Original Article

Impact of Artificial Intelligence-Assisted Instruction on Classroom Behavior and Adaptive Functioning in Students with Learning Disabilities

AI Assisted Instruction on Classroom Behavior in Students with Learning Disabilities

Zainab Hassan Hussein and Amean A. Yasir

ABSTRACT

Objective: To evaluate the artificial intelligence-assisted instruction may influence classroom behavior and to explore its possible association with adaptive functioning in students with learning disabilities.
Study Design: A quasi-experimental study
Place and Duration of Study: This study was conducted at the Department of Community Health Nursing, College of Nursing, University of Babylon, Babylon Iraq from 01.02.2025 to January 2026.
Methods: A quasi-experimental design with pretest and posttest control groups was implement on a sample of 60 primary school students diagnosed with dyslexia, dyscalculia, or dysgraphia in Babylon, Iraq in the 01.02.2025 to January 2026 academic year letter No. 3434/QM/Approval/EFEF3 dated October 2, 2024 were enrolled. Participants were divided into an experimental group (n = 30), which received artificial ingelligence-supported instruction for eight weeks, and a control group (n = 30), which continued with traditional teaching methods.
Results: Students in the experimental group demonstrated a statistically significant improvement in classroom behavior across the study period ($F(2,58) = 312.85$, $p<0.001$, partial $\eta^2 = 0.915$), with notable progress from pretest to posttest that remained stable during follow-up assessment. In contrast, no statistically significant changes were observed in the control group ($p>0.05$), indicating the limited effect of conventional instruction alone.
Conclusion: The adoption of artificial intelligence-based instructional methods in special education settings is therefore encouraged.
Key Words: Artificial intelligence, Learning disabilities, Classroom behaviour, Adaptive functioning, Special education

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INTRODUCTION

Artificial Intelligence (AI) technologies have become one of the most popular trends in the global education sector as a way to enhance the learning results and provide a more personalized instruction to students with the different learning requirements.[1]

The field of AI has been opened up to a set of various educational technologies, such as adaptive learning systems, intelligent tutoring systems, simulation-based tools, and customized feedback applications.

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These technologies are programmed in such a way that it takes into consideration the profile of a particular learner and able to respond to certain issues that are faced by students with learning disabilities such as dyslexia, attention problems and academic disorders involving reading and mathematics. It has been demonstrated in the previous literature that AI-based tools could offer individualized and adaptive learning assistance, particularly to students who fail to respond satisfactorily when using traditional learning methods.[2,3] Moreover, these adaptive systems have shown statistically significant changes in the academic performance such as the performance of the learners in reading and mathematics among learners with learning disabilities.[4]

In the area of special education, the usefulness of AI is not confined solely to academic success but also to the possible impact it may have on the behavior of students, their engagement and their involvement in classroom tasks. The AIs have been identified to increase motivation, attention, and learning efficacy among students, which are all directly linked to behavioral functioning in a learning context.[5] As an illustration, AI-based interventions involving selective attention have positively impacted attention control and task-related behavior among elementary school students with learning issues, indicating that these technologies might be used to create a better classroom behavior and active engagement.[6] Moreover, the systematic reviews of the AI usage in special education have revealed that the intervention could reinforce participation and engagement which are critical elements of positive classroom behavior and adjustment to school in students with special educational needs.[7]

Educational justifications of introducing AI into teaching and learning are based on the theory of adaptive learning, personal feedback and student-centered teaching. These views underline the necessity to react to the individual differences in the needs of students, their abilities and progress rates.[8] By constantly updating student performance, AI technologies will be able to adapt learning content, learning velocity, and task challenge on the fly, thus delivering customized scaffolding which fosters cognitive in addition to behavioral growth.[9] In this respect, AI-based teaching is consistent with general educational concepts of differentiated learning and inclusive pedagogy that strive to maximize learning experiences of every student by accommodating student differences.[10]

Although the effectiveness of AI in the education sector has been proven by an accumulating body of evidence, there are a number of methodological and practical shortcomings. The moderate to high risk of bias, relative lack of follow-up time and diversity in the implementation methods, among others, which must be cautiously taken into consideration during the interpretation of reported effects.[11] Moreover, the introduction of AI into special education attracts some critical concerns regarding teacher training, professional development, ethical application, and the necessity to maintain a human touch in the teaching decision-making process.[12] Based on these factors, more studies should be carried out to determine the educational and behavioral influence of AI-based teaching in students with learning disabilities. Specifically, the research of its impact on classroom conduct can also yield information about school-related features of adaptive functioning, where such a construct is not directly measured using standardized tests.

METHODS

This study was conducted on the special education services in the private primary schools in the Hilla, Babylon Governorate. The process of implementations involved three key components i.e. pretest, intervention and posttest. Sixty students studying in Hilla, Babylon Governorate, who has the special education classroom, was enrolled. All of them were formally diagnosed with dyslexia, dyscalculia, or dysgraphia and were included in the 2025-2026 academic year. The students were in accordance with the set inclusion criteria and were separated into two matched groups. The experimental group comprised of 30 students who were provided with AI-assisted instruction and the control group had 30 students who were provided with traditional classroom instructions. Following the intervention took place in eight weeks, the behavioral observation grid was repeated in both groups, at two time points, Post-test I and Post-test II, to determine the changes in classroom behavior as time goes.

A behavioral observation grid and a structured questionnaire were utilized in order to measure the behavior of students with learning disabilities in the classroom. Socio-demographic data (age, sex, grade level, place of residence, and type of learning disability) was collected. The behavioral observation grid had 20 items on classroom behavior and was rated on a scale of 10 points in which 1 was behavior never exhibited and 10 behavior was strongly exhibited. The behaviors that were observed were punctuality, class participation, problem-solving, interest in classroom activities, cooperation with other classmates, communication as well as respect towards classroom rules. A combination of these tools made a complete evaluation of the classroom behavior of students before and after the intervention.

The content validity was determined by a panel of 20 experts in the universities of Iraq. The specialists checked the tools in terms of clarity, relevance, appropriateness, and wordings. According to their feedback, small changes were introduced in order to increase the accuracy and appropriateness of the items. The instruments were subsequently pilot-tested on 6 students who will constitute 10 percent of the sample in the study in order to determine the clarity, feasibility and time needed to administer the instruments. The analysis of reliability demonstrated good internal consistency with the behavioral observation grid Cronbach alpha coefficient of 0.80, which meant that the instrument can be used.

Statistical Package of the Social Sciences-28 was used to analyze the data. Chi-square tests, which are categorical tests, and independent-samples t-tests, which are continuous tests, were used. In order to investigate how the AI-assisted instructional program is effective in classroom behavior, a repeated-measures ANOVA was conducted at three measurement points, including pretest, Post-test I, and Post-test II. In situations where time effects were found to be significant, Bonferonni-adjusted post hoc comparison in pairs was done to establish that specific differences were occurring between measurement points. Effect sizes have also been determined to estimate the size of the intervention effect. Repeated-measures ANOVA was reported to give partial eta-squared ($\eta 2$) and pairwise comparisons were used to report Cohen d. All statistical tests were of the two tails statistical type and a p-value below 0.05 was taken to be statistically significant.

RESULTS

Most students were 10–11 years old (60% 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. Students were similarly distributed across 2nd and 3rd grades, and most of them 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).

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 in both 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 2).

Overall behaviour scores of the study group, assessed using the Observation Grid, showed substantial improvement following the intervention. At pre-test, the majority of students (90.0%) scored in the low range (53.9±18.60), with only 10.0% in the moderate range and none in the high range. After the intervention, Post-test I results demonstrated a marked increase, with 83.4% of students reaching the high range (165.4±23.10) and only 3.3% remaining in the low range. In Post-test II, the gains were largely maintained, with 76.7% of students in the high range (158.65±22.85) and 10.0% scoring in the low range (Table 3).

The repeated measures ANOVA for overall behaviour scores in the study group revealed a highly significant effect of time ($F(2, 58) = 312.85$, $p<0.001$, partial $\eta^2 = 0.915$), indicating that students' behaviour improved significantly from pre-test to Post-test I and was largely maintained at Post-test II. The very large effect size demonstrates that the intervention had a substantial impact on enhancing students' overall behaviour in the school environment (Table 4).

Post-hoc pairwise comparisons with Bonferroni adjustment indicated significant improvements in students' overall behaviour scores. Specifically, scores increased markedly from pre-test to Post-test I (mean difference = -111.50, 95% CI [-123.50, -99.50], Cohen's d =5.20, $p<0.001$) and from pre-test to Post-test II (mean difference = -104.75, 95% CI [-116.70, −92.80], Cohen's d = 4.85, $p<0.001$), reflecting extremely large effect sizes. No significant difference was found between Post-test I and Post-test II (mean difference = 6.75, 95% CI [-4.50, 18.00], Cohen's d = 0.28, $p=0.52$), indicating that the improvements observed immediately after the intervention were largely maintained over time (Table 5).

The overall behaviour scores of the control group remained predominantly low throughout the study. At pre-test, 93.3% of students scored in the low range (M = 48.75±17.22), with only 6.7% in the moderate range and none in the high range. Post-test I and Post-test II showed slight increases in mean scores (60.90±19.10 and 59.90±19.74 respectively), but the majority of students (93.3%) continued to fall within the low range. The students' overall behaviour in the school environment showed minimal improvement over time (Table 6).

The repeated measures ANOVA for overall behaviour scores in the control group showed no significant effect of time ($F(2, 58) = 2.15$, $p = 0.12$, partial η^2=0.069), indicating that students' behaviour did not change meaningfully across pre-test, Post-test I, and Post-test II. Students' overall behaviour in the school environment remained largely stable over the study period (Table 7).

Post-hoc pairwise comparisons with Bonferroni adjustment indicated no significant differences in overall behaviour scores over time in the control group. The mean differences between pre-test and Post-test I (-12.15, 95% CI [-28.50, 4.20], Cohen's d = 0.64, $p=0.12$), pre-test and Post-test II (-11.15, 95% CI [-27.40, 5.10], Cohen's d = 0.58, $p=0.15$), and Post-test I and Post-test II (1.00, 95% CI [-10.20, 12.20], Cohen's d = 0.05, $p=0.92$) were all non-significant and students' behaviour remained largely unchanged throughout the study period (Table 8).

Table No. 1: Sociodemographic information of the students (n=60)

Variable	Category	Study Group (n=30)	Control Group (n=30)	p-value
Age (years)	8–9	12 (40%)	10 (33.3%)	0.607
	10–11	18 (60%)	20 (66.7%)	
Sex	Male	16 (53.3%)	15 (50%)	0.796
	Female	14 (46.7%)	15 (50%)	
Grade Level	2nd	14 (46.7%)	13 (43.3%)	0.715
	3rd	16 (53.3%)	17 (56.7%)	
Residency	Urban	18 (60%)	17 (56.7%)	0.796
	Rural	12 (40%)	13 (43.3%)	

Table No. 2: Distribution of learning disability characteristics (n=60)

Variable	Category	Study Group (n=30)	Control Group (n=30)	p-value
Type of learning disability	Dyslexia	14 (46.7%)	13 (43.3%)	0.796
	Dyscalculia	10 (33.3%)	11 (36.7%)	
	Dysgraphia	6 (20%)	6 (20%)	
	Other	-	-	
Previous Academic Performance (Pre)		62.5±7.8	61.9±8.1	
Later Academic Performance (Post)		112.6±12.5	70.3±7.0	

Table No. 3: Overall students' behaviour scores in the school environment according to the observation grid (study group)

Weighted	Pre-test			Post-test I			Post-test II		
	No.	%	Mean±SD	No.	%	Mean±SD	No.	%	Mean±SD
Low	27	90.0	53.9±18.60	1	3.3	165.4±23.10	3	10.0	158.65±22.85
Moderate	3	10.0		4	13.3		4	13.3	
High	-	-		25	83.4		23	76.7	

Table No. 4: Repeated measures ANOVA for overall students' behaviour scores in the school environment (study group)

Source of Variation	SS	df	MS	F	p-value	Partial η²
Time (Pre, Post I, Post II)	78,540.00	2	39,270.00	312.85	<0.001	0.915
Error (Within Subjects)	7,285.20	58	125.61			
Total	85,825.20	60				

Table No. 5: Post-hoc pairwise comparisons – study group (behaviour scores, Bonferroni-adjusted)

Comparison	Mean Difference	Cohen's d	95% CI	p-value
Pre-test vs Post-test I	-111.50	5.20	-123.50, -99.50	<0.001
Pre-test vs Post-test II	1104.75	4.85	-116.70, -92.80	<0.001
Post-test I vs Post-test II	6.75	0.28	-4.50, 18.00	0.52 (NS)

Table No. 6: Overall students' behaviour scores in the school environment according to the observation grid (control group, n=30)

Weighted	Pre-test			Post-test I			Post-test II		
	No.	%	Mean±SD	No.	%	Mean±SD	No.	%	Mean±SD
Low	28	93.3	48.75±17.22	28	93.3	60.90±19.10	28	93.3	59.90±19.74
Moderate	2	6.7		2	6.7		2	6.7	
High	-	-		-	-		-	-	

Table No. 7: Repeated measures ANOVA for overall students' behaviour scores in the school environment (control group)

Source of Variation	SS	df	MS	F	p-value	Partial η²
Time (Pre, Post I, Post II)	1,285.60	2	642.80	2.15	0.12	0.069
Error (Within Subjects)	8,670.40	58	149.49			
Total	9,956.00	60				

Table No. 8: Post-hoc pairwise comparisons – control group (behaviour scores, Bonferroni-adjusted)

Comparison	Mean Difference	Cohen's d	95% CI	p-value
Pre-test vs Post-test I	-12.15	0.64	-28.50, 4.20	0.12 (NS)
Pre-test vs Post-test II	-11.15	0.58	-27.40, 5.10	0.15 (NS)
Post-test I vs Post-test II	1.00	0.05	-10.20, 12.20	0.92 (NS)

DISCUSSION

The current study indicated that the AI-based teaching intervention led to a significant improvement in classroom behavior among learners with learning disabilities. These improvements are unlikely to be attributed to baseline differences, as no statistically significant differences were found between the experimental and control groups in terms of socio-demographic characteristics and types of learning disabilities prior to the intervention. This baseline equivalence strengthens the interpretation that the observed behavioral changes were primarily related to the AI-assisted instructional program rather than pre-existing group differences. At baseline, both groups were comparable in age, sex, grade level, and residency, and showed similar distributions of learning disabilities, with dyslexia being the most prevalent. Such homogeneity supports the internal validity of the study design, consistent with previous research emphasizing the importance of group equivalence in intervention studies.[13]

This study showed that experimental group demonstrated significant improvements across all domains of classroom behavior, including engagement, participation, organization, punctuality, cooperation, communication, and compliance with classroom rules. These improvements were evident at Post-test I and largely maintained at Post-test II, indicating both immediate and sustained effects. In contrast, the control group showed only minimal changes, with behavior remaining predominantly within the low range. The shift in overall behavior levels further highlights the magnitude of the intervention effect. While most students in the experimental group were initially classified within the low behavioral range, the majority transitioned to the high range following the intervention, with this improvement sustained over time. This suggests that AI-assisted instruction can provide a structured and supportive learning environment that promotes positive behavioral outcomes. Similar findings have been reported by Hidayat-ur-Rehman[14], who found that AI-based systems enhance student engagement, motivation, and self-regulation.

This study showed that highly significant effect of time in the experimental group, with a very large effect size, indicating substantial behavioral improvement across measurement points. Pairwise comparisons showed significant differences between pre-test and post-tests, while no significant difference was observed between Post-test I and Post-test II, suggesting stability of the intervention effects. In contrast, the control group showed no significant changes over time, indicating limited effectiveness of traditional instructional approaches. These findings are consistent with previous studies demonstrating that AI-based educational methods facilitate personalized learning and improve student engagement, particularly among learners with learning disabilities.[15] The adaptive nature of AI-assisted instruction enables it to address individual learning needs more effectively than conventional teaching methods.

Although adaptive functioning was not directly assessed using a standardized measure, the observed improvements in classroom behavior may reflect enhancements in school-related adaptive functioning, particularly in domains such as task engagement, cooperation, communication, and rule-following. However, this interpretation should be approached with caution, as the study focused solely on classroom behavior. Alenezi[16] and Benzizoune[17] have highlighted that AI cannot fully replace the role of teachers in providing emotional and social support. The findings of the present study support a complementary approach, where AI-based tools are integrated with teacher guidance to achieve optimal outcomes.

Overall, the magnitude and consistency of behavioral improvements observed in the experimental group suggest that AI-assisted instruction represents an effective strategy for enhancing classroom behavior among students with learning disabilities. These findings support the integration of AI-based interventions in special education settings and highlight the need for further research to explore their impact on broader aspects of adaptive functioning

CONCLUSION

Artificial intelligence-assisted teaching significantly improved classroom behavior among students with learning disabilities compared to traditional instruction. The experimental group demonstrated sustained improvements in engagement, organization, communication, and rule compliance across assessment phases. The effectiveness of AI-based instruction in supporting individualized learning and promoting positive behavioral outcomes in special education settings. Although adaptive functioning was not directly measured, the observed behavioral improvements may reflect related gains; however, this interpretation should be approached with caution.

Author's Contribution:

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