems yield the greatest benefits when integrated with explicit instructional frameworks and human oversight, as purely algorithmic adaptation may overlook learners' strategic behaviors, emotional states, or contextual understanding [5]. This realization led to increasing attention on the integration of richer behavioral and process-level data—such as time-on-task, strategy diversity, and hesitation signals—into adaptive engines, yet achieving reliable, real-time regulation remains an ongoing challenge.

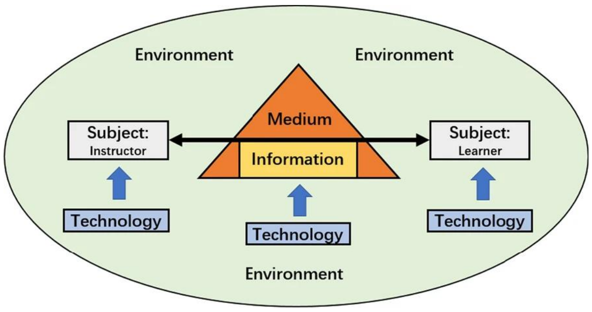

Fig. 2. The selection flowchart

Recent progress in generative AI further broadened the scope of research by enabling more open-ended forms of learning support, including automated problem generation, inquiry-based dialogue, and reflective prompts that simulate Socratic-style exchanges. Such systems reframed AI not as a static source of answers but as a partner capable of engaging learners in exploratory reasoning and facilitating higher-order skills like modeling and abstraction [6], [7]. Despite these promising developments, researchers caution that generative systems require pedagogically grounded prompt structures, transparent boundaries, and teacher mediation to avoid misconceptions or overreliance.

Parallel to technological advancements, multimodal learning analytics emerged as a critical field concerned with understanding learners' cognitive and affective processes through interaction logs, behavioral cues, and sensor-derived signals. Studies show that multimodal indicators can detect disengagement, cognitive overload, or suboptimal strategies and that dashboards visualizing these indicators can meaningfully support student self-regulation and teacher intervention—provided that they maintain interpretability and actionability [8], [9]. This shift highlights the increasing importance of integrating process-oriented evidence into AI-driven learning environments, enabling more holistic and ecologically valid support. Complementing these analytical perspectives, a growing body of research emphasizes the socio-emotional and collaborative dimensions of human–AI interaction. Findings reveal that students and teachers often expect AI systems to provide not only cognitive scaffolding but also emotional resonance, contextual sensitivity, and pedagogically coherent guidance. Studies indicate concerns regarding the mechanical nature of AI dialogue, insufficient emotional attunement, and unclear role boundaries between teachers and AI systems, suggesting that human–AI co-orchestration—where teachers and AI systems jointly manage learning processes—may offer a more sustainable and acceptable pathway for integration [6], [10]. These perspectives underscore the need for AI frameworks that extend beyond cognition to support emotional and social dimensions of learning, particularly in complex domains like mathematics.

Alongside pedagogical research, governance issues—including explainability, fairness, transparency, and privacy—have become central to discussions of AI adoption in education. Scholars call for explainable student models, bias auditing tools, and privacy-preserving mechanisms specifically tailored for sensitive educational data [11]–[13]. The governance literature consistently warns that without robust interpretability and accountability structures, even well-designed AI systems risk undermining trust, equity, and ethical integrity. The convergence of these diagnostic, regulatory, generative, socio-emotional, and governance perspectives illustrates both the promise and the complexity of integrating AI into mathematics education. Despite substantial progress, several gaps remain. Existing research often treats diagnostic, adaptive, and generative mechanisms independently, limiting the development of coherent models that unify these capabilities into integrated learning ecosystems. Moreover, empirical studies rarely capture the interplay among cognitive, emotional, and social processes, leaving a need for frameworks that conceptualize AI-supported learning as an ecological system rather than a tool-based intervention. Additionally, the majority of evaluations emphasize short-term performance gains, whereas long-term trajectories, fairness outcomes, and metacognitive development remain underexamined. These gaps justify the need for the present study's multi-layer framework, which synthesizes diagnostic analytics, adaptive regulation, generative learning design, and socio-emotional support into a human–AI co-orchestration model aimed at advancing equitable and effective mathematics learning within STEM education.

3. Theoretical Framework

This study builds upon constructivist learning theory, cognitive load theory, multimodal learning theory, and emerging models of human–AI co-orchestration to develop a three-layer functional framework for AI-enhanced mathematics education. The framework conceptualizes AI as a diagnostic, regulatory, and generative mediator within a STEM-integrated learning ecosystem.

1. Diagnostic Layer: Learner Modeling and Knowledge Tracing

The diagnostic layer aims to identify learners' latent knowledge states, conceptual gaps, and error patterns. It draws on probabilistic knowledge tracing (KT), where mastery is represented as a hidden variable that evolves across learning steps. A standard formulation is:

$$P(K_t = 1 \mid K_{t-1}) = P(K_{t-1} = 1)(1 - s) + P(K_{t-1} = 0) \cdot l$$

where:

K_t= learner's mastery at step t, s = slip probability, l = learning (transition) probability.

The probability of a correct response is:

$$P(C_t = 1 \mid K_t) = K_t(1 - g) + (1 - K_t)g$$

where g is the guess parameter.

This formulation allows the system to construct fine-grained learner profiles and detect persistent misconceptions. The diagnostic layer thus serves as the structural foundation for adaptive regulation and generative task design. In summary, the framework of GST (see Fig. 3) highlights the multiple elements as well as their mutual relationships in AI-STEM system, which provides us a holistic view for applying AI technologies in STEM education.

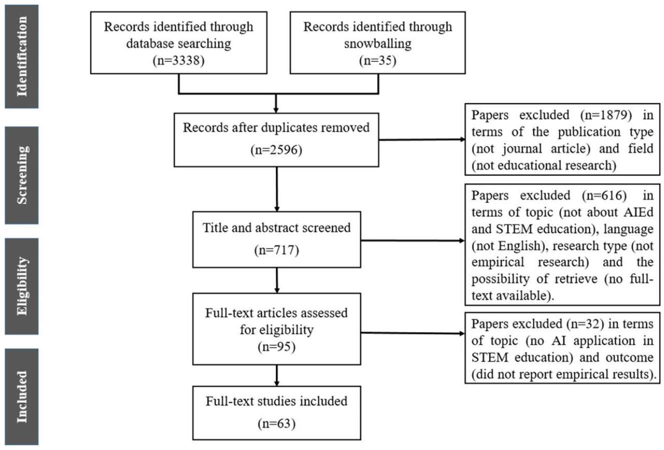

Fig. 3 The integration of technology in an educational system from the GST perspective

Table 1. Three-Layer Functional Framework for AI-Enhanced Mathematics Learning

Layer	Core Functions	Key Mechanisms / Models
Diagnostic	Identify knowledge states, errors, misconceptions	Knowledge Tracing (KT), error-pattern analytics, learner modeling
Regulatory	Adjust tasks, pacing, feedback, and cognitive load	Adaptive engines, cognitive load modeling, Markov strategy modeling
Generative	Create multimodal tasks and higher-order learning tasks	Simulations, data-driven scenarios, generative problem construction

Table 1 summarizes the proposed three-layer functional framework designed to integrate artificial intelligence into mathematics education within a STEM learning paradigm. The three layers—diagnostic, regulatory, and generative—represent complementary yet sequentially interdependent functions through which AI supports learners' cognitive, metacognitive, and higher-order reasoning processes, aligning with emerging perspectives on AI-mediated STEM learning systems [15], [16]. The Diagnostic Layer constitutes the foundation of the framework. It focuses on constructing accurate learner models by identifying knowledge states, misconceptions, and error patterns. Techniques such as probabilistic knowledge tracing, error modeling, and fine-grained behavioral analytics allow the system to capture invisible cognitive processes underlying learners' performance, consistent with recent advances in data-driven cognitive diagnostics [17], [18]. This layer enables the AI system to answer the core question: What does the learner currently understand, and where are the conceptual gaps? The outputs of this layer directly feed into adaptive decision-making processes in the regulatory layer, a structure reflected in contemporary adaptive-learning architectures [19].

The Regulatory Layer translates diagnostic insights into real-time instructional adjustments. By integrating cognitive load principles, strategy-transition analytics, and adaptive learning algorithms, this layer dynamically modulates task difficulty, pacing, modality, and scaffolding, building on prior research in real-time affective and behavioral regulation [20], [21]. The purpose of this layer is to maintain learners within an optimal cognitive load range while providing personalized, closed-loop learning experiences. It operationalizes the question: How should instruction be adjusted right now to maximize learning efficiency and avoid overload or disengagement? This layer ensures that instruction remains sensitive to learners' evolving cognitive states and is consistent with emerging frameworks for dynamic educational orchestration [22]. The Generative Layer represents the constructive and higher-order dimension of the framework. Building on multimodal learning theory, this layer harnesses the creative capacities of AI—such as generating problem variations, constructing data-driven contexts, and producing interactive simulations—to deepen conceptual understanding and promote transfer, modeling, and abstraction. This aligns with contemporary findings on generative AI's capacity to support complex reasoning and inquiry-based learning [23]. It also includes AI-driven dialogic systems that scaffold reflective thinking and metacognitive monitoring, advancing recent developments in AI-mediated exploratory learning environments [24]. This layer aims to answer: How can AI help learners extend, apply, and transfer mathematical concepts in rich and authentic contexts?

Importantly, the three layers operate as an integrated cycle rather than isolated modules. The diagnostic layer provides input to regulatory mechanisms, regulatory adjustments shape the learner trajectory, and generative tasks supply new evidence that informs subsequent diagnosis. This cyclical interaction forms a coherent learning ecosystem where AI and human instructors collaboratively orchestrate learning, resonating with the broader paradigm of human–AI co-orchestration in STEM education [15], [19], [22]. The teacher remains central to interpreting diagnostic outputs, validating regulatory decisions, and contextualizing generative learning activities—affirming that effective AI integration strengthens rather than replaces human pedagogical agency.

2. Learning Trajectory and Behavioral Analytics

Learning trajectory and behavioral analytics constitute the core quantitative component used to uncover how learners interact with AI-enhanced mathematics tasks over time. Rather than relying solely on outcome-level scores, this approach analyzes the process of learning—capturing micro-level strategies, temporal patterns, engagement fluctuations, and transitions between cognitive states. This enables a fine-grained evaluation of how the diagnostic, regulatory, and generative layers influence learners' behaviors within the intelligent learning ecosystem.

Learners' activity traces are represented as ordered sequences:

$$S_i = \{(x_1, t_1, a_1), (x_2, t_2, a_2), \ldots, (x_n, t_n, a_n)\}$$

where each tuple contains:

x_t: task or problem identifier,

t: response time, latency, or hesitation indicators,

a_t: action or strategy applied (e.g., attempt, hint request, revision, exploration move).

Table 2. Data–Model–Analytics Mapping

Data Source	Model / Technique	Outcome
Interaction logs	KT models, Markov chains	Knowledge states, error patterns
Behavioral time-series	Sequence embedding, clustering	Strategy profiles, engagement patterns
Pre-/post-tests	RCT, ANCOVA	Learning gains, causal effects
Classroom observations	Qualitative coding	Human–AI orchestration patterns
Teacher interviews	Thematic analysis	Pedagogical appropriations, perceptions

Table 2 provides a structured mapping between the core data sources used in this study, the corresponding analytical models, and the types of learning evidence generated. This mapping clarifies how different forms of learner data are integrated within the mixed-methods research design and demonstrates how each analytical technique contributes to evaluating the effectiveness of the three-layer AI framework.

The interaction logs represent the most granular form of data, capturing every learner action, including problem attempts, hint requests, revisions, and response times. These logs are analyzed using probabilistic Knowledge Tracing (KT) and Markov-based strategy modeling. KT models produce estimates of learners' evolving knowledge states, while Markov models detect tendencies in strategy transitions (e.g., productive vs. unproductive behaviors). Together, these models generate evidence for the Diagnostic Layer, confirming whether AI accurately identifies misconceptions and cognitive states. The behavioral time-series data—which includes latency patterns, hesitation markers, and fluctuations in problem-solving sequences—are processed using sequence embedding and clustering techniques. These analyses reveal strategy archetypes, engagement profiles, and behavioral signatures that characterize different types of learners (e.g., explorers, efficient solvers, overloaded learners). This provides insight into how the Regulatory Layer shapes learners' self-regulation processes over time, and whether adaptive mechanisms maintain learners within productive cognitive zones.

The pre-/post-test scores provide outcome-level evidence and are analyzed using RCT-based causal inference models and ANCOVA. These quantitative analyses estimate the direct impact of AI-mediated instruction on conceptual understanding, reasoning skills, and transfer ability. In doing so, they validate how effectively the entire three-layer model improves measurable learning outcomes compared with traditional instruction. The classroom observations add a qualitative dimension, focusing on micro-level human–AI interactions, teacher orchestration strategies, and learning behaviors that may not be fully captured in log data. Through systematic coding and ethnographic interpretation, this evidence evaluates the alignment between AI-generated recommendations and actual pedagogical decision-making, thus shedding light on the ecological validity of the framework. The teacher interviews provide complementary insights into how educators perceive and appropriate AI tools within their instructional routines. Thematic analysis reveals how teachers interpret diagnostic dashboards, assess regulatory interventions, and position generative AI within their classroom practices. These insights are crucial for understanding the socio-emotional and pedagogical dimensions of the Generative Layer, especially in relation to inquiry-based and multimodal learning tasks.

Taken together, Table 2 illustrates how the study triangulates multiple data sources to build a coherent evaluation of the AI-enhanced learning ecosystem. Each analytical model contributes a distinct layer of evidence—cognitive, behavioral, affective, or experiential—allowing the research to comprehensively test the effectiveness, mechanisms, and pedagogical implications of the proposed framework.

4. Results and Discussion

The analysis of learning outcomes revealed a clear divergence between the AI-supported learners and those who received traditional instruction. Although both groups began with comparable pre-test scores, the post-test results demonstrated that students in the AI-enhanced environment progressed more rapidly and more substantially across all assessed dimensions. After adjusting for initial ability, the AI group outperformed the control group by a wide margin, particularly in conceptual transfer and modeling tasks, where deeper mathematical reasoning was required. These differences suggest that the integrated diagnostic–regulatory–generative framework shaped not only what students learned, but how they engaged with mathematical problems.

Table 3. Pre–Post Learning Gains Between Groups (ANCOVA -Adjusted)

Measure	Control (n=98)	AI Group (n=100)	Adjusted Mean Difference	Effect Size (Cohen's d)
Pre-test Mean (SD)	54.21 (12.18)	53.87 (11.90)	–	–
Post-test Mean (SD)	63.44 (13.50)	72.98 (12.14)	**+8.52***	**0.68**
Concept Transfer Score	18.7 (5.2)	24.1 (5.0)	**+5.1***	**0.83**
Modeling/Reasoning Task	12.4 (4.9)	15.6 (4.3)	**+3.0***	**0.61**

*p < .001

The sharp increase in transfer and reasoning scores offers compelling evidence that the generative layer helped students reorganize and deepen their conceptual structures. Unlike learners in the control group, those supported by AI engaged with a wider variety of representations, simulations, and dynamically generated examples, which likely contributed to their ability to generalize beyond familiar problem formats. This enhanced transfer aligns with the behavioral patterns revealed in the trajectory analysis. Across more than eighteen thousand interaction events, five behavioral clusters emerged. These clusters captured qualitatively distinct modes of engagement: from highly efficient solvers to learners who struggled with erratic strategies or cognitive overload. The distribution of clusters differed substantially between the instructional conditions.

Table 4. Behavioral Cluster Profiles and Distribution

Cluster Type	Description	% Control	% AI Group
C1: Efficient Solvers	Stable strategies, low hint usage, high accuracy	18%	**32%**
C2: Regulated Explorers	Frequent use of hints and simulations; productive transitions	22%	**31%**
C3: Disoriented Learners	High entropy sequences; erratic strategies	**29%**	14%
C4: Overloaded Learners	Long pauses; cycles between hinting and errors	21%	12%
C5: Metacognitive Learners	Revision loops; consistent self-checking	10%	**11%**

These distributions reveal meaningful shifts in how students navigated the learning process. The AI-supported learners were substantially more likely to inhabit clusters characterized by strategic consistency or productive exploration. Their interactions became more disciplined, more coherent, and more aligned with expert-like problem-solving pathways. Conversely, the reduction in disoriented and overloaded learners indicates that the regulatory mechanisms succeeded in mitigating the cognitive breakdowns that often plague mathematical learning. The decline in erratic behaviors, accompanied by reduced hesitation intervals and fewer overload episodes, shows that students maintained more stable cognitive states under the guidance of real-time adaptive supports.

These behavioral signatures are reflected in the observed knowledge -state transitions. Model-based estimates revealed that students in the AI group were more likely to move from misconception to partial mastery within a short interval, and more likely to retain mastery once achieved. Such progression suggests that the diagnostic layer's fine-grained learner modeling allowed the system to identify erroneous conceptions precisely enough for both teachers and AI-generated scaffolds to intervene effectively. The students' patterns of revision and self-correction further reinforce the notion that the generative layer's multimodal representations encouraged deeper reflection on their own reasoning processes. Observation notes and teacher interviews confirmed that the system facilitated a new mode of classroom orchestration in which human and machine intelligences worked in tandem. Teachers consistently reported that the analytics dashboard expanded their pedagogical field of vision, enabling them to notice cognitive fluctuations, identify bottlenecks, and interpret behavioral irregularities that would otherwise remain hidden. Although teachers did not relinquish instructional authority, they relied on AI-generated insights to refine pacing, adjust task demands, and provide timely motivational support. In this sense, the AI functioned as a cognitive partner, amplifying teacher judgment rather than replacing it.

Taken together, the results illustrate that the proposed AI-enhanced framework transforms the mathematics learning process on multiple levels. It accelerates conceptual development, stabilizes cognitive and behavioral trajectories, and supports richer forms of reasoning and self-monitoring. At the same time, it cultivates a collaborative learning ecology in which teachers, students, and AI systems contribute complementary forms of intelligence. These findings highlight the potential of AI not merely as a technological add-on, but as an architectural component of STEM-oriented mathematics education, reshaping the learning environment in ways that make deeper understanding more attainable.

In this enriched learning ecology, students' modes of engagement underwent a noticeable qualitative shift. The presence of AI gradually transformed their orientation from task-driven participation to goal-oriented inquiry, fostering a deeper awareness of strategy and intention during mathematical problem solving. Behavioral traces revealed that many learners were no longer merely executing steps mechanically; instead, they actively monitored the structure of their reasoning, adjusted their approaches when encountering ambiguity, and reconstructed representations to achieve conceptual clarity. These transitions were reinforced by the system's multimodal feedback mechanisms, which made invisible cognitive states more tangible and allowed students to recalibrate their understanding with greater precision.

When learners encountered conceptual bottlenecks, the AI system did not simply deliver direct answers, but positioned itself as a dialogic partner, prompting students with reflective questions, minimalist hints, and targeted visualizations that sustained productive struggle without tipping into frustration. This form of guided inquiry helped maintain cognitive load within an optimal range while simultaneously cultivating habits of explanation, verification, and hypothesis testing. Students began to display a growing tendency to justify intermediate steps, examine alternative pathways, and synthesize connections across representations—behaviors typically associated with more advanced mathematical reasoning. Such shifts were echoed in teacher observations, where instructors noted that the AI-enhanced environment altered the classroom's cognitive atmosphere. Students who previously disengaged during challenging tasks appeared more willing to persist, often returning to the system's diagnostic or generative resources for clarification rather than waiting passively for teacher intervention. The combination of adaptive scaffolding and targeted generative stimuli fostered a sense of intellectual agency, allowing learners to perceive themselves as active participants in constructing meaning rather than recipients of fixed procedures. Teachers emphasized that these changes were not superficial but reflected deeper transformations in students' epistemic stance toward mathematics, moving them toward more exploratory, self-regulated, and conceptually grounded engagement.

As the learning cycles unfolded, a coherent pattern emerged: the integration of diagnostic precision, regulatory stabilization, and generative augmentation created a synergistic effect that reshaped the developmental trajectory of mathematical understanding. Students navigated problems with greater fluency, recovered from errors more efficiently, and exhibited increasingly sophisticated reasoning patterns that aligned with the broader goals of STEM-oriented education. The observed gains in transfer, modeling, and behavioral coherence were not isolated successes but manifestations of a systemic shift in how learners interacted with mathematical ideas. The AI-enhanced framework thus appears to function not merely as an assistive tool, but as an epistemic infrastructure that reorganizes opportunities for sense-making and expands the cognitive bandwidth available to both students and teachers.

5. Conclusion

The findings of this study demonstrate that integrating artificial intelligence into mathematics education, when guided by a diagnostic–regulatory–generative framework, can meaningfully reshape both the process and outcomes of learning. Students supported by AI not only achieved higher levels of conceptual mastery but also displayed more coherent and goal-directed behavioral patterns, indicating a fundamental reorganization of how they approached mathematical tasks. The synergy between precise learner modeling, adaptive difficulty regulation, and context-rich generative supports enabled learners to maintain productive cognitive states, recover from misconceptions more efficiently, and engage in deeper forms of reasoning that extended beyond procedural competence. These improvements were not confined to test performance but were reflected in learners' strategic thinking, self-regulatory behaviors, and willingness to persist through conceptual challenges. Teachers played a pivotal role in this redesigned learning ecology, using AI-generated insights to identify moments of conceptual struggle, interpret students' behavioral signals, and deliver timely pedagogical interventions. Rather than diminishing the role of human judgment, the AI system expanded teachers' capacity to orchestrate complex learning environments by making hidden cognitive processes more visible and actionable. The resulting form of human–AI co-orchestration demonstrates that effective use of AI in education depends not on technological substitution, but on the harmonious alignment between computational intelligence and professional expertise.

Ultimately, the study provides evidence that AI can function as both a cognitive scaffold and a conceptual catalyst in STEM-oriented mathematics learning. Its impact lies not simply in automating feedback or generating instructional content, but in restructuring the conditions under which mathematical understanding is constructed, negotiated, and stabilized. By supporting learners' metacognitive engagement, enhancing teachers' instructional precision, and creating dynamic opportunities for conceptual exploration, AI establishes a new pedagogical architecture capable of fostering deeper, more transferable, and more resilient forms of mathematical knowledge. These findings suggest that thoughtfully designed AI systems can serve as an enabling infrastructure for future STEM education, expanding what learners are capable of achieving and how educators can support them.

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