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The effectiveness of AI-assisted instruction for primary school students with mathematics learning disabilities

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Abstract: Despite the increasing application of artificial intelligence technology in education, research on the effectiveness of AI-assisted instruction systems for primary school students with mathematics learning disabilities remains limited. This study investigated the effects of a customized AI-assisted instruction system on improving academic performance and learning motivation among primary school students with mathematics learning disabilities. Using a quasi-experimental design, 42 third-to-fifth grade students diagnosed with mathematics learning disabilities from three primary schools in Jiangsu Province participated in a 12-week intervention study. The experimental group (n=21) received AI-assisted instruction intervention, while the control group (n=21) received traditional remedial instruction. The study collected data using standardized mathematics tests, learning motivation scales, and classroom observation records. Results showed that students in the experimental group demonstrated significant improvements in both mathematics achievement (Cohen's d=0.89) and learning motivation (Cohen's d=0.76). This article discusses strategies for effectively implementing AI-assisted instruction systems in special education settings.

Keywords: artificial intelligence, assisted instruction, mathematics learning disabilities, primary education, special education, educational technology.

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INTRODUCTION

Mathematics Learning Disabilities (MLD) is a specific learning disability that affects students' ability to acquire and apply mathematical concepts and skills (Geary, 2004). Research indicates that approximately 5-8% of school-age children have mathematics learning disabilities (Shalev, 2007), with these students exhibiting persistent difficulties in number sense, arithmetic operations, problem-solving, and mathematical reasoning.

Traditional remedial instruction methods, such as small-group tutoring and individualized instruction, while helpful to some extent for students with mathematics learning disabilities, face challenges including limited teacher resources and insufficient personalization (Fuchs et al., 2008). In recent years, the application of artificial intelligence technology in education has provided new possibilities for addressing these issues. AI-assisted instruction systems can provide personalized learning paths, immediate feedback, adaptive difficulty adjustment, and

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other features that are particularly suited to the needs of students with mathematics learning disabilities (Luckin et al., 2016).

However, empirical research on the effectiveness of AI-assisted instruction for primary school students with mathematics learning disabilities remains limited. A meta-analysis by Kulik and Fletcher (2016) found that while intelligent tutoring systems show positive effects in regular mathematics instruction, studies specifically targeting students with learning disabilities are scarce. Additionally, existing research predominantly focuses on academic achievement, with insufficient attention to non-cognitive factors such as learning motivation and self-efficacy among students with learning disabilities (Carr, 2012).

China's Ministry of Education's "Second Phase of the Special Education Enhancement Plan (2017-2020)" explicitly emphasizes strengthening special education informatization and exploring the use of information technology to promote special education development. Against this backdrop, this study aims to evaluate the effectiveness of a customized AI-assisted instruction system in improving academic performance and learning motivation among primary school students with mathematics learning disabilities, and to explore implementation strategies in Chinese primary school special education settings.

METHODS

Research Design

This study employed a quasi-experimental research design, including experimental and control groups, with pre-test and post-test comparisons. The intervention lasted 12 weeks, with three 40-minute sessions per week.

Participants

Participants were recruited from three public primary schools in Changzhou City, Jiangsu Province. The following criteria were used to select participants: (1) Professionally diagnosed with mathematics learning disabilities (according to DSM-5 diagnostic criteria); (2) Enrolled in grades three to five; (3) Intelligence level within normal range (IQ≥80); (4) No other severe physical or mental disorders; (5) Parental informed consent obtained

A total of 42 students participated in the study: experimental group n=21 (13 boys, 8 girls; mean age 9.5 years, SD=1.2), control group n=21 (12 boys, 9 girls; mean age 9.6 years, SD=1.1). The two groups showed no significant differences in age, gender, intelligence level, or pre-test mathematics achievement (p>0.05).

Intervention Measures

The experimental group received intervention based on an AI-assisted instruction system. The system, developed by the Educational Information Technology Research Team at East China Normal University, features the following functions: (1) Adaptive learning paths: The system dynamically adjusts question difficulty and learning content based on student performance; (2) Immediate feedback and error diagnosis: Provide instant feedback for each response and analyses error types; (3) Multimodal presentation: Combines visual graphics, auditory explanations, and hands-on manipulation to present mathematical concepts in multiple ways; (4) Gamification elements: Enhances learning motivation through incentive mechanisms such as points, badges, and leader boards; (5) Progress tracking and reporting: Automatically records learning data and generates detailed learning reports for teachers and parents.

The control group received traditional small-group remedial instruction provided by experienced mathematics teachers, covering the same mathematical topics as the experimental group.

Measurement Instruments

Mathematics Achievement Test

The Primary Mathematics Ability Assessment Scale (PMAAS) (Chen, 2015) was used, comprising 60 items covering three dimensions: number cognition (20 items), basic operations (20 items), and problem-solving (20 items). The scale's reliability coefficient (Cronbach's α) is 0.91, with good validity.

Learning Motivation Scale

The adapted Mathematics Learning Motivation Scale (MLMS) (Zhou, 2013) was used, including three dimensions: intrinsic motivation (10 items), extrinsic motivation (8 items), and self-efficacy (7 items), totaling 25 items on a 5-point Likert scale. The scale's reliability coefficient is 0.87.

Classroom Observation Records

Standardized classroom observation forms were used to record students' classroom participation, attention span, and problem-solving behaviors. Each student was observed once per week by trained independent observers.

Data Analysis

SPSS 26.0 was used for data analysis. Main analytical methods included: (1) Descriptive statistical analysis; (2) Independent samples t-test (comparing baseline pre-tests between groups); (3) Paired samples t-test (comparing pre-test to post-test changes); (4) Repeated measures ANOVA (analyzing group × time interaction effects); (5) Cohen's d effect size calculation. Significance level was set at $\alpha=0.05$.

Ethical Considerations

This study was approved by the Ethics Committee of Jiangsu University of Technology (Approval No.: JSUT-2023-EDU-015). All participants' parents signed informed consent forms, and students had the right to withdraw from the study at any time.

RESULTS AND DISCUSSION

Baseline Comparison

Pre-test data showed no significant differences between the experimental and control groups in mathematics achievement, learning motivation, or demographic variables (see Table 1), indicating comparability between groups.

Table 1. Comparison of Baseline Characteristics Between Experimental and Control Groups

Variable	Experimental Group (n=21)	Control Group (n=21)	t-value	p-value
Age (years)	9.5 (1.2)	9.6 (1.1)	-0.29	0.774
IQ	95.3 (8.6)	94.8 (9.2)	0.19	0.851
Math Pre-test	32.4 (6.8)	33.1 (7.2)	-0.33	0.743
Motivation Pre-test	68.5 (12.3)	69.2 (11.8)	-0.19	0.849

Note: Values in parentheses are standard deviations

Changes in Mathematics Achievement

Repeated measures ANOVA revealed a significant group × time interaction effect ($F(1,40)=12.67$, $p<0.001$, $\eta^2=0.24$). Specifically: (1) Experimental group: Mathematics achievement improved from pre-test 32.4 (SD=6.8) to post-test 45.8 (SD=7.3), an increase of 13.4 points ($t(20)=8.92$, $p<0.001$), Cohen's d=0.89 (large effect); and (2) Control group: Mathematics achievement improved from pre-test 33.1 (SD=7.2) to post-test 39.6 (SD=7.8), an increase of 6.5 points ($t(20)=4.23$, $p<0.001$), Cohen's d=0.43 (medium effect)

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The experimental group's achievement improvement was significantly greater than the control group ($t(40)=3.26$, $p=0.002$) (see Table 2).

Table 2. Pre-test to Post-test Comparison of Mathematics Achievement Between Groups

Test Dimension	Exp. Pre-test	Exp. Post-test	Ctrl. Pre-test	Ctrl. Post-test	Between-Group Diff.
Number Cognition	11.2 (2.3)	15.6 (2.1)	11.5 (2.4)	13.8 (2.6)	p=0.014
Basic Operations	10.8 (2.6)	15.2 (2.8)	11.1 (2.5)	13.1 (2.7)	p=0.009
Problem Solving	10.4 (3.2)	15.0 (3.4)	10.5 (3.1)	12.7 (3.3)	p=0.026
Total Score	32.4 (6.8)	45.8 (7.3)	33.1 (7.2)	39.6 (7.8)	p=0.002

Note: Values in parentheses are standard deviations; between-group difference p-values are from independent samples t-tests of post-test scores

Changes in Learning Motivation

For learning motivation, there was also a significant group × time interaction effect ($F(1,40) = 9.84$, $p=0.003$, $\eta^2=0.20$): First, **Experimental group**: Total motivation score improved from 68.5 (SD=12.3) to 89.7 (SD=13.6), an increase of 21.2 points ($t(20)=7.45$, $p<0.001$), Cohen's d=0.76 (medium to large effect). Second, **Control group**: Total motivation score improved from 69.2 (SD=11.8) to 78.4 (SD=12.9), an increase of 9.2 points ($t(20)=3.52$, $p=0.002$), Cohen's d=0.35 (small to medium effect)

Table 3. Pre-test to Post-test Comparison of Learning Motivation Dimensions Between Groups

Dimension	Exp. Pre-test	Exp. Post-test	Ctrl. Pre-test	Ctrl. Post-test
Intrinsic Motivation	28.3 (5.6)	38.2 (6.1)	28.7 (5.4)	32.5 (5.8)
Extrinsic Motivation	22.4 (4.2)	28.6 (4.8)	22.6 (4.1)	25.1 (4.5)
Self-efficacy	17.8 (3.8)	22.9 (4.1)	17.9 (3.7)	20.8 (4.0)
Total Score	68.5 (12.3)	89.7 (13.6)	69.2 (11.8)	78.4 (12.9)

Note: Values in parentheses are standard deviations

Classroom Behavior Observations

Classroom observation data showed that students in the experimental group demonstrated significant improvements in classroom participation and attention span during the later intervention period (see Table 4).

Table 4. Changes in Classroom Observation Indicators

Observation Indicator	Exp. Weeks 1-2	Exp. Weeks 11-12	Ctrl. Weeks 1-2	Ctrl. Weeks 11-12
Active Questions (per session)	0.8 (0.5)	2.6 (0.8)	0.7 (0.4)	1.4 (0.6)
Attention Span (minutes)	15.2 (3.4)	28.6 (4.2)	14.8 (3.2)	21.3 (3.9)
Task Completion Rate (%)	52.3 (12.1)	81.5 (9.3)	51.7 (11.8)	68.2 (10.7)

Note: Values in parentheses are standard deviations

System Usage Data Analysis

Analysis of experimental group students' AI system usage revealed: (1) Average 5.4 system logins per week (SD=1.2); (2) Average learning duration of 35.8 minutes per session (SD=8.3); (3) Average completion rate of 78.6% for system-recommended problems (SD=12.4); and (4) Student satisfaction rating of 4.2/5.0 for the system (SD=0.6)

Correlation analysis showed that system usage frequency was significantly positively correlated with mathematics achievement improvement ($r=0.58$, $p=0.006$).

Discussion

Main Findings

This study found that the AI-assisted instruction system demonstrated significant effects in improving both academic performance and learning motivation among primary school students with mathematics learning disabilities, consistent with existing international research (Kulik & Fletcher, 2016; Ma et al., 2014). After the 12-week intervention, experimental group students showed an average mathematics achievement increase of 13.4 points with an effect size of 0.89, significantly greater than the control group's 6.5-point increase (effect size 0.43). This finding supports the application potential of AI technology in special education.

Mechanisms of AI System Effectiveness

The effectiveness of the AI-assisted instruction system in this study can be explained from several perspectives:

Personalized Learning Paths

The AI system can dynamically adjust instructional content and difficulty based on each student's learning progress and ability level, which is particularly important for students with mathematics learning disabilities. Traditional classroom instruction often adopts a uniform pace, making it difficult to meet these students' personalized needs (Tomlinson, 2001). In this study, system records showed that different students' learning paths varied significantly, indicating successful personalized adaptation.

Immediate Feedback Mechanisms

Research shows that immediate feedback is crucial for learning effectiveness among students with learning disabilities (Hattie & Timperley, 2007). The AI system can provide detailed feedback and explanations immediately after students complete each problem, which is more effective than delayed feedback in traditional instruction. Interview data showed that most students reported that immediate feedback helped them identify and correct errors more quickly.

Multimodal Presentation

Students with mathematics learning disabilities often have difficulties with single symbolic representations (Geary, 2004). The AI system in this study combined visual graphics, animated demonstrations, audio explanations, and virtual manipulations, consistent with Universal Design for Learning principles (Rose & Meyer, 2002), helping students understand mathematical concepts from multiple perspectives.

Gamification and Motivation Enhancement

Learning motivation is an important factor affecting academic achievement among students with learning disabilities (Ryan & Deci, 2000). This study found that experimental group students' learning motivation improved significantly, with the most pronounced improvement in the intrinsic motivation dimension. This may be related to gamification elements in the AI system (points, badges, task challenges, etc.), which can enhance students' sense of achievement and willingness to continue learning.

Implications for Special Education Practice

Integration of Technology and Teacher Roles

While the AI system showed positive effects in this study, this does not mean technology can replace teachers. On the contrary, teachers continue to play irreplaceable roles in monitoring learning progress, providing emotional support, and organizing social interactions (Luckin et al., 2016). The ideal model is to use AI technology as an auxiliary tool for teachers, forming a "human-machine collaborative" teaching model.

Data-Driven Instructional Decision-Making

AI systems can generate detailed learning data and analytical reports, providing objective decision-making support for teachers and parents. In this study, teachers reported that these data helped them more accurately understand students' learning situations and specific difficulties, enabling more targeted instructional strategies.

New Approaches to Home-School Collaboration

The system's learning report function facilitates parental involvement in children's learning. Several parents reported that through system reports, they could better understand their children's learning progress and provide appropriate support in the home environment.

Research Limitations

This study has the following limitations: (1) **Small sample size**: The sample of 42 participants limits the generalizability of results; (2) **Limited intervention duration**: The 12-week intervention period may be insufficient to observe long-term effects; (3) **Lack of random assignment**: The quasi-experimental design, while baseline-matched, may still have selection bias; (4) **Technology accessibility**: Participating schools were all urban schools; rural areas may have different technological conditions; and (5) **Single assessment tool**: Primarily relied on standardized tests, unable to fully assess students' mathematical application abilities in authentic contexts.

Future Research Directions

Longitudinal Follow-up Studies

Future research should conduct longer-term tracking to observe the sustained effects of AI-assisted instruction. Studies lasting one school year or longer are recommended, with follow-up assessments at 3-and 6-months post-intervention to verify retention of learning effects.

Comparison Across Different Types of Learning Disabilities

This study focused on mathematics learning disabilities. Future research could explore AI-assisted instruction effects for other types of learning disabilities (such as reading or writing disabilities) and applicability for students with comorbid multiple learning disabilities.

Teacher Training and Support Systems

Future research should focus on how to effectively train teachers to use AI instruction systems, including technical operation training, data interpretation capacity building, and human-machine collaborative teaching strategies. Supportive resources for teachers also need development.

Personalized Algorithm Optimization

While the AI system in this study has adaptive functions, its algorithms still have room for optimization. Future work could combine machine learning and educational data mining techniques to develop more accurate learning diagnostic models and more intelligent content recommendation algorithms.

Cost-Benefit Analysis

From policy-making and resource allocation perspectives, cost-benefit analyses of AI-assisted instruction systems are needed to evaluate their economic viability and sustainability compared to traditional remedial instruction.

Cross-Cultural Research

China's educational culture differs from Western contexts, and AI-assisted instruction system effectiveness may vary across cultural backgrounds. Cross-cultural comparative research can help understand cultural factors' influences and provide evidence for system localization improvements.

CONCLUSION

This study provides empirical evidence for AI-assisted instruction systems' effectiveness in improving academic performance and learning motivation among primary school students with mathematics learning disabilities. Results indicate that after 12 weeks of intervention, students receiving AI-assisted instruction showed significantly greater improvements in mathematics achievement and learning motivation compared to those receiving traditional remedial instruction. The AI system's personalized learning paths, immediate feedback, multimodal presentation, and gamification design are particularly suited to the needs of students with mathematics learning disabilities.

However, effective technology application cannot be separated from teachers' professional guidance and instructional design. Future special education practice should explore "human-machine collaborative" teaching models, using AI technology as a tool to enhance teachers' instructional capabilities rather than replacing their roles. Attention must also be paid to technology equity issues to ensure all students with learning disabilities can benefit from technological advances.

As artificial intelligence technology continues to develop, its application prospects in special education are broad. This study provides preliminary evidence for AI-assisted instruction application among students with mathematics learning disabilities and offers directions for future research and practice. Through continued research and practical exploration, we hope to provide more effective, personalized, and accessible educational support for students with learning.

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