Research on AIGC-Driven Personalized Mathematics Learning System

Chenggang Wang

Digital Media Technology Program, Liaoning Communication University, shenyang, China

Abstract. This paper comprehensively explores the development, implementation, and impact of an AIGC (Artificial Intelligence-Generated Content)-driven personalized mathematics learning system. In an era where education faces increasingly diverse learning needs, traditional teaching methods often fall short of addressing individual differences. Leveraging advanced artificial intelligence technologies, this system aims to provide tailored learning experiences that cater to each student's unique needs, strengths, and weaknesses. By integrating generative AI models, adaptive learning algorithms, and real-time feedback mechanisms, the system seeks to enhance student engagement, improve learning outcomes, and foster a deeper understanding of mathematical concepts. This paper particularly focuses on the application of AIGC in recreating historical mathematical scenarios, enabling students to better understand the origins and significance of mathematical theorems.

Keywords: AIGC, Personalized Learning, Mathematics Education, Historical Scenarios, Adaptive Learning.

1. Introduction

Mathematics education has long been a cornerstone of academic development, yet it remains one of the most challenging subjects for many students. The abstract nature of mathematical concepts, combined with varying levels of prior knowledge and cognitive abilities among students, creates a significant barrier to effective learning. Traditional one-size-fits-all teaching methods often fail to address these individual differences, leading to disengagement, frustration, and suboptimal learning outcomes.

Recent advancements in Artificial Intelligence (AI) and generative content technologies (AIGC) offer innovative solutions to these long-standing challenges. AIGC, which involves the use of generative AI models to create original content such as text, images, and videos, has the potential to revolutionize education by providing highly personalized and adaptive learning experiences. This paper proposes an AIGC-driven personalized mathematics learning system designed to address the diverse needs of students and enhance their learning outcomes. Specifically, it explores how AIGC can recreate historical mathematical scenarios to help students gain a deeper understanding of the background and development of mathematical theorems.

2. Theoretical Foundations

2.1 Personalized Learning

Personalized learning is an educational approach that tailors instruction to meet the individual needs, preferences, and goals of each student. It emphasizes student-centered learning, where the pace, content, and methodology are adapted based on the learner's unique profile. Key components of personalized learning include adaptive content delivery, real-time feedback, and data-driven insights, which together create a dynamic and responsive learning environment.

2.2 AIGC in Education

AIGC refers to the use of generative AI models, such as GPT (Generative Pre-trained Transformer) and DALL-E, to create original content across various media formats. In education, AIGC can be applied to generate customized learning materials, automate assessments, and facilitate interactive learning environments. Unlike traditional content creation methods, AIGC enables the rapid production of high-quality, contextually relevant materials that can be tailored to the specific needs of individual learners. For example, AIGC-generated historical scenarios can help students better understand the origins and practical applications of mathematical theorems.

2.3 Challenges in Mathematics Education

Mathematics learning is inherently complex, involving abstract concepts, logical reasoning, and problem-solving skills. Students often struggle with these elements due to cognitive differences, varying levels of prior knowledge, and a lack of engagement. Traditional teaching methods, which rely on standardized curricula and uniform instructional approaches, are ill-equipped to address these challenges. By introducing historical scenarios, students can understand the formation of theorems within their historical context, thereby deepening their comprehension of abstract concepts.

3. System Architecture

The proposed AIGC-driven personalized mathematics learning system is designed to provide scalable, adaptive, and interactive learning experiences. Its architecture comprises four key modules:

3.1 Student Profile Module

This module serves as the foundation of the system, collecting and analyzing data on students' learning preferences, knowledge levels, and performance history. It employs machine learning algorithms to create individualized learning profiles, which are continuously updated as students progress through the system. By understanding each student's strengths, weaknesses, and learning styles, the module ensures that the content and activities are tailored to their specific needs.

3.2 Content Generation Module

Powered by AIGC technologies, this module generates personalized learning materials, including practice problems, explanations, and visual aids. The content is dynamically adjusted based on the student's progress, learning style, and performance. For instance, students struggling with algebraic equations might receive additional practice problems with step-by-step solutions, while those excelling in geometry might be challenged with more advanced problems and interactive visualizations. Additionally, the module can generate historical mathematical scenarios, recreating the discoveries of famous mathematicians to help students understand the background and practical significance of theorems.

3.3 Adaptive Learning Engine

The adaptive learning engine is the core of the system, responsible for optimizing the learning path for each student. It employs reinforcement learning algorithms to analyze student data and recommend activities, adjust difficulty levels, and provide targeted interventions. The engine ensures that students are neither overwhelmed by the material nor under-challenged, maintaining an optimal balance that promotes continuous growth.

3.4 Real-Time Feedback Mechanism

This mechanism provides immediate feedback on student performance, highlighting areas for improvement and reinforcing correct understanding. It includes interactive elements, such as virtual tutors and gamified challenges, to enhance engagement and motivation. For example, a student who makes a mistake in solving a problem might receive instant feedback explaining the error and suggesting a corrected approach.

4. Application of Historical Scenarios

To help students better understand the origins and significance of mathematical theorems, the system incorporates AIGC-generated historical scenarios. These scenarios vividly recreate important mathematical discoveries, allowing students to immerse themselves in the thought processes of mathematicians. Specific examples include:

4.1 Pythagorean Theorem

Through AIGC-generated 3D scenes, students can "travel back" to ancient Greece, observing how Pythagoras and his school discovered and proved the Pythagorean theorem by studying geometric patterns and architectural structures. The system also generates interactive problems, requiring students to verify the theorem through hands-on activities.

4.2 Newton and Leibniz's Calculus Debate

The system creates virtual dialogues and scenarios to showcase the contributions and disputes between Newton and Leibniz in the development of calculus. Students can simulate the thinking processes of these mathematicians to understand the fundamental concepts and applications of calculus.

4.3 Euler's Seven Bridges Problem

Using AIGC-generated virtual maps and interactive games, students can simulate Euler's thought process in solving the Königsberg bridge problem, thereby understanding the origins of graph theory and its applications in modern mathematics.

4.4 Archimedes' Bathtub Epiphany

The system recreates the scene of Archimedes discovering the principle of buoyancy. Students can conduct interactive experiments to observe Archimedes' thought process and understand the practical significance of the principle.

5. Experimental Design

5.1 Participants

The study involved 200 middle school students from diverse backgrounds, representing varying levels of mathematical proficiency. The participants were randomly assigned to either the experimental group (using the AIGC-driven system) or the control group (receiving traditional classroom instruction).

5.2 Data Collection

Data were collected through a combination of pre- and post-assessments, student surveys, and system logs. The pre-assessment established a baseline for each student's mathematical knowledge and skills, while the post-assessment measured their progress after the intervention. Student surveys provided insights into their engagement, motivation, and satisfaction with the system, while system logs offered detailed data on their interactions with the platform.

5.3 Procedure

The experimental group used the AIGC-driven personalized mathematics learning system for 12 weeks, while the control group followed the standard curriculum with traditional teaching methods. Both groups were evaluated at the end of the study to compare their learning outcomes, engagement levels, and overall satisfaction.

6. Results and Discussion

6.1 Improved Learning Outcomes

Students in the experimental group showed significant improvements in test scores compared to the control group. The personalized approach effectively addressed individual learning gaps and reinforced key concepts. Particularly, the use of historical scenarios helped students gain a deeper understanding of theorems and their practical applications.

6.2 Enhanced Engagement

The interactive and adaptive nature of the system increased student motivation and participation. The introduction of gamified elements and historical scenarios made the learning process more engaging and enjoyable. Students reported high levels of interest in the historical scenarios, as these helped them visualize the background and significance of theorems.

6.3 Teacher Feedback

Teachers reported that the system reduced their workload by automating routine tasks such as grading and content generation. The inclusion of historical scenarios also allowed them to provide more comprehensive explanations of theorems, enhancing the overall teaching effectiveness.

7. Conclusion

This study demonstrates the feasibility and effectiveness of an AIGC-driven personalized mathematics learning system. By leveraging advanced AI technologies, the system offers a dynamic, adaptive, and engaging learning experience that caters to the unique needs of each student. The incorporation of historical mathematical scenarios significantly enhances students' understanding of the origins and practical significance of theorems, fostering deeper engagement and improved learning outcomes. As AI continues to evolve, its role in education is expected to expand, paving the way for more innovative, inclusive, and effective learning environments.

References

1. Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. The Journal of the Learning Sciences, 4(2), 167-207. https://doi.org/10.1207/s15327809jls0402_2
2. Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In Learning Analytics (pp. 61-75). Springer. https://doi.org/10.1007/978-1-4614-3305-7_4
3. Bruner, J. S. (1966). Toward a Theory of Instruction. Harvard University Press.
4. Devlin, K. (2012). Introduction to Mathematical Thinking. Stanford University.
5. Dillenbourg, P. (2013). Design for classroom orchestration. Computers & Education, 69, 485-492. https://doi.org/10.1016/j.compedu.2013.04.013
6. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
7. Koedinger, K. R., & Aleven, V. (2007). Exploring the assistance dilemma in experiments with cognitive tutors. Educational Psychology Review, 19(3), 239-264. https://doi.org/10.1007/s10648-007-9049-0
8. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097-1105.
9. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence unleashed: An argument for AI in education. Pearson Education.
10. Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are few-shot learners. arXiv preprint arXiv:2005.14165.
11. Shaffer, D. W. (2006). Epistemic frames for epistemic games. Computers & Education, 46(3), 223-234. https://doi.org/10.1016/j.compedu.2005.11.004
12. Sweller, J., Ayres, P., & Kalyuga, S. (2011). Cognitive Load Theory. Springer. https://doi.org/10.1007/978-1-4419-8126-4
13. VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and

other tutoring systems. Educational Psychologist, 46(4), 197-221. https://doi.org/10.1080/00461520.2011.611369

14. Vygotsky, L. S. (1978). Mind in Society: The Development of Higher Psychological Processes. Harvard University Press.
15. Wenger, E. (1998). Communities of Practice: Learning, Meaning, and Identity. Cambridge University Press.
16. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16(1), 39. https://doi.org/10.1186/s41239-019-0171-0
17. Zhang, J., & Patel, V. L. (2006). Distributed cognition, representation, and affordance. Pragmatics & Cognition, 14(2), 333-341. https://doi.org/10.1075/pc.14.2.07zha