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Research Article

EFFECTS OF SCAFFOLDING ON STUDENTS' EXTRANEOUS COGNITIVE LOAD IN THE DEEP LEARNING APPROACH

Eri Hasna Safira[1], Ismail Fikri Natadiwijaya[2]
[1] Universitas Negeri Yogyakarta, Indonesia
[2] Universitas Negeri Yogyakarta, Indonesia

Corresponding Author:
Eri Hasna Safira,
Department of Natural Science Education, Faculty of Mathematics and Natural Sciences, Yogyakarta State University.
Jl. Colombo No.1, Karang Malang, Caturtunggal, Kec. Depok, Kabupaten Sleman, Daerah Istimewa Yogyakarta 55281, Indonesia
Email: erihasna.2022@student.uny.ac.id

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Abstract
This study explores how scaffolding, when blended with a deep learning approach, can ease students' extraneous cognitive load during junior high school science lessons. A quasi-experimental Nonequivalent Control Group Design was used because the research took place in real classroom settings, where random assignment was not possible. To reduce potential selection bias, both classes were matched based on prior science achievement and taught by the same teacher using comparable learning materials. A total of 62 seventh-grade students participated, with 31 in the experimental group and 31 in the control group. In the experimental class, scaffolding was implemented through step-by-step guidance, worked examples, prompts, and gradually reduced support as students progressed through deep learning activities such as exploring problems, connecting concepts, and reflecting on their thinking. Data were collected using an Extraneous Cognitive Load Questionnaire adapted from Paas, van Merriënboer, and Sweller (2021) and analyzed with an Independent Samples t-test. The findings revealed a significant difference between the two groups, $t(60) = 9.03$, $p < .001$, with the experimental class ($M = 2.52$) reporting a substantially lower cognitive load than the control class ($M = 4.41$). The 1.89-point decrease reflects a meaningful practical improvement, showing that students experienced less unnecessary mental effort while engaging with complex material. Overall, the study shows that combining scaffolding with deep learning strategies not only strengthens students' understanding but also makes the learning process mentally more manageable, leading to a more effective and engaging science learning experience.

Keywords: deep learning, cognitive load theory, extraneous load, science learning

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INTRODUCTION

The transformation of education in Indonesia through the Merdeka Curriculum positions the deep learning approach as one of the central orientations of classroom instruction. This approach emphasizes students' active involvement in constructing meaning, connecting concepts to real life contexts, and engaging in reflective thinking to develop enduring and transferable understanding (Ministry of Education and Culture, 2023). Historically, the concept of deep learning traces back to Mystakidis, (2023), who distinguished between deep and surface approaches to learning, and it has since evolved into a pedagogical framework that promotes critical reasoning and meaningful knowledge integration (Mystakidis, 2023)**.** However, the implementation of deep learning within the Merdeka Curriculum is not without challenges. Variations in teacher readiness, limited alignment between deep learning principles and existing assessment practices, and the potential increase in students' cognitive load often hinder its optimal realization in the classroom. These issues highlight the need for empirical studies that explore instructional strategies capable of supporting deep learning while reducing unnecessary mental demands on students.

However, the implementation of science learning in schools often does not achieve the characteristics of deep learning due to the high cognitive load experienced by students. The complexity of instructional content, unstructured presentation of information, and inefficient multimedia use may generate extraneous cognitive load cognitive effort that does not contribute to knowledge construction (Chen, Kalyuga, & Sweller, 2023). This condition hinders students' ability to integrate concepts, leading learning to become short-term memorization rather than conceptual understanding.

A number of studies have shown that scaffolding techniques can serve as effective strategies for managing cognitive load in complex learning environments. Hülsmann et al. (2024) found that scaffolding in science learning reduces extraneous load and improves information processing efficiency. Bransen et al., (2024) reported that gradually faded scaffolding supports the optimization of working memory capacity and enhances students' independent thinking skills. Nevertheless, the majority of such studies have been conducted at the senior high school or tertiary level, while research at the junior secondary level remains limited. Moreover, studies on deep learning at the junior secondary level have generally not explicitly integrated Cognitive Load Theory (CLT) into their instructional design.

This gap highlights the need for a science learning model that integrates the deep learning approach with CLT based scaffolding, enabling students to process complex information in a gradual, structured, and meaningful manner. Such integration has the potential to reduce extraneous load while simultaneously increasing germane load, namely the cognitive resources allocated to conceptual schema formation.

Based on this urgency, the present study aims to examine the influence of CLT based scaffolding techniques within a deep learning instructional approach on students' extraneous cognitive load in science learning at the junior secondary level.

RESEARCH METHOD

Research Design

This study employed a quasi-experimental Posttest Only Nonequivalent Control Group Design, selected because the participating classes had been formed prior to the research, making random assignment impractical. To reduce potential threats to internal validity arising from pre existing group differences, both classes were matched based on prior science achievement records, demographic characteristics, and teacher assignment. Additionally, a preliminary equivalence check was conducted using students' previous semester scores to ensure that the two groups were comparable before the intervention. The experimental group received deep learning instruction supported by structured scaffolding, while the control group experienced the same deep learning sequence without scaffolding. Data were collected through two validated instruments: an Extraneous Cognitive Load Questionnaire adapted from Chen, Kalyuga, & Sweller, (2023) and a Conceptual Understanding Test developed according to the curriculum's learning objectives. This design allowed the researchers to examine the extent to which scaffolding enhanced deep learning influenced students' extraneous cognitive load and conceptual understanding with strengthened methodological rigor. (Chen, Kalyuga, & Sweller, 2023).

The design adapted the experimental framework used by Hülsmann et al. (2024), who investigated the influence of scaffolding techniques on cognitive load in biology learning. In their study, two groups (with and without researcher provided instructional tips) engaged in a multi step experimental activity on animal adaptation to cold temperatures. After each phase, a cognitive load questionnaire was administered to monitor changes in cognitive load during the learning process.

Although Hülsmann et al. (2024) implemented a multi session design with repeated measurements, the present study adjusted the approach into a posttest-only format to fit the instructional context of junior secondary education. This adjustment allowed data collection to focus on final cognitive load outcomes after the completion of the deep learning sequence, rather than repeated measures across instructional cycles. Thus, the design maintains the core purpose of evaluating the instructional intervention's influence on extraneous cognitive load while applying a format that is efficient and contextually appropriate for Indonesian classrooms. Table 1 below illustrates the research design used in this study.

Table 1. Research Design

Group	Treatment	Posttest
X_1	-	O_1
X_2	X	O_2

Description:

X_1 : Control class (deep learning without scaffolding)

X_2 : Experimental class (deep learning with scaffolding)

O_1, O_2 : Posttest scores on the Extraneous Cognitive Load Questionnaire

Research Target/Subject

The population in this study consisted of 190 seventh-grade students at a junior secondary school implementing the Merdeka Curriculum. From this population, 62 students were selected using convenience sampling based on recommendations from the subject teacher, with consideration of academic consistency, learning participation, and representation of student ability levels. The sample was then divided into two groups: an experimental class that received deep learning instruction with scaffolding support and a control class that received deep learning instruction without scaffolding.

Research Procedure

The research procedure was carried out in two main phases. First, the experimental class was taught using a deep learning approach integrated with scaffolding, where support was provided gradually through scaffolded questioning, worked examples, and reflective feedback to assist students in developing a deeper understanding of science concepts (Zuo, 2023; Van Nooijen et al., 2024; Hülsmann et al., 2024). Meanwhile, the control class followed similar deep learning activities but without the scaffolding component. Second, after the completion of the instructional sequence, both groups were administered the Extraneous Cognitive Load Questionnaire to measure perceived external cognitive load.

Instruments, and Data Collection Techniques

The instrument was adapted from Chen, Kalyuga, & Sweller, (2023) and employed a 9-point Likert scale ranging from 1 (very low load) to 9 (very high load), which has been widely validated for measuring subjective cognitive load. Chen, Kalyuga, & Sweller, (2023)

Data Analysis Technique

Data analysis was conducted using an Independent Samples t-test to determine whether there were statistically significant differences in extraneous cognitive load between the experimental and control groups. This test was chosen because it is appropriate for comparing two independent groups with interval scale data that meet the assumption of normal distribution.

RESULTS AND DISCUSSION

The learning instruments developed in this study applied the principles of Cognitive Load Theory (CLT) within a deep learning instructional approach, utilizing scaffolding techniques to support the gradual construction of concepts and reduce students' extraneous cognitive load. Chen, Kalyuga, & Sweller, (2023); Skulmowski & Xu, (2023). The instruments were designed to provide cognitive support that corresponds to the level of task difficulty, enabling students to focus on understanding core concepts without being burdened by irrelevant information.

Figures 1 portray how the principles of Cognitive Load Theory (CLT) were brought to life through a carefully structured series of scaffolding strategies embedded across different stages of the science lesson. At the start, students used concept diagrams to map out key ideas, helping them sort information and lessen the inherent complexity of the topic (Yen & Tu, 2023). During instruction, visual cues such as highlighted links, color distinctions, and simple step indicators were added to help students focus on what mattered most and avoid unnecessary cognitive effort. Van Nooijen et al., (2024) As the learning activities became more complex, guiding questions were introduced to nudge students toward deeper analysis and to encourage productive cognitive engagement. Webb & Blanchard, (2024). Over time, this support was gradually reduced: visual hints were removed, prompts became more open ended, and students were encouraged to take more control of their thinking as they became ready.

To understand how well these scaffolding strategies worked, students completed an Extraneous Cognitive Load Questionnaire and a Conceptual Understanding Test aligned with the learning objectives. The results showed a clear pattern: students who learned with scaffolding consistently reported lower extraneous cognitive load and demonstrated stronger conceptual understanding. Zuo, (2023) More importantly, the benefits were visible in their learning behavior. Students in the scaffolded class showed more organized reasoning during problem-solving, were better able to explain their thinking, and retained essential concepts more accurately during follow up tasks. Singh & Fong, (2024) Taken together, these findings show that thoughtfully designed CLT based scaffolding does more than reduce cognitive strain it creates a learning environment where students can process information more efficiently and build deeper, longer lasting understanding. Here's the flow:

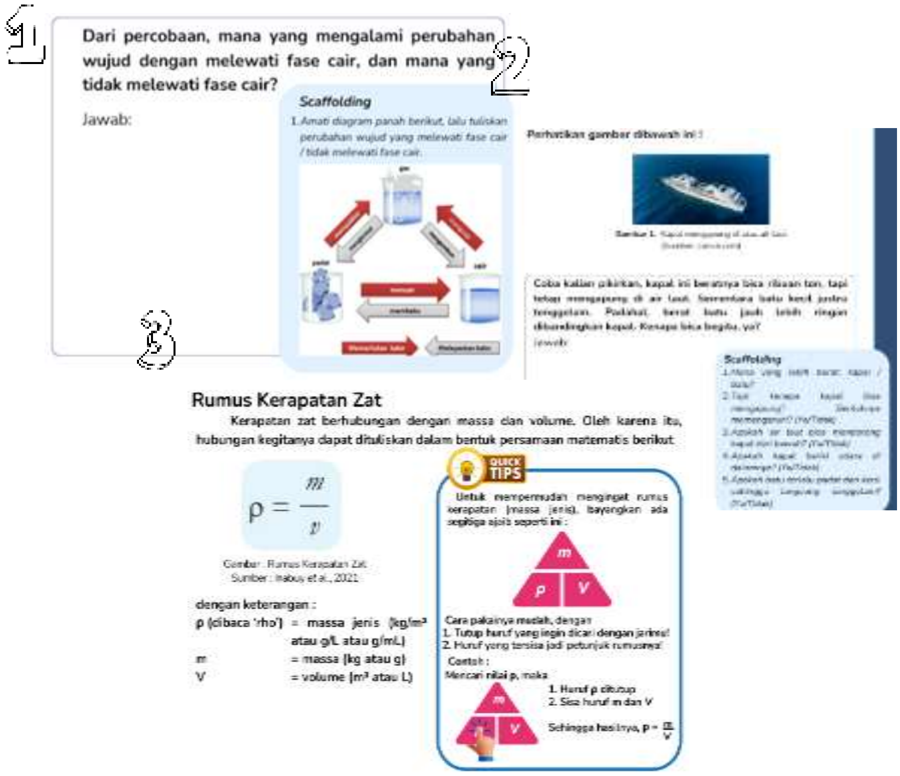

Figure 1. Deep Learning Learning Materials Designed with CLT Principles

The results of the analysis showed that the implementation of deep learning supported by scaffolding significantly reduced extraneous cognitive load. The experimental class (E), which received scaffolding, reported lower cognitive load (M = 2.52; SD = 0.64) compared to the control class (C) without scaffolding (M = 4.41; SD = 0.98), as shown in Figure 2.

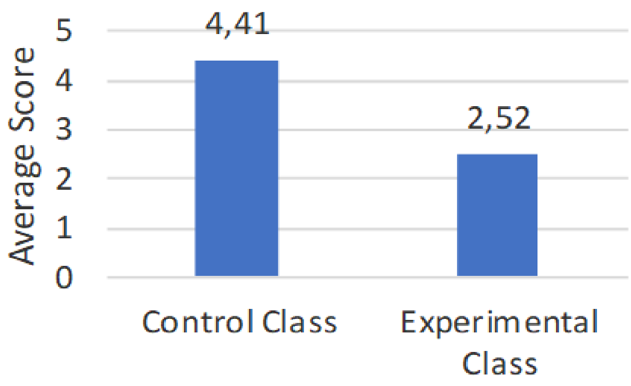

Figure 2. Comparison of mean cognitive load scores between Control Class and Experimental Class

a. Reduction of Extraneous Load

An independent samples t-test was conducted using SPSS 25 to determine the significance of differences in students' cognitive load after participating in deep learning instruction with and without scaffolding.

Table 2. T-test results to find out the average difference between the experimental class and the control class

	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
	F	Sig	t	df	Sig.(2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances Assumed	2.485	.120	9.027	60	.000	1.89539	.20998	1.47537	2.31541
Equal variances not assumed			9.027	51.414	.000	1.89539	.20998	1.47393	2.31686

The findings demonstrate that the deep learning approach supported by scaffolding was significantly effective in reducing students' extraneous cognitive load during science learning. The independent samples t-test confirmed a substantial difference between the control group (without scaffolding) and the experimental group (with scaffolding), where the experimental group showed a considerably lower mean cognitive load ($M = 2.25$, $SD = 0.64$) compared to the control group ($M = 4.41$, $SD = 0.98$), with $t(60) = 9.03$, $p < .001$.

These results highlight the role of scaffolding as a mechanism for regulating the flow of information into working memory. Gradual, structured support enables students to manage complex information more efficiently (van Nooijen et al., 2024). Scaffolding allows students to focus on essential learning elements without being overwhelmed by irrelevant details one of the primary sources of extraneous load as described in CLT. Chen, Kalyuga, & Sweller, (2023). The instructional design used in this study, including concept diagrams, guiding questions, and mnemonic visuals (Figure 1), reflects the direct application of CLT principles in deep learning. These tools help minimize unproductive cognitive effort and promote meaningful schema construction. Bransen et al., (2024).

b. Cognitive Load Theory (CLT)

The findings reinforce core principles of CLT (Chen, Kalyuga, & Sweller, 2023; Hoogerheide, Paas, & van Merriënboer, (2024), which emphasize that effective learning depends on efficient use of working memory resources. Cognitive load is composed of intrinsic load, extraneous load, and germane load. Scaffolding reduces extraneous load by reorganizing information and directing students' attention to relevant aspects. Skulmowski & Xu, (2023). Reducing extraneous load enables working memory to allocate resources to higher-order thinking and conceptual understanding (Bransen et al., 2024). This aligns with research suggesting that scaffolding provides strategic support that is then gradually faded as student independence increases (Appiah-Twumasi, 2024; Zuo, 2023). Similar findings by Hülsmann et al. (2024) demonstrate that CLT based scaffolding avoids split-attention and integrates verbal and visual information more effectively.

c. Zone of Proximal Development (ZPD)

The use of scaffolding in this study aligns with Vygotsky's (1978) Zone of Proximal Development, which refers to the difference between what students can achieve independently and what they can accomplish with guidance from a more knowledgeable other. As explained by Wood, Bruner, and Ross (1976), scaffolding functions as temporary support that is gradually withdrawn as students' competence increases. In this study, scaffolding was provided through guiding questions, metacognitive reflection prompts, and step-by-step worked examples. These supports enabled students to focus on essential concepts and avoid confusion, thereby reducing extraneous cognitive load and increasing germane cognitive load. Chen, Kalyuga, & Sweller, 2023; Hoogerheide, Paas, & van Merriënboer, (2024). The findings indicate that scaffolded deep learning not only enhances conceptual understanding but also fosters gradual development of cognitive independence.

d. Deep Learning Approach

The results show that students who participated in scaffolded deep learning experienced lower cognitive load than those in conventional learning conditions. This supports the view that deep learning involves interpreting, analyzing, and reflecting on concepts rather than memorizing information. Mystakidis, (2023). Scaffolding structured students' cognitive processes and prevented overwhelming demands on working memory. Gradual reduction of support (fading) also contributed to independent problem solving abilities, as documented by Hülsmann (2024) Thus, deep learning combined with scaffolding does not simplify learning, but makes it more structured and meaningful.

e. Instructional Implications

The findings underscore the need for learning designs that incorporate CLT principles, particularly in constructing worksheets, handouts, and learning media. Instruction should integrate text and visuals coherently, avoid split attention effects, and adjust conceptual depth to students' prior knowledge. Skulmowski & Xu, (2023). Scaffolding should be applied as temporary, adjustable support, and gradually faded to promote self-regulated learning and transfer of knowledge to new contexts. Zuo, (2023). Monitoring cognitive load is essential to ensure that scaffolding effectively reduces extraneous load and supports germane load (Bransen et al., 2024). Ultimately, deep learning requires opportunities for independent reflection and problem solving, ensuring meaningful and transferable understanding.

CONCLUSION

This study concludes that the implementation of a deep learning approach supported by scaffolding techniques effectively reduces students' extraneous cognitive load during science learning. The Independent Samples T-Test revealed a significant difference between the control class ($M = 4.41$, $SD = 0.98$) and the experimental class ($M = 2.52$, $SD = 0.64$), $t(60) = 9.03$, $p < .001$, indicating that students who received structured scaffolding experienced lower non-essential cognitive demands compared to those who did not. These findings suggest that gradual and adaptive instructional support enables students to process information more efficiently by directing attention toward conceptually relevant elements while minimizing cognitive interference. More over, the integration of deep learning encourages deeper cognitive engagement, strengthens the relationship between prior and new knowledge, and fosters more meaningful and enduring conceptual understanding. Overall, this study provides empirical evidence that the combination of deep learning and scaffolding constitutes an effective pedagogical strategy for optimizing cognitive resources and enhancing the quality of science learning.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Research data collector; Validation; Writing Review and Editing.
Author 2: Conceptualization; Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest related to the conduct, authorship, or publication of this study. All research procedures and reporting were carried out objectively and independently, without any financial or personal relationships that could have influenced the results.

REFERENCES

Ali, W., & Hamad, M. (2023). Adaptive e-scaffolding systems and student performance in hybrid learning. *Computers & Education: Artificial Intelligence*, *4*, 100140. https://doi.org/10.1016/j.caeai.2023.100140

Appiah Twumasi, E. (2024). Scaffolding as a cognitive load reduction strategy for teaching atomic and nuclear physics. *Momentum: Physics Education Journal*, 8(2). https://doi.org/10.21067/mpej.v8i2.9580

Barzilai, S., & Blau, I. (2023). Metacognitive scaffolding for critical digital literacy in online learning environments. *Computers & Education*, *194*, 104671. https://doi.org/10.1016/j.compedu.2023.104671

Bransen, D., et al. (2024). Scaffolding cognitive processing in complex learning tasks: A cognitive load perspective. *Educational Psychology Review*, 36(12). https://doi.org/10.1007/s10648-024-09841-8

Chang, C., & Wu, H. (2023). Guided experimentation with structured scaffolding to support conceptual change in physics learning. *Research in Science Education*, *53*, 1109–1131. https://doi.org/10.1007/s11165-022-10010-5

Chen, O., Kalyuga, S., & Sweller, J. (2023). Cognitive load effects in online multimedia learning environments: A review. *Educational Psychology Review*, *35*, 1–20. https://doi.org/10.1007/s10648-022-09676-x

Eitel, A., & Kienitz, C. (2024). Managing cognitive load in inquiry learning through adaptive guidance. *Learning and Instruction*, *86*, https://doi.org/10.1016/j.learninstr.2023.101648

Hadwin, A., Panadero, E., & Miller, M. (2023). Socially shared regulation in collaborative learning: Current trends. *Educational Psychologist*, *58*(2), 125–145.https://doi.org/10.1080/00461520.2023.2180936

He, J., & Chen, Z. (2024). Enhancing higher-order thinking using layered scaffolding in digital PBL environments. *Journal of Computer Assisted Learning*, *40*(3), 589–603. https://doi.org/10.1111/jcal.12832

Hidayat, R., & Pradana, M. (2023). Integrating ARCS motivational model in vocational e-learning to enhance student persistence. *Journal of Technical Education and Training*, *15*(4), 127–140. https://publisher.uthm.edu.my/ojs/index.php/jtet/article/view/13570

Hoogerheide, V., Paas, F., & van Merriënboer, J. (2024). Cognitive load across instructional design models: A comparative synthesis. *Educational Psychology Review*, *36*, 22. https://doi.org/10.1007/s10648-024-09852-7

Hülsmann, M., Richter, T., Köller, O., et al. (2024). Scaffolding and cognitive load in biology learning: An experimental study. *Journal of Science Education*, *52*(3), 455–472. https://doi.org/10.1007/s11165-024-10012-4

Jatmoko, D., Suyitno, S., Rasul, M. S., Nurtanto, M., Kholifah, N., & Masek, A. (2023). The Factors Influencing Digital Literacy Practice in Vocational Education: A Structural Equation Modeling Approach. *European Journal of Educational Research*, *12*(2), 1109-

1121. https://doi.org/10.12973/eu-jer.12.2.1109 European Journal of Educational Research

Kim, N., & Lim, K. (2023). Guided tutoring in PBL settings: Effects on problem-solving performance and cognitive load. *Learning and Instruction, 84*, 101605. https://doi.org/10.1016/j.learninstr.2023.101605

Kirschner, P., & de Bruin, A. (2023). Effective guidance and scaffolding for SRL. *Educational Psychology Review*, *35*, 411–434.https://doi.org/10.1007/s10648-022-09670-3

Leppink, J. (2023). The role of cognitive load in inquiry-based and problem-based learning. *Instructional Science, 51*, 421–440.https://doi.org/10.1007/s11251-023-09617-7

Lim, J., & Choi, H. (2024). AI-based scaffolding feedback in digital classrooms. *Computers & Education*, *205*, 105043. https://doi.org/10.1016/j.compedu.2024.105043

Martin, F., Chen, Y., & Ritzhaupt, A. (2023). Systematic review of online scaffolding in higher education. *The Internet and Higher Education, 57*, 100873. https://doi.org/10.1016/j.iheduc.2023.100873

Mystakidis, S. (2023). Meaningful e-learning in immersive environments: A systematic review. *Education and Information Technologies, 28*, 1445–1468. https://doi.org/10.1007/s10639-022-11303-6

Ong, C. P., & Shahrill, M. (2023). Effects of guided instruction on student learning outcomes in science. *Research in Science Education, 53*, 155–172.https://doi.org/10.1007/s11165-022-10050-x

Prastowo, T., & Wibowo, R. (2023). Student engagement and learning outcomes in vocational science classes supported by digital scaffolding. *Journal of Technical Education and Training*, *15*(2), 88–102.https://publisher.uthm.edu.my/ojs/index.php/jtet

Rahmatullah, R., & Susanto, A. (2023). ARCS-based instructional model to enhance motivation and learning effectiveness in vocational education. *International Journal of Instruction*, *16*(3), 155–170. https://doi.org/10.29333/iji.2023.16310a

Reid, J., & Ayres, P. (2023). Cognitive architecture and its implications for instructional design in digital learning contexts. *Educational Technology Research and Development, 71*, 1023–1042. https://doi.org/10.1007/s11423-023-10199-9

Rostaminezhad, M., & Behzadpoor, S. (2023). Reducing extraneous cognitive load through optimized multimedia design in science education. *Journal of Science Education and Technology, 32*, 455–468. https://doi.org/10.1007/s10956-022-10031-2

Sami, N., & Saleh, M. (2024). Digital scaffolding strategies to support inquiry-based STEM learning in higher education. *Education and Information Technologies, 29*(2), 1887–1908. https://doi.org/10.1007/s10639-023-11872-4

Setiawan, R., & Mahmud, S. (2024). Inquiry scaffolding to enhance conceptual mastery in biology laboratory activities. *Education Sciences, 14*(2), 98. https://doi.org/10.3390/educsci14020098

Shao, J., Chen, Y., Wei, X., Li, X., & Li, Y. (2023). Effects of regulated learning scaffolding on regulation strategies and academic performance: A meta-analysis. *Frontiers in Psychology*, *14*, 1110086. https://doi.org/10.3389/fpsyg.2023.1110086

Singh, A., & Fong, L. (2024). Promoting deep learning using collaborative online learning models. *Journal of Computer Assisted Learning, 40*(2), 401–420.https://doi.org/10.1111/jcal.12810

Skulmowski, A., & Xu, K. (2023). Managing cognitive load in multimedia learning: New evidence. *Computers in Human Behavior, 146*, 107778. https://doi.org/10.1016/j.chb.2023.107778

Suyitno, S., Jatmoko, D., Primartadi, A., & Ab-Latif, Z. (2023). Industrial practice platform based on work based learning: A solution to improve student competence. *Jurnal Pendidikan Vokasi*, *13*(1), 98-106. https://doi.org/10.21831/jpv.v13i1.54589

Tovar, M., & García, B. (2024). Digital scaffolding to enhance students' complex problem-solving skills in blended learning. *Interactive Learning Environments*, 32(4), 552–569. https://doi.org/10.1080/10494820.2022.2123457

Van Nooijen, C., de Koning, B. B., & Bramer, W. (2024). Expert scaffolding in visual problem-solving tasks: Enhancing learning efficiency. *Educational Psychology Review*, *36*, 12.https://doi.org/10.1007/s10648-024-09848-3

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes.* Harvard University Press. https://archive.org/details/mindinsocietydev0000vygo

Wang, S., & Adesope, O. (2023). Effects of adaptive scaffolding on students' metacognition in digital learning environments: A systematic review. *Computers & Education*, *197*, 104724. https://doi.org/10.1016/j.compedu.2023.104724

Webb, M., & Blanchard, S. (2024). Scaffolding strategies in digital PBL classrooms: Implications for cognitive engagement. *Journal of Computer Assisted Learning*, *40*(1), 133–149.https://doi.org/10.1111/jcal.12781

Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry*, *17*(2), 89–100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x

Yen, C., & Tu, Y. (2023). Enhancing inquiry based science learning through dynamic scaffolding. *Research in Science Education*, *53*, 1245–1262. https://doi.org/10.1007/s11165-022-10020-3

Yusuf, M., & Subekti, H. (2023). The influence of guided project-based learning on vocational students' performance and safety awareness. *International Journal of Instruction*, *16*(4), 145–162. https://doi.org/10.29333/iji.2023.1649a

Zhang, Z., & Chen, L. (2024). Tutor–student interaction and scaffolding effectiveness in online PBL. *The Internet and Higher Education*, *61*, 100878.https://doi.org/10.1016/j.iheduc.2023.100878

Zuo, M. (2023). The effects of using scaffolding in online learning: A meta-analysis. *Education Sciences*, *13*(7), 705. https://doi.org/10.3390/educsci13070705