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THE IMPORTANCE OF ARTIFICIAL INTELLIGENCE SYSTEMS IN TEACHING MATHEMATICS

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Abstract: The integration of artificial intelligence (AI) systems into mathematics education is reshaping the way students learn and teachers instruct. AI tools offer a wide range of benefits, including automated problem solving, adaptive feedback, personalized learning experiences, and real-time assessment. This paper explores the educational value of AI systems in mathematics instruction by analyzing key technological components such as information extractors, reasoning engines, explainers, and data-driven modeling. The review draws upon recent studies and applications such as Photomath, GeoGebra, and intelligent tutoring systems (ITS) to highlight how AI enhances conceptual understanding, supports individual learning paths, and transforms classroom dynamics. By synthesizing findings from educational technology research, the paper also discusses future directions and challenges for integrating AI responsibly and effectively into teaching practices.

Keywords: Artificial Intelligence (AI), Mathematics Education, Intelligent Tutoring Systems (ITS), Adaptive Learning, Educational Technology, Machine Learning, Problem Solving, Student Modeling, Explainable AI

Introduction

Artificial intelligence (AI) is becoming increasingly influential in modern education, especially in subjects like mathematics where structured reasoning and abstract thinking are essential. As educational methods evolve in the digital era, AI provides a foundation for transforming conventional instruction into more personalized, responsive, and interactive learning experiences. Unlike traditional approaches that heavily rely on teacher-led explanations, AI-based tools promote learner autonomy, adapting in real time to students' needs and learning styles.

AI systems now support mathematics education in multiple ways: scanning and interpreting equations from handwritten or printed text, solving problems, presenting solutions step-by-step, and analyzing student behavior to adjust content and feedback. A comprehensive classification of these AI systems is presented by Van Vaerenbergh and Pérez-Suay (2021), who identify four primary functions: extracting information, automated reasoning, explanatory feedback, and data-driven modeling. Each function corresponds to different instructional goals and stages in the learning process.

Many researchers have examined how AI enhances mathematics teaching and learning. For instance, Webel and Otten (2015) discuss Photomath, an AI-powered app that solves math problems from images. While it aids in understanding, they caution that such tools might discourage students from developing their own problem-solving strategies if used improperly.

In another example, Kovács and Recio (2020) explore GeoGebra's automated theorem proving feature, which helps verify geometric constructions. Despite the power of such engines, the lack of human-readable proofs makes them difficult to use effectively in instructional contexts—highlighting the need for AI systems that are not only intelligent but also interpretable.

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The ViLLe intelligent tutoring system (Kurvinen et al., 2020) exemplifies the role of big data in personalizing learning. It monitors user behavior and performance to make data-informed adjustments to each student's learning path. Similarly, Baker et al. (2010) demonstrate how AI algorithms can detect when a learner truly understands a concept, paving the way for adaptive feedback and targeted support.

Together, these studies show that AI tools are reshaping math education by automating routine tasks, supporting conceptual understanding, and providing real-time insights into learning behavior. However, their effectiveness depends on careful integration into pedagogical frameworks that respect both technological capabilities and human learning processes.

Main part

Artificial intelligence systems used in mathematics education can be classified based on their functional roles in the learning process. Van Vaerenbergh and Pérez-Suay (2021) provide a foundational framework that organizes these systems into four major categories: information extractors, reasoning engines, explainers, and data-driven modeling systems. These categories reflect the broad range of AI applications in educational tools, from parsing mathematical problems to guiding individual learners with adaptive instruction.

Information extractors are AI systems that capture and transform real-world data—such as text, images, or speech—into structured mathematical representations. These systems are essential for bridging the gap between human input and machine-readable formats.

A prominent example is the optical character recognition (OCR) used in mobile applications like Photomath and Microsoft Math Solver, which scan printed or handwritten equations and convert them into digital form for analysis. More advanced extractors, such as those using convolutional neural networks (CNNs), can identify mathematical structures from images, diagrams, or even spoken language. In GeoGebra, for instance, image recognition algorithms assist in translating geometric constructions into algebraic representations.

Some projects, such as Socratic by Google, go a step further by extracting information from word problems written in natural language, interpreting the question semantically, and mapping it to a solvable mathematical expression.

Reasoning engines are the "problem-solving brains" of AI educational tools. They accept structured input—such as an equation or logic statement—and apply algorithms to derive a solution. At their simplest, they act as symbolic solvers using rule-based systems or computational engines like WolframAlpha and Maple.

More sophisticated systems incorporate machine learning (ML) and deep learning to improve performance on tasks such as theorem proving, symbolic reasoning, or even solving word problems. Neural network models trained on millions of examples (e.g., Saxton et al., 2019) have demonstrated moderate success in solving algebraic and calculus-based problems.

In intelligent tutoring systems, reasoning engines are responsible for evaluating student responses, detecting errors, and providing immediate feedback. These engines are sometimes paired with expert models that simulate correct solution paths and compare student input to expected behavior.

One of the major challenges in AI-based learning environments is not just solving problems, but explaining solutions in a human-understandable way. Explainers are AI modules that convert computational results into step-by-step narratives, often resembling a teacher's written feedback.

These systems are crucial in educational contexts, as they help students understand why a solution is correct, not just what the answer is. For example, Photomath and mathsteps

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provide explanatory sequences for solving algebraic equations, showing intermediate steps and logical justifications.

In more advanced systems, explainability is linked to the field of Explainable AI (XAI), which aims to develop models that are transparent and interpretable by design. This is especially important when AI is used to make educational decisions or assessments, where transparency and fairness are critical.

AI systems that rely on data-driven modeling use statistical and machine learning techniques to analyze large amounts of student-generated data. These systems are widely used in intelligent tutoring systems and learning analytics platforms to create student models—digital representations of learners' knowledge, skills, and behaviors.

Such models enable systems to predict future performance, recommend personalized tasks, detect misconceptions, or even adapt the pacing of instruction. For instance, clustering algorithms may group learners into categories (e.g., novice, intermediate, advanced), while classification models might identify students at risk of failure.

The ViLLe system (Kurvinen et al., 2020) and the TIDES system (Danine et al., 2006) are examples of AI-powered ITSs that use Bayesian networks and other probabilistic models to personalize learning paths and offer real-time interventions.

Furthermore, data-driven modeling contributes to curriculum evaluation by identifying widespread errors across classrooms or regions, thereby informing teacher training and educational policy decisions

Results

Artificial intelligence systems bring numerous pedagogical benefits to mathematics education. They enable automated problem solving, which helps students instantly verify their solutions and understand the correct procedures. AI-powered tools provide adaptive feedback tailored to each student's learning pace and style, increasing learner engagement and motivation.

Personalized learning experiences are facilitated through intelligent tutoring systems that analyze student performance and adjust difficulty levels accordingly, promoting mastery-based progression. Tools like GeoGebra and Photomath offer visual and interactive representations that enhance conceptual understanding and support diverse learning preferences. AI's real-time assessment capabilities allow teachers to monitor student progress continuously and intervene promptly, improving overall learning outcomes.

These applications transform traditional classroom dynamics by shifting the teacher's role from information deliverer to learning facilitator, promoting learner autonomy and encouraging deeper mathematical reasoning.

Despite their benefits, integrating AI systems into mathematics education faces several challenges and ethical concerns. One major issue is the risk of over-reliance on AI tools, which may discourage students from developing independent problem-solving skills. As Webel and Otten (2015) note, improper use of apps like Photomath could reduce critical thinking development if students depend solely on automated solutions.

Another challenge lies in the interpretability of AI outputs. Some reasoning engines, such as those in GeoGebra, produce proofs or solutions that are difficult for students and educators to comprehend fully, which can limit instructional effectiveness. This highlights the need for Explainable AI (XAI) approaches that make AI reasoning transparent and accessible.

Privacy and data security concerns arise with AI systems that collect and analyze student data to personalize learning. Ensuring ethical use of data and protecting learner

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confidentiality is paramount. Moreover, equitable access to AI technologies remains a challenge, as disparities in resources may widen educational inequalities.

Teachers also require sufficient training to effectively integrate AI tools into pedagogy, avoiding a mere substitution of traditional teaching with technology rather than meaningful enhancement.

AI System Function	Examples	Pedagogical Benefits	Challenges / Issues
Information Extractors	Photomath, Microsoft Math Solver	Recognize and digitize handwritten or printed formulas, speeding up problem-solving and increasing engagement	Difficulty fully recognizing complex mathematical structures
Reasoning Engines	GeoGebra, WolframAlpha	Solve problems and provide step-by-step solutions, enhancing conceptual understanding	Results may be hard to interpret or too complex for learners
Explainers	Photomath, mathsteps	Explain solution steps clearly, supporting deeper understanding and knowledge retention	Need for explanations to be clear, fair, and trustworthy
Data-driven Modeling	ViLLe, TIDES	Personalize learning paths, detect errors, and adapt instruction to individual needs	Privacy concerns and data security challenges

Conclusion

Artificial intelligence systems are poised to revolutionize mathematics education by providing adaptive, personalized, and interactive learning experiences. Their ability to automate routine tasks and deliver real-time feedback supports both learners and educators in achieving better educational outcomes. However, careful integration that considers pedagogical principles, ethical standards, and accessibility is essential to fully realize AI's potential in teaching mathematics.

Future research and development should focus on creating transparent, interpretable AI tools that empower learners without undermining critical thinking and fostering equitable access to technology-enhanced education. The analysis of recent studies and applications demonstrates that artificial intelligence (AI) systems significantly enhance mathematics education by providing diverse functionalities that support both students and teachers.

Firstly, AI-powered information extractors such as those in Photomath and Microsoft Math Solver enable accurate recognition and digitization of handwritten and printed mathematical expressions, allowing students to interact with problems seamlessly and reducing barriers related to inputting complex formulas. This functionality increases student engagement and accelerates problem-solving processes.

Secondly, reasoning engines integrated into intelligent tutoring systems effectively solve a wide variety of mathematical problems, from algebraic equations to geometric proofs. These engines provide step-by-step solutions that help students follow the logic behind answers, improving conceptual understanding. For example, GeoGebra's theorem proving tool aids in validating geometric constructions, although its complexity requires further development to improve interpretability for learners.

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Thirdly, explainers that provide transparent, human-readable feedback are crucial in bridging the gap between automated problem solving and meaningful learning. Applications like Photomath not only offer solutions but also detail the reasoning process, which supports deeper cognitive processing and knowledge retention. The advancement of Explainable AI (XAI) models further contributes to this by enhancing the clarity and trustworthiness of AI-generated explanations.

Finally, data-driven modeling systems such as the ViLLe intelligent tutoring system use student interaction data to create personalized learning paths. These systems adapt content and pacing according to individual needs, helping to identify misconceptions early and tailor instruction to maximize learning efficiency. The ability to aggregate data across learners also supports teachers in curriculum design and targeted interventions.

However, challenges remain regarding student dependence on AI tools, the need for improved explainability of AI outputs, privacy concerns, and equitable access to these technologies. Addressing these issues is essential for the sustainable integration of AI in mathematics education.

In summary, the results indicate that AI systems, when properly designed and integrated, can transform mathematics teaching and learning by automating routine tasks, enhancing feedback quality, and personalizing instruction.

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