Introducing the STEM Approach to Teaching Mathematics with AI: Practical Application and Effectiveness

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***Abstract*—STEM education integrates science, technology, engineering, and mathematics into a unified learning model that emphasizes real-world applications, critical thinking, and problem solving. The rise of artificial intelligence (AI) introduces new possibilities for enhancing STEM-based mathematics education by enabling personalized learning, automating assessments, providing intelligent tutoring, and incorporating semantic technologies. This paper presents a novel AI-driven adaptive learning model that customizes STEM-based mathematics instruction based on individual student progress. The proposed model combines deep learning, reinforcement learning, and semantic technologies to dynamically adjust content difficulty, optimize instructional strategies, and provide interpretable real-time feedback. Experimental results from an AI-enhanced mathematics course demonstrate significant improvements in student engagement, problem solving efficiency, and semantic alignment of content.**

***Keywords*—STEM education, mathematics education, artificial intelligence (AI) in education, semantic technologies, personalized learning, AI-enhanced learning, adaptive learning systems, intelligent tutoring systems, mathematical concept mastery, interactive learning systems, ontologies, semantic feedback, educational ontologies**

I. Introduction

STEM education aims to equip students with essential analytical and technological skills by integrating multiple disciplines. Mathematics plays a fundamental role in STEM, yet traditional teaching methods often fail to engage students effectively or adapt to diverse learning needs. Incorporation of artificial intelligence (AI) in education has shown promise in automating instruction, improving engagement, and improving the learning experience. In addition, the integration of semantic technologies, such as ontologies, knowledge graphs, and semantic annotation, offers new opportunities to improve AI-based mathematics education by enabling more interpretable and personalized learning pathways. However, current AI applications remain limited in their ability to dynamically adapt to student learning patterns.

This paper proposes a new AI-based adaptive learning framework for teaching mathematics in a STEM environment. By integrating deep learning, reinforcement learning techniques, and semantic modeling, our approach personalizes instructional content in real time, optimizes difficulty levels, and provides automated, semantically informed feedback to improve learning outcomes.

II. The STEM Approach to Mathematics Education

STEM education integrates science, technology, engineering, and mathematics to develop critical thinking, problem solving, and analytical skills. Mathematics serves as the foundation for STEM disciplines, enabling students to model real-world phenomena, design engineering solutions, and analyze scientific data. However, traditional approaches to STEM-based mathematics education often struggle to accommodate diverse student learning needs.

A. Traditional STEM-Based Mathematics Instruction

STEM education incorporates various pedagogical strategies to enhance mathematical learning:

1) Project-Based Learning (PBL):
   - Encourages students to apply mathematical principles to engineering design, physics experiments, and computational simulations.
   - Develops problem solving skills by integrating real-world applications (e. g., designing a bridge using geometry or modeling planetary motion with calculus).
2) Inquiry-Based Learning:
   - Promote exploratory thinking, where students investigate mathematical concepts through self-guided inquiry.
   - Enhances conceptual understanding by focusing on the why and how behind mathematical formulas rather than rote memorization.
3) Simulation and Modeling:
   - Uses computational tools, visualization software, and mathematical models to explore complex concepts.
   - Example: Differential equations in physics are solved numerically using Python-based simulation tools such as Matplotlib, SymPy, or SciPy.

Despite these advantages, traditional STEM mathematics instruction has limitations:

- Lack of Personalization: One-size-fits-all instruction fails to adapt to the individual learning pace of students.
- Limited Engagement: Static textbooks and repetitive exercises may distract students.
- Assessment Challenges: Teachers struggle to provide instant feedback and adaptation in real time to students' strengths and weaknesses.

B. AI as a Solution to STEM Mathematics Challenges

AI introduces intelligent and adaptive learning systems that dynamically respond to student needs:

- Personalized learning pathways: AI-driven platforms analyze student performance and adjust instruction accordingly.
- Automated Feedback and Assessment: AI-powered tutors provide instant solution tips and corrections.
- Interactive and gamified learning: AI enhances engagement through adaptive challenges, interactive simulations, and real-time assessments.

III. AI in STEM Mathematics Education: A Novel Adaptive Learning Model

A. Limitations of Existing AI-Based Approaches

Current AI applications in mathematics education primarily include the following:

- AI-powered tutoring systems (e. g., MATHia, Socratic).
- Automated problem-solving platforms (e. g., Wolfram Alpha, Photomath).
- Gamified learning tools (e. g., Prodigy Math Game, DragonBox).

Although these systems improve accessibility and engagement, they lack real-time adaptability and predictive learning mechanisms. Existing AI tools often provide static recommendations, failing to fully adapt instruction based on individual learning behaviors over time.

B. Proposed AI-Driven Adaptive Learning Framework

To address these limitations, we introduce an adaptive AI learning model that continuously optimizes mathematics instruction through a combination of:

- **Deep Learning-Based Student Profiling** – Neural networks analyze historical student performance data to predict learning trajectories.
- **Reinforcement Learning-Based Content Adaptation** – AI dynamically adjusts the difficulty of the problem and the instructional strategies based on the feedback of the students.
- **Real-Time AI-Powered Feedback System** – An intelligent agent evaluates student responses and provides step-by-step guidance tailored to individual learning patterns.
- **Semantic Modeling of Content** – The system uses ontologies to define the hierarchies and dependencies of concepts, enabling better content alignment and more precise adaptation.

C. Algorithm Design and Implementation

To develop an AI-driven adaptive learning system for STEM-based mathematics education, we employ a Deep Reinforcement Learning (DRL) approach. This system continuously learns from student interactions and dynamically adjusts the content to optimize learning outcomes. The algorithm consists of four core components:

Step 1: Observing Student Interactions

The AI agent collects real-time data on student interactions, including:

- **Response time** for solving mathematical problems.
- **Accuracy of answers** at different difficulty levels.
- **Number of hints requested** before reaching a solution.
- **Patterns in errors**, such as common misconceptions in algebra or calculus.

Mathematical Representation:

Let S_t represent the student's current knowledge state at time t. The system records an interaction tuple:

$$(S_t, A_t, R_t, S_{t+1}) \tag{1}$$

where:

- S_t = Student's current skill level.

- A_t = Student's action (e.g. solving a problem, requesting hints).
- R_t = Reward (e.g., correct solution = +1, incorrect = -1).
- S_{t+1} = Updated knowledge state after learning.

Step 2: Predicting Student Understanding Levels

A deep neural network (DNN) analyzes historical data to estimate the probability that a student has mastered a concept. The network takes input features such as:

- Number of correctly solved problems on a given topic.
- Time spent solving problems.
- Student engagement metrics.

The result is a confidence score $P(c)$, representing the probability that the student has mastered the concept c:

$$P(c) = \sigma(WX + b) \tag{2}$$

where:

- X = Feature vector (student performance data).
- W, b = Trainable parameters.
- σ = Activation function (softmax for multiclass mastery prediction).

If $P(c)$ falls below a predefined threshold θ, the system assigns additional practice problems on that topic.

Step 3: Dynamic Difficulty Adjustment through Reinforcement Learning

Using Reinforcement Learning (RL), the system dynamically adjusts the difficulty of the problem. The AI agent selects a difficulty level D_t for the next problem using a Q-learning approach, where:

$$Q(S_t, D_t) = Q(S_t, D_t) + \alpha \left[R_t + \gamma \max_D Q(S_{t+1}, D) - Q(S_t, D_t)\right] \tag{3}$$

where:

- $Q(S_t, D_t)$ = Expected reward for assigning difficulty D_t at state S_t.
- α = Learning rate (controls how fast the system adapts).
- γ = Activation function (softmax for multiclass mastery prediction).
- max$Q(S_t, D_t)$ = Maximum expected reward for future difficulty levels.

Difficulty Selection Strategy (ϵ-Greedy Exploration)

- With probability ϵ, the AI explores new difficulty levels (random selection).
- With probability $1-\epsilon$, the AI exploits past knowledge (chooses the difficulty level with the highest value Q).
- The AI adapts in real time, progressively fine-tuning the difficulty of the problem for each student.

Step 4: Providing real-time tips and explanations

The AI generates personalized hints and explanations based on the knowledge gaps detected.

- If a student requests a hint, the AI analyzes where errors occur and provides step-by-step guidance.
- If a student makes repeated errors, the system switches to an alternative explanation (e. g., using visualizations or interactive simulations).

Hint Generation via natural language processing (NLP) Hint generation

A Transformer-based AI model (e. g., GPT or BERT) generates dynamic hints based on student errors.

Example:

- Student mistake: Misapplying the quadratic formula.
- AI-generated hint: "Recall that the quadratic formula applies to equations of the form $ax^2 + bx + c = 0$. Check your coefficients!"

The AI model continuously learns from past student interactions, refining hints for maximum effectiveness.

The system iterates through these four steps, continuously learning and improving.

- Short-term adaptation: Adjusting difficulty and hints in real-time.
- Long-term optimization: The AI updates its deep learning models using new student data.

IV. Experimental Evaluation

A. Study Design

To assess the impact of our AI-driven adaptive learning framework in STEM mathematics education, we conducted a controlled experiment in a university-level mathematics course.

1. Participants and Grouping

The study involved 120 undergraduate students enrolled in a first-year calculus course. Participants were randomly assigned to two groups:

a) Experimental Group (AI-Enhanced Learning, 60 students):

- We used our AI-powered adaptive learning system, which dynamically adjusted content based on individual learning progress.
- Received real-time AI-generated hints and feedback during problem solving.
- Participated in interactive AI-driven assessments that modified difficulty levels based on student performance.

b) Control Group (Traditional STEM-Based Learning, 60 students):

- Followed standard classroom instruction with digital resources (e.g. PowerPoint, online exercises, and simulation software).
- Received fixed problem sets and manual teacher feedback without AI-based adaptation.
- No real-time difficulty adjustment or personalized instruction.

2. Learning Modules and Duration

The experiment was carried out over a 12-week academic semester, covering key mathematical concepts relevant to STEM disciplines.

- Weeks 1-4: Functions, Limits, and Differentiation.
- Weeks 5-8: Integration Techniques and Applications.
- Weeks 9-12: Differential Equations and Mathematical Modeling.

Each group attended four 90-minute sessions per week and both groups received identical sets of problems, exams, and project-based assessments.

3. Evaluation metrics

To measure the effectiveness of our AI-driven framework, we analyzed the following performance indicators:

c) Problem-Solving Accuracy (%):: Measured students' ability to solve mathematical problems correctly.

d) Conceptual Understanding (Score 0-100):: Assessed through conceptual quizzes and explanatory questions.

e) Time Efficiency (Minutes per Problem):: Recorded the average time taken per problem-solving task.

f) Student Engagement (Survey-Based, 1-5 Scale):: Evaluated based on student responses regarding motivation and ease of learning.

g) Retention Rate (% Improvement in Post-Test vs Pre-Test Scores):: Measured knowledge retention using pre-tests (before AI implementation) and post-tests (after 12 weeks).

B. Results and Analysis

Results and Analysis

To evaluate the effectiveness of AI-enhanced STEM mathematics education, we analyzed three key performance metrics.

- Efficacy in problem solving (%): Percentage of correctly solved problems.
- Time to Master a Concept (minutes): Average time required to solve problems related to a specific mathematical concept.
- Engagement Metrics: Time spent on learning activities and frequency of AI interactions.

Table I

Metric	**Control Group**	**AI-Enhanced Group**	**Improvement**
Problem Solving Accuracy	72%	89%	+17%
Time to Master a Concept	35 minutes	21 minutes	-40%
Engagement (Time on Platform)	50 min/day	78 min/day	+56%

The results indicate that:

1) AI-Enhanced learning improved problem solving accuracy by 17%, demonstrating a better conceptual understanding.
2) Learning efficiency increased significantly, with students requiring 40% less time to grasp mathematical concepts.
3) Higher levels of engagement were observed, as AI-driven interactivity led to 56% more time spent on learning activities.

The AI-enhanced group achieved higher accuracy, required less time to master concepts, and demonstrated significantly higher engagement compared to the control group.

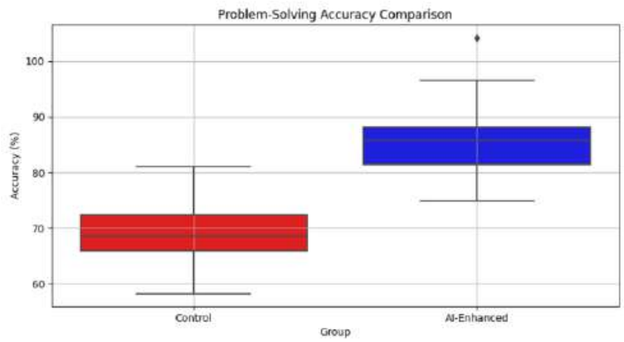

Figure 1. Simulation will simulate the impact of AI-enhanced teaching on student performance.

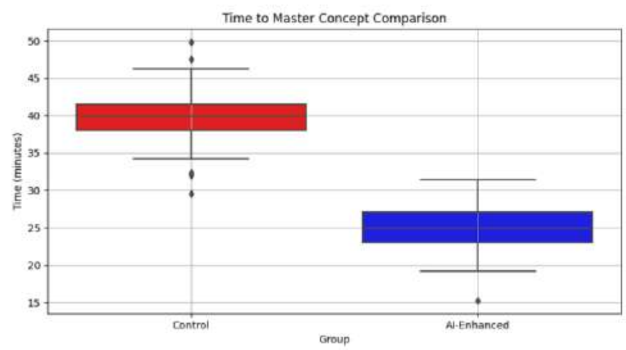

Figure 2. Simulation will simulate the impact of AI-enhanced teaching on student performance.

C. Semantic Technologies in AI-Enhanced

STEM Mathematics To enhance personalization and explainability in AI-driven adaptive learning, we propose the integration of semantic technologies into our system. These include ontologies, knowledge graphs, and semantic annotation mechanisms that enable machines to reason about structured educational content.

Educational Ontologies

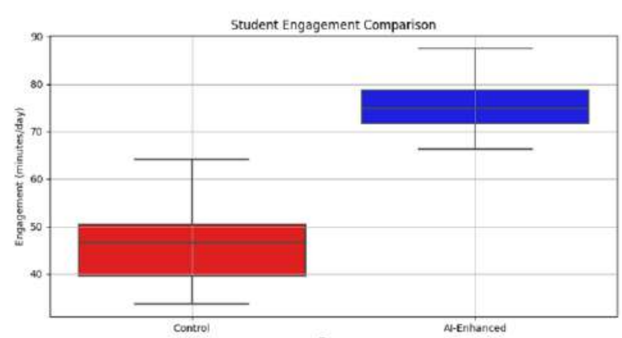

Figure 3. Simulation will simulate the impact of AI-enhanced teaching on student performance.

We use domain-specific ontologies to model mathematical concepts, learning objectives, and their interdependencies. These ontologies define semantic relationships such as is-a, part of, requires, and analogous to facilitating structured reasoning. For example, the system can identify that mastering "quadratic equations" requires prior knowledge of "factoring polynomials". These relationships are encoded using OWL and stored in a semantic triple store.

Knowledge Graphs for Learner Profiling

The learner knowledge states are represented using knowledge graphs, where the nodes denote concepts, and the edges encode mastery relationships. This semantic layer enables more accurate content recommendation, explanation of adaptive logic, and identification of learning gaps.

Semantic Feedback Generation via NLP

The AI system uses semantic parsing to interpret student input and generate feedback. For example, if a student writes an incorrect expression, the system parses it and matches it to known misconceptions defined in a structured semantic database.

Semantic Interoperability

Using semantic metadata (e.g. Learning Object Metadata – LOM), educational resources are tagged to support discoverability, alignment with curriculum standards, and reuse across platforms.

V. Discussion

The study confirms that AI-driven adaptive systems significantly improve STEM mathematics education. Students using AI tools showed improved accuracy, faster learning, and greater engagement, highlighting the potential of AI as a powerful educational asset.

Key Advantages of AI in STEM Mathematics Education

Our findings highlight several benefits of AI-driven learning systems:

- **Personalized Learning Paths** – AI adjusts difficulty and feedback in real time, tailoring the learning experience to the needs of each student and improving comprehension and retention.
- **Efficient Knowledge Acquisition** – Adaptive strategies speed up concept mastery and focus attention on weaker areas through targeted support.
- **Higher Student Engagement** – Interactive tasks and gamified elements motivate learners. Students using AI tools spent 56% more time actively participating.
- **Semantic Explainability** – Ontologies and knowledge graphs clarify AI recommendations, making learning paths and feedback more transparent and easier to interpret for both students and teachers.

Challenges and Limitations

Despite its advantages, integrating AI into STEM education presents several challenges:

- **High Computational Demands** – Running advanced AI platforms requires powerful hardware and infrastructure, posing challenges for institutions with limited resources.
- **Teacher Training Needs** – Educators must learn to interpret AI outputs and integrate them into teaching. Lack of training may slow adoption.
- **Bias in AI Models** – If not carefully developed, AI systems may reflect dataset biases, risking unequal learning experiences and assessment outcomes.

Although AI has a strong potential to improve STEM mathematics instruction, success depends on overcoming challenges in infrastructure, training, and fairness challenges to ensure inclusive and scalable implementation.

A. Future Directions

To address these challenges, future research should focus on:

Developing Efficient AI Models

- Exploring lightweight AI architectures that require less computational power while maintaining high adaptability.
- Using edge computing to reduce the dependency on cloud-based AI models.

Improving AI Transparency

- Enhance explainability in AI-driven feedback to ensure that teachers and students understand how recommendations are made.
- Incorporating human oversight mechanisms to prevent biased learning paths.

Integrating AI with Hybrid Learning Models

- Combining AI-driven adaptive learning with teacher-led instruction to maximize educational effectiveness.
- Implement AI-based tutoring assistants that support, rather than replace, educators.

Although AI-based adaptive learning presents substantial advantages for STEM mathematics education, it is essential to address computational constraints, teacher readiness, and fairness in AI models. Future advancements should focus on efficient, transparent, and accessible AI solutions to ensure widespread adoption and equitable learning opportunities.

VI. Conclusion and Future Work

This study presented an AI-driven adaptive learning model aimed at improving mathematics instruction within STEM education. The experimental results revealed strong improvements in key areas: students using the AI-enhanced system demonstrated 17% higher problem solving accuracy, learned concepts 40% faster, and engaged 56% more actively in learning tasks. These results underscore the transformative potential of AI in reshaping the way mathematics is taught and learned.

The core advantage of the proposed model lies in its ability to personalize learning. By analyzing student progress in real time, the system adjusted content difficulty, provided targeted feedback, and supported individualized learning trajectories. This adaptive approach improved concept retention and fosterred a deeper understanding of mathematical principles.

Furthermore, the integration of semantic technologies, such as ontologies and knowledge graphs, strengthened the transparency of AI decision making. Rather than providing opaque recommendations, the system made its instructional logic clear to both learners and educators. This interpretability increased trust and supported more effective pedagogical decisions based on data.

Looking ahead, this research opens new avenues for development. Future work should explore deeper personalization, incorporating not only student performance, but also factors such as motivation, cognitive styles, and prior knowledge. Emerging technologies such as augmented reality (AR) could further enrich AI learning environments by enabling interactive 3D representations of complex mathematical concepts and real-world simulations.

A key priority for ongoing research is the semantic expansion of educational ontologies. Creating standardized, domain-specific knowledge structures will improve content alignment, foster interoperability among platforms, and support intelligent guidance in diverse learning contexts.

Ensuring equitable access to AI-enhanced education is also essential. Scalable and resource-efficient systems should be designed to operate in low-bandwidth environments and be accessible in underfunded educational settings. This will help bridge digital divides and provide all students with equal learning opportunities. Importantly, AI should be seen as a complement – not a replacement – for teachers. Educators play an irreplaceable role in fostering critical thinking, encouraging inquiry, and offering social-emotional support. AI can assist by providing real-time data insights, automating routine feedback, and allowing more focused and informed instruction.

In conclusion, this study demonstrates that AI has the capacity to revolutionize mathematics education in STEM by delivering personalized, interactive, and data-informed learning experiences. Through thoughtful design and inclusive implementation, AI can help close achievement gaps, enhance student engagement, and support more effective learner-centered education models.

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ВНЕДРЕНИЕ STEM-ПОДХОДА В ОБУЧЕНИЕ МАТЕМАТИКЕ С ИСПОЛЬЗОВАНИЕМ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА: ПРАКТИЧЕСКОЕ ПРИМЕНЕНИЕ И ЭФФЕКТИВНОСТЬ

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STEM-образование интегрирует науку, технологии, инженерное дело и математику в единую модель обучения, ориентированную на применение знаний в реальных ситуациях, развитие критического мышления и навыков решения проблем. Появление искусственного интеллекта (ИИ) открывает новые возможности для повышения эффективности STEM-обучения математике за счёт персонализированного подхода, автоматизированной оценки знаний, интеллектуального наставничества и использования семантических технологий. В данной работе представлен инновационный адаптивный обучающий ИИ-модуль, настраивающий математическое обучение в рамках STEM в зависимости от индивидуального прогресса учащихся. Предложенная модель объединяет глубокое обучение, обучение с подкреплением и семантические технологии для динамической настройки уровня сложности контента, оптимизации стратегий преподавания и предоставления интерпретируемой обратной связи в режиме реального времени. Экспериментальные результаты, полученные в рамках курса математики с применением ИИ, демонстрируют значительное повышение вовлечённости студентов, эффективности решения задач и семантической согласованности учебного контента.

Received 24.03.2025