International Journal of Advance Social Sciences and Education (IJASSE)
Vol. 4, No. 3, 2026: 271-286

The Effect of Prior Knowledge and Instructional Design on Students' Cognitive Load and Mathematical Problem Solving Ability

Siti Atfiah[1], Cecep Anwar Hadi Firdos Santosa[2]*, Hepsi Nindiasari[3]
Universitas Sultan Ageng Tirtayasa
Corresponding Author: Cecep Anwar Hadi Firdos Santosa
cecepanwar@untirta.ac.id

A R T I C L E I N F O

Keywords: Instructional Design, Prior Knowledge, Cognitive Load, Problem Solving Ability

Received: 19, April
Revised: 20, May
Accepted: 30, June

A B S T R A C T

This study investigates the effects of instructional design and prior knowledge on students' mathematical problem-solving ability and cognitive load. Using a quantitative approach with a 2×2 factorial experimental design, the study involved 88 eleventh-grade students selected through cluster random sampling. Data were collected using a mathematical problem-solving test and a cognitive load questionnaire and analyzed using Two-Way ANOVA after meeting normality and homogeneity assumptions. The findings show that both prior knowledge and instructional design significantly affect mathematical problem-solving ability and cognitive load, and that an interaction exists between these variables. Students with high prior knowledge demonstrate better problem-solving ability and lower cognitive load. Segmenting is more effective for high prior-knowledge students, whereas pre-training benefits low prior-knowledge students.

DOI: https://doi.org/10.59890/ijasse.v4i3.12
ISSN-E: 2988-2133
https://journalijasse.my.id/index.php/ijasse

INTRODUCTION

In the 21st century, education is oriented toward preparing learners to face rapid and complex changes. Students are expected not only to master knowledge, but also to develop independent learning abilities and effective problem-solving skills. In the context of mathematics education, problem-solving ability is considered one of the core competencies that must be acquired, as it plays a crucial role in fostering reasoning, critical thinking, and decision-making across various situations (Amalina & Vidákovich, 2023; Kain et al., 2024; Mustafic et al., 2019; Popham et al., 2020; Stadler et al., 2019). Therefore, strengthening students' mathematical problem-solving skills has become a key focus in mathematics instruction in schools (Putri et al., 2025).

Mathematical problem-solving ability is a complex process that involves multiple stages, ranging from understanding the problem, devising a solution plan, implementing strategies, to reflecting on the obtained solution. This process requires not only mastery of concepts but also the ability to systematically integrate various pieces of information (Boonen et al., 2016; Hartmann et al., 2021; Hafidhoh et al., 2026). However, numerous studies indicate that students' mathematical problem-solving abilities remain relatively low and continue to pose a significant challenge in learning (Putri et al., 2025). This suggests that more effective efforts are needed to enhance these abilities.

This condition is also reflected in the results of international studies, which indicate that Indonesian students' mathematical performance remains below the international average. Furthermore, observations conducted at one public high school in Banten province, Indonesia, revealed that the majority of students experience difficulties in solving mathematical problem-solving tasks. Most students are not yet able to comprehend problems in depth and struggle to determine appropriate solution strategies. Only a small proportion of students with high prior knowledge are able to solve problems effectively. This situation highlights the existence of a performance gap that requires careful attention in the learning process.

One of the factors contributing to the low level of students' mathematical problem-solving ability is the complexity of the material they are required to learn. Mathematical content often consists of multiple interrelated concepts that must be processed simultaneously. This complexity demands a high level of cognitive capacity and can place a substantial load on students' working memory (Chen et al., 2023; Endres et al., 2023). When this cognitive load exceeds the available capacity, the learning process becomes less optimal, and students' understanding of the material is hindered. Therefore, instructional strategies are needed to help students effectively manage the complexity of such information.

From the perspective of Cognitive Load Theory, cognitive load is distinguished into intrinsic cognitive load and extraneous cognitive load (Chen et al., 2024; Endres et al., 2023). Intrinsic cognitive load is related to the inherent complexity of the material, whereas extraneous cognitive load is associated with the manner in which information is presented (Martin et al., 2023; Sweller, 2023). If instructional materials are not designed effectively, extraneous cognitive load may increase and hinder the learning process.

Managing cognitive load through instructional design is crucial. Instructional design itself is understood as a systematic process of designing, developing, and delivering learning materials to ensure greater effectiveness and efficiency. Educators can minimize cognitive load by selecting appropriate instructional designs, as well as by organizing and revising the content of textbooks (Santosa et al., 2018). Cognitive Load Theory has also become one of the most influential theoretical foundations in the development of instructional design.

Cognitive load is the result of appropriate instructional design strategies, such as pre-training and segmenting. The pre-training strategy provides an initial introduction to fundamental concepts before the core instruction begins, enabling students to establish an adequate knowledge base. Meanwhile, the segmenting strategy involves dividing the material into smaller parts that are presented gradually to facilitate comprehension. Both strategies can help reduce cognitive load and enhance students' understanding of the material (Huang, 2018; Jung et al., 2021; Nilawati et al., 2025).

The effectiveness of these instructional strategies cannot be separated from the role of students' prior knowledge. Prior knowledge serves as the foundation upon which students interpret and understand new information. Students with high prior knowledge tend to integrate new concepts more easily, whereas those with low prior knowledge are more susceptible to difficulties when dealing with complex material (Chen, 2023). Therefore, differences in prior knowledge must be taken into account in the implementation of instructional strategies to achieve optimal outcomes.

Previous studies have examined the effectiveness of pre-training and segmenting strategies in learning. Huang (2018) hypothesized that pre-training would be more effective for students with low prior knowledge, whereas segmenting would be more effective for those with high prior knowledge. However, the findings did not fully support this hypothesis, indicating that the relationship between instructional strategies and prior knowledge remains inconsistent. In addition, other studies have shown that the gradual presentation of material can enhance students' attention and learning performance (Shang et al., 2023). Nevertheless, these studies still have limitations, particularly in linking instructional strategies to mathematical problem-solving abilities, and have not been widely conducted at the secondary education level. Based on the foregoing discussion, there is a research gap that warrants further investigation, namely how pre-training and segmenting strategies influence students' cognitive load and mathematical problem-solving abilities at the senior high school level, with consideration of prior knowledge. This study is important as it can provide a more comprehensive understanding of the effectiveness of instructional design in mathematics learning. This study aims to analyze the effects of pre-training and segmenting strategies on students' cognitive load and mathematical problem-solving abilities, as well as to examine the interaction between instructional strategies and students' prior knowledge. The findings are expected to contribute to the development of more effective mathematics instruction, particularly in enhancing problem-solving skills through the appropriate management of cognitive load.

LITERATURE REVIEW

Cognitive Load Theory (CLT)

Cognitive Load Theory (CLT) is a learning theory developed by John Sweller that explains how learning effectiveness is influenced by the limited capacity of working memory in processing new information. This theory emphasizes that learning becomes more effective when instructional design is able to manage the cognitive load experienced by learners. Cognitive load consists of three types: intrinsic cognitive load, which arises from the complexity of the learning material itself; extraneous cognitive load, which results from ineffective methods of information presentation; and germane cognitive load, which is associated with the construction and refinement of knowledge schemas in long-term memory. In mathematics education, Cognitive Load Theory serves as an important theoretical foundation for designing instructional strategies that facilitate students' understanding of complex concepts (Santosa et al., 2019). Instructional strategies that align with the principles of CLT are expected to reduce irrelevant cognitive load, thereby enabling students to allocate their cognitive resources more effectively to conceptual understanding and mathematical problem solving (Santosa & Filiz, 2025).

Huang (2018) found that the pre-training strategy was more effective than segmenting in reducing students' intrinsic cognitive load. The study also revealed that prior knowledge influenced the effectiveness of the instructional strategies employed. Similarly, Huang (2018) reported that pre-training significantly benefited students with low prior knowledge by reducing intrinsic cognitive load, although these advantages were not consistently observed among students with high prior knowledge. These findings suggest that both instructional design and prior knowledge are important factors influencing students' cognitive load during the learning process.

H1: There is a significant difference in cognitive load between students who learn through the pre-training instructional design and those who learn through the segmenting instructional design.

H2: There is a significant difference in cognitive load between students with high prior knowledge and those with low prior knowledge.

H3: There is a significant interaction effect between instructional design and prior knowledge on students' cognitive load.

Mathematical Problem-Solving Ability

Mathematical problem-solving ability refers to students' capacity to understand problems, devise solution strategies, implement the selected strategies, and evaluate the obtained results. This ability represents one of the primary goals of mathematics education because it is closely associated with critical, logical, systematic, and creative thinking in addressing various mathematical challenges. According to Pólya, problem solving consists of four stages: understanding the problem, devising a plan, carrying out the plan, and looking back to evaluate the solution. Students' success in progressing through these stages is strongly influenced by their prior knowledge as well as their ability to manage the information processed within working memory. Santosa et al. (2022) found that students with high prior knowledge demonstrated superior mathematical problem-solving performance compared to those with low prior knowledge. Furthermore, Shang et al. (2023) reported that the segmenting strategy enhanced learning effectiveness by helping students focus on relevant information and better understand the relationships among concepts. Huang (2018) also demonstrated that pre-training supports students in developing the foundational understanding necessary for solving more complex mathematical problems.

H4: There is a significant difference in mathematical problem-solving ability between students who learn through the pre-training instructional design and those who learn through the segmenting instructional design.

H5: There is a significant difference in mathematical problem-solving ability between students with high prior knowledge and those with low prior knowledge.

H5: There is a significant interaction effect between instructional design and prior knowledge on students' mathematical problem-solving ability.

Conceptual Framework

This study employs two independent variables, namely prior knowledge and instructional design. Prior knowledge is classified into two categories: high prior knowledge and low prior knowledge. Instructional design is also divided into two approaches: pre-training and segmenting. These independent variables are assumed to influence two dependent variables, namely cognitive load and mathematical problem-solving ability. Based on Cognitive Load Theory, students with high prior knowledge possess more established knowledge schemas, enabling them to process new information with lower cognitive load. In contrast, students with low prior knowledge tend to experience higher cognitive load when confronted with complex learning materials. Furthermore, instructional designs developed in accordance with CLT principles, such as pre-training and segmenting, are expected to reduce cognitive load while enhancing students' mathematical problem-solving ability. Therefore, this study examines the main effects of prior knowledge and instructional design, as well as their interaction effects, on cognitive load and mathematical problem-solving ability.

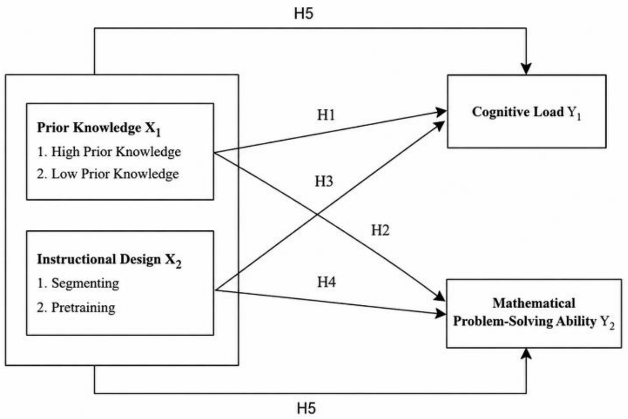

Figure 1. Conceptual Framework

METHODOLOGY

This study employed a quantitative approach using a 2×2 factorial experimental design. This factorial design was selected because it enables researchers to simultaneously examine the effects of two independent variables, namely prior knowledge and instructional design, on two dependent variables, namely students' mathematical problem-solving ability and cognitive load (Santosa & Filiz, 2025). In addition, this design also allows for the examination of potential interaction effects between the two independent variables in influencing the dependent variables.

In this study, the prior knowledge variable was classified into two categories: high prior knowledge (B_1) and low prior knowledge (B_2). Meanwhile, the instructional design variable consisted of two types of treatment, namely pre-training (A_1) and segmenting (A_2). Accordingly, the combination of these two variables resulted in four experimental groups: (1) A_1B_1 (students with high prior knowledge who received the pre-training treatment), (2) A_2B_1 (students with high prior knowledge who received the segmenting treatment), (3) A_1B_2 (students with low prior knowledge who received the pre-training treatment), and (4) A_2B_2 (students with low prior knowledge who received the segmenting treatment). The 2×2 factorial design is presented in the following table.

Table 1. 2×2 Factorial Design for Mathematical Problem-Solving Ability

Prior Knowledge	**Instructional Design**	
	Pre-training (A_1)	Segmenting (A_2)
High (B_1)	A_1B_1 High prior knowledge Pre-training group	A_2B_1 High prior knowledge segmenting group
Low (B_2)	A_1B_2 Low prior knowledge pretraining group	A_2B_2 Low prior knowledge segmenting group

The population of this study consisted of all eleventh-grade students at one public senior high school in Banten Province, Indonesia, during the current academic year. The research sample comprised two classes selected from this population. Each class consisted of 44 students, resulting in a total sample of 88 students. The sampling technique employed was cluster random sampling, in which samples were randomly selected based on intact classroom groups, under the assumption that each class possessed relatively homogeneous characteristics. The two selected classes were then assigned as experimental groups, each receiving a different treatment. One class was administered the *pre-training* instructional design, in which learning began with the provision of foundational information or prerequisite concepts before introducing the main material. Meanwhile, the other class was administered the *segmenting* instructional design, in which the learning material was presented gradually in segmented units to reduce students' cognitive load during the learning process. The data collected in this study were quantitative in nature, consisting of posttest scores measuring students' mathematical problem-solving ability and cognitive load questionnaire scores. The research instruments employed consisted of two types: a mathematical problem-solving ability test and a cognitive load questionnaire. The mathematical problem-solving ability test was constructed in the form of essay questions based on indicators of problem-solving ability, including understanding the problem, devising a solution strategy, implementing the strategy, and evaluating the solution obtained. Meanwhile, the cognitive load questionnaire was used to measure the level of mental effort perceived by students during the learning process. Cognitive load was assessed using a 9-point Likert scale, ranging from 1 (very, very low*) to 9 (*very, very high*)*, as presented in Table 2.

Table 2. Cognitive Load Scale Assessment

Scale	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	Very, Very Low	Very low	Low	Moderately Low	Neither Low nor High	Moderately High	High	Very high	Very, very high

Before their use in the study, the instruments underwent an expert judgment process to ensure content validity. Subsequently, empirical validity testing was conducted using the Pearson product–moment correlation technique to determine the validity of each test item. Reliability testing was then performed using Cronbach's Alpha coefficient with the assistance of SPSS software to ensure the internal consistency of the instruments.

The research procedure was carried out in several stages. The first stage involved administering a prior knowledge test to all students in the sample to determine their level of prior knowledge. The test results were subsequently used to classify students into high and low prior knowledge categories based on the median score. Students who obtained scores equal to or below the median were categorized as the low prior knowledge group, whereas those who obtained scores above the median were categorized as the high prior knowledge group

The third stage involved administering a posttest to measure students' mathematical problem-solving ability after the treatment had been implemented. At the same time, students were also asked to complete a cognitive load questionnaire to assess the level of mental effort they perceived during the learning process.

Data analysis was conducted in two stages, namely descriptive statistical analysis and inferential statistical analysis. Descriptive statistics were employed to summarize the data in terms of mean scores, standard deviations, maximum scores, and minimum scores. Before conducting inferential analysis, prerequisite assumption tests were performed, including a normality test using the Shapiro–Wilk test and a homogeneity of variance test using Levene's test. Subsequently, hypothesis testing was conducted using a Two-Way ANOVA (two-way analysis of variance). This analysis was performed separately for each dependent variable, namely mathematical problem-solving ability and cognitive load. The purpose of this analysis was to determine: (1) the main effect of prior knowledge on the dependent variables, (2) the main effect of instructional design on the dependent variables, and (3) the interaction effect between prior knowledge and instructional design on the dependent variables. By employing this design and procedure, this study is expected to provide a comprehensive understanding of the effectiveness of pre-training and segmenting instructional designs, viewed in relation to students' prior knowledge, in enhancing mathematical problem-solving ability and managing students' cognitive load.

RESULT AND DISCUSSION

Sample Characteristics

The implementation of the pre-training and segmenting instructional designs was conducted in three sessions, namely the prior knowledge test, the instructional session, and the posttest session. Prior to the implementation of the pre-training and segmenting instructional designs, students first completed a prior knowledge test to assess their respective levels of prior knowledge. Based on the calculation of prior knowledge scores for the entire sample of 88 students, the following results were obtained.

Table 3. Number of Students in Each Group

Prior Knowledge	**Instructional Design**	
	Pre-training (A_1) 44 students	Segmenting (A_2) 44 students
High (B_1) 42 students	A_1B_1 Low Prior knowledge, pre-training class: 20 students	A_2B_1 Low Prior knowledge, Segmenting class: 22 students
Low (B_2) 46 students	A_1B_2 High prior knowledge pre-training class: 24 siswa	A_2B_2 High prior knowledge Segmenting class 22 siswa

Description
1. *Pre-training* with high prior knowledge (A_1B_1)
2. *Pre-training* with low prior knowledge (A_1B_2)
3. *Segmenting* with high prior knowledge (A_2B_1)
4. *Segmenting* with low prior knowledge (A_2B_2)

After classifying students based on their prior knowledge levels and obtaining the posttest scores, the data were subsequently analyzed using SPSS, resulting in the following findings. The posttest data on students' mathematical problem-solving ability are presented in the following table.

Research Instruments

This study employed three research instruments: a prior knowledge test, a mathematical problem-solving ability test, and a cognitive load questionnaire. The validity test results indicated that all items in the prior knowledge test and the mathematical problem-solving ability test met the established validity criteria. Therefore, all items were considered valid and appropriate for use in this study. The results of the instrument validity testing are presented in Table 2.

Table 4. Validity Test of Initial Knowledge Test Instruments

Item	r_{value}	r_{table}	Intrepretation
Item 1	0,547	0,304	Valid
Item 2	0,622	0,304	Valid
Item 3	0,805	0,304	Valid
Item 4	0,727	0,304	Valid
Item 5	0,759	0,304	Valid
Item 6	0,782	0,304	Valid
Item 7	0,674	0,304	Valid
Item 8	0,773	0,304	Valid
Item 9	0,703	0,304	Valid
Item 0	0,714	0,304	Valid

Table 5. Validity Test of Problem-Solving Ability Test Instruments

Item	r_{value}	r_{table}	Intrepretation
Item 1	0,939	0,304	Valid
Item 2	0,813	0,304	Valid
Item 3	0,883	0,304	Valid
Item 4	0,522	0,304	Valid

The reliability testing results indicated that the prior knowledge test and mathematical problem-solving ability test. questionnaire demonstrated good internal consistency. The obtained reliability coefficients exceeded the recommended minimum threshold, indicating that all instruments were reliable and suitable for use in this study. The results of the instrument reliability testing are presented in Table 5.

Table 6. Reliability test

Variable	Cronbach's Alpha	Number of Items	Category
Mathematical Problem-Solving Ability	0,842	5	Reliabel
Prior Knowledge	0,890	10	Reliabel

Descriptive Statistics

After classifying students based on their prior knowledge levels and obtaining the posttest scores, the data were subsequently analyzed using SPSS, resulting in the following findings. The posttest data on students' mathematical problem-solving ability are presented in the following table.

Table 7.Descriptive Statistics of Post-Test Data

Instructional Design		Mean	Std.	N
Pre-Ttraining	High	81,25	5,82	20
	Low	76,67	6,703	24
	Total	78,75	6,65	44
Segmenting	High	87,86	8,72	22
	Low	62,50	7,98	22
	Total	75,18	15,25	44
Total	High	84,71	8,11	42
	Low	69,89	10,19	46
	Total	76,97	11,84	88

Table 7 presents the descriptive statistics of students' mathematical problem-solving ability based on instructional design and prior knowledge. Overall, students with high prior knowledge achieved higher mean scores (M = 84.71, SD = 8.11) than those with low prior knowledge (M = 69.89, SD = 10.19). Differences in mean scores were also observed across the pre-training and segmenting groups. These findings suggest potential differences in mathematical problem-solving ability across prior knowledge levels and instructional design conditions, which were subsequently examined using inferential statistical analysis.

Table 8. Descriptive statistics of Cognitive Load

Instructional Design		Mean	Std. Dev	N
Pre-training	Tinggi	5,800	0,35	20
	Rendah	6,133	0,27	24
	Total	5,982	0,35	44
Segmenting	Tinggi	4,300	0,35	22

	Rendah	6,218	0,41	22
	Total	5,259	1,04	44
Total	Tinggi	5,014	0,83	42
	Rendah	6,174	0,34	46
	Total	5,620	0,85	88

Table 8 presents the descriptive statistics of students' cognitive load based on instructional design and prior knowledge. Overall, students with high prior knowledge exhibited lower cognitive load (M = 5.014, SD = 0.83) than those with low prior knowledge (M = 6.174, SD = 0.34). In the pre-training group, the mean cognitive load scores for students with high and low prior knowledge were 5.800 and 6.133, respectively. Similarly, in the segmenting group, the corresponding mean scores were 4.300 and 6.218. These descriptive findings indicate differences in cognitive load across prior knowledge levels and instructional design conditions, which were subsequently examined through inferential statistical analyses.

Assumption Testing

Table 9.Normality Test of Cognitive Load Questionnaire Data

Data	Shapiro-wilk			Conclusion
	Statistic	df	sig	
Standardized Residual for Cognitive Load	0,978	88	0,136	Normal
Standardized Residual for Posttest	0,976	88	0,94	Normal

Based on Table 9, it can be observed that the significance values (Sig.) in the Shapiro–Wilk test for both datasets are greater than 0.05. Therefore, it can be concluded that the cognitive load data are normally distributed. Accordingly, both datasets satisfy the assumption of normality and are suitable for further parametric statistical analyses.

Table 10. Homogeneity Test of Cognitive Load Questionnaire Data

Data	*F*	df_1	df_2	*Sig.*	Conclusion
Cognitive Load	0,556	3	84	0,639	Homogen
Posttest	1,165	3	84	0,328	Homogen

Based on the homogeneity test results presented in the table, the significance values (Sig.) obtained for both datasets were 0.328 and 0.539, respectively. Since both values exceed the significance level of 0.05, the population variances can be considered homogeneous. Therefore, it can be concluded that there are no significant differences in variance among the groups. Accordingly, both datasets satisfy the assumption of homogeneity and are suitable for further parametric statistical analyses.

Hypothesis Testing

Table 11. Results of the Two-Way ANOVA Test on Mathematical Problem-Solving Ability

Source	**df**	**Mean Square**	**F**	**Sig.**
Prior Knowledge	1	4912,049	89,442	0,000
Instructional Design	1	312,464	5,690	0,019
Prior Knowledge*Instructional Design	1	2365,161	43,067	0,000

Based on Table 11, the results of the two-way ANOVA test for each variable indicate that, for the first hypothesis concerning the prior knowledge factor, the significance value obtained was 0.000 < 0.005. This condition indicates that H_0 was rejected and H_1 was accepted. Therefore, the hypothesis stating that there is a significant difference in mathematical problem-solving ability between students with high prior knowledge and those with low prior knowledge was accepted in this study. It can thus be concluded that prior knowledge has a significant effect on students' mathematical problem-solving ability.

For the second hypothesis concerning the effect of instructional design, the significance value obtained was 0.019 < 0.05. This result indicates that H_0 was rejected and H_1 was accepted. Therefore, the hypothesis stating that there is a significant difference in mathematical problem-solving ability between students in the pre-training class and those in the segmenting class was accepted in this study. It can thus be concluded that instructional design has a significant effect on students' mathematical problem-solving ability.

The calculation of the interaction significance between prior knowledge and instructional design yielded a value of 0.000 < 0.05. Since the significance value is less than 0.05, H_0 was rejected. Therefore, it can be interpreted that there is an interaction effect between prior knowledge and instructional design on students' mathematical problem-solving ability.

Furthermore, the results of the two-way ANOVA test regarding the effects of prior knowledge (high and low), instructional design (pre-training and segmenting), and the interaction between the two on cognitive load can be seen in the following table.

Table 12. Two-Way ANOVA Results for Cognitive Load Questionnaire Data

Source	**df**	**Mean Square**	**F**	**Sig.**
Prior Knowledge	1	27,766	221,996	0,000
Instruksional Design	1	10,969	87,701	0,000
Prior Knowledge* Instructional Design	1	13,757	109,995	0,000

Based on Table 11, the results of the two-way ANOVA test for each variable indicate that, for the first hypothesis concerning the prior knowledge factor, the significance value obtained was 0.000 < 0.005. This result indicates that H_0 was rejected and H_1 was accepted. Therefore, the hypothesis stating that there is a significant difference in cognitive load between students with high prior knowledge and those with low prior knowledge was accepted in this study. It can thus be concluded that prior knowledge has a significant effect on students' cognitive load.

For the second hypothesis concerning the effect of instructional design, the significance value obtained was 0.019 < 0.05. This result indicates that H_0 was rejected and H_1 was accepted.

Therefore, the hypothesis stating that there is a significant difference in students' cognitive load between those in the pre-training class and those in the segmenting class was accepted in this study. It can thus be concluded that instructional design has a significant effect on students' cognitive load.

The calculation of the interaction significance between prior knowledge and instructional design yielded a value of 0.000 < 0.05. Since the significance value is less than 0.05, H_0 was rejected. Therefore, it can be interpreted that there is an interaction effect between prior knowledge and instructional design on students' cognitive load.

The subsequent findings indicate that prior knowledge has an effect on students' cognitive load. Students with higher prior knowledge tend to experience lower cognitive load because they already possess knowledge structures that facilitate the processing of new information. According to Cognitive Load Theory, schemas that have been formed in long-term memory enable more efficient information processing, thereby reducing the demands placed on working memory (Huang, 2018). These findings reinforce previous research showing that prior knowledge is an important factor in reducing cognitive load during learning.

This study also reveals that instructional design influences students' cognitive load. The findings indicate that the way learning materials are presented determines the amount of mental effort required for students to understand information. In line with Cognitive Load Theory, effective instructional design can minimize extraneous cognitive load and help students focus on relevant information (Sweller et al., 2011; Huang, 2018). Consequently, students can process information more efficiently and achieve better understanding.

Finally, an interaction between prior knowledge and instructional design was found in relation to cognitive load. This result suggests that the effect of instructional design on cognitive load depends on students' level of prior knowledge. Students with high prior knowledge are more capable of benefiting from instructional support because they already possess schemas that facilitate information processing, whereas students with low prior knowledge require greater instructional support to avoid excessive cognitive load. This finding highlights the importance of aligning instructional design with students' characteristics to ensure more effective and efficient learning processes (Huang, 2018; Sweller et al., 2011)

CONCLUSIONS AND RECOMMENDATIONS

Based on the research findings, it can be concluded that prior knowledge and instructional design significantly influence students' mathematical problem-solving ability and cognitive load, and that there is an interaction between these two factors. Students with high prior knowledge tend to demonstrate better mathematical problem-solving ability and lower cognitive load compared to students with low prior knowledge. In addition, differences in instructional design produce varying effects on both dependent variables, indicating that learning effectiveness is influenced by the alignment between instructional design and students' levels of prior knowledge. Therefore, in instructional practice, teachers are advised to consider students' prior knowledge characteristics when determining appropriate instructional designs to optimize learning outcomes. Furthermore, instructional approaches such as pre-training and segmenting may serve as effective alternatives for enhancing mathematical problem-solving ability while simultaneously managing students' cognitive load. For future research, it is recommended to examine other relevant variables and to broaden the scope of participants and research contexts in order to obtain more comprehensive findings.

FURTHER STUDY

This study has several limitations. First, the participants were drawn from a single senior high school, which may limit the generalizability of the findings to other educational contexts. Second, cognitive load was measured using a self-report instrument, which may be influenced by students' subjective perceptions. Third, the study focused on a specific mathematics topic; therefore, the effectiveness of the instructional design may differ when applied to other mathematical domains. Finally, only prior knowledge and instructional design were examined, whereas other factors such as motivation, self-efficacy, and learning engagement may also influence cognitive load and mathematical problem-solving performance.

ACKNOWLEDGMENT

The author would like to sincerely thank the supervisor for guidance and support throughout this research, the school for permitting the study, and the students for their participation. Appreciation is also extended to everyone who contributed directly or indirectly to the completion of this work.

REFERENCES

Amalina, I. K., & Vidákovich, T. (2023). Cognitive and socioeconomic factors that influence the mathematical problem-solving skills of students. Heliyon, 9(9). https://doi.org/10.1016/j.heliyon.2023.e19539

Boonen, A. J. H., de Koning, B. B., Jolles, J., & van der Schoot, M. (2016). Word Problem Solving in Contemporary Math Education: A Plea for Reading Comprehension Skills Training. Frontiers in Psychology, 7.

Chen, D. (2023). Toward an understanding of 21st-century skills: From a systematic review. International Journal for Educational and Vocational Guidance, 23(2), 275–294. https://doi.org/10.1007/s10775-021-09511-1

Chen, O., Kai Yin Chan, B., Anderson, E., O'sullivan, R., Jay, T., Ouwehand, K., Paas, F., & Sweller, J. (2024). The effect of element interactivity and mental rehearsal on working memory resource depletion and the spacing effect. Contemporary Educational Psychology, 77.

Chen, O., Retnowati, E., Castro-Alonso, J. C., Paas, F., & Sweller, J. (2023). The Relationship between Interleaving and Variability Effects: A Cognitive Load Theory Perspective. Education Sciences, 13(11).

Endres, T., Lovell, O., Morkunas, D., Rieß, W., & Renkl, A. (2023a). Can prior knowledge increase task complexity? – Cases in which higher prior knowledge leads to higher intrinsic cognitive load. British Journal of Educational Psychology, 93(S2), 305–317.

Hafidhoh, R., Santosa, C. A. H. F., & Mutaqin, A. (2026). The Effect of Worked-Examples on Students' Learning Outcomes in Complex Mathematics Materials. *Jurnal Pendidikan Matematika*, *16*. https://doi.org/10.22437/edumatica.vl6i1.46293

Hartmann, L. M., Krawitz, J., & Schukajlow, S. (2021). Create your own problem! When given descriptions of real-world situations, do students pose and solve modelling problems? ZDM - Mathematics Education, 53(4), 919–935.

Huang, Y. H. (2018). Influence of instructional design to manage intrinsic cognitive load on learning effectiveness. Eurasia Journal of Mathematics, Science and Technology Education, 14(6), 2653–2668.

Jung, J., Shin, Y., & Zumbach, J. (2021). The effects of pre-training types on cognitive load, collaborative knowledge construction and deep learning in a computer-supported collaborative learning environment. Interactive Learning Environments, 29(7), 1163–1175.

Kain, C., Koschmieder, C., Matischek-Jauk, M., & Bergner, S. (2024). Mapping the landscape: A scoping review of 21st century skills literature in secondary education. In Teaching and Teacher Education (Vol. 151). Elsevier Ltd.

Martin, A. J., Ginns, P., Nagy, R. P., Collie, R. J., & Bostwick, K. C. P. (2023). Load reduction instruction in mathematics and English classrooms: A multilevel study of student and teacher reports. Contemporary Educational Psychology, 72.

Mustafic, M., Yu, J., Stadler, M., Vainikainen, M. P., Bornstein, M. H., Putnick, D. L., & Greiff, S. (2019). Complex Problem Solving: Profiles and Developmental Paths Revealed via Latent Transition Analysis. Developmental Psychology, 55(10), 2090–2101.

Nilawati, Santosa, C. A. H. F., & Effendi, A. (2025). *Effect of Example-Based Learning Model on Micro Level Cognitive Load and Knowledge Transfer* (Vol. 7, Number 1).

Putri, Z. A. H., Santosa, C. A. H. F., & Novaliyosi, N. (2025). The Effect of Video Modeling Example, Worked-Example, and Practice Problem on

Mathematics Learning. *Edumatica : Jurnal Pendidikan Matematika*, *15*(3), 446–455. https://doi.org/10.22437/edumatica.v15i3.46296

Popham, M., Adams, S., & Hodge, J. (2020). Self-Regulated Strategy Development to Teach Mathematics Problem Solving. Intervention in School and Clinic, 55(3), 154–161.

Santosa, C. A. H. F., & Filiz, M. (2025). Investigating the limit of peer collaboration: Insight from worked-example in multivariable calculus. *Infinity Journal*, *14*(2), 461–482. https://doi.org/10.22460/infinity.v14i2.p461-482

Santosa, C. A. H. F., Prabawanto, S., & Marethi, I. (2019). Fostering Germane Load Through Self-Explanation Prompting In Calculus Instruction. *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, *1*(1), 37–47. https://doi.org/10.23917/ijolae.v1i1.7421

Santosa, C. A. H. F., Suryadi, D., Prabawanto, S., & Syamsuri, S. (2018). The role of worked-example in enhancing students' self-explanation and cognitive efficiency in calculus instruction. Jurnal Riset Pendidikan Matematika, 5(2), 168–180. https://doi.org/10.21831/jrpm.v0i0.19602

Shang, X., Li, R., & Li, Y. (2023). The effect of structured stepwise presentations on students' fraction learning: an eye-tracking study. Frontiers in Psychology, 14. https://doi.org/10.3389/fpsyg.2023.1125589

Stadler, M., Herborn, K., Mustafić, M., & Greiff, S. (2019). Computer-based collaborative problem solving in PISA 2015 and the role of personality. Journal of Intelligence, 7(3). https://doi.org/10.3390/jintelligence7030015

Sweller, J. (2023). The Development of Cognitive Load Theory: Replication Crises and Incorporation of Other Theories Can Lead to Theory Expansion. Educational Psychology Review, 35(4).