European Journal of Science and Mathematics Education, 2026, **14**(2), 187-202
ISSN: 2301-251X (Online)

OPEN ACCESS

Research Article

Using Sweller's cognitive load theory to improve learning of derivative concepts

Esma Canhasi-Kasemi [1]
0000-0001-6885-6057

Senad Orhani [2*]
0000-0003-3965-0791

Ismet Temaj [1]
0000-0002-5413-9097

[1] Faculty of Education, University of Prizren "Ukshin Hoti", Prizren, KOSOVO
[2] Faculty of Education, University of Prishtina "Hasan Prishtina", Prishtina, KOSOVO
[*] Corresponding author: senad.orhani@uni-pr.edu

Citation: Canhasi-Kasemi, E., Orhani, S., & Temaj, I. (2026). Using Sweller's cognitive load theory to improve learning of derivative concepts. *European Journal of Science and Mathematics Education, 14*(2), 187-202. https://doi.org/10.30935/scimath/18060

ARTICLE INFO

Received: 12 Jul 2025
Accepted: 4 Jan 2026

ABSTRACT

This study investigates the effectiveness of applying Sweller's (1988) cognitive load theory (CLT) principles to improve the learning of derivative concepts among first-year university students. The research employed a quasi-experimental pre-/post-test control group design to evaluate the impact of CLT-based instructional strategies–worked examples, visual scaffolds, and structured problem-solving–on students' achievement and perceived cognitive load. A total of 60 students were randomly assigned to either an experimental group, receiving CLT-based instruction, or a control group, receiving traditional teaching. Data were collected using achievement tests and the cognitive load scale, assessing intrinsic, extraneous, and germane load components. Quantitative data were analyzed using independent samples t-tests and two-way and mixed-design ANOVA, with effect sizes (Cohen's d, partial η^2) reported to determine the magnitude of observed effects. Results indicated that the CLT-based instruction led to significantly higher achievement scores, reduced extraneous cognitive load, and increased germane processing compared to traditional methods. The findings support the theoretical validity of CLT and its practical applicability for mathematics instruction, suggesting that structured visual and example-based learning can optimize students' cognitive resources and promote deeper understanding of calculus concepts.

Keywords: cognitive load theory, conceptual learning, derivatives, mathematics, pedagogical strategies

INTRODUCTION

Cognitive load theory (CLT), originally formulated by Sweller (1988), is one of the most powerful approaches in the field of cognitive psychology and education, focusing on ways to optimize learning and teaching. It addresses the limitations of working memory and provides practical guidance for designing materials and didactic methods that minimize ineffective cognitive load, directing students' mental resources toward processing the essence of information (Sweller et al., 2011). CLT distinguishes three types of cognitive load: Intrinsic load is related to the complexity of the learning material and the interaction between conceptual elements. External load arises from inefficient ways of presenting information, which often unnecessarily loads working memory. Extrinsic load represents the useful efforts that contribute to the construction of cognitive schemas and the sustainable acquisition of knowledge (Paas & van Merriënboer, 1994; Sweller et al., 2011).

In mathematics teaching, derivative concepts are often characterized by high intrinsic load and unnecessary extrinsic load due to disorganized materials. By applying strategies such as worked examples and graphical visualizations, it is possible to reduce unnecessary load and increase relevant load that supports the construction of sustainable knowledge (Ngu & Phan, 2022). Given this, the application of CLT is particularly promising for facilitating conceptual learning in this area. For example, the use of strategies such as visual analogies worked as examples, and clear structuring of learning material has been shown to improve understanding and application of derivative concepts (Retnowati et al., 2022).

Recent studies have demonstrated the success of these methodologies, showing a significant reduction in cognitive load and improved learning outcomes in experimental groups compared to control groups (Greefrath et al., 2023a). This suggests that CLT provides a practical framework for improving mathematics education and addressing the challenges that come with learning complex concepts. CLT to improve the learning of derivatives, focusing on designing theory-based methods and materials to help students overcome conceptual challenges and develop a deeper understanding of mathematical analysis.

In this context, this study aims to apply the principles of CLT to structure didactic materials that minimize external load, balance internal load, and maximize relevant load, with the aim of improving the learning of derivative concepts among first-cycle students.

Problem Identification

Learning derivative concepts in calculus represents one of the most cognitively demanding areas in undergraduate mathematics education. Students often struggle to link the symbolic, graphical, and conceptual representations of derivatives, resulting in fragmented understanding and procedural learning rather than conceptual mastery (Artigue, 1991; Orton, 1983). Several studies have highlighted that traditional lecture-based instruction fails to adequately address the cognitive complexity inherent in calculus concepts (Habre & Abboud, 2006; Tall, 1993). Such challenges emphasize the importance of designing instructional materials that account for learners' limited working memory capacity and information processing limitations (Paas et al., 1994; Sweller, 1988).

CLT, developed by Sweller (1988), provides a theoretical framework for optimizing instructional design by balancing the demands on working memory. It distinguishes among three types of cognitive load: intrinsic load, related to the inherent complexity of the material; extraneous load, caused by ineffective instructional design; and germane load, which contributes to schema construction (Kalyuga, 2011; Sweller et al., 2011). The effective management of these load types is crucial in teaching mathematical concepts, particularly derivatives, which require simultaneous processing of algebraic and geometric reasoning (Ngu & Phan, 2022; Retnowati et al., 2022).

Recent research suggests that CLT-based strategies, such as worked examples, visual scaffolds, and fading guidance, can significantly enhance learners' conceptual understanding and problem-solving skills in mathematics (Ayres, 2013; Greefrath et al., 2023b; Leong et al., 2021). Worked examples reduce extraneous load by guiding novice learners through step-by-step problem-solving procedures (Paas & van Merriënboer, 1994; Renkl, 2014), while visual representations facilitate the integration of symbolic and spatial knowledge (Yohannes & Chen, 2023). In calculus instruction, where learners must connect multiple representations–formulas, graphs, and contextual meanings–such designs are particularly valuable (Slemp & Ayres, 2023).

Despite extensive theoretical work on CLT, its empirical application to derivative learning remains limited, especially in higher education contexts in developing countries. Many instructors still rely on rote and procedural teaching, overlooking the cognitive limitations that impede conceptual understanding (Liu & Zhang, 2024; Maryati et al., 2022). Therefore, the present study seeks to investigate the impact of CLT-based instructional strategies on students' achievement and cognitive load when learning derivatives. Specifically, it examines whether structured and visually supported learning materials, grounded in CLT, can reduce cognitive overload and improve learning outcomes in calculus courses.

Purpose of the Study

The main goal of this research is to explore and apply the principles of CLT to improve the learning process of derivatives concepts. This study aims to identify teaching strategies and tools that can reduce students' cognitive load when learning derivatives, focusing on improving conceptual understanding and problem-solving skills.

Specifically, this research aims to

(1) evaluate the effectiveness of methods based on worked examples and visual materials in reducing cognitive load when learning derivatives,

(2) analyze the impact of strategies designed according to CLT on students' ability to transfer knowledge to solve complex problems, and

(3) develop new teaching materials and methods based on this theory to make the complex concepts of derivatives more accessible to students.

Research Questions

1. What is the impact of CLT-based instructional strategies on students' understanding and problem-solving performance in learning derivatives?
2. How does CLT-based instruction influence the reduction of students' perceived cognitive load during derivative learning?
3. To what extent do CLT-oriented learning materials enhance the transfer of derivative knowledge to real-world problem contexts?
4. How does CLT-based instruction affect students' motivation and attitudes toward learning calculus?

LITERATURE REVIEW

CLT, formulated by Sweller (1988), provides a powerful framework for understanding how working memory constraints affect the learning process. According to Sweller et al. (2011), effective teaching requires minimizing external load, managing internal load, and maximizing the relevant load that supports the construction of cognitive schemas. This framework has been tested in various fields, but its application to the teaching of mathematical derivatives remains limited and dependent on the methodological context of each study.

Ngu and Phan (2022) show that the use of structured analogies and worked examples can significantly reduce cognitive load during the learning of linear equations. However, this study uses a relatively small sample (n = 40) and a short intervention period (two weeks), which limits the general validity of the findings. Its strength lies in the controlled experimental design and the use of validated instruments to measure perceptual load, which are relevant to the current study that follows a similar experimental approach.

Similarly, Retnowati et al. (2022) analyzed the impact of worked examples on learning derivatives and found significant improvement in knowledge retention and transfer. A strength of this study is the use of a pre-post design with a control group, providing clear empirical evidence for the effectiveness of the intervention. However, the main limitation lies in the lack of long-term measures that would assess the sustainability of learning, as well as the lack of qualitative analysis on how students perceive CLT strategies.

Leong et al. (2021) emphasize the importance of linking theoretical concepts with visual applications through graphics and animations, promoting conceptual understanding of the derivative. This study has practical value due to the involvement of teachers in real classroom situations, however, it suffers from limitations in cross-cultural generalization, as it was conducted in a specific educational context (Singapore). For your study, this suggests the need to adapt CLT strategies to local pedagogical realities.

According to Greefrath et al. (2023a), students' mental models of the derivative are influenced by the way visual and symbolic materials are combined in teaching. This study uses conceptual analysis and in-depth interviews, providing rich perspectives on how cognitive load shapes mathematical thinking. However, the lack of a direct experimental comparison limits the ability to draw causal conclusions something that your study addresses through a control group and experimental design.

Another important contribution is that of Yohannes and Chen (2023), who analyzed the use of GeoGebra to reduce cognitive load through visual interaction. Their results show increased engagement and improved conceptual understanding. The strength of this study is the systematic approach of reviewing the literature

(2010-2020), but a limitation lies in the lack of direct empirical analysis of student performance, which your study compensates for through statistical tests and measures of perceived workload.

In contrast, Radha et al. (2015) analyze flipped learning as a tool for managing cognitive load in mathematics teaching. They found that a preparatory structure before class helps students reduce overload during active learning sessions. However, this study does not specify objective measures of workload, relying only on self-reports, which limits the reliability of the results.

Recent studies by Liu and Zhang (2024) introduced a neurocognitive approach to measuring cognitive load in real-world learning contexts, using subjective and neurophysiological data. This represents an important step towards validating CLT instruments but requires advanced technology that is hardly available in most educational contexts, including Kosovo.

Finally, the study by Maryati et al. (2022) highlights the role of combining listening and reading of worked examples in reducing stress and cognitive load. However, their largely descriptive design does not allow for the inference of cause-and-effect relationships.

Overall, the existing literature strongly supports the idea that CLT is an effective tool for improving mathematics teaching, but a large part of the studies has limitations in generalizability, long-term design, and methodological diversity. This creates a clear research gap that your study aims to fill, applying a controlled experimental design with pre- and post-intervention measurements, and combining quantitative instruments with perceptual analysis, to assess the effectiveness of CLT-based strategies in teaching derivative concepts.

Challenges in Applying CLT to Derivatives

Although the literature shows positive results of the application of CLT in education, some studies highlight the methodological and practical difficulties that accompany its implementation, especially in complex mathematical contexts such as derivatives. According to Ayres (2013), the main challenge lies in balancing the isolated elements of learning. In cases where concepts are highly interconnected (e.g., limit, slope, function, and infinite change), excessive separation of material can lead to fragmentation of meaning, preventing the integration of concepts into a single meaningful structure. This indicates that the mechanical application of CLT principles can reduce the effectiveness of learning rather than improve it.

Another important challenge is the management of intrinsic load. In mathematics, this load is inherent due to the complexity of the relationships between concepts. Kalyuga (2011) points out that students with different levels of expertise require differentiated approaches to materials design. For example, while beginners benefit from worked examples and detailed instructions, more advanced students may experience the effect of expert overload, where excessive information becomes a barrier to learning. This requires that learning materials be adaptable to the level of knowledge, something that your study aims to address by differentiating tasks according to students' knowledge levels.

Another challenge highlighted by Sweller et al. (2011) is the accurate assessment of cognitive load. Subjective measures through self-report questionnaires are often limited by individual student interpretation, while objective measures (e.g., neurophysiological, as in Liu & Zhang, 2024) are difficult to apply in university settings due to the cost and infrastructure required. Therefore, many studies, including yours, use a combination of subjective instruments and performance tests to assess the effects of CLT in a balanced manner.

Ayres (2013) also argues that one of the main obstacles to implementing CLT is identifying points of high load within an instructional sequence. In many cases, teachers fail to determine at which stages students experience maximum load, for example, during the transition from the concept of limit to derivative as the slope of a tangent line. This requires the use of step-by-step diagnostic analyses to understand where conceptual difficulties occur and to intervene with targeted strategies (e.g., partial worked examples or dynamic visualizations).

In contexts like Kosovo, where technological resources and teacher training may be limited, an additional challenge lies in the practical transfer of CLT principles to the classroom. As Slemp and Ayres (2023) point out, the lack of professional preparation for the use of CLT-based design models often leads to partial or incorrect implementation, limiting the real impact of the theory on learning outcomes. For this reason, your study is particularly important as it integrates pre-service teacher training and materials structured according to the three types of workloads, providing a more complete implementation of the theory in practice.

In summary, the literature suggests that, although CLT has high potential for improving the learning of derivatives, its success depends on

(1) identifying the phases of maximum workload and targeted intervention,

(2) adapting the materials to the level of student expertise,

(3) combining subjective and objective measures of workload, and

(4) adapting CLT to the institutional and cultural reality of local education.

These methodological aspects justify the design of study, which aims to test the effectiveness of CLT in a university context with real constraints, contributing to the literature on its transferability and sustainability in mathematics teaching.

METHODOLOGY

Study Design

To answer the research questions and achieve the study goals, a quantitative approach with an experimental design based on the comparison between a control group and an experimental group was used. The research was conducted using an experimental design where the control group learned through traditional teaching methods, while the experimental group incorporated strategies based on the CLT. The present study adopted a quantitative quasi-experimental design with pre-test and post-test control groups. This design was chosen because the main objective of the study was to measure the causal impact of instructional strategies based on CLT on students' achievement and perceived cognitive load. A quantitative experimental approach enables precise statistical comparison between groups, providing objective evidence about the effectiveness of the intervention (Campbell & Stanley, 1963; Creswell & Creswell, 2018).

Alternative approaches such as qualitative or mixed-methods designs were considered but deemed less appropriate for this investigation. A qualitative design would allow for a deeper exploration of students' perceptions and experiences, but it would not provide the statistical rigor required to test hypotheses about causal relationships between CLT-based instruction and learning outcomes. Similarly, a mixed-methods approach, though valuable for triangulating results, would have extended beyond the current study's scope and resources.

The quantitative experimental model was therefore selected because it offers a controlled environment to isolate the effects of the intervention, minimize potential confounding variables, and quantify learning gains using standardized instruments such as achievement tests and cognitive load scales. This design aligns with the recommendations of Sweller et al. (2011) and Paas and van Merriënboer (1994), who emphasize that experimental methods are the most suitable for testing the effectiveness of instructional designs derived from CLT.

In summary, this research design ensures internal validity, allows for replicability, and provides robust evidence of the relationship between CLT-based teaching strategies and student learning performance, making it the most appropriate model for the study's aims.

Population and Sample

The population of this study consisted of all first-year students enrolled in the faculty of education at the University of Prizren "Ukshin Hoti" from Republic of Kosovo. From this population, a total of 60 students were selected to participate in the research. Participants were drawn from two intact classes taking the "basic mathematics II" course, both taught by the same instructor to ensure consistency in delivery and minimize instructor bias.

The sample was divided into two groups of 30 students each: the experimental group, which received instruction designed according to CLT, and the control group, which followed traditional lecture-based teaching methods. The groups were balanced with respect to gender, with 31 females (52%) and 29 males

(48%) distributed proportionally across both groups (experimental: 16 females, 14 males; control: 15 females, 15 males).

Participants shared similar academic backgrounds and had comparable exposure to digital learning tools such as GeoGebra, Desmos, and learning management systems used in previous mathematics courses. Prior to the intervention, a brief diagnostic survey confirmed that both groups had equivalent levels of technological familiarity and mathematical achievement, ensuring baseline comparability.

The sampling technique employed was a simple random sampling method applied at the class level. Two intact classes were randomly assigned to the experimental and control groups using a random number generator. This approach ensured fairness in group allocation and avoided potential bias while maintaining ecological validity within the natural classroom setting.

The choice of simple random sampling was justified because it provides equal probability for each unit to be selected and is particularly effective when the population is homogeneous in key characteristics, such as academic background and course level (Creswell & Creswell, 2018). This method allowed for the generalization of results to similar cohorts of first-year education students learning calculus-related topics.

Data Collection

CLT included the followings:

1. **Worked examples:** To reduce unnecessary cognitive load and promote understanding of basic structures.
2. **Graphical and interactive visualizations:** To help students connect abstract concepts with concrete representations.
3. **Structured exercises:** To test and reinforce student understanding.

Data collection in this study followed a structured and sequential process spanning three main phases: pre-intervention, intervention, and post-intervention. Each phase was carefully planned to ensure consistency, control over variables, and the validity of collected data.

The implementation process included several main stages:

1. **Pre-intervention phase:** Before the start of the instructional intervention, both the experimental and control groups completed a pre-test designed to assess their baseline knowledge of derivative concepts. The pre-test consisted of 20 items (10 multiple-choice and 10 problem-solving questions) developed and validated by subject experts. Simultaneously, participants filled out the cognitive load scale (Leppink et al., 2013) to measure their initial perceptions of cognitive load related to calculus learning tasks. This phase also included a diagnostic survey to confirm that both groups were equivalent in prior mathematical achievement and technological familiarity. The survey helped ensure that any post-intervention differences could be attributed to the instructional strategy rather than pre-existing disparities.
2. **Learning intervention:** The instructional intervention lasted for three consecutive weeks, comprising a total of six teaching sessions (two sessions per week). Each session lasted 45 minutes, resulting in a total of nine hours of direct instructional contact for each participant. During these sessions, the experimental group received instruction explicitly designed according to the principles of CLT. The teacher implemented CLT-based materials that incorporated worked examples, where step-by-step solutions were first presented and later followed by partially completed examples to encourage guided practice (Renkl, 2014). Visual scaffolds such as diagrams and graphs were used to connect symbolic and conceptual representations of derivatives, while segmented instruction divided the content into short, meaningful units to prevent cognitive overload. Collaborative discussions were also integrated to foster germane processing through peer interaction and reflective thinking. The teacher acted as a facilitator, modeling problem-solving strategies, reducing extraneous cognitive load (ECL) through clear explanations, and providing feedback, whereas students were active participants who analyzed worked examples and completed guided problem-solving activities. In contrast, the control group received traditional lecture-based instruction on the same topics and for the same duration, but without CLT-based design elements. The teacher followed a conventional approach, explaining derivative concepts

verbally, solving examples on the board, and assigning exercises for homework. Students in this group primarily listened, took notes, and followed the instructor's explanations with minimal interaction or visual support. To ensure instructional consistency and internal validity, both groups were taught by the same instructor, and sessions were observed to maintain fidelity in implementation.

3. **Achievement tests (pre- and post-test):** To assess students' understanding of derivative concepts before and after the instructional intervention, two parallel achievement tests were developed a pre-test and a post-test. Both instruments were designed by the research team in consultation with three experts in mathematics education to ensure content validity and alignment with the intended learning outcomes.

Each test consisted of 20 items, divided into two sections:

1. Section A (10 multiple-choice questions) assessing conceptual understanding of derivative definitions, notations, and interpretations of slope and rate of change.
2. Section B (10 problem-solving tasks) requiring procedural fluency, application of derivative rules, and analysis of graphical and real-world contexts.

The maximum achievable score for each test was 100 points, with equal weight assigned to both sections. Items were designed to reflect various cognitive levels based on Bloom's taxonomy (knowledge, comprehension, application, and analysis). Prior to the main study, a pilot test was conducted with 10 first-year mathematics students from the same institution (not included in the main sample) to evaluate item clarity, difficulty, and discrimination indices. Based on pilot results, three questions were revised for clarity and one was replaced due to low discrimination (< 0.20). The content validity index computed from expert ratings was 0.92, indicating excellent agreement on item relevance. Reliability analysis yielded a Cronbach's alpha coefficient of 0.88 for the pre-test and 0.91 for the post-test, suggesting high internal consistency. Additionally, to ensure scoring accuracy for open-ended responses, two independent raters evaluated 20% of the responses randomly selected from the dataset. The inter-rater reliability, computed using the Cohen's kappa coefficient, was 0.93, demonstrating strong agreement between raters. The same test format and time allocation (45 minutes) were maintained for both assessments to ensure comparability of performance measures across the two groups.

1. **Post-test**: After the intervention, students in both groups underwent a final test to assess the improvement in their performance.
2. **Cognitive load questionnaires:** To measure students' perceived cognitive load, the study employed the cognitive load scale developed by Leppink et al. (2013). The instrument consists of ten items, distributed across three subscales:
   a. Intrinsic cognitive load–3 items
   b. ECL–3 items
   c. Germane cognitive load–4 items

Each item was rated on a 10-point Likert scale ranging from 1 (very low) to 10 (very high) cognitive effort. The questionnaire has demonstrated strong construct validity and has been widely used in mathematics and instructional design studies (e.g., Klepsch et al., 2017; Leppink et al., 2013). In the present study, the internal consistency reliability of the subscales was high, with Cronbach's alpha coefficients of 0.84 for intrinsic load, 0.87 for extraneous load, and 0.90 for germane load. The overall reliability for the full scale was $\alpha = 0.89$, indicating a satisfactory level of reliability for research purposes. Students completed the instrument immediately after the post-test phase to ensure accurate reporting of cognitive perceptions related to the instructional methods used.

Data Analysis

The data analysis process in this study focused on measuring the effects of the instructional intervention on students' learning outcomes and cognitive load. Quantitative data obtained from the achievement tests (pre-test and post-test) and the cognitive load questionnaire were analyzed separately but interpreted collectively to evaluate the impact of CLT-based instruction. Data were coded and entered into IBM SPSS Statistics for analysis. Initially, descriptive statistics (means, standard deviations, and frequencies) were computed to summarize students' performance and perceived cognitive load in both groups. Before conducting inferential tests, assumptions of normality, homogeneity of variance, and independence of observations were verified using the Shapiro-Wilk test, Levene's test, and inspection of Q-Q plots. For the achievement data, an independent samples t-test was used to compare the post-test means between the experimental and control groups, while a two-way ANOVA examined the interaction effects between group and prior knowledge level. Additionally, Cohen's d and partial eta squared (η^2_p) were calculated to determine the magnitude of the effects.

1. **Testing of statistical assumptions:** Before conducting inferential analyses (independent samples *t*-tests and two-way ANOVA), all relevant statistical assumptions were examined to ensure the validity of the tests.
   a. Normality–The normal distribution of the dependent variables (pre- and post-test scores) was verified using both the Shapiro-Wilk test and Q-Q plots. Results indicated that the data did not significantly deviate from normality ($p > 0.05$ for all tests).
   b. Homogeneity of variances–The assumption of equal variances across groups was tested using Levene's test for equality of variances. The results were non-significant ($p > 0.05$), confirming the homogeneity assumption for both pre-test and post-test scores.
   c. Independence of observations–The independence assumption was ensured by the experimental design itself: participants were randomly assigned to either the control or the experimental group, and there was no interaction between groups during the intervention period.
   d. Absence of outliers–Outlier analysis using boxplots and standardized z-scores revealed no extreme values ($|z| < 3.29$), suggesting that all observations were suitable for inclusion in the analyses.

   Collectively, these tests confirmed that the dataset met the assumptions required for parametric statistical procedures, validating the use of independent *t*-tests and ANOVA for comparing group performance.
2. **Effect size measures:** In addition to significance testing, effect sizes were computed to evaluate the practical magnitude of differences between groups and the strength of relationships identified in the analysis. For the independent samples t-tests comparing pre- and post-test scores, Cohen's *d* was calculated using the pooled standard deviation. Cohen's (1988) conventional benchmarks were applied for interpretation: $d = 0.20$ (small), $d = 0.50$ (medium), and $d = 0.80$ (large). For the two-way ANOVA, η^2_p was reported as a measure of effect size, indicating the proportion of variance in the dependent variable explained by the independent factors (group, prior knowledge level) and their interaction. The interpretation followed Cohen's (1988) thresholds: $\eta^2_p = 0.01$ (small), $\eta^2_p = 0.06$ (medium), and $\eta^2_p = 0.14$ (large). Reporting both p-values and effect sizes provides a comprehensive understanding of statistical and practical significance, aligning with recommendations from the APA manual (7th ed.) and Field (2020) for transparent quantitative reporting.
3. **Statistical analysis**: To compare the results of the two groups, using t-tests and analysis of variance (ANOVA) to determine statistically significant differences.
4. **Cognitive load pre-post analysis:** To evaluate whether the instructional intervention significantly reduced cognitive load, a 2 (group: experimental vs. control) × 2 (time: pre- vs. post-test) mixed-design ANOVA was conducted on the three subscales of the cognitive load scale (intrinsic, extraneous, and Germane). The within-subjects factor was time (pre vs. post), and the between-subjects factor was group (experimental vs. control). This analysis examined both the main effect of time (whether cognitive load decreased overall) and the group × time interaction (whether the magnitude of reduction differed between groups).

Ethical Considerations

This study was conducted in accordance with the ethical standards for research involving human participants. Prior to data collection, ethical approval was obtained from the Ethics Committee of the Faculty of Education, University of Prizren "Ukshin Hoti". Participation in the study was voluntary, and all participants were informed about the purpose, procedures, and confidentiality of the research. Informed consent was

Table 1. Test scores: Pre- and post-test results

Group	Test	Mean score	Standard deviation	N
Experimental	Pre-test	55	5.2	30
Experimental	Post-test	85	6.4	30
Control	Pre-test	54	5.8	30
Control	Post-test	65	7.1	30

Table 2. Combined t-test and group performance

Group	Mean (pre-test)	Mean (post-test)	Mean improvement	Standard deviation (post-test)	t	df	p-value (2-tailed)	Mean difference	Standard error mean
Experimental	55	85	30	6.4	12.45	58	0.00	19.0	1.53
Control	54	65	11	7.1	5.22	58	0.00	11.0	2.11

obtained from all participants before their involvement in the study. Participants were assured that their responses would remain anonymous and that they could withdraw from the study at any stage without penalty. The research was carried out following the principles of the Declaration of Helsinki (2013) and the European Code of Conduct for Research Integrity (ALLEA, 2017).

RESULTS

The main results of this study were obtained through the analysis of data collected from tests before and after the learning intervention, as well as from questionnaires on the perception of cognitive load.

Key Results from Performance Tests

The results of the experimental and control groups show that after implementing methods based on the CLT, the experimental group showed a significant improvement in the results of the derivative concept acquisition tests. While the control group, which used traditional methods, recorded a more modest improvement.

The results of **Table 1** show that at the beginning of the study, the pre-intervention test for both groups showed similar performances in understanding derivatives, indicating that their initial levels of knowledge were comparable. The experimental group in the post-intervention test recorded an average score of 85%, compared to 65% in the control group, indicating a clear benefit from the new pedagogical approach.

The results presented in **Table 2** show a significant difference between the performance of the experimental and control groups, both before and after the pedagogical intervention. The experimental group, which followed an approach based on CLT, showed significant improvements in performance compared to the control group, which continued with traditional methods. The experimental group scored an average of 55 points on the pre-intervention test, which reflects the initial level of students' knowledge. After the intervention, this group recorded an average of 85 points on the post-test, reflecting an average improvement of 30 points. This result indicates that teaching strategies based on CLT significantly helped in the acquisition of complex concepts such as derivatives. The standard deviation of 6.4 suggests a narrow distribution of results, indicating that most students benefited similarly from this approach. In comparison, the control group scored an initial mean of 54 points on the pre-intervention test and a mean of 65 points on the post-test, indicating an average improvement of only 11 points. This more modest increase suggests that traditional teaching methods are less effective in facilitating the learning of complex concepts. The standard deviation of 7.1 for this group suggests a wider distribution of scores, indicating greater variation in student gains.

To address research question 1, which examined the impact of CLT-based instructional strategies on students' understanding and problem-solving performance in learning derivatives, achievement test results were analyzed using independent samples t-tests. As shown in **Table 2**, students in the experimental group demonstrated significantly higher post-test scores compared to the control group, $t(58) = 12.45$, $p < .001$, with a large effect size ($d = 1.62$). These findings indicate that CLT-based instruction substantially enhanced students' conceptual understanding and problem-solving performance.

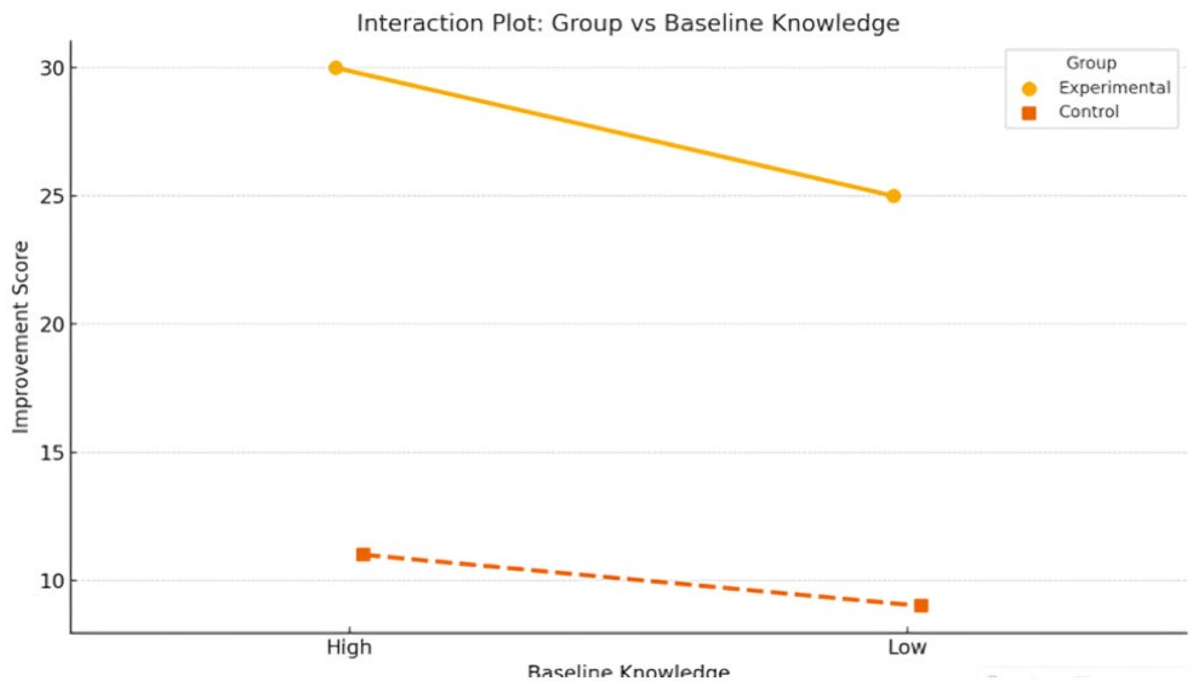

Figure 1. Interaction plot for ANOVA (Source: Authors' analysis, 2026)

Table 3. Two-way ANOVA results for group and prior knowledge level

Source of variation	SS	df	MS	F	p-value	Partial η^2
Group	5,120.4	1	5,120.4	32.13	< .001	0.365
Prior knowledge level	1,280.6	1	1,280.6	8.04	0.006	0.126
Group × prior knowledge	640.8	1	640.8	4.02	0.049	0.067
Error	8,920.2	56	159.3			
Total	15,962	59				

The interaction graph (**Figure 1**) for the ANOVA illustrates the impact of two main factors on the improvement of students' performance. Group (experimental and control) and level of basic knowledge (high and low). The results show a significant difference between the groups. The experimental group has shown significantly greater improvement than the control group, regardless of the level of basic knowledge. This indicates that the pedagogical intervention used in the experimental group has been much more effective compared to the traditional approach. When analyzing students with high knowledge, the improvement is greater in both groups, with a clear advantage for the experimental group. On the other hand, for students with low knowledge, the pedagogical intervention in the experimental group has had a particular impact, showing a more pronounced effect for this category. In the control group, the improvement is lower and less influenced by the level of basic knowledge. An important aspect that stands out in the interaction graph is the fact that the lines are not parallel, suggesting an interaction effect between the group and the level of basic knowledge. This interaction shows that the impact of the pedagogical intervention is greater for low-achieving students in the experimental group. In the control group, the improvement remains minimal, highlighting the limitations of traditional teaching methods for this category.

The results of the two-way ANOVA revealed significant main effects for both the instructional group and prior knowledge level, as well as a statistically significant interaction effect. **Table 3** summarizes the ANOVA outcomes, including the F-values, degrees of freedom, p-values, mean squares, and η^2_p values. The results indicate a significant main effect of instructional group, $F(1,56) = 32.13$, $p < .001$, $\eta^2_p = .37$, suggesting that the CLT-based intervention substantially improved learning outcomes compared to traditional instruction. The main effect of prior knowledge was also significant, $F(1,56) = 8.04$, $p = .006$, $\eta^2_p = .13$, indicating that students with higher baseline knowledge benefited more overall. Additionally, the interaction between group and prior knowledge was significant, $F(1,56) = 4.02$, $p = .049$, $\eta^2_p = .07$, demonstrating that the intervention had a particularly strong effect for students with initially lower knowledge levels. These findings confirm that the pedagogical strategies based on CLT were effective across different learner profiles.

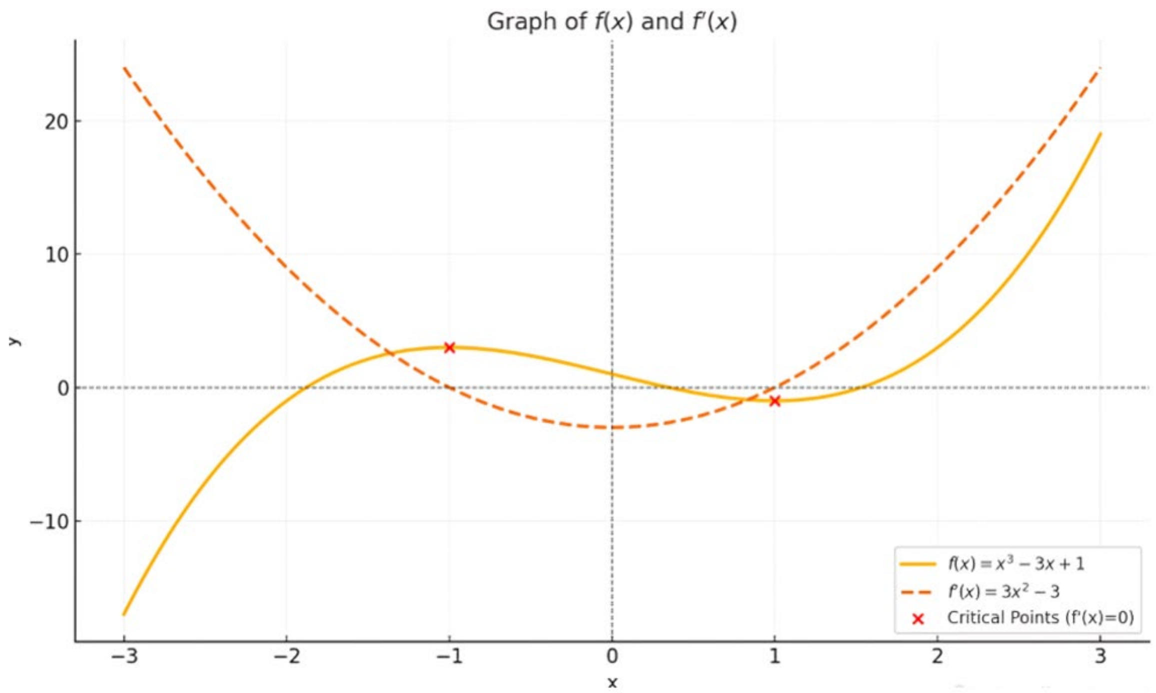

Figure 2. Graph of the function $f(x) = x^3 - 3x + 1$and its derivative $f'(x) = 3x^2 - 3$ (Source: Authors' design using GeoGebra)

These results clearly demonstrate that the use of pedagogical strategies based on CLT has a significant positive impact on the learning of derivative concepts. The significant improvement in the performance of the experimental group suggests that minimizing cognitive load and focusing mental resources on essential aspects of learning help students overcome conceptual difficulties and achieve better results. In contrast, the control group, which followed traditional methodologies, had more limited benefits, highlighting the need to incorporate more modern and theory-based approaches to teaching.

To answer research question 3, the transfer of derivative knowledge was examined through application-based post-test tasks and real-world problem scenarios. Students exposed to CLT-based instruction successfully applied derivative concepts to optimization and rate-of-change problems, demonstrating improved conceptual transfer. The graphical and worked-example-based approach supported students in connecting symbolic, graphical, and contextual representations of derivatives (see **Figure 2**).

Results from Worked Example and Graphical Visualization

In this example, the function $f(x) = x^3 - 3x + 1$ and its derivative $f'(x) = 3x^2 - 3$ are explained step by step to help students understand the concept of the derivative as the slope of the tangent to the graph.

In this lesson, the function $f(x) = x^3 - 3x + 1$ and its derivative $f'(x) = 3x^2 - 3$ are analyzed using a combination of a worked example and a graphical visualization to help students understand the concept of the derivative as the slope of the tangent on the graph of the function. First, students were presented with a worked example, where the derivative was calculated step by step using the basic rules of differentiation. Next, students identified critical points by solving the equation, where two critical points $f'(x) = 0$ and $x = 1$ were found $x = -1$. These points represent the local maximum and minimum of the function. To reinforce this analysis, a graphical visualization of the function and its derivative was used. The graph $f(x)$ showed the behavior of the function, while the graph $f'(x)$illustrated the slope of the tangent at various points. The critical points, where $f'(x) = 0$, were represented as local maximums and minimums on the graph of $f(x)$. Furthermore, students observed that when $f'(x) > 0$, the function is increasing, and when $f'(x) < 0$, the function is decreasing. Through this procedure, they gained the ability to interpret the derivative not only as a mathematical formula but also as a tool for analyzing the behavior of a function and understanding its practical applications.

In this real-world situation, the function $f(x) = x^3 - 3x + 1$ was used to model the net profit of a business depending on the resources invested. The analysis showed that the first derivative, $f'(x) = 3x^2 - 3$, helps identify critical points where profit is maximum or minimum, while the second derivative, $f''(x) = 6x$, determines the nature of these points. In this case, the local maximum is located at $x = -1$, suggesting that careful use of resources maximizes profit, while the local minimum at $x = 1$ indicates that excessive use of resources causes a decrease in profit. This analysis helps the business understand the relationship between invested resources and financial results, aiding in strategic decision-making and optimizing the use of resources. Furthermore, the situation illustrates how derivatives and critical points can be used to address practical problems and understand the behavior of complex systems, making mathematics a valuable tool for real-world applications. This approach connects theory with practice, increasing the learning value for students and professionals.

Results from Perception of Cognitive Load

Cognitive load questionnaire results showed that students in the experimental group reported a significant reduction in their perception of the difficulty of the material. The strategies used, such as work examples and visual materials, helped minimize mental overload and facilitated the understanding of complex concepts.

The mixed-design ANOVA revealed a significant main effect of time, $F(1,58) = 46.27$, $p < .001$, $\eta^2_p = .44$, indicating that overall cognitive load scores decreased significantly from pre-test to post-test across participants. Research question 2 investigated whether CLT-based instruction reduced students' perceived cognitive load. A 2 × 2 mixed-design ANOVA revealed a significant group × time interaction, $F(1,58) = 21.36$, $p < .001$, $\eta^2_p = .27$, indicating that cognitive load decreased significantly more for students in the experimental group. Follow-up paired-sample t-tests confirmed that the experimental group exhibited significant reductions in extraneous load (Mdiff = -1.9, $t[29] = 5.14$, $p < .001$) and increases in germane load (Mdiff = +1.1, $t[29] = 3.72$, $p = .001$), while the control group showed no statistically significant changes (all $p > .05$). Specifically, extraneous load was reduced while germane load increased, demonstrating that CLT-based materials optimized cognitive resources during derivative learning.

The results of the perception of cognitive load show significant differences between the experimental group and the control group in three main dimensions: intrinsic load, extrinsic load, and germane load. The experimental group reported a moderately low intrinsic load (3.5), indicating that the material was well-organized and accessible to students. Furthermore, the extrinsic load was very low (2.8), reflecting the use of structured strategies that eliminated confusion and distractions. The germane load in this group was very high (4.6), indicating high engagement and maximum concentration in acquiring the material.

Research question 4 explored how CLT-based instruction influenced students' motivation and attitudes toward learning calculus. Results from the cognitive load questionnaire (**Figure 3**) indicate that students in the experimental group reported lower frustration, higher engagement, and greater confidence compared to the control group. These findings suggest that reducing unnecessary cognitive load positively affected students' motivational and affective responses to calculus learning. In contrast, the control group exhibited a higher intrinsic load (4.2), suggesting that the material was more difficult to acquire. The extrinsic load in this group was also very high (4.5), reflecting the lack of clarity and structure in the learning materials. Furthermore, the German load was lower (3.2), indicating lower engagement and reduced focus on core tasks.

These results clearly show that the structured approaches used in the experimental group significantly reduced unnecessary load and increased focus on important tasks, significantly improving learning. Meanwhile, the control group had greater difficulty coping with the materials, which had a negative impact on their performance. This analysis highlights the importance of minimizing unnecessary cognitive load to increase the effectiveness of the teaching process.

Student attitudes clearly show the advantages of using structured strategies and visualizations interactive to improve learning. The experimental group reported an improved experience, reflecting a greater sense of security and engagement, while the control group encountered significant difficulties. These findings highlight the importance of teaching methods that reduce cognitive load and support the development of positive attitudes toward mathematics and learning in general.

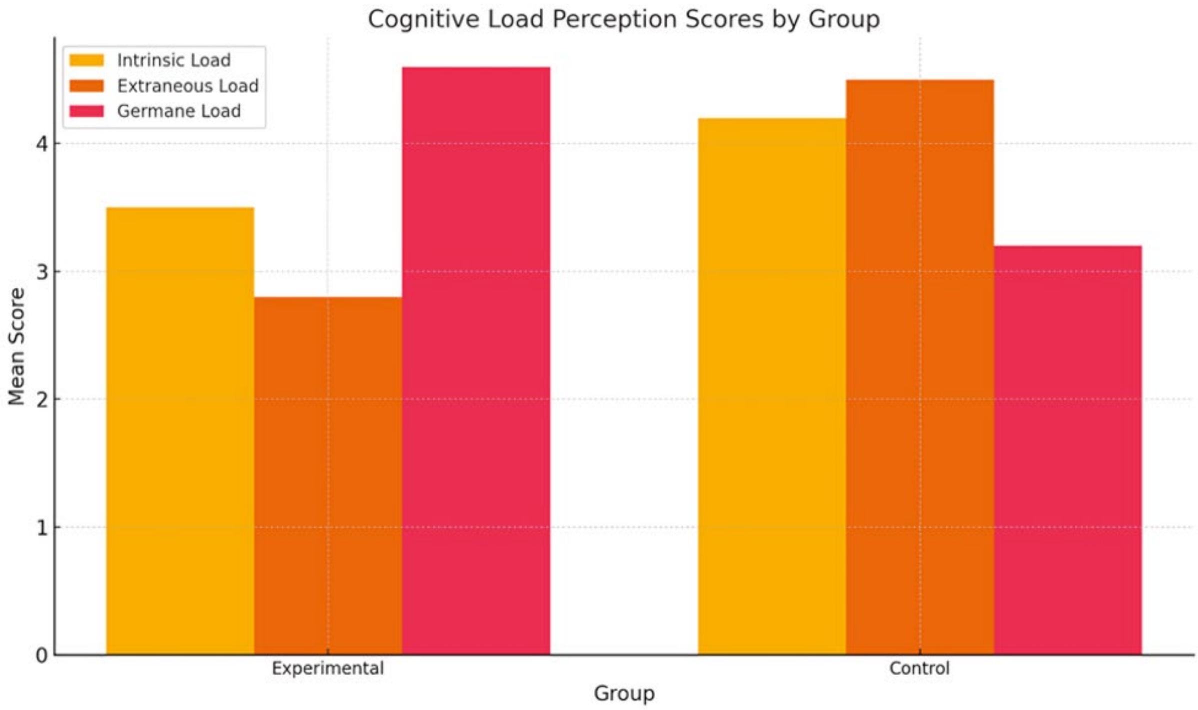

Figure 3. Cognitive load perception scores by group (Source: Authors' data visualization, 2026)

DISCUSSION

The findings of this study demonstrate that instructional design guided by CLT effectively enhances the learning of derivative concepts. Beyond confirming statistical improvements, these results offer insight into how structured pedagogical approaches optimize students' cognitive processing and motivation in mathematics education. Rather than reiterating numerical outcomes, this discussion focuses on the theoretical and practical implications of the findings in relation to previous research.

A central implication of this study is the validation of CLT's core proposition that instructional efficiency improves when the limited capacity of working memory is managed through targeted design principles (Sweller et al., 2011). The observed improvements in understanding and engagement suggest that the intervention successfully reduced extraneous load and redirected cognitive resources toward germane processing. This supports the claim by Paas and van Merriënboer (1994) that instructional control over cognitive load promotes schema automation, especially in complex learning tasks such as derivatives, which require simultaneous handling of abstract symbolic and graphical representations.

Importantly, the reduction in perceived cognitive load observed among students in the experimental group aligns with the conceptual framework proposed by Leppink et al. (2013) and the empirical validation of multi-dimensional cognitive load measures. In this context, visual scaffolds and worked examples served not merely as tools for simplification but as cognitive mediators that enhanced students' intrinsic motivation and confidence. As Yohannes and Chen (2023) argue, integrating interactive visualization technologies like GeoGebra fosters the mental integration of conceptual and procedural knowledge, making abstract mathematical concepts more tangible and easier to manipulate.

Another interpretive dimension emerges from how CLT-based methods promote knowledge transfer. While traditional instruction often limits learning to procedural recall, structured learning activities in this study appear to have facilitated a more flexible and meaningful understanding of derivatives. This is consistent with Leong et al. (2021), who found that connecting symbolic manipulation with graphical and contextual representations fosters deeper comprehension. The success of this intervention suggests that the principles of CLT can be adapted to bridge the gap between abstract theory and applied problem-solving, providing evidence that "learning by design" can translate conceptual mastery into practical competence.

The motivational and affective gains observed in the experimental group further highlight the psychological relevance of cognitive load reduction. As students experienced less confusion and frustration, they demonstrated higher engagement and persistence–findings that echo Maryati et al. (2022) and Slemp and Ayres (2023), who emphasize the reciprocal relationship between cognitive clarity and learner motivation. By structuring tasks to progressively build from simple to complex, the intervention may have reduced anxiety and promoted a sense of accomplishment, which, according to Kalyuga (2011), is a critical condition for sustaining intrinsic motivation in high-demand cognitive domains.

From a pedagogical perspective, these findings provide actionable implications. Mathematics educators should design materials that explicitly manage the three types of cognitive load: minimizing extraneous elements (e.g., redundant text), optimizing intrinsic complexity through segmentation, and fostering germane load by encouraging reflection and explanation. The use of worked examples, especially when coupled with visual and interactive tools, appears to be an effective vehicle for implementing these principles in classroom practice. Moreover, as Ayres (2013) points out, instructional strategies must be sensitive to learners' prior knowledge–since what reduces load for novices might induce overload for advanced learners. This underscores the need for adaptive instruction that calibrates support levels dynamically.

While the intervention yielded promising outcomes, its broader implications extend to curriculum design and teacher preparation. Embedding CLT principles in teacher education can equip educators with strategies to recognize and modulate cognitive load in real time. Additionally, integrating digital learning platforms may amplify the benefits of CLT-based design by providing feedback loops that adjust instructional complexity according to learner progress.

The results of this study demonstrate that CLT-based instructional design can effectively enhance learning performance and reduce cognitive load. Similarly, research in educational data science has shown that machine learning models, when trained on prior performance data, achieve high accuracy in predicting academic success and can serve as valuable support tools for personalizing instruction and adaptive feedback (Orhani et al., 2025). Integrating such data-driven insights with cognitive load principles could further optimize individualized learning experiences in mathematics education.

Despite these contributions, the study's limitations must be acknowledged. The relatively small sample size and short duration constrain generalizability, and the reliance on self-report measures for cognitive load introduces potential bias. Nevertheless, the consistency between subjective perceptions and performance gains lends credibility to the findings. Future studies should incorporate objective cognitive load measures, such as eye-tracking or EEG data (Liu & Zhang, 2024) to validate and deepen understanding of the cognitive mechanisms underlying mathematical learning.

In conclusion, this study contributes to the growing body of evidence that CLT offers a powerful framework for improving mathematical learning by optimizing mental effort, enhancing motivation, and fostering transfer. By emphasizing the qualitative interpretation of the results rather than their numerical repetition, this discussion highlights that the significance of CLT-based pedagogy lies not only in producing higher test scores but in reshaping the cognitive and motivational landscape of mathematics education.

Limitations

Although the experimental design provides a high level of control, this study had several limitations. The limited sample size may affect the generalizability of the findings. The duration of the intervention may be insufficient to observe profound conceptual changes. This methodology was designed to provide a clear and measured understanding of the impact of CLT on the learning of derivative concepts and to evaluate the effectiveness of new teaching approaches.

CONCLUSIONS

The results of this study indicate that using Sweller's (1988) CLT to improve learning of derivative concepts was highly effective. The experimental group, which followed a theory-based approach, showed a significant improvement in their performance compared to the control group. Students in the experimental group benefited from structured methods, such as worked examples and graphical visualizations, which reduced external load and improved focus on core content.

The findings show that minimizing unnecessary load through well-designed materials not only aids in knowledge acquisition but also improves the transfer of theoretical knowledge to practical situations. Furthermore, pedagogical intervention based on CLT has demonstrated significant improvements in student motivation and engagement, creating a more conducive learning environment.

In conclusion, this study shows that pedagogical approaches based on CLT are a powerful tool for improving mathematics education. Their application to other areas of mathematics and beyond can bring significant benefits to students' acquisition and application of knowledge.

Author contributions: EK-C: formal analysis, data curation, validation, visualization, writing – review & editing; **SO:** conceptualization, methodology, investigation, writing – original draft, supervision, resources; **IT:** project administration, writing – review & editing, supervision. All authors approved the final version of the article.

Funding: The authors received no financial support for the research and/or authorship of this article.

Acknowledgments: The authors would like to thank the students at University of Prizren in Kosovo, for their invaluable participation in this study.

Ethics declaration: This study was approved by the Ethics Committee of the Faculty of Education, University of Prizren "Ukshin Hoti". All participants provided informed consent prior to their inclusion in the study. No personally identifiable data were collected or stored. Data were anonymized and used solely for research purposes. All figures (Figures 1–3) were created by the authors based on original data and are published under the CC BY 4.0 license.

AI statement: No artificial intelligence or artificial intelligence-assisted generative tools were used in the preparation of this manuscript, except for linguistic editing to improve clarity and readability.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

ALLEA – All European Academies. (2017). *The European code of conduct for research integrity* (Revised Edition). Berlin: ALLEA – All European Academies.

Artigue, M. (1991). Analysis. In D. Tall (Ed.), *Advanced mathematical thinking* (pp. 167-198). Kluwer. https://doi.org/10.1007/0-306-47203-1_11

Ayres, P. (2013). Can the isolated-elements strategy be improved by targeting points of high cognitive load for additional practice? *Learning and Instruction, 23*, 115-124. https://doi.org/10.1016/j.learninstruc.2012.08.002

Campbell, D. T., & Stanley, J. C. (1963). *Experimental and quasi-experimental designs for research*. Houghton Mifflin.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE.

Field, A. (2020). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE.

Greefrath, G., Oldenburg, R., & Siller, H. S. (2023a). Mathematics students' characteristics of basic mental models of the derivative. *Journal für Mathematik-Didaktik, 44*, 143-169. https://doi.org/10.1007/s13138-022-00207-9

Greefrath, G., Siller, H. S., & Blum, W. (2023b). Teaching mathematical modeling with cognitive load in mind. *ZDM Mathematics Education, 55*, 987-1002.

Habre, S., & Abboud, M. (2006). Students' conceptual understanding of a function and its derivative in an experimental calculus course. *Journal of Mathematical Behavior, 25*(1), 57-72. https://doi.org/10.1016/j.jmathb.2005.11.004

Kalyuga, S. (2011). Cognitive load theory: How many types of load does it really need? *Educational Psychology Review, 23*, 1-19. https://doi.org/10.1007/s10648-010-9150-7

Klepsch, M., Schmitz, F., & Seufert, T. (2017). Development and validation of two instruments measuring intrinsic, extraneous, and germane cognitive load. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.01997

Leong, Y. H., Cheng, L. P., Toh, W. Y. K., & Kaur, B. (2021). Teaching students to apply formula using instructional materials: A case of a Singapore teacher's practice. *Mathematics Education Research Journal, 33*(3), 521-540. https://doi.org/10.1007/s13394-019-00290-1

Leppink, J., Paas, F., Van Gog, T., Van der Vleuten, C. P. M., & Van Merriënboer, J. J. G. (2013). The development of an instrument for measuring different types of cognitive load. *Behavior Research Methods, 45*(4), 1058-1072. https://doi.org/10.3758/s13428-013-0334-1

Liu, X., & Zhang, Y. (2024). Re-examining cognitive load measures in real-world learning: Evidence from both subjective and neurophysiological data. *British Journal of Educational Psychology, 94*(2), 415-432. https://doi.org/10.1111/bjep.12729

Maryati, W. E., Retnowati, E., & Thoe, N. K. (2022). Learning mathematics formulas by listening and reading worked examples. *Indonesian Journal of Teaching in Science, 2*(1), 61-74. https://doi.org/10.17509/ijotis.v2i1.45801

Ngu, B. H., & Phan, H. P. (2022). Unpacking the complexity of linear equations from a cognitive load theory perspective. *Educational Psychology Review, 28*, 95-118. https://doi.org/10.1007/s10648-015-9298-2

Orhani, S., Canhasi-Kasemi, E., & Temaj, I. (2025). Predicting probabilities of getting a high grade in mathematics: Probability analysis based on previous scores using machine learning techniques. *Human Research in Rehabilitation, 15*(2), 490-502. https://doi.org/10.21554/hrr.092519

Orton, A. (1983). Students' understanding of differentiation. *Educational Studies in Mathematics, 14*(3), 235-250. https://doi.org/10.1007/BF00410540

Paas, F., & van Merriënboer, J. J. G. (1994). Instructional control of cognitive load in the training of complex cognitive tasks. *Educational Psychology Review, 6*(4), 351-371. https://doi.org/10.1007/BF02213420

Radha, T., Vasuki, M., & Kumar, A. D. (2015). Bridging theory and practice: Exploring effective approaches in math education. *Journal of Engineering, Scientific Research and Applications, 1*(2), 112-125.

Renkl, A. (2014). Toward an instructionally oriented theory of example-based learning. *Cognitive Science, 38*(2), 1-37. https://doi.org/10.1111/cogs.12086

Retnowati, E., Maryati, W. E., & Thoe, N. K. (2022). Worked on example designs to facilitate retention and transfer capability in derivatives of algebraic functions. *International Journal of Teaching in Science*, *34*, 355–380.

Slemp, G. R., & Ayres, P. (2023). The effects of blended learning on mathematics cognitive demand and cognitive load in learning calculus of several variables at universities in Ethiopia. *International Journal of Mathematical Education in Science and Technology, 55*(1), 18-33. https://doi.org/10.1080/0020739X.2024.2392854

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

Tall, D. (1993). *Students' difficulties in calculus*. Proceedings of Working Group 3 on Students' Difficulties in Calculus, ICME-7 Conference, Québec, Canada, 1992. Reprinted in Proceedings of the Seventh International Congress on Mathematical Education (ICME-7).

Yohannes, A., & Chen, H. L. (2023). GeoGebra in mathematics education: A systematic review of journal articles published from 2010 to 2020. *Interactive Learning Environments, 31*(6), 1065-1084. https://doi.org/10.1080/10494820.2021.2016861