# Effectiveness of Cognitive Load-Managed Math Instruction (CLM-Maths) in Improving Problem-Solving Performance of Students with Learning Disabilities

Mehtab Hussain[1]

## Abstract

This study was conducted to evaluate the effectiveness of Cognitive Load-Managed Math Instruction (CLM-Maths), a CLT (Cognitive Load Theory) based phased instruction plan, to improve the problem-solving skills in students with learning disabilities. A sample of 40 LD (Learning Disabilities) students was selected randomly from a special education institute and were assigned into experimental and control groups. Experimental group ($n$ = 20) received CLM-Maths for a period of four weeks. Control group ($n$ = 20) continued with the traditional instruction. A 15-point math problem-solving test (KR-20 = 0.88) was used to collect the data. Data were analysed using descriptive statistics, t-tests, ANCOVA and Cohen's *d*. Baseline performance of the both groups was similar ($p$ = .30). Control group did not show considerable improvement across the tests ($p$ = .54). In contrast, experimental group displayed a substantial improvement in performance after intervention ($p$ < .001). Posttest between group analysis also confirmed that the experimental group performed significantly better than the control group ($p$ < .001). ANCOVA results corroborated the effectiveness of the intervention while controlling pretest score ($p$ < .001). Cohen's *d* established that the effect size of intervention was large ($d$ = 1.27). Hence evidenced that CLM-Maths is an efficacious strategy to improve the problem-solving abilities in LD students.

***Keywords:*** *Cognitive Load Theory, Learning Disabilities, Mathematics Instruction, Problem-solving, Special Education*

## 1. Introduction

Mathematics is a critical skill in academics but students with learning disabilities often suffer in mathematical problem solving. LD students have a comparatively restricted short-term memory and slower processing, so they face difficulties while handling auditory and visual information simultaneously (Geary, 2004; Swanson & Jerman, 2008). Traditional practices exercised in schools are designed so that the auditory and visual information are presented at a time which overload the working memory of the LD students and insert an extraneous

[1] M.Phil. Scholar, Department of Special Education, Allama Iqbal Open University Islamabad (AIOU) Email: 21pri00046@aiou.edu.pk

cognitive load. As a result, their performance in mathematical problem-solving declines.

Cognitive Load theory (CLT) was initially anticipated by Sweller (1988). CLT contends that a lesson can be premeditated to manage the cognitive load of learners to boost their learning (Sweller et al., 2011). CLT communicates about three kinds of cognitive loads; intrinsic, extraneous, and germane. Intrinsic load is complicatedness of the learning material itself. Extraneous load is caused by the method of delivery. Germane load is related to meaningful learning. It is important to minimize the extraneous load while teaching LD students so that their working memory may be augmented and henceforth, they can perform sounder.

Past studies have established that segmenting the instructional material optimizes the working memory by reducing the extraneous load and boosts the performance of the learners (Jordan et al., 2020; Castro-Alonso et al., 2021). Recent research has confirmed the importance of CLT in the development of evidence-based instruction design and future perspectives towards maximizing learning outcomes (Zou et al., 2025). Recent studies in education also highlight the relevance of CLT in the context of designing instruction to benefit the students with mathematics learning challenges (Barbieri & Rodrigues, 2025). Still the effectiveness of phased cognitive load managed strategies to improve the mathematical performance in the field of special education ought to be explored. This research seeks to fill the gap by inspecting the effectiveness of the Cognitive Load-Managed Math instruction (CLM-Maths) to improve the problem-solving skills amongst the LD students.

The independent variable of the study is Cognitive Load-Managed Math Instruction (CLM-Maths) and the dependent variable is the mathematical problem-solving performance of LD students. This study investigates the effectiveness of a CLT based structured, phased instructional model to help LD students to achieve better problem-solving performance than conventional instruction. Recent studies address the need to handle cognitive load in order to positively influence the learning process of LD students.

## 1.1 Objective of the Study

Objective of the study included to:

1. examine the effectiveness of Cognitive Load-Managed Math instruction (CLM-Maths) to improve problem-solving amongst learning disabilities students.

## 1.2 Hypotheses of the Study

Following hypotheses were formulated for the investigation:

$H_0$: There is no significant difference in the mathematical problem-solving performance of LD students taught through CLM-Maths as compared to those taught through traditional instruction.

$H_1$: There is a significant difference in the mathematical problem-solving performance of LD students taught through CLM-Maths compared to those taught through traditional instruction.

### 1.3 Significance of the Study

This study gives theoretical and practical approach for the employment of dedicated mathematical instruction in special education settings. The study fills the gap in literature by developing CLM-Maths, a CLT-based instructional program for LD students and inspecting its effectiveness. Past research has discovered the individual CLT principles e.g. segmenting and modality, still very few studies have been performed to integrate these principles into one phased instructional program, targeting the cognitive needs of LD students.

The study provides an evidence based instructional plan that go parallel with the cognitive needs of LD students. CLM-Maths is a practical framework that is established to minimizes extraneous cognitive load through phased instruction to improve learning of LD students. CLM-Maths is a classroom-friendly, low-cost instructional method for LD students and it can be operated in several educational contexts. The study also contributes to the advancement of CLT by evidencing its applicability in special education settings. It also emphasises that CLT-based phased instruction has a capability to improve introductory mathematical concept e.g. fractions.

Findings of this study provide implications for special/inclusive education teachers, teacher educators, curriculum developers, and policy makers. The CLM-Maths emphasizes the need of adoption of CLT-based instructions in curriculum and teacher training programs particularly for complex subjects like mathematics.

## 2. Literature Review

Cognitive Load Theory (Sweller, 1988) offers a framework for instructional plan by managing the learner's cognitive load and optimizing the short-term memory. According to the theory there are three categories of cognitive loads i.e. intrinsic, extraneous, and germane. Intrinsic load is the intricacy of the instructional material. Extraneous load is linked to the methods used to convey the instructions. Germane load is the effort necessitated to handle the working memory to make it a schema (Sweller et al., 2011). If these cognitive loads are managed carefully, the learning process could be enhanced (Chandler & Sweller, 1991). Past studies have also shown that if the cognitive burden is handled, the short-term memory is optimized and as a result the learning outcomes are improved (Paas et al., 2003). An effective instructional plan may be designed if these three types of cognitive load are balanced in a way to optimize the working memory (Sweller et al., 2011).

Concept of limitation of short-term memory is especially important in the case of LD students. The LD students often experience the difficulties of the limited memory as well as slow processing speed and it is hard for them` to process the multisensory information simultaneously (Pennington, 2022). Learners face cognitive overload on their working memory when the multisensory information is presented simultaneously (Turoman, & Vergauwe, 2024). If the information from different sensory channels is fragmented, the learning can be enhanced (Kalyuga et al., 1998). It has been confirmed in past studies that mathematics performance is correlated to working memory (Peng et al., 2023). In mathematics, where the auditory and visual information is presented simultaneously and need to be processed simultaneously (Zhang & Cai, 2021), it becomes even harder for the LD students to perform adequately who already face the challenges of limited working memory and slow processing speed (Daniel et al., 2022). Under these circumstances, it is needed that there should be a program focused on the limitations and special needs of the LD students to manage the load on working memory to enhance mathematical performance.

LD students have weaker procedural and conceptual knowledge than their peers and this makes mathematics even difficult for them (Kaya et al., 2022). Traditional methods used to teach mathematics to LD students are not capable of producing the desired outcomes (Faragher & Clarke, 2020). Traditional methods don't take the cognitive needs of learners in account, and as a result are unable to produce the desired results (Wen et al., 2020). Numerous interventions have been designed to reduce the cognitive load; using several strategies e.g. worked examples, step-by-step prompts, and guided practice; and have been tested. Howie et al. (2023) have advised that integrating CLT based techniques into mathematical instruction can be a beneficial.

As per CLT recommendations, segmenting the instructional designs into phases can be a way to manage the cognitive load. In their study, Hostetler and Luo (2021) segmented complex multimedia instructions in small segments to demonstrate the effectiveness of the phased instructions. On the other hand, a study of Tremblay et al. (2023) shows that the germane load may be boosted if the level of difficulty is increased gradually. The techniques of phased instructions have also been applied in special education settings, where they are proved to be effective in enhancing learning outcomes in reading (Cooper & Sweller, 2008) and science (Ayres & Paas, 2012). Phased instructions align with the principles of CLT and are proven to enhance the learning (Surbakti et al., 2024). Recent research has emphasized the emerging trends and innovations in CLT, such as learner factors and instructional individualization to maximize the cognitive processing (Ouwehand et al, 2025). Furthermore, modern studies have started to investigate the interactions of CLT with educational neuroscience and artificial intelligence to better understand the effectiveness of the learning process (Gkintoni et al, 2025). These findings urge the development of instructional design that is based on CLT principles of phased instructions to target the LD students who are facing challenges in mathematics.

There are several studies conducted to investigate the effectiveness of CLT based techniques to enhance the mathematical performance of LD students (Bishara, 2022). Sozio et al. (2024) conducted a study to investigate the effectiveness of worked examples strategy and found it effective as compared to traditional methods. Kadkhodavand and Momeni (2024) worked with a split-attention reduction strategy and found it effective. Comparison of quasi experimental studies shows that if the worked example strategy and self-explanation prompts are combined, they can produce a large effect improvement in mathematics performance of LD students (Barbieri et al., 2023).

CLT principles have also been integrated in the professional training of special education teachers. Sweller et al., (2011) presented a CLT based protocol for the training of teachers based on segmenting, modality, and redundancy principles to reduce the extraneous load. Field studies in inclusive setup reveal that the teachers who are trained in CLT deliver more efficiently (Timothy et al., 2023). These types of training in special education settings are associated with better teaching and learning outcomes (Kennedy & Romig, 2024). CLT based training of special education teachers affects the teachers' delivery and students' learning positively.

Although a sufficient amount of research has been conducted on CLT principles and techniques, still the gaps remain in applying CLT based phased instruction in mathematics in special education settings. Many studies have been conducted on isolated CLT principles but there is a need for a structured phased instructional design that is based on multiple CLT strategies. A multi-strategy and comprehensive CLT based intervention can help in improving mathematics performance in LD students (Sweller et al., 2011). Designing and evaluating a CLT based mathematics program to target the LD students will address this gap in research and practice. Hence, there is a critical need to examine the effectiveness of the Cognitive Load-Managed Math Instruction (CLM-Maths) program.

## 3. Research Methodology

### 3.1 Research Design

This study is quantitative in nature that employs a randomized pretest posttest control group experimental design to quantify the effectiveness of CLM-Maths for the mathematical performance of LD students.

### 3.2 Population and Sample

The students diagnosed with specific learning disabilities were the population of the study, however, the accessible population entailed of students enrolled in special education schools in Rawalpindi. A total of 40 students (24 boys, 16 girls; age ranging between 10 to 14 years) were selected as a sample utilising a simple random sampling technique meeting the inclusion criteria, i.e. students must be formally identified as LD, have standardized math test scores below the 25$^{th}$ percentile and do not have any other visual or hearing impairments. These randomly selected participants were then randomly allotted to experimental group ($n$ = 20) and control group ($n$ = 20). An informed consent was obtained from parents before the intervention took place.

### 3.3 Instrumentation

A 15-item multi-step mathematics problem-solving test was utilized as both the pretest and posttest to compute students' performance. Each item was recorded dichotomously, i.e. each correct answer received 1 point and each incorrect answer received 0 point. In this way the produced overall scores ranged from 0 to 15. The test was constructed in a way that it could line up with the content being taught during the intervention. It was kept in mind that the test could condense linguistic complexity as it is recommended for the math tests that are premeditated for LD students (Geary, 2004; Swanson & Jerman, 2008).

Test was swotted by experts to certify the content validity, including two mathematics teacher and one special education teacher. These experts gauged the relevance of the test items. To establish internal consistency reliability, a pilot study was performed with a small comparable group. Kuder–Richardson Formula 20 (KR-20) was calculated, which is suitable for dichotomously scored instruments (Paas, 1992). The resulted reliability coefficient value was KR-20 = 0.88, that discloses a strong internal consistency of the test.

The instrument was used to collect pretest and posttest data and was administered under uniform circumstances. The score obtained using the instrument supplied primary quantitative data to evaluate the intervention's effectiveness.

### 3.4 Intervention Plan

A four weeks intervention (with three 40-minute sessions per week; total 12 sessions) was conducted to investigate the effectiveness of CLM-Maths. A pretest was conducted using 15-item multi-step mathematics problem-solving test (KR-20 reliability = 0.88) before the intervention to assess the baseline performance. Then 20 participants were allocated to control group and remaining 20 to the experimental group randomly. Experimental group received specially designed intervention i.e. CLM-Maths for next 12 weeks. These instructions were delivered into three sequential phases, i.e. the visual phase, the auditory phase and the integration phase. Control group didn't partake the CLM-Maths, rather they continued with the traditional classroom instructions.

The solitary instructional content that was used throughout the intervention was the topic of fraction. The choice of this topic is on account of its underlying importance in mathematics and its applicability in miscellaneous grades. The experimental group was given cognitive load managed instructions which were phased and approached in a modality specific manner. It broke the content into three phases. The problem in the first, Visual Phase was presented visually without any verbal description. During the second, Auditory Phase, the teacher explained the same problem in a verbal way, without using any visual materials. During the third, the Integration Phase, the problem was presented both visually and orally to the students so that they could combine visual and auditory information. Meanwhile, the control group was subjected to the same materials content based on the fraction as a part of the traditional instructional practice.

Once the intervention has been completed, a posttest was administered on all participants ($n$ = 40) using the same 15-item multi-step mathematics problem-solving test. To determine the effectiveness of the intervention, pretest and posttest data were analysed by means of descriptive statistics, normality tests and t-tests. Also, ANCOVA was applied to determine if the intervention had a noteworthy outcome on posttest scores while controlling for pretest results. Cohen's *d* test was benefited for calculation of effect size.

### 3.5 Ethical Consideration

Ethical standards were strictly followed to safeguard the rights and wellbeing of the participants. A conversant consent was taken from the parents before intervention, after discussing the purpose of study, benefits and prospective risks. Participants of the study took part in the experiment voluntarily and they had a prerogative to pull out from the study at any stage. Pseudonyms of the participants were used for anonymizing individual results to maintain the confidentiality of their identities. All the data were stored securely in a way that no other than the researcher could access it and after the completion of analysis, the data were demolished. Special attention was paid to minimize the intervention related stress and the intervention was designed in a way that could reinforce rather than thwart the learning of participants. If any issue was raised by the participants or parents, it was addressed in a respectful manner.

## 4. Data Analysis and Interpretation

The data were analysed by means of descriptive and inferential statistics. The Shapiro-Wilk test was executed to establish the normality. Once the normality was established successfully, future analysis was accomplished using parametric tests. For hypothesis testing, independent and paired sample t-tests were administered to make a comparison of results within and between groups. ANCOVA was applied to determine the effects of intervention after controlling pretest scores. Effect size (Cohen's *d*) was calculated to quantify the extent of differences in posttest scores between groups.

### 4.1 Descriptive Statistics

To provide a summary of performance of students, Tests of descriptive statistics were performed to understand overall trends and variations in data.

Table 1

*Descriptive Statistics*

| Group | Test | *n* | *M* | *SD* |
|---|---|---|---|---|
| Control | Pretest | 20 | 5.85 | 1.67 |
| Control | Posttest | 20 | 6.35 | 2.19 |
| Experimental | Pretest | 20 | 5.40 | 1.76 |
| Experimental | Posttest | 20 | 8.80 | 2.68 |

Table 1 shows the summary of descriptive statistics indicating that initially both groups had similar mean scores in the pretest ($M \approx 5.85$, $M \approx 5.40$). After intervention, the experimental group exhibited a significant higher improvement ($M \approx 8.80$) then the control group ($M \approx 6.35$).

Figure 1

*Line graph of mean scores*

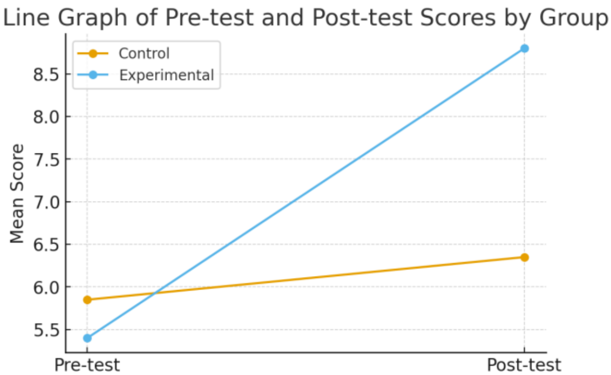
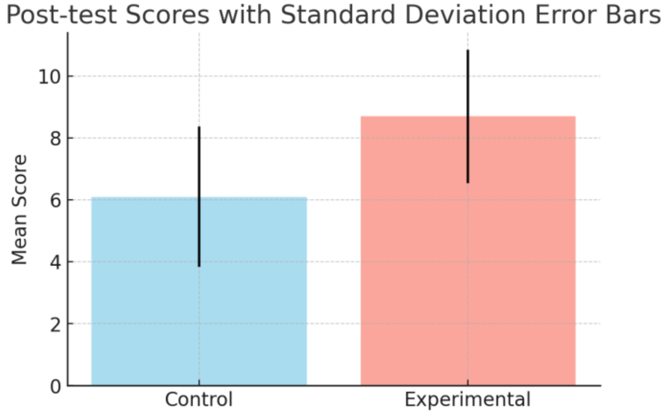



Figure 1 shows the line graph to illustrate changes in performance of participants both groups visually across tests. Only a little improvement was noted in scores of the control group ($M \approx 5.85$ to $M \approx 6.35$). A significant improvement was observed in the score of experimental group ($M \approx 5.40$ to $M \approx 8.80$). It reveals that the intervention had an affirmative influence on the performance of participants of experimental group.

Figure 2

*Bar chart of posttest mean and SD error bars*




This bar chart (Figure 2) demonstrated that there is noteworthy dissimilarity in posttest scores of both groups. The mean score of experimental group ($M \approx 8.80$, $SD = 2.68$) is higher than control group ($M \approx 6.35$, $SD = 2.19$). It is indicated by the error bars that the experimental group performed significantly better than the control group in posttest score in defiance of some variability.

Figure 3

*Boxplots showing the distribution of scores.*

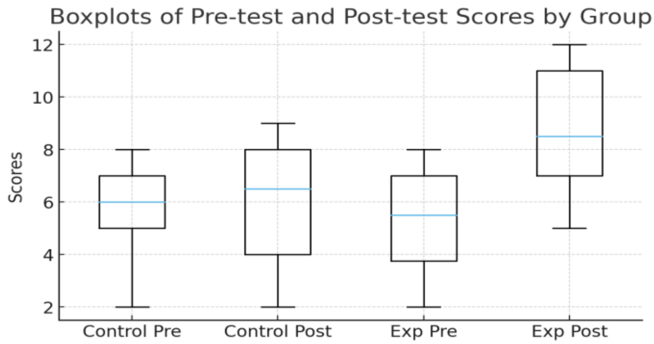



Figure 3 (the boxplots) gives a detailed visualization of distribution of scores of both groups across tests. Scores of the control group across time are overlapping considerably which indicate that the improvement in the posttest score was minimal. Post intervention scores of the experimental group marked an upward shift and this distribution visually confirms usefulness of intervention.

## 4.2 Normality Test

Before hypothesis testing, normality test i.e. Shapiro-Wilk test was applied on collected data to establish if the data are normally distributed and fulfils assumptions required for the parametric analysis.

Table 2

*Shapiro–Wilk Test of Normality of Data*

| Group | Test Time | *W* Statistic (Shapiro-Wilk) | *p*-value | Normality Assumption |
|---|---|---|---|---|
| Control | Pretest | 0.91 | 0.077 | not violated |
| Control | Posttest | 0.93 | 0.146 | not violated |
| Experimental | Pretest | 0.92 | 0.080 | not violated |
| Experimental | Posttest | 0.94 | 0.235 | not violated |

Table 2 demonstrate the outcomes of Shapiro-Wilk test ($W$ values from 0.91 to 0.94 and $p$-values > 0.05 ($p$ = 0.077 to 0.235)) that confirmed that the data are normally distributed and no significant deviation from normality in any group was noted and this established that the data are suitable for utilization of parametric tests for further analysis.

## 4.3 Pretest Group Comparison

An independent sample t-test was administered on pretest data of both groups to make sure that there was no significant baseline difference between groups in initial math performance before the intervention.

Table 3

*Independent Samples t-Test to compare Pretest Scores:*

| Group | *n* | Mean | Var | *t*-value | *df* | *p*-value |
|---|---|---|---|---|---|---|
| Experimental | 20 | 5.8 | 3.01 | 1.06 | 38 | 0.30 |
| Control | 20 | 5.2 | 3.43 | | | |

Table 3 displays the results of independent samples t-test which confirmed that there was no statistically significant baseline difference between groups, $t$ (38) = 1.06, $p$ = .30. This suggested that the baseline scores of both groups were equivalent before the intervention.

## 4.4 Within-Group Comparison (Control Group)

To evaluate the changes in performance of participants of the control group, a paired samples t-test was applied.

Table 4

*Paired Samples t-Test for Control Group*

| Test | *n* | Mean | Var | *t*-value | *df* | *p*-value |
|---|---|---|---|---|---|---|
| Pretest | 20 | 5.8 | 3.01 | -0.62 | 19 | 0.54 |
| Posttest | 20 | 6.1 | 5.15 | | | |

Table 4 displays the results of the paired samples t-test which indicate that there is no significant difference in performance of control group across tests, *t*(19) = -0.62, *p* = .54. It suggests that control group did not exhibit any statistically significant improvement during the intervention period.

**4.5 Within-Group Comparison (Experimental Group)**

Likewise, to assess the changes in performance of participants of the experimental group, a paired samples t-test was applied.

Table 5

*Paired Samples t-Test for Experimental Group*

| Test | *n* | Mean | Var | *t*-value | *df* | *p*-value |
|---|---|---|---|---|---|---|
| Pretest | 20 | 5.2 | 3.43 | -4.84 | 19 | < .001 |
| Posttest | 20 | 8.7 | 4.64 | | | |

Table 5 illustrates the results of the paired samples t-test which disclose that there is a significant difference in scores of experimental group across tests, *t*(19) = -4.84, *p* < .001. It reveals that the intervention had a significant positive outcome.

**4.6 Posttest Between-Groups Comparison**

In order to determine the efficacy of the intervention, an independent sample t-test was applied to the posttest scores of both groups.

Table 6

*Independent Samples t-Test to compare Posttest Scores:*

| Group | *n* | Mean | Var | *t*-value | *df* | *p*-value |
|---|---|---|---|---|---|---|
| Experimental | 20 | 6.1 | 5.15 | -3.72 | 38 | 0.00065 |
| Control | 20 | 8.7 | 4.64 | | | |

Table 6 shows the results of the independent sample t-test. This analysis reveals a statistically significant difference between posttest score between groups, *t*(38) = -3.72, *p* < 0.001. These results indicate that experimental group performed significantly better than control group after the intervention i.e. CLM-Maths.

**4.7 ANCOVA**

To determine if the intervention had a considerable positive influence on the posttest scores, the ANCOVA was performed, while controlling for pretest scores, thereby adjusting for any baseline differences between groups.

Table 7

*ANCOVA (Analysis of Covariance)*

| Source | Sum of Squares | *df* | *F* | *p*-value |
|---|---|---|---|---|
| Group | 68.32 | 1 | 13.66 | 0.0007 |
| Pretest | 0.92 | 1 | 0.18 | 0.67 |
| Residual | 185.08 | 37 | | |

Table 7 shows the results of ANCOVA which indicate that the intervention had a significant positive effect after controlling for pretest scores, *F*(1, 37) =

13.66, $p = 0.0007$. It confirms the effectiveness of CLM-Maths intervention.

### 4.8 Effect Size (Cohen's d)

To quantify the magnitude of improvement, Cohen's d Effect Size was calculated.

Table 8

*Cohen's d Effect Size for Posttest Scores:*

| Group | *M* | *SD* | *n* | Cohen's *d* |
|---|---|---|---|---|
| Control | 6.10 | 2.27 | 20 | |
| Experimental | 8.70 | 2.15 | 20 | |
| Between Groups | | | | 1.27 |

Table 8 shows the results of Cohen's d effect size. It revealed large effect size of intervention, $d = 1.27$. It indicates that the intervention i.e. CLM-Maths had a considerable positive impact on math performance.

## 5. Discussion and Conclusion

The outcomes of this study have established that mathematical problem-solving skills in LD students can be improved significantly through CLM-Maths. The participants of the experimental group showed a substantial improvement in performance. This rejects the null hypothesis and supports the alternative hypothesis. Results reveal that CLM-Maths helps LD students to perform better in mathematical problem solving by reducing the extraneous load.

Cognitive Load Theory (CLT) states that working memory can be augmented by dropping the extraneous load and consequently the performance of the learners can be improved (Sweller et al., 2011). Finding of this study aligns with this stance of the CLT. These results also highlight that if learning material is designed in instructional phases, i.e. visual, auditory and integrated phases, it allows LD students to understand and perform better. Since the participants of control group did not demonstrate significant improvement, it suggests that simultaneous instruction overloads the cognitive memory capacity and it generates challenges for LD students especially while multifaceted information e.g. mathematical problem solving is being communicated. The findings underscore the importance of cognitive load management as an intervention approach in a special education classroom.

Findings of the study line up with the prior research. Results are coherent with the evidence from contemporary meta-analytic studies that mathematical problem solving draws a high cognitive load in LD students (Ji & Guo, 2023; Kroesbergen et al., 2022). Instructional plans founded on CLT principles are effective to reduce cognitive load and produce better learning outcomes in LD students (Çeken & Taşkın, 2022; Murtianto & Herlambang., 2022). Phased construction of CLM-Maths is an example of application of these CLT principles to develop a targeted instruction for LD students. Prevailing literature from the discipline of special and inclusive education asserts that CLT provides a practical framework to cope with cognitive overload in students with disabilities (Kennedy & Romig, 2024). Instructional plans that are developed to manage cognitive load are effective to enhance mathematical performance (Evans et al., 2024).

This study provides a low-cost solution and a scalable intervention to improve the performance of LD students. Learning can be improved by reducing cognitive load if the lessons are structured through phased instructions rather than being presented simultaneously. The intervention with significant gains and a large effect size is beneficial in special education.

## 6. Recommendations

Following recommendations are being anticipated on the basis of findings of the study:

1. Based on the significant improvement and large effect size observed in the experimental group, mathematics instruction for LD students may be delivered through phased instructions to reduce extraneous cognitive load.
2. Because no significant improvements were observed under the traditional instruction, teacher training programs may be implemented to equip teachers with CLT-based instructional strategies, particularly for mathematics teaching.
3. Since cognitive load management principles were found to be effective in this study, these principles may be incorporated by curriculum developers in instructional material for LD students, particularly in areas that are conceptually challenging, e.g. fractions.

## References

Ayres, P., & Paas, F. (2012). Cognitive load theory in educational practice. In S. Tobias & T. M. Duffy (Eds.), *Constructivist instruction: Success or failure?* (pp. 223–238). Routledge.

Barbieri, C. A., Miller-Cotto, D., Clerjuste, S. N., & Chawla, K. (2023). A meta-analysis of the worked examples effect on mathematics performance. *Educational Psychology Review, 35*(1), Article 11. https://doi.org/10.1007/s10648-023-09745-1

Barbieri, C. A., & Rodrigues, J. (2025). Leveraging cognitive load theory to support students with mathematics difficulty. *Educational Psychologist, 60*(3), 208–232. https://doi.org/10.1080/00461520.2025.2486138

Bishara, S. (2022). Linking cognitive load, mindfulness, and self-efficacy in college students with and without learning disabilities. *European Journal of Special Needs Education*, *37*(3), 494-510. https://doi.org/10.1080/08856257.2021.1911521

Castro-Alonso, J. C., de Koning, B. B., Fiorella, L., & Paas, F. (2021). Five Strategies for Optimizing Instructional Materials: Instructor- and Learner-Managed Cognitive Load. *Educational Psychology Review, 33*(4), 1379-1407. https://doi.org/10.1007/s10648-021-09606-9

Çeken, B., & Taşkın, N. (2022). Multimedia learning principles in different learning environments: A systematic review. *Smart Learning Environments*, *9*(1), 19. https://doi.org/10.1186/s40561-022-00200-2

Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction*, *8*(4), 293–332. https://doi.org/10.1207/s1532690xci0804_2

Cooper, G., & Sweller, J. (2008). Cognitive load theory for the design of worked examples. *Journal of Educational Psychology*, *100*(3), 608–615. https://doi.org/10.1037/a0013461

Daniel, M., John, R., Rajkumar, E., George, A. J., & Abraham, J. (2022). Cognitive style and working memory among adolescents with specific learning disability. *Journal of Education and Health Promotion*, *11*(1), 196. https://doi.org/10.4103/jehp.jehp_1556_21

Evans, P., Vansteenkiste, M., Parker, P., Kingsford-Smith, A., & Zhou, S. (2024). Cognitive load theory and its relationships with motivation: A self-determination theory perspective. *Educational Psychology Review*, *36*(1), 7. https://doi.org/10.1007/s10648-023-09841-2

Faragher, R. M., & Clarke, B. A. (2020). Inclusive practices in the teaching of mathematics: Some findings from research including children with Down syndrome. *Mathematics Education Research Journal*, *32*(1), 121-146. https://doi.org/10.1007/s13394-019-00294-x

Geary, D. C. (2004). Mathematics and learning disabilities. *Journal of Learning Disabilities*, *37*(1), 4–15. https://doi.org/10.1177/00222194040370010201

Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulos, C. (2025). Challenging Cognitive Load Theory: The Role of Educational Neuroscience and Artificial Intelligence in Redefining Learning Efficacy. *Brain Sciences*, *15*(2), 203. https://doi.org/10.3390/brainsci15020203

Hostetler, K., & Luo, T. (2021). Managing cognitive load in information literacy instruction. *Educational Technology Research and Development*, *69*(2), 583–606. https://doi.org/10.1007/s11423-021-09962-x

Howie, E. E., Dharanikota, H., Gunn, E., Ambler, O., Dias, R., Wigmore, S. J., ... & Yule, S. (2023). Cognitive load management: an invaluable tool for safe and effective surgical training. *Journal of surgical education*, *80*(3), 311-322. https://doi.org/10.1016/j.jsurg.2022.12.010

Ji, Z., & Guo, K. (2023). The association between working memory and mathematical problem solving: A three-level meta-analysis. *Frontiers in psychology*, *14*, 1091126. https://doi.org/10.3389/fpsyg.2023.1091126

Jordan, J., Wagner, J., Manthey, D. E., Wolff, M., Santen, S., & Cico, S. J. (2020). Optimizing Lectures From a Cognitive Load Perspective. *AEM Education and Training*, *4*(3), 306-312. https://doi.org/10.1002/aet2.10389

Kadkhodavand, F., & Momeni Rad, A. (2024). Investigating the effect of split attention and self-regulation in multimedia learning environments on students' learning and perceived cognitive load. *Technology of Education Journal (TEJ)*, *18*(4), 859-874. https://doi.org/10.22061/tej.2024.10617.3036

Kalyuga, S., Chandler, P., & Sweller, J. (1998). Levels of expertise and instructional design. *Human Factors*, *40*(1), 1–17. https://doi.org/10.1518/001872098779480587

Kaya, Z., Kaya, O. N., Aydemir, S., & Ebenezer, J. (2022). Knowledge of Student Learning Difficulties as a Plausible Conceptual Change Pathway Between Content Knowledge and Pedagogical Content Knowledge. *Research in Science Education*, *52*(2), 691-723. https://doi.org/10.1007/s11165-020-09971-5

Kennedy, M. J., & Romig, J. E. (2024). Cognitive load theory: An applied reintroduction for special and general educators. *TEACHING Exceptional Children, 56*(6), 440-451. https://doi.org/10.1177/00400599211048214

Kroesbergen, E. H., Huijsmans, M. D., & Friso-van den Bos, I. (2023). A meta-analysis on the differences in mathematical and cognitive skills between individuals with and without mathematical learning disabilities. *Review of Educational Research, 93*(5), 718-755. https://doi.org/10.3102/00346543221132773

Murtianto, Y. H., & Herlambang, B. A. (2022). Cognitive load theory on virtual mathematics laboratory: systematic literature review. *KnE Social Sciences*, 413-420. https://doi.org/10.18502/kss.v7i19.12461

Ouwehand, K., Lespiau, F., Tricot, A., & Paas, F. (2025). Cognitive Load Theory: Emerging Trends and Innovations. *Education Sciences, 15*(4), 458. https://doi.org/10.3390/educsci15040458

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics. *Journal of Educational Psychology, 84*(4), 429–434. https://doi.org/10.1037/0022-0663.84.4.429

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38*(1), 1–4. https://doi.org/10.1207/S15326985EP3801_1

Peng, P., Wang, C., & Zhang, J. (2023). Working memory and mathematical learning difficulties: A meta-analytic review. *Journal of Experimental Child Psychology, 228*, 105579. https://doi.org/10.1016/j.jecp.2023.105579

Pennington, A. F. (2022). Short-Term Memory Processes In Children With Learning Disabilities. *Educatio: Jurnal Pendidikan STAIM Nganjuk*, 6(4), 315-323.

Sozio, G., Agostinho, S., Tindall-Ford, S., & Paas, F. (2024). Enhancing Teaching Strategies through Cognitive Load Theory: Process vs. Product Worked Examples. *Education Sciences, 14*(8). https://doi.org/10.3390/educsci14080813

Surbakti, R., Umboh, S. E., Pong, M., & Dara, S. (2024). Cognitive load theory: Implications for instructional design in digital classrooms. *International Journal of Educational Narratives*, *2*(6), 483-493. https://doi.org/10.70177/ijen.v2i6.1659

Swanson, H. L., Jerman, O., & Zheng, X. (2008). Growth in working memory and mathematical problem solving in children at risk and not at risk for serious math difficulties. *Journal of Educational Psychology*, *100*(2), 343–379. https://doi.org/10.1037/0022-0663.100.2.343

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J. (2010). Element interactivity and intrinsic, extraneous, and germane cognitive load. *Educational Psychology Review*, *22*(2), 123–138. https://doi.org/10.1007/s10648-010-9128-5

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Springer. https://doi.org/10.1007/978-1-4419-8126-4

Timothy, V., Fischer, F., Watzka, B., Girwidz, R., & Stadler, M. (2023). Applying Cognitive Load Theory in Teacher Education: An Experimental Validation of the Scale by Leppink et al. *Psychological Test Adaptation and Development*, *4*(1), 246–256. https://doi.org/10.1027/2698-1866/a000052

Tremblay, M. L., Rethans, J. J., & Dolmans, D. (2023). Task complexity and cognitive load in simulation-based education: A randomised trial. *Medical Education*, *57*(2), 161-169. https://doi.org/10.1111/medu.14941

Turoman, N., & Vergauwe, E. (2024). The Effect of Multisensory Distraction on Working Memory: A Role for Task Relevance?. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *50*(8), 1220. https://doi.org/10.1037/xlm0001323

Wen, Z. A., Silverstein, E., Zhao, Y., Amog, A. L., Garnett, K., & Azenkot, S. (2020, October). Teacher views of math e-learning tools for students with specific learning disabilities. In *Proceedings of the 22nd International*

*ACM SIGACCESS Conference on Computers and Accessibility* (pp. 1-13). https://doi.org/10.1145/3373625.3417029

Zhang, H., & Cai, J. (2021). Teaching mathematics through problem posing: insights from an analysis of teaching cases. *ZDM–Mathematics Education, 53*(4), 961-973. https://doi.org/10.1007/s11858-021-01260-3

Zou, L., Zhang, Z., Mavilidi, M., Chen, Y., Herold, F., Ouwehand, K., & Paas, F. (2025). The synergy of embodied cognition and cognitive load theory for optimized learning. *Nature Human Behaviour, 9*, 877–885 https://doi.org/10.1038/s41562-025-02152-2

**Citation of this Article:**

Hussain, M. (2025). Effectiveness of Cognitive Load-Managed Math Instruction (CLM-Maths) in Improving Problem-Solving Performance of Students with Learning Disabilities. *International Journal of Innovation in Teaching and Learning (IJITL)*, *11*(2), 39-56.