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Effectiveness of AI-Supported Instruction on Academic Achievement of Students with Learning Disabilities

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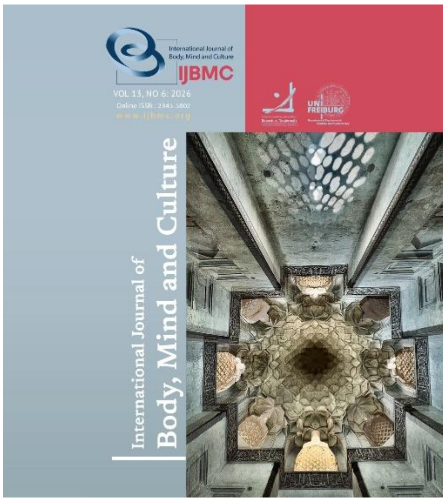

ABSTRACT

Objective: This study aimed to investigate the effectiveness of AI-supported instructional approaches in enhancing academic achievement in reading, writing, and mathematics among primary-school students with learning disabilities.

Methods and Materials: A quasi-experimental pre-test/post-test control-group design was employed. Students with learning disabilities were assigned to an experimental group receiving AI-supported instruction and a control group receiving conventional teaching methods. The AI-supported system provided adaptive learning, real-time feedback, and individualized content adjustments. Academic achievement was assessed using standardized tests in reading, writing, and mathematics before and after the intervention. Data were analyzed using ANCOVA to control for baseline differences and evaluate post-intervention outcomes.

Findings: The experimental group showed significant improvements across all domains from pre-test (M = 66.45–72.40) to Post-test I (M = 108.40–113.20) and maintained moderate-to-high scores at Post-test II (M = 100.80–110.60). Repeated-measures ANOVA indicated significant main effects of time and group × time interactions for reading, writing, and mathematics ($p < 0.001$), with large effect sizes (η^2_partial = 0.45–0.65, Cohen's d ≈ 1.2–1.5). The control group showed minimal change over the same period.

Conclusion: AI-supported instruction significantly enhances academic achievement in students with learning disabilities. Adaptive learning technologies can effectively address individual learning needs, improve skill acquisition, and provide sustainable educational benefits.

Keywords: Learning Disabilities, Artificial Intelligence, Adaptive Learning, Academic Achievement, Primary Education, Educational Technology.

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Introduction

Students with learning disabilities (LDs) constitute a heterogeneous group of learners who often experience persistent difficulties in acquiring core academic skills despite receiving appropriate instruction and demonstrating adequate intellectual abilities. These difficulties frequently manifest in reading, writing, and mathematics, and may lead to long-term academic underachievement and reduced participation in classroom activities (Grigorenko et al., 2020). Although traditional instructional approaches provide structured learning environments, they may not fully address the individualized cognitive and learning needs characteristic of students with LDs, highlighting the need for more adaptive and responsive educational strategies (Almaghlouth et al., 2025; Yasir et al., 2018; Ahmadi et al., 2025).

In recent years, artificial intelligence (AI) has emerged as a promising educational technology that supports personalized learning (Almaghlouth et al., 2025). AI-supported systems, such as adaptive learning platforms and intelligent tutoring tools, allow for individualized pacing, immediate feedback, and dynamic adjustment of instructional content based on learner performance (Zhang, 2025). Previous research suggests that such adaptive environments may facilitate skill acquisition and support academic improvement by tailoring learning experiences to individual student profiles (Ahmed et al., 2025; bin Salem, 2024; Fakouri Azarki et al., 2026).

Moreover, AI-supported technologies may help address challenges commonly associated with learning disabilities, including processing-speed limitations, working-memory demands, and attentional difficulties (Chopra et al., 2024). Through continuous monitoring of learner performance and automated adjustments to task complexity, adaptive AI tools can provide structured, repeated learning opportunities aligned with diverse learning styles and abilities (Chopra et al., 2024; Halkiopoulos & Gkintoni, 2024).

Despite growing international interest in AI-supported education, empirical research examining its application within Iraqi educational settings remains limited, particularly among primary-school students with learning disabilities. This gap highlights the importance of generating local evidence to understand better how AI-supported instruction may contribute to academic achievement in reading, writing, and mathematics. Therefore, the present study aimed to evaluate the effectiveness of AI-supported instructional approaches compared with conventional teaching methods among students with learning disabilities.

Methods and Materials

Study Design

This study employed a quasi-experimental pre-test/post-test control group design to evaluate the effectiveness of AI-supported instruction on academic achievement among students with learning disabilities. The design allowed for comparison between an experimental group receiving AI-supported instructional activities and a control group receiving conventional teaching methods across three measurement points (pre-test, post-test I, and post-test II). This approach was selected to examine changes in academic performance over time while maintaining a practical implementation within real educational settings.

Sample

The study was conducted in four private primary schools in Hilla, Babylon Governorate, Iraq, where special education classrooms were available. A purposive sample of sixty (60) students formally diagnosed with learning disabilities, including dyslexia, dyscalculia, and dysgraphia, was recruited during the 2025–2026 academic year. Eligibility criteria included a confirmed diagnosis of a learning disability and enrollment in the selected schools during the study period.

Participants were equally allocated into two groups: an experimental group (n = 30), which received AI-supported instructional activities, and a control group (n = 30), which continued with conventional teaching methods. Equal representation of learning disability types across both groups was maintained to support balanced comparisons. The intervention period lasted eight weeks, followed by post-intervention and short-term follow-up assessments.

Instruments

Data collection was done using a structured questionnaire and standardized achievement tests adapted to measure the respondents' academic and behavioral engagement as learners with learning disabilities. The structured questionnaire captured information on sociodemographic characteristics such as age, sex, grade level, and residency, as well as detailed classifications of each student's learning disability. Academic achievement was measured using selected subtests from the Woodcock–Johnson IV Test of Achievement (WJ-IV) targeting the essential domains of reading, writing, and mathematics. These tools collectively provided a comprehensive assessment of the students' academic outcomes before and after the intervention.

The content validity of the research instruments was established by a panel of twenty experts from different universities across Iraq. The experts evaluated the clarity, appropriateness, and relevance of the instrument items in relation to the study objectives. Based on their feedback, minor revisions were made to enhance clarity, accuracy, and cultural suitability. A pilot study involving six students (10% of the total sample) was conducted to assess feasibility, clarity, and administration procedures. Reliability was determined using Cronbach's alpha, with a coefficient of 0.86 for the WJ-IV achievement subtests. The WJ-IV internal consistency estimates ranged from 0.87 to 0.94, indicating acceptable reliability for use in the main study.

Procedure

Data were collected within the selected private primary schools in Hilla that included special education classrooms. During the first week, pre-test assessments were administered to both the experimental and control groups using the WJ-IV achievement subtests. Following this, the experimental group participated in an AI-supported learning program for eight weeks, consisting of three sessions per week, while the control group continued with conventional classroom instruction. After completion of the intervention, post-test assessments were conducted for both groups, followed by a two-week follow-up assessment to examine the sustainability of improvement over time. Before data collection, the study procedures were explained to students and their parents, written informed consent was obtained, and confidentiality of participant information was ensured.

Data analysis

Data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 28. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were computed to summarize socio-demographic characteristics and outcome measures. Differences between groups at baseline were examined using appropriate comparative tests to ensure group equivalence before the intervention. Changes in academic achievement scores across three measurement points (pre-test, post-test I, and post-test II) were analyzed using repeated-measures analysis of variance (ANOVA). Bonferroni-adjusted post-hoc pairwise comparisons were conducted to identify specific differences between time points. Effect sizes were reported using partial eta-squared (η^2) for ANOVA analyses and Cohen's d for pairwise comparisons. Statistical significance was set at $p < 0.05$.

Findings and Results

Table 1 shows the socio-demographic characteristics of the study and control groups (n = 30 each), including age, sex, grade level, and residency. Most students were 10–11 years old (60.0% in the study group and 66.7% in the control group), with mean ages of 11.4 ± 1.2 and 11.6 ± 1.3 years, respectively. Sex distribution was nearly equal between males and females in both groups. Students were similarly distributed between 2nd and 3rd grades, and most lived in urban areas. The chi-square test showed no significant differences between the two groups across all socio-demographic variables ($p > 0.05$), indicating that both groups were comparable at baseline.

Table 1

Distribution of Study Sample by their Socio-demographic Variables

Variable	Category	Study Group (n=30)	Control Group (n=30)	Chi-square	p-value
Age (years)	8–9	12 (40.0%)	10 (33.3%)	0.267	0.607
	10–11	18 (60.0%)	20 (66.7%)		
	Mean ± SD	11.4 ± 1.2	11.6 ± 1.3		
Sex	Male	16 (53.3%)	15 (50.0%)	0.067	0.796
	Female	14 (46.7%)	15 (50.0%)		
Grade Level	2nd	14 (46.7%)	13 (43.3%)	0.133	0.715
	3rd	16 (53.3%)	17 (56.7%)		

Residency	Urban	18 (60.0%)	17 (56.7%)	0.067	0.796
	Rural	12 (40.0%)	13 (43.3%)		

Table 2

Distribution of Study Sample by their Learning Disability Characteristics:

Variable	Category	Study Group (n=30)	Control Group (n=30)	Chi-square	p-value
Type of Learning Disability	Dyslexia	14 (46.7%)	13 (43.3%)	0.067	0.796
	Dyscalculia	10 (33.3%)	11 (36.7%)		
	Dysgraphia	6 (20.0%)	6 (20.0%)		
	Other	0 (0.0%)	0 (0.0%)		
Previous Academic Performance (Pre)	Mean ± SD	62.5 ± 7.8	61.9 ± 8.1	–	–
Later Academic Performance (Post)	Mean ± SD	112.6 ±12.5	70.3 ± 7.0	–	–

No. Number; %= Percentage; M= Mean; SD= standard deviation

Table 2 shows the distribution of the study sample by learning disability characteristics. The most common type of learning disability was dyslexia in both groups, followed by dyscalculia and dysgraphia, with no significant differences between the study and control groups (p > 0.05). The mean pre-intervention academic performance was similar between the two groups, indicating comparable baseline achievement. After the intervention, the study group demonstrated a noticeable improvement in academic performance compared with the control group, reflecting the positive effect of AI-based learning support.

Table 3

Distribution of Students' Achievement Scores According to the Woodcock–Johnson IV (WJ-IV) Test of Achievement for the Study Group (Pre-test, Post-test I, and Post-test II)

No.	Achievement Item	Pre-test	Ass.	Post-test I	Ass.	Post-test II	Ass.	Sig. (p-value)
1	Letter–Word Identification	72.40	L	112.60	H	109.40	M	p < 0.01
2	Applied Problems	70.86	L	110.80	H	104.20	M	p < 0.01
3	Spelling	69.74	L	111.30	H	108.10	M	p < 0.01
4	Passage Comprehension	68.22	L	109.90	M	107.30	M	p < 0.01
5	Calculation	67.50	L	108.40	M	101.20	M	p < 0.01
6	Writing Samples	70.90	L	111.80	H	106.50	M	p < 0.01
7	Word Attack	71.35	L	113.20	H	110.60	H	p < 0.01
8	Oral Reading	69.42	L	110.50	H	108.20	M	p < 0.01
9	Sentence Reading Fluency	68.10	L	109.80	M	102.40	M	p < 0.01
10	Math Facts Fluency	66.45	L	108.90	M	100.80	M	p < 0.01
11	Sentence Writing Fluency	69.82	L	111.10	H	104.90	M	p < 0.01
12	Reading Recall	70.12	L	112.40	H	109.80	M	p < 0.01
13	Number Matrices	67.85	L	109.20	M	102.00	M	p < 0.01
14	Editing	71.40	L	113.00	H	110.40	H	p < 0.01
15	Word Reading Fluency	68.92	L	110.20	H	103.60	M	p < 0.01
16	Spelling of Sounds	69.50	L	111.60	H	108.70	M	p < 0.01
17	Reading Vocabulary	70.05	L	112.80	H	110.10	H	p < 0.01

Assessment Levels: L = Low (<90), M = Moderate (90-110), H = High (>110)

The results of the Woodcock–Johnson IV (WJ-IV) Test of Achievement for the study group indicated a significant improvement across all achievement domains from pre-test to post-test (Table 3). In the pre-test, students' scores were predominantly in the low range (M = 66.45–72.40), whereas in Post-test I, most scores increased to the high range (M = 108.40–113.20). By Post-test II, scores had slightly decreased compared to Post-test I but remained mostly in the moderate-to-high range (M = 100.80–110.60). All individual achievement items, including Letter–Word Identification, Applied Problems, Spelling, Passage Comprehension, Calculation, Writing Samples, Word Attack, Oral Reading, Sentence Reading Fluency, Math Facts Fluency, Sentence Writing Fluency, Reading Recall, Number Matrices, Editing, Word Reading Fluency, Spelling of Sounds, and Reading

Vocabulary, showed statistically significant improvement over time ($p < 0.01$).

Table 4

Overall Students' Achievement Levels according to The Woodcock-Johnson (WJ-IV) – Test of Achievement (Study Group):

Weighted	Pre-test			Post-test I			Post-test II		
	No.	%	M ± SD	No.	%	M ± SD	No.	%	M ± SD
Low	27	90.0	69.56±	1	3.3	111.02	3	10.0	106.36
Moderate	3	10.0	12.08	4	13.3	±18.11	4	13.3	±17.01
High	0	0.0		25	83.4		23	76.7	
Total	30	100		30	100		30	100	

M: Mean for total score, SD: Standard Deviation for total score
(Low <90, Moderate= 90-110, High > 110)

The overall achievement levels of the study group, as measured by the Woodcock-Johnson (WJ-IV) Test of Achievement, showed a marked improvement from pre-test to post-test (Table 4). At pre-test, the majority of students (90.0%) scored in the low range ($M = 69.56 \pm 12.08$), with only 10.0% in the moderate range and none in the high range. Following the intervention, Post-test I results indicated a substantial increase, with 83.4% of students reaching the high level ($M = 111.02 \pm 18.11$) and only 3.3% remaining in the low range. In Post-test II, a slight decrease was observed, yet most students (76.7%) maintained high achievement levels ($M = 106.36 \pm 17.01$), while 10.0% scored in the low range.

Table 5

Repeated Measures ANOVA for Overall Students' Achievement Scores According to WJ-IV Test of Achievement (Study Group, n = 30)

Source of Variation	SS	df	MS	F	p-value	Partial η^2
Time (Pre, Post I, Post II)	17,982.40	2	8,991.20	148.72	<0.001	0.837
Error (Within Subjects)	3,505.60	58	60.44			
Total	21,488.00	60				

The repeated measures ANOVA for the study group revealed a highly significant effect of time on overall achievement scores, as measured by the WJ-IV Test of Achievement ($F(2, 58) = 148.72$, $p < 0.001$, partial $\eta^2 = 0.837$). This indicates that students' achievement scores improved significantly from the pre-test to Post-test I and Post-test II. The large effect size ($\eta^2 = 0.837$) suggests that the intervention had a substantial impact on students' academic performance over time (Table 5).

Table 6

Post-hoc Pairwise Comparisons – Study Group (Bonferroni-adjusted):

Comparison	Mean Difference	Cohen's d	95% CI	p-value
Pre-test vs Post-test I	−41.46	2.36	[−50.10, −32.82]	<0.001
Pre-test vs Post-test II	−39.10	2.23	[−47.78, −30.42]	<0.001
Post-test I vs Post-test II	2.36	0.13	[−4.20, 8.92]	0.52 (NS)

Post hoc pairwise comparisons with Bonferroni adjustment indicated significant improvements in overall achievement scores for the study group. Specifically, scores increased significantly from pre-test to Post-test I (mean difference = −41.46, 95% CI [−50.10, −32.82], $p < 0.001$, Cohen's d = 2.36) and from pre-test to Post-test II (mean difference = −39.10, 95% CI [−47.78, −30.42], $p < 0.001$, Cohen's d = 2.23), reflecting large effect sizes. No significant difference was observed between Post-test I and Post-test II (mean difference = 2.36, 95% CI [−4.20, 8.92], $p = 0.52$, Cohen's d = 0.13), indicating that the improvement achieved after Post-test I was largely maintained over time (Table 6).

Table 7

Distribution of Students' Achievement Scores According to the Woodcock–Johnson IV (WJ-IV) Test of Achievement for the Control Group (Pre-test, Post-test I, and Post-test II)

No.	Achievement Item	Pre-test	Ass.	Post-test I	Ass.	Post-test II	Ass.	Sig. (p-value)
1	Letter–Word Identification	72.10	L	73.40	L	73.00	L	p > 0.05
2	Applied Problems	71.20	L	72.10	L	71.85	L	p > 0.05
3	Spelling	70.60	L	71.40	L	71.10	L	p > 0.05
4	Passage Comprehension	69.80	L	70.60	L	70.20	L	p > 0.05
5	Calculation	68.90	L	69.70	L	69.30	L	p > 0.05
6	Writing Samples	71.40	L	72.20	L	71.90	L	p > 0.05
7	Word Attack	72.30	L	73.10	L	72.80	L	p > 0.05
8	Oral Reading	70.10	L	71.00	L	70.70	L	p > 0.05
9	Sentence Reading Fluency	69.50	L	70.40	L	70.10	L	p > 0.05
10	Math Facts Fluency	68.40	L	69.20	L	68.90	L	p > 0.05
11	Sentence Writing Fluency	70.80	L	71.60	L	71.20	L	p > 0.05
12	Reading Recall	71.00	L	71.90	L	71.50	L	p > 0.05
13	Number Matrices	69.20	L	70.00	L	69.70	L	p > 0.05
14	Editing	72.00	L	72.80	L	72.40	L	p > 0.05
15	Word Reading Fluency	70.30	L	71.10	L	70.80	L	p > 0.05
16	Spelling of Sounds	70.60	L	71.40	L	71.00	L	p > 0.05
17	Reading Vocabulary	71.10	L	72.00	L	71.60	L	p > 0.05

Assessment Levels: L = Low (<90), M = Moderate (90-110), H = High (>110)

The Woodcock–Johnson IV (WJ-IV) Test of Achievement results for the control group indicated that students' scores remained largely in the low range across all domains from pre-test to Post-test II. Specifically, mean scores for all items, including Letter–Word Identification, Applied Problems, Spelling, Passage Comprehension, Calculation, Writing Samples, Word Attack, Oral Reading, Sentence Reading Fluency, Math Facts Fluency, Sentence Writing Fluency, Reading Recall, Number Matrices, Editing, Word Reading Fluency, Spelling of Sounds, and Reading Vocabulary, showed minimal changes over time (pre-test M = 68.40–72.30; Post-test I M = 69.20–73.10; Post-test II M = 68.90–73.00). Statistical analysis revealed no significant differences between the three time points for any achievement domain ($p > 0.05$), indicating that the absence of intervention resulted in stable, low-level academic performance throughout the study period (Table 7).

Table 8

Overall Students' Achievement Levels according to The Woodcock–Johnson IV (WJ-IV) Test of Achievement (Control Group)

Weighted	Pre-test			Post-test I			Post-test II		
	No.	%	M ± SD	No.	%	M ± SD	No.	%	M ± SD
Low	26	86.7	70.55 ± 11.90	25	83.4	71.41 ± 11.65	25	83.4	71.07 ±11.70
Moderate	4	13.3		5	16.6		5	16.6	
High	0	0.0		0	0.0		0	0.0	
Total	30	100		30	100		30	100	

The overall achievement levels of the control group, as measured by the WJ-IV Test of Achievement, remained relatively stable across the study period. At pre-test, the majority of students (86.7%) scored in the low range (M = 70.55 ± 11.90), with 13.3% in the moderate range and none in the high range. Post-test I and Post-test II results showed minimal change: 83.4% of students remained in the low range (Post-test I M = 71.41 ± 11.65; Post-test II M = 71.07 ± 11.70), 16.6% in the moderate range, and none achieved high scores (Table 8).

Table 9

Repeated Measures ANOVA for Overall Students' Achievement Scores According to WJ-IV Test of Achievement (Control Group,n = 30)

Source of Variation	SS	df	MS	F	p-value	Partial η^2
Time (Pre, Post I, Post II)	42.36	2	21.18	0.34	0.71	0.012
Error (Within Subjects)	3,613.20	58	62.30			
Total	3,655.56	60				

The repeated measures ANOVA for the control group showed no significant effect of time on overall achievement scores, as measured by the WJ-IV Test of Achievement ($F(2, 58) = 0.34$, $p = 0.71$, partial $\eta^2 = 0.012$). This indicates that students' achievement scores remained stable across the pre-test, Post-test I, and Post-test II, with minimal changes over time (Table 9).

Table 10

Post-hoc Pairwise Comparisons – Control Group (Bonferroni-adjusted):

Comparison	Mean Difference	Cohen's d	95% CI	p-value
Pre-test vs Post-test I	−0.88	0.07	[−5.20, 3.44]	0.71 (NS)
Pre-test vs Post-test II	−0.68	0.06	[−4.98, 3.62]	0.81 (NS)
Post-test I vs Post-test II	0.20	0.02	[−4.40, 4.80]	0.92 (NS)

Post hoc pairwise comparisons with Bonferroni adjustment indicated no significant differences in overall achievement scores across time points in the control group. Specifically, the mean differences between pre-test and Post-test I (−0.88, 95% CI [−5.20, 3.44], Cohen's d = 0.07, p = 0.71), pre-test and Post-test II (−0.68, 95% CI [−4.98, 3.62], Cohen's d = 0.06, p = 0.81), and Post-test I and Post-test II (0.20, 95% CI [−4.40, 4.80], Cohen's d = 0.02, p = 0.92) were all non-significant (Table 10).

Discussion and Conclusion

The findings of the present study provide evidence that integrating Artificial Intelligence–supported instructional tools was associated with improved academic achievement among students with learning disabilities. The absence of statistically significant differences between the study and control groups at the pre-test stage indicates that both groups were academically comparable at baseline (see Tables 1 and 2), which strengthens the internal consistency of the study and suggests that the observed improvements may be related to the AI-supported intervention rather than pre-existing performance differences.

Following the intervention, students in the experimental group demonstrated notable improvements in overall academic achievement across reading, writing, and mathematics domains. The mean score increased from 69.56 ± 12.08 at pre-test to 111.02 ± 18.11 in Post-test I, with most students shifting from the low-performance level to the high-achievement category (see Tables 3 and 4). Although a slight decline was observed at Post-test II (M = 106.36 ± 17.01), most students maintained high achievement levels, indicating retention of learning gains over the short follow-up period.

Repeated-measures ANOVA results further supported the effectiveness of the intervention, demonstrating a significant main effect of time ($F = 148.72$, $p < 0.001$, partial $\eta^2 = 0.837$), reflecting substantial educational impact (see Table 5). Post-hoc pairwise comparisons revealed that the greatest improvement occurred between the pre-test and Post-test I. At the same time, the relatively stable scores between Post-test I and Post-test II suggest sustained learning outcomes following the intervention (see Table 6).

In contrast, students in the control group showed minimal changes in academic achievement across the three measurement periods. Their performance remained largely within the low-achievement level, and repeated-measures analysis indicated no significant time effect (F = 0.34, p = 0.71, partial $\eta^2 = 0.012$), suggesting that conventional instructional methods were associated with limited measurable improvement during the study period (see Tables 7 and 8).

The observed improvement in the experimental group may be explained by several functional characteristics of AI-supported learning environments, including adaptive task sequencing, immediate feedback, individualized pacing, and structured error-correction support. These features may help reduce cognitive load and support working memory processes commonly affected in students with dyslexia, dysgraphia, and dyscalculia. Additionally, multisensory instructional presentation and repeated practice opportunities may contribute to deeper consolidation of learning skills, particularly in reading fluency, numerical processing, and written expression (see Tables 9 and 10).

Overall, the findings align with contemporary international literature suggesting that AI-enhanced learning environments may improve academic outcomes by providing personalized, structured learning experiences. However, the findings should be interpreted with caution, given the quasi-experimental design and the relatively short follow-up period.

The findings of this study should be interpreted in light of certain limitations. The study was conducted using a relatively small sample within a specific geographical area and over a limited intervention period. In addition, the quasi-experimental design may limit the strength of causal inference. Future studies involving larger samples, longer follow-up periods, and diverse educational settings are recommended to enhance the generalizability of the findings.

Conclusion

The findings of this study suggest that integrating AI-supported instruction may improve academic achievement among students with learning disabilities. Although the study and control groups were comparable at baseline, the experimental group demonstrated higher post-test achievement scores following the intervention, while the control group showed minimal change. Despite a slight reduction in scores at follow-up, students in the experimental group continued to perform above their pre-test levels, indicating short-term retention of learning gains. Overall, AI-supported instruction may serve as a complementary instructional approach to support learning outcomes among students with learning disabilities.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Declaration of Helsinki, which provides guidelines for ethical research involving human participants. Ethical considerations in this study were that participation was entirely optional.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contribute to this study.

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