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Effectiveness of an AI-Assisted Cognitive Load Management Intervention to Improve Geometry Performance Among Students with Learning Disabilities: An Experimental Study

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Abstract

Children with learning disabilities (LDs) often experience the cognitive overload. It makes mathematics, and more specifically geometry, particularly challenging for them. Traditional instructional approaches usually fail to address the unique cognitive needs of LD students. This study developed and evaluated an AI-Assisted Cognitive Load Management Strategy (AI-CLMS) for improving geometry performance in LD students. AI-CLMS was designed to manage the cognitive load in LD students using AI platforms which can provide adaptive and personalized instructions. An experimental study was conducted to evaluate whether the AI-CLMS is an effective strategy to improve geometry performance in LD students. A total of 32 purposively selected students were randomly assigned to a control group (n=16) and an experimental group (n=16). The experimental group received three weeks intervention through an AI platform incorporating CLT principles such as content segmenting and progressive complexity while the control group continued with traditional instructions. An 18-item Geometry Performance Assessment (KR-20 = 0.74) was used as a pre-test and post-test data collection tool. Descriptive statistics, Shapiro-Wilk tests, Levene's test, t-tests and Cohen's d were performed for data analysis. The data analysis revealed that there was no significant difference in baseline scores of both groups (p = .944). The control group didn't show significant improvement in post-test (p = .518). Whereas the improvement in post-test scores of the experimental group was significant (t (15) = -4.84, p < .001, d=2.87). Post-test between group comparisons also revealed that the experimental group outperformed the control group (t (30) = -4.68, p < .001) with a large effect size (d = 1.65). These results confirmed that AI-CLMS is an effective strategy to improve the mathematical performance among the LD students. Findings of this study also confirm that AI platforms can be effectively integrated with CLT in order to improve learning in special education.

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Keywords: Artificial Intelligence (AI), Cognitive Load Theory (CLT), AI-CLMS, Learning disabilities, special education, Mathematics, Geometry

Introduction

Mathematics is a complex subject and one of the most difficult for the students with learning disabilities. LD students find it challenging to perform abstract reasoning, problem-solving and retention of basic mathematical concepts. LD students suffer from limitations of working memory and have relatively slow processing speed, which makes learning mathematics even harder. Geometry is an area of mathematics that deals with properties and characteristics of shapes and spatial relationships. LD students face challenges while processing visual information. These challenges can cause additional hurdles. Cognitive load exerted by complex concepts of geometry overload the working memory. Traditional methods commonly fail to address these special cognitive needs of LD students.

Cognitive Load Theory (CLT) provides a framework to manage the cognitive load to enhance the learning, as it differentiates between intrinsic load (complexity of the task), extraneous load (inefficiency of the presentation), and germane load (refers to the construction of schemas). According to CLT if the cognitive load is managed, the working memory can be optimized and the learning outcomes can be improved. Artificial Intelligence (AI) is an emerging field and it is being used in education to improve the teaching and learning experiences. Worldwide, teachers are using Artificial Intelligence (AI) to teach students with learning disabilities and remove barriers. If the CLT principles are integrated in the AI, the learning outcomes can be enhanced.

The purpose of this study was to present empirical evidence that AI-based instructional techniques, based on the principles of CLT, have the potential to enhance the learning outcome of LD learners in difficult academic domains, such as geometry. An instructional plan is developed for this study. It is an AI assisted learning strategy grounded in CLT principles incorporating CLT techniques of segmentation (to decrease extraneous load) and progressive complexity (to manage the intrinsic load while facilitating increased germane processing). Given the availability of AI tools and the cognitive needs of LD students, it is important to evaluate the effectiveness of AI-CLMS to improve the mathematical performance of LD students.

Background of the Study

Mathematics learning disability (MLD) is one of the most persistent and challenging learning disorders (Geary, 2004), and it negatively affects the learner's ability to process numerical information, reasoning and problem solving (Rivera, 1997). MLD students frequently display weaknesses in working memory, processing speed and visual–spatial reasoning (Zhang et al., 2018) and it hampers both basic and advanced computational skills (Kroesbergen, Huijsmans & Friso-van den Bos, 2022). These deficiencies result in difficulties understanding and handling mathematical symbols and relationships, and they cannot achieve the mathematical performance as their peers in the same age group can (Alenizi, 2015).

Studies have revealed that the heterogeneity in MLD students is due to their unique cognitive and perceptual profiles. According to Zhang et al., (2018) early difficulties in working memory, phonological processing and spatial reasoning can predict the risk of MLD in future. MLD students have a great deficit in executive functioning and cognitive flexibility (Alenizi, 2015). Traditional methods used to teach mathematics rely on rote calculations and abstract reasoning and they often fail to address the unique need of MLD students (Rivera, 1997).

Recently the perspective has been shifted from focusing on deficit to understating differences while teaching mathematics to LD students (Lewis, 2014). It refers to adaptive (scaffolded) instruction that supports rather than remediates individual cognitive processing. This paradigm shift has prompted the reorientation of instructional design towards the evidence-based instructional interventions that minimize extraneous cognitive load.

Meta-analytic results are consistent in indicating that didactic, systematic, and strategy-based instruction makes substantial contributions to increasing the mathematical performance of students with LD (Jitendra et al., 2018; Marita & Hord, 2017). Teaching methods that involve gradual release of support have shown to be effective for secondary readers (Jones, Wilson, & Bhojwani, 1997; McKenna, Shin, & Ciullo, 2015). Geometry is, however, one of the most difficult areas for students as it involves abstract spatial reasoning and visualization of multi-dimensional relationships (Zhang, 2020).

Instructional strategies have been designed to address these limitations through concrete–representational–abstract (CRA) and these strategies help LD students in building conceptual links using examples (Liu, Bryant, Kiru & Nozari 2019; AL-salahat 2022). CRA-based geometry instruction leads to significantly greater knowledge of perimeter, shapes and spatial relationships in LD learners (AL-salahat, 2022). Video supports, including video modeling and explicit instruction are also effective in the teaching of geometry concepts and problem-solving strategies (Satsangi, Hammer, & Hogan, 2018; Satsangi, Hammer, & Bouck, 2020). It is further noted in literature that incorporation of real-life and contextual mathematics instruction is also helpful to improve problem solving skills (Şanal & Elmalı, 2024). It is also documented that the way MLD students process mathematical language and visual information are unique and this indicates that cognitive and linguistic demands play a substantial role for variability in performance (Yip et al., 2020).

Analysis of Literature highlight the importance to plan an instructional design in a way to meet the unique needs of LD students. The persistent difficulties of learning geometry brought up the need for minimizing cognitive complexity and chunking down information to a given manageable size (Zhang, 2020; Bryant, 2021). Here comes the Cognitive Load Theory (CLT) which provides an attractive model for reaching this balance. CLT distinguishes between three types of cognitive loads i.e. intrinsic load (the complexity of the material being taught itself), extraneous load (emerges due to suboptimal instructional design), and germane load (mental effort devoted to establishing relevant schema) (Sweller, 1994; Sweller, van Merriënboer, & Paas, 2019; Paas & van Merriënboer, 2020). Good teaching attempts to reduce extraneous load, guide intrinsic load and support germane processing. Methods like segmentation and modality variation are some of the proven ways to increase learning efficiency by addressing the constraints imposed on working memory (Kalyuga & Singh, 2016; Young, van Merriënboer, Durning, & ten Cate, 2014).

Cognitive load has been investigated extensively in educational settings, and a considerable amount of research has refined the measurement and use of cognitive load. Improved validity of load measurement tools has been achieved using subjective and physiological assessment (Krieglstein et al., 2022; Krieglstein et al., 2023). More recent meta-analyses have again found that cognitive load has a critical and enduring association with the learning effectiveness in digital and interactive environments (Ekin, Krejtz, & Krejtz, 2025). In literature it has also been identified that individual levels of working memory are the critical determinants of cognitive load effects (Sweller, 2024). It highlights that the instruction design should be planned according to the cognitive profile of students, especially for those with LD (Paas & Ayres, 2014; Sweller, 2020).

Integration of CLT principles with AI based instructions can be a fruitful frontier for special education. AI can provide adaptive learning environments that can monitor performance of students, assess the cognitive load and adapt task complexity in real time (Duran et al., 2022). By incorporating CLT into AI based systems, dynamic and iterative management of intrinsic and extraneous load is possible which could generate personalized pathway that facilitates efficient schema formation (Kirschner, Sweller, Kirschner & Zambrano Ramírez, 2018). Preliminary evidence abounds in support of the potential benefits for AI-mediated instruction based on CLT approach to improve learning performance of students with MD, by overcoming overload and sustaining interaction (Hanham, Castro-Alonso & Chen, 2023).

Although strong evidence exists for both CLT and AI, teachers are not adapting these theories as well as their methodologies in furthering LD students learning of geometry. Explicit and scaffolded instructions have been established to be effective teaching methods but there is very little literature available on how AI technologies and CLT principles can be systematically integrated to calibrate cognitive load to promote mathematical understanding (Nelson et al., 2022). There is a need to develop an instructional design integrating the CLT principles and AI technologies to address the unique needs of LD students while teaching geometry.

This study is designed to fill this gap by exploring whether AI-based instructional design which is integrated with CLT principles of segmentation and progressive complexity, is an effective strategy to improve geometry learning in LD students.

LD Students experience problems in mathematics due to cognitive overload and a restricted working memory. Although AI tools and platforms are being used in education, there is a paucity of empirical evidence, especially from the Global South, if AI assisted instructions are effective when designed around CLT principles. This void is more pronounced in the context of Pakistan where AI supported teaching methodologies amongst special education teachers have not been examined adequately. Without such evidence, special education schools encounter difficulties in embracing AI-assisted methods that could be helpful in improving learning outcomes of LD children. This study aims to fill in this gap by exploring effectiveness of an AI-Assisted Cognitive Load Management Strategy (AI-CLMS) to improve the geometry performance in the LD students.

❖ Research Objective

The main objective of this study is to evaluate whether AI-Assisted Cognitive Load Management strategies (AI-CLMS) is an effective strategy in improving geometry performance among children with learning disabilities.

❖ Research Hypotheses

Hypotheses of the study are:

H_0: AI-Assisted Cognitive Load Management strategies (AI-CLMS) do not significantly improve geometry performance in children with learning disabilities.
H_1: AI-Assisted Cognitive Load Management strategies (AI-CLMS) significantly improve geometry performance in children with learning disabilities.

Methodology

❖ Research Design

This study is quantitative in nature and a pre-test post-test control group experimental design was used to evaluate whether AI-Assisted Cognitive Load Management strategies (AI-CLMS) is an effective strategy in improving geometry performance among children with learning disabilities. This design was suitable to evaluate baseline differences, within group improvements and between group comparisons of improvement.

❖ Population, Sample, Sampling and Grouping

The population of the study included children with learning disabilities (LD) who have problems learning mathematical concepts because of their limitations in cognitive processing. To make it accessible, the population was delimited to LD students studying at the Special School of learning disabilities in Rawalpindi.

The sample size used was 32 students aged 9–12 (M = 10.3, SD = 0.9) with formally identified learning disabilities, primarily having mathematical learning disability (MLD) or problems in mathematics (dyscalculia), who were selected out of the accessible population. This sample was selected through the purposive sampling technique and then was randomly divided into two groups (experimental, n = 16; control, n = 16) to ensure equivalence and minimize selection bias. Purposive sampling was used to select the students who are meeting the inclusion criteria.

Participants were included if they (1) they had a formal diagnosis of learning disability, (2) had a score below 25th percentile in standard mathematics achievement test, (3) had been referred for special education service, and (4) currently studying at primary level.

All those students were excluded from the study who either (1) had severe visual or hearing impairments, (2) had any additional neurological or psychiatric conditions, or (3) were not regularly attending the school during the intervention period.

The experimental group was provided with the designed intervention, applying AI-based Cognitive Load Management (CLM) strategies that are taught with the help of the modified AI platform. The control group was taught the same mathematical concepts by the traditional teaching methods without the implementation of AI-based scaffolding.

❖ Instrumentation

The 18-point Geometry Performance Assessment Scale (Appendix A) was designed and employed to measure geometry performance. The test had 18 dichotomously scored questions (correct/incorrect) that included three fundamental geometry concepts: triangles, rectangles, and squares (6 questions each). The items consist of identification of shapes, measurement of sides and calculation of perimeter. Each correct score received 1 point and each incorrect response received 0 point. The internal consistency of the instrument was acceptable with a pilot-tested KR-20 reliability of 0.74, which implies that the instrument can be used in the experimental research, still acknowledged as a modest limitation.

❖ Materials

The teaching materials were based on the subject of simple geometry and in particular: Triangles, Rectangles and Squares (identification, measurement of sides and calculation of perimeter). The experimental group was guided by an AI platform, which was altered by the teacher to include CLM strategies, including dividing the content into manageable units and progressively increasing the complexity. The control group was provided with the same content without AI and CLM-based changes.

❖ Intervention Plan

The experimental group used Flexi by CK-12, (Appendix B) as the AI tool. The teacher made modification to the platform by adjusting the lesson sequence and feedback settings according to CLT principles of segmentation and incremental complexity. Three modular units were developed (Triangles, Rectangles, Squares), each of them containing micro-lessons (recognition, measurement, perimeter). Segmentation was enforced in the platform so that learners could access only one micro-task at a time. A progressive complexity was introduced by coding the task to become more complex over the micro-lessons.

Flexi's adjustability was at the same time providing real-time, automated feedback. On each correct answer, a short reinforcement message appeared on screen; while on each incorrect answer, a context-based hint appeared. If it was considered necessary, sometimes a brief demonstration was provided to support the next try. Flexi's dashboard gave the teacher a clear, live overview on the performance of the students. Wherever platform hinting was not quite enough, the teacher himself provided feedback. Students in the experimental group used school-supplied computers and mainly worked on the platform during experimental sessions.

The intervention lasted three weeks and included three sessions a week (40-50 minutes each). In the first week of intervention the participants of the experimental group were trained to the concept of triangles where they were taught to identify them, measure the sides and lastly how to measure the perimeter. The second week of intervention was devoted to the topic of rectangles, and the same order of the tasks was used: recognition, measuring sides, and calculation of a perimeter. In the third week the participants learned about squares, where they followed the same sequence of identifying the shape, measuring its sides and finding the perimeter. This gradual development guaranteed that the students developed the insights on geometry gradually without encountering the cognitive load.

The control group was instructed on the same geometry concepts (triangles, rectangles, and squares) through a traditional teacher directed approach that is typical of how mathematics is taught in special education classrooms. Handouts and textbooks were used as learning materials, and the instructions were provided through lecture and demonstration. At the end of the demonstration, the students in control group, completed the practice work on worksheets and used rulers to measure sides. There was no digital of AI assisted content and all feedback was given by the teacher.

The total instructional time, sequence of topics and learning objectives were identical to those in the experimental group. The only difference was the mode of delivery and absence of AI-assisted segmentation and adaptive feedback.

❖ Data Collection and Analysis

The 18-item Geometry Performance Assessment Scale was used to collect pre-test and post-test data in both groups. The scoring of responses was done in a dichotomous manner and summed up to total scores. The analysis of the data was done through descriptive statistics (mean, standard deviation, variance) and inferential statistics. Normality was measured with the help of the Shapiro-Wilk test and homogeneity of variances was measured with the help of Levene' test. To test hypotheses, independent samples t-tests were used to make a comparison between experimental and control groups at pre-test and post-test. Changes in scores between pre-test and post-test were evaluated using paired samples t -tests. The effect sizes (Cohen d) have been computed to explain the size of differences.

❖ Ethical Considerations

The research followed the ethical code of ethics in research involving human subjects. Data collection was done with permission of the school administration. Parents and the guardians of all the students who participated were informed and gave their consent. Participants' identities and personal information was anonymous to maintain the required level of confidentiality and the results were only reported in the aggregate. The intervention was done keeping the educational advantage of the students in mind and that no student was disadvantaged or harmed due to the study.

Data Analysis and Results

Several statistical tests were performed to analyse the data collected in pre-test and post-test including; descriptive statistics (mean, standard deviation, and variance) normality test (Shapiro–Wilk test), homogeneity of variances (Levene's test), hypothesis testing (Independent samples t-tests, and Paired samples t-tests) and effect size (Cohen's d).

❖ Descriptive Statistics

Tests of descriptive statistics (mean, standard deviation, and variance) were applied to the pre-test and pos-test data.

Table 1.
Descriptive Statistics for Pre-test and Post-test Scores of Control and Experimental Group

Group	Test	N	Mean	SD	Variance
Control Group	Pre-test	16	7.69	2.65	7.03
Control Group	Post-test	16	8.00	2.48	6.13
Experimental Group	Pre-test	16	7.63	2.33	5.45
Experimental Group	Post-test	16	12.19	2.59	6.70

Results of descriptive statistics showed that both groups were equal in performance at the start of intervention, the control group showed only a marginal improvement ($\Delta M = +0.31$) while the experimental group showed a significant gain in post-test score ($\Delta M = +4.56$).

❖ Assumption checks

Shapiro–Wilk test was used to check the normality of the data.

Table 2.
Shapiro–Wilk Normality Tests

Group	Test	N	W	p	Interpretation
Control Group	Pre-test	16	0.943	0.393	Normality assumption met

Control Group	Post-test	16	0.905	0.095	Normality assumption met
Experimental Group	Pre-test	16	0.958	0.626	Normality assumption met
Experimental Group	Post-test	16	0.928	0.226	Normality assumption met

None of the data groups showed significant deviation from normality (all p > .05). Levene's test was performed to check the homogeneity of variances

Table 3.
Levene's Test for Equality of Variances

Comparison	**F**	**df1**	**df2**	**p**	**Interpretation**
Control vs. Experimental (Pre-test)	0.383	1	30	0.541	Equal variances assumed
Control vs. Experimental (Post-test)	0.304	1	30	0.586	Equal variances assumed

It is confirmed in the Levene's test that there is no significant difference in variances between groups for either pre-test or post-test scores (p > .05).

These results confirm the normal distribution of data and equivalence of variance and we are good to go with parametric tests for hypothesis testing.

- **Hypothesis Testing**

An independent sample t-test was conducted on pre-test data of the control and the experimental groups to make sure that there was no statistically significant difference between the control and experimental groups in math performance prior to the intervention.

Table 4
Independent Samples t-Test to Compare Pre-Test Scores of Control and Experimental Groups

Group	**n**	**Mean**	**Variance**	**t-value**	**df**	**p-value**
Experimental	16	7.63	5.45	0.07	30	.944

Control	16	7.69	7.03

Results of pre-test group comparison show that the two groups did not differ significantly at baseline (t (30) = 0.07, p = .944)

To evaluate the changes in performance of participants of the control group, a paired samples t-test was applied to make comparison between pre and post test scores.

Table 5
Paired Samples t-Test for Pre and Post Test Scores of Control Group

Test	**n**	**Mean**	**Variance**	**t-value**	**df**	**p-value**
Pre-Test	16	7.69	7.03	0.66	15	.518
Post-Test	16	8.00	6.13			

Results of within-group comparison of control group revealed that there is no significant difference between pre-test and post-test scores of the control group (t (15) = 0.66, p = .518)

To assess the changes in performance of participants of the experimental group, a paired samples t-test was applied to make comparison between pre and post test scores.

Table 6
Paired Samples t-Test for Pre and Post Test Scores of Experimental Group

Test	**n**	**Mean**	**Variance**	**t-value**	**df**	**p-value**
Pre-Test	16	7.63	5.45	-4.84	15	< .001
Post-Test	16	12.19	6.70			

Results of within-group comparison of the experimental group revealed that there is a significant difference between pre-test and post-test scores of the experimental group (t(15) = 11.48, p < .001), and it indicates that the intervention had a significant positive effect.

In order to determine the effectiveness of the intervention an independent sample t-test was applied to the post test scores of the control and the experimental groups

Table 7
Independent Samples t-Test to Compare Post-Test Scores Between Control and Experimental Groups

Group	n	Mean	Variance	t-value	df	p-value
Experimental	16	12.19	6.70	−4.68	30	< .001
Control	16	8.0	6.13			

Results of post-test between group comparisons revealed a statistically significant difference between post test score between the control and the experimental (t(30) = −4.68, p < .001) These results indicate that the experimental group outperformed the control group after the intervention.

- **Effect Size**

Cohen’s d tests were conducted to quantify the magnitude of difference in pre-test and post-test scores of the experimental group and post-test scores between the control and experimental groups.

Table 9
Cohen’s d Effect Sizes for Group Comparisons

Comparison	Test Type	Cohen’s d	Effect Size Interpretation
Experimental (Pre vs Post)	Paired	2.87	Very large
Post-test (Control vs Experimental)	Independent	1.65	Large

Results of Cohen's d effect size test revealed a very large effect size (d = 2.87) in pre-test and post-test comparison of the experimental group while a large effect size (d = 1.65) in post-test between group comparison and it indicates that the intervention had a considerable positive impact on math performance of participants. The very large effect size (d = 2.87) for the experimental group's improvement, while promising, must be interpreted with caution due to the small sample size and should be investigated in larger trials.

Discussion

This study provides empirical evidence supporting the effectiveness of AI-based CLM strategies for improving mathematics performance in students with LDs. Although the experimental and the control groups started at the same baseline, it was only the experimental that statistically improved in a significant way between the pre-test and the post-test. These findings are consistent with CLT which underlines the importance of maximizing working memory capacity through minimizing extraneous cognitive load and presenting information in manageable chunks. The effectiveness of the intervention implies that AI-supported settings can help to optimize the working memory in a better way than standard teaching strategies, particularly in the case of LD students who are especially susceptible to cognitive overload.

The research also reinforces previous research in the international studies which have emphasized the effectiveness of adaptive technologies in special education. The AI-based platform offered progressive complexity, immediate feedback, and task segmentation, which created a learning environment through which students could learn the basic concepts without feeling overwhelmed. Contrary to this, students in the control group who were taught in the conventional way did not exhibit any significant improvement. This comparison supports the fact that conventional instruction might not be effective enough to meet the special needs of LD learners.

Altogether, the results indicate that the AI integration with the CLT-informed approaches can not only be viewed as a pedagogically right but extremely practical strategy in the context of Pakistan, where novel approaches to learning among children with learning disabilities are in dire need.

Conclusion

This research came up with a conclusion that AI-based Cognitive Load Management interventions are very effective in enhancing geometry performance in children with learning disabilities. The intervention which was mandated using the AI platform, had a great impact on the learners as they were made to be able to identify, measure, and compute perimeters of simple geometric shapes. The control group where traditional instruction was offered did not show any significant improvements by comparison. The data, therefore, confirm the alternative hypothesis according to which AI-supported CLM strategies have a significant academic benefit to LD students.

Recommendations

Based on the results, a number of recommendations are put forward:

1. The learning platforms powered by AI are to be implemented in schools serving children with learning disabilities adjusted to the principles of CLT to improve the learning of geometry performance.
2. Teachers are to be equipped with skills in the application of AI-based CLM strategies such as task segmentation and progressive scaffolding.
3. The adaptive digital tools should be integrated in the special education curriculum to make learning materials accessible, engaging, and student-cantered based on their LD needs.
4. Further research is needed on how AI-based CLM strategies can be implemented in different subject fields besides mathematics and in inclusive classrooms.

Limitations

Although the research produced encouraging outcomes, there are a number of limitations which need to be mentioned. First, the sample was quite small (n = 32) which limits the generalizability and restricts the extrapolation of the results about the bigger audiences. Second, the research was carried out in one special school in Rawalpindi to the extent that the findings may be generalized to other learning environments. Third, the intervention was also short-term (three weeks) and entirely based on basic geometry; more extensive interventions in various fields of mathematics could offer a more holistic picture. Fourth, the outcome measure only focuses on basic topics of geometry and do not assess long-term retention or transfer of learning to the other domains. Lastly, the research was based on quantitative performance only and did not allow the inclusion of qualitative data like student perceptions or teacher feedback, which would have deepened the insights into the effectiveness of the intervention.

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Appendix A

8-Point Geometry Performance Assessment Scale

Domain	Item	Score
Triangle	1. Identify the triangle in a diagram among other shapes.	
	2. Identify the type of triangle	
	3. Measure side AB of the triangle using given units.	
	4. Measure side BC of the triangle.	
	5. Measure side AC of the triangle.	
	6. Calculate perimeter of the triangle using the measured sides.	
Rectangle	7. Identify the rectangle in a set of different shapes.	
	8. Identify the length and width in a given rectangle diagram.	
	9. Measure the length of the rectangle.	
	10. Measure the width of the rectangle.	
	11. Measure another side (length or width) to check consistency.	
	12. Calculate the perimeter of the rectangle using measured sides.	
Square	13. Identify the square among other shapes.	
	14. Measure one side of the square.	
	15. Measure another side of the square (should be equal).	
	16. Verify all sides are equal using measurement.	
	17. Calculate the perimeter using one side × 4.	
	18. Solve: “If one side of the square is 5 cm, what is the perimeter?”	
	Total Score	

Scoring: (Each correct response = 1 point, Incorrect = 0 points, Total = 18 points)

KR-20 Reliability (Pilot) ≈ 0.74 – indicating good internal consistency for the scale.

Appendix B

AI-Assisted Cognitive Load Management Intervention Plan

Objective: To improve geometry performance in LD students.

Population: Children with learning disabilities in Pakistani special schools.

Topics: Triangle, Rectangle, and Square

CLT Strategies: Segmentation, and Progressive Complexity

AI Tool: Flexi by CK-12, modified to align with CLT strategies

Duration: 3 weeks, 3 sessions per week, 40-50 minutes per session

Week/Domain	Step 1: Introduction and Identification	Step 2: Measurement of Sides	Step 3: Perimeter
W1: Triangle	1. Introduction to the Triangle and its types 2. Identification of triangles in real life examples 3. Shape recognition using Flexi AI	1. Measurement of sides 2. Flexi uses segmenting by presenting one measurement task at a time. 3. Scaffolding and visual clues.	1. Sum of all sides. 2. Start with simple task and increasing complexity to reach multi step problems 3. AI provides hints.
Rectangle	1. Introduction to the rectangle 2. Identification of rectangle in real life examples 3. Shape recognition using Flexi AI	1. Measurement of length and width 2. Flexi uses segmenting by presenting one measurement task at a time. 3. Scaffolding and visual clues.	1. 2×(length+width). 2. Start with simple task and increasing complexity to reach multi step problems 3. AI provides hints.

Square	1. Introduction to the square 2. Identification of square in real life examples 3. Shape recognition using Flexi AI	1. Measurement of one side (all sides are equal) 2. Flexi uses segmenting by presenting one measurement task at a time. 3. Scaffolding and visual clues.	1. 4×length 2. Start with simple task and increasing complexity to reach multi step problems 3. AI provides hints.

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