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Effect of Example-Based Learning Model on Micro Level Cognitive Load and Knowledge Transfer

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ABSTRACT

Students often face difficulties in solving math problems due to high cognitive load. This load can interfere with optimal information processing, particularly at the micro-level, such as in problem-solving steps. Although many studies have examined cognitive load, most focus on macro-level, with limited exploration of micro-level cognitive processing. To address this, an effective learning approach is needed to optimize students' working memory capacity and promote knowledge transfer. This study aims to investigate the effect of an example-based learning model on cognitive load and knowledge transfer in mathematics learning. A quasi-experimental method was conducted involving 78 eighth-grade students from a school in Serang City, divided into two groups: an experimental group applying the example-based learning model and a control group using a problem-solving model. Data were collected using a mental effort rating scale and essay questions to measure cognitive load at each problem-solving step, along with retention and near-transfer tests. Analysis using Two-Way ANOVA showed that the example-based learning model significantly reduced cognitive load throughout the problem-solving stages. It also produced better outcomes in retention and near-transfer tests, indicating more effective knowledge transfer. These findings suggest that example-based learning can be a valuable instructional strategy to improve mathematical problem-solving, particularly for students with limited background knowledge. The novelty of this study rests on the simultaneous examination of retention and transfer, focusing on students' micro-level cognitive processing during example-based learning. Structured examples were shown to reduce cognitive burden while fostering transferable problem-solving strategies.

Keywords: Example-based learning, Cognitive Load, Knowledge Transfer, Retention, Near-Transfer**.**

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Introduction

Education is fundamental to enhancing the quality of human resources, which serves as a crucial element in driving the progress of a country amid global competition. The quality of education plays a pivotal role in shaping future generations by cultivating critical thinking, innovation, and adaptability. Mathematics, in particular through mathematics education, students can develop skills to identify problems, analyze information, and design innovative solutions. NCTM (2000) identifies five core standards in mathematics education: problem-solving, reasoning and proof, communication, connection, and representation. Among these competencies, problem-solving occupies a central position, as it is essential for fostering higher-order thinking skills.

Problem-solving in mathematics requires both cognitive and affective processes (Widodo et al., 2018). Students must overcome obstacles, understand concepts, and apply strategies, including formulating problems and synthesizing previously acquired knowledge (Septhiani, 2022; Widodo et al., 2018). However, research indicates that a significant number of students still have difficulties in problem-solving. For example, Hermawati et al. (2021) reported that students' abilities in spatial geometry were low, while Anggraini et al. (2022) found that most students' problem-solving abilities fell into the medium category. A significant contributor to this challenge is the disparity in students' foundational knowledge. Those with limited prior knowledge often struggle to grasp new concepts and require additional support to build their understanding (Sholikhah & Fahmi, 2022; Tias Anggraini, 2023). Increases the likelihood of cognitive overload when confronted with new mathematical concepts.

Various approaches have been explored to address this issue. One effective strategy involves using structured solution steps, which guide students through a systematic problem-solving process (Chen et al., 2023). However, numerous prior studies have primarily emphasized the measurement of cognitive load at the macro level, after the entire problem has been solved (Chen et al., 2019). This approach overlooks the detailed examination of cognitive load at each stage of the problem-solving process, creating a gap in understanding students' cognitive processes. Measuring cognitive load at the micro level step by step provides a more accurate insight into the dynamics of student learning (Chen et al., 2019).

Furthermore, the ability of students to transfer acquired knowledge to now situations remain suboptimal. Transfer refers to students' ability to apply limited knowledge to identify and correct errors that arise when facing new tasks (Nokes, 2009). Knowledge transfer to new, similar contexts is crucial for students' success in problem-solving tasks (Ardiana & Retnowati, 2022; Mayer, 2002; Uzun & Arslan, 2023). Research by Pransisca and Gazali (2022) found that limited problem-solving skills negatively impact students' ability to transfer knowledge in mathematics learning. Knowledge transfer is typically assessed through retention and near-transfer tests. Retention tests evaluate students' ability to recall learned material, while near-transfer tests assess their ability to solve new problems that share similar concepts but vary in complexity (Agustin et al., 2022; Lutz & Huitt, 2018; Valderama & Oligo, 2021).

To address these challenges, Sweller et al. (2011) propose the cognitive load theory, which emphasizes the importance of instructional designs that minimize unnecessary cognitive load. Cognitive load reflects the mental effort required for students to process information in working memory (Sweller, 2023). Cognitive load theory serves as a framework in instructional design, emphasizing the role of schema acquisition and automation in the learning process. This theory advocates for the development of instructional materials that align with the capacity limitations of working memory (Retnowati & Fadlila, 2023). One of the goals of this theory is to reduce extraneous cognitive load. By reducing extraneous load, students can process and retain information more effectively in long-term memory (Jamaludin, 2022; Renkl, 2014). One approach aligned with this principle is example-based learning, which provides complete examples that guide students through problem-solving steps, reducing the cognitive burden of finding solutions independently (Atkinson et al., 2000; Fischer et al., 2018; Santosa & Filiz, 2025). Research by Santosa et al. (2022) and Chen et al. (2023) confirm that worked examples improve problem-solving abilities and knowledge transfer by gradually reducing cognitive load.

The novelty of this research is exploring the effect of example-based learning on students' cognitive load at the micro-level on the material of the system of linear equations of two variables. Prior research shows that students of various ability levels still experience difficulties with the material of the system of linear equations of two variables (Munthe & Hakim, 2022; Nari et al., 2023; Nurhayati et al., 2021). Unfortunately, the cognitive load assessment is still at the macro level, so it does not provide a detailed picture of the difficulties experienced by students at each stage of completion. To further understand the learning proces it is crucial to investigate each step of the solution at the micro level, including how the initial and final steps in problem solving affect learning.

This research aims to investigate the micro-level cognitive load experienced by students during each step of the problem-solving process, offering a deeper understanding of how the example-based learning strategy can optimize the learning process in mathematics education. Example-based learning offers worked examples that illustrate problem-solving strategies and support students in comprehending each step of the process (Hiller et al., 2020). This approach encourages active engagement, as students explain each step and reinforce their understanding. Example-based learning provides opportunities for students to learn by understanding directly from the examples given and actively explaining the steps they have taken. By presenting clear examples, the strategy also minimizes the chance of students getting distracted by irrelevant information, allowing them to focus more effectively on solving the problem (Gog & Rummel, 2010). This focused approach is expected to enhance students' knowledge transfer abilities, which will be assessed through retention and near-transfer tests.

The present study compares the effects of the example-based learning model and the problem-solving model on students' cognitive load at each step of problem-solving process (Steps 1, 2, and 3). In addition, it examines how these models affect knowledge transfer in mathematics learning. By analyzing the impact of each method, the research aims to contribute to the development of more effective teaching strategies. Ultimately, these strategies will help improve students' understanding and ability to apply mathematical concepts in various contexts.

Methods

This research used experiment design to identify the effects of example-based learning model on students' micro level cognitive load and knowledge transfer ability in mathematics learning. This research design used 2×3 and 2×2 factorial which are measured to identify the effects between the independent variable and the dependent variable. The research design is presented in Table 1 and Table 2.

Table 1. *Research design 2 x 3*

Learning model (A) / **Cognitive load at the micro level (B)**	**Example-based learning**	**Problem-solving**
Step 1	(A_1B_1)	(A_2B_1)
Step 2	(A_1B_2)	(A_2B_2)
Step 3	(A_1B_3)	(A_2B_3)

Where:
A_1B_1: Average cognitive load score students learned with example-based learning in Step 1.
A_1B_2: Average cognitive load score students learned with example-based learning in Step 2.
A_1B_3: Average cognitive load score students learned with example-based learning in Step 3.
A_2B_1: Average cognitive load scores students learned with problem-solving in step 1.
A_2B_2: Average cognitive load scores students learned with problem-solving in step 2.
A_2B_3: Average cognitive load scores students learned with problem-solving in step 3

Table 2. *Research design 2 x 2*

Learning model (A) / **Knowledge transfer(B)**	**Example-based learning**	**Problem-solving**
Retention test	(A_1B_1)	(A_2B_1)
Near transfer test	(A_1B_2)	(A_2B_2)

Where:
A_1B_1: Average student learning scores with example-based learning based on retention tests.
A_1B_2: Average student learning scores with example-based learning based on near transfer tests.
A_2B_1: Average student learning scores with problem-solving based on retention tests.
A_2B_2: Average student learning scores with problem-solving based on near transfer tests.

The research involving eighth-grade students from a junior high school in Serang during the second semester of the 2023/2024 academic year. A total of 78 students, 41 male and 37 female participated as research subjects. They were evenly divided into two groups: the experimental group (n = 39), which received instruction using the example-based learning model, and the control group (n = 39), which was taught through the problem-solving model.

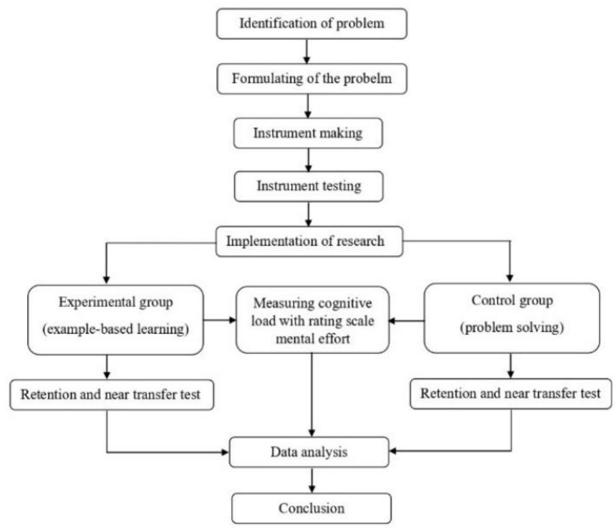

Figure 1. *Research Procedures*

This research consisted of three main stages: preparation, implementation, and finalization. During the preparation stage, the researcher developed research instruments based on a literature review of cognitive load theory and knowledge transfer. Lesson plans were designed to suit the instructional approaches used in each group. The example-based learning group received mathematical problems accompanied by fully worked-out solution steps, following the framework of (Ritter et al., 2007). Conversely, the problem-solving group was given similar problems but was required to solve them independently, in line with the model proposed by (Putra & Budihardjo, 2018). Before starting the research, the retention and near-transfer test instruments were empirically tested to determine the level of validity and reliability. The validity of the instrument was calculated by pearson product moment correlation, while the reliability was calculated by cronbach Alpha. The instrument is valid if $r_{xy} \geq r_{table}$ and reliable if $r_{11} \geq 0{,}7$. The results of instrument tests are provided in Table 3.

Table 3. *Results of the instrument test*

		Retention test			**Near transfer test**		
		1	**2**	**3**	**4**	**5**	**6**
	r_{xy}	0,799	0,811	0,766	0,805	0,863	0,868
Validity	r_{table}		0,361			0,361	
	Description	valid	valid	valid	valid	valid	valid
	Item variance	0,920	0,805	0,837	1,236	1,247	1,550
	Number of item variances		2,564			4,034	
Reliability	Total number of variances		4,860			8,717	
	r_{11}		0,708			0,805	
	Description		reliable			Reliable	

In the implementation stage, both groups were assigned essay-based mathematics tasks. The intervention was implemented during four sessions, with three sessions allocated for learning activities and the last session for the posttest. During the learning phase, the experimental group received problems supported by detailed work examples, while the control group completed the same problems without guidance. This process was divided into three main stages, which were modified from the stages according to (Maydawati, 2024). The problem-solving process was categorized into three primary steps: (1) translating the problem into a mathematical model, (2) The second step is to perform the elimination calculation operation process, (3) The third step is to perform the substitution calculation operation process. Worked example with complete steps in Table 4.

Table 4. *Complete worked example*

Question	Answer
Adel and Dita went to a traditional market to buy fruits. Adel bought 4 kilograms of oranges and 1 kilogram of apples for Rp. 16,000. While Dita bought 6 kilograms of oranges and 1 kilogram of apples for Rp. 20,000. How much money is needed to buy 2 kilograms of oranges and 3 kilograms of apples?	**Step 1: Create a mathematical model** It is known: 4 kilograms of oranges and 1 kilogram of apples = Rp. 16,000 6 kilograms of oranges and 1 kilogram of apples = Rp. 20,000 Let Price of 1 kilogram of oranges= x Price of 1 kilogram of apples= y the mathematical model obtained is: $4x + y = 16.000$ (i) $6x + y = 20.000$ (ii) **Step 2: Perform the elimination calculation operation** To find the value of x, eliminate y in equations (i) and (ii) $4x + y = 16.000$ $\underline{6x + y = 20.000}$ - $-2x = -4.000$ $x = \frac{-4.000}{-2}$ $x = 2.000$ **Step 3: Perform the substitution calculation operation** To determine the value y, substitute x into equation (i) $4x + y = 16.000$ $4(2.000) + y = 16.000$ $8.000 + y = 16.000$ $y = 16.000 - 8.000$ $y = 8.000$ Therefore, the cost of 1 kilogram of oranges is Rp. 2,000, while the cost of 1 kilogram of apples is Rp. 8,000. The cost of 2 kilograms of oranges and 3 kilograms of apples is $2x + 3y$ $= 2(2.000) + 3(8.000)$ $= 4.000 + 24.000$ $= 28.000$ So, the price of 2 kilograms of oranges and 3 kilograms of apples is Rp. 28,000

To measure micro-level cognitive load, students evaluated their mental effort at each problem-solving step using a seven-point scale adapted from Paas (1992), as outlined in Table 5. Upon completing the lesson, students took retention and near-transfer tests, each consisting of three essay questions and a total duration of 70 minutes. The retention test assessed their ability to recall previously learned material (El-Shaer & Gaber, 2014; Mayer, 2002; Valderama & Oligo, 2021). Meanwhile, near transfer measures the application of concepts to similar problems but different contexts (Agustin et al., 2022; Sala et al., 2019). The test was designed in the form of an essay and was based on indicators of representation, understanding, and student experience (Dixon & Brown, 2012).

Table 5. *Rating scale of mental effort*

	1	2	3	4	5	6	7
Scale	Very low	low	Rather low	Neither low nor high	Rather high	High	Very high

In the final stage, data analysis was performed using both descriptive and inferential statistics. Descriptive statistics were employed to compare the means and standard deviations between the two groups. Normality and homogeneity were assessed using the Kolmogorov–Smirnov and Levene's tests, respectively, as prerequisites for further statistical analysis. To evaluate the impact of instructional models on cognitive load and knowledge transfer, a repeated measures ANOVA was conducted to analyze main, simple, and interaction effects. When interaction effects reached significance, Holm's was implemented for post hoc analysis.

Results and Discussion

Cognitive load during learning

Based on the prerequisite test with a significance level of $\alpha = 0.05$, it shows that the data on students' micro level cognitive load is normal distributed and homogeneous. The significance value of the normality test for each step of example-based learning group is $0.377, 0.2, 0.185$ and problem-solving group is $0.074, 0.176, 0.284$. The significance value of the homogeneity test for both classes were $0.555, 0.844, 0.959$. Descriptive statistical analysis of students' cognitive load is presented in Table 6.

Table 6. *Descriptive analysis of students' cognitive load data*

Cognitive load	Learning model	N	Mean	Standard deviation
Step 1	Example-based learning	39	5.078	0.956
	Problem solving	39	6.771	0.869
Step 2	Example-based learning	39	5.059	0.864
	Problem solving	39	6.100	0.899
Step 3	Example-based learning	39	4.356	0.954
	Problem solving	39	6.030	0.987

Table 6 presents the descriptive analysis of students' cognitive load across the three problem-solving steps in the example-based learning and problem-solving groups. In Step 1, the mean cognitive load was

5.078 (SD = 0.956) for the example-based group, compared to 6.771 (SD = 0.869) in the problem-solving group. In Step 2, the example-based group had a mean score of 5.059 (SD = 0.864), while the problem-solving group scored 6.100 (SD = 0.899). The trend continued in Step 3, where the example-based group recorded a mean of 4.356 (SD = 0.954), the problem-solving group reported 6.030 (SD = 0.987).

The next step is hypothesis testing using repeated measures ANOVA. To determine the effect of the learning model on cognitive load at the micro level, a repeated measures ANOVA 2 (Example-based learning vs Problem-solving) x 3 (step 1, step 2, and step 3) was tested. The results of the students' cognitive load hypothesis are presented in Table 7.

Table 7. *Results of the hypothesis test of students' cognitive load*

Repeated measures ANOVA		df	F	p	η^2
Between subject effect	Learning model	1	91.951	< .001	0.364
Within subject effect	Cognitive load	2	17.708	< .001	0.060
	Cognitive load and Learning models	2	4.564	0.012	0.016
Simple effect	Step 1	1	67.021	< .001	
	Step 2	1	27.164	< .001	
	Step 3	1	58.039	< .001	

The main effect of cognitive load showed significant results, $F(1,76) = 91.951,\ p < .001,\ \eta^2 = 0.364$, indicating that over all the example-based learning model reported significantly lower cognitive load than the problem-solving model group. The effect of the problem-solving step on cognitive load was also significant $F(2,152) = 17.708,\ p < .001,\ \eta^2 = 0.060$. Next are the results of a simple effects analysis of cognitive load at the micro level at each step. The example-based learning group reported significantly lower levels of cognitive load at each step compared to the problem-solving group. Step 1: $F(1,76) = 67.021,\ p < .001$. Step 2: $F(1,76) = 27.164,\ p < .001$. Step 3: $F(1,76) = 58.039$, $p < .001$. Interaction between the application of learning models on students' cognitive load at the micro level $F(2,152) = 4.564,\ p = 0.012,\ \eta^2 = 0.016$. After significant interactions were found, analysis was carried out at each step using the Holm Test. The example-based learning group reported significantly lower levels of cognitive load at all stages compared to the problem-solving group, with a consistent decreasing pattern at each step. Step 1: $t(76) = -8.187, p < .001$. Step 2: $t(76) = -5.212, p < .001$. Step 3: $t(76) = -7{,}618, p < {,}001$.

This study indicates that the application of the example-based learning model reduces students' cognitive load compared to the problem-solving model at each stage of the problem-solving process. This finding aligns with the research of Chen et al. (2023), which reported students who learned through worked examples experienced reduced cognitive load compared with those engaged in cognitive learning through problem-solving. The reduction in cognitive load occurred consistently at each step, starting step 1, step

2, and step 3, demonstrating a clear pattern of reduced cognitive effort across the micro-level stages. These consistent differences suggest that the provision of worked examples effectively reduces students' mental effort during each phase of problem-solving. The lower cognitive load observed in the example-based learning group aligns with cognitive load theory, which posits that instructional designs minimizing extraneous load can enhance learning efficiency by freeing up cognitive resources for schema construction and automation.

The example-based learning model provides students with a complete worked example at the beginning of instruction to help reduce cognitive burden. By observing and understanding the example, students can identify the structure and logic of the solution process without being immediately faced with complex tasks. After this phase, students gradually solve problems with some steps removed, taking on more responsibility as their understanding deepens. The gradual reduction of support optimizes cognitive load, allowing for more efficient use of working memory in schema construction and consolidation (Santosa et al., 2018). In contrast, students learning through the problem-solving model experience higher cognitive load because they are immediately required to solve problems without prior exposure to worked examples (Lee & Ayres, 2024). During this process, students may resort to trial-and-error strategies, leading to confusion and inefficiency. They must identify appropriate strategies independently, which becomes particularly challenging for students with limited prior knowledge. As a consequence, the cognitive resources are overwhelmed, which makes it challenging to complete tasks effectively and increases cognitive overload.

This validates a theoretical foundation from Sweller (2024) cognitive load theory, which emphasizing the importance of minimizing cognitive effort to ensure that information can be effectively processed before it is processed in long-term memory**.** The application through worked examples within learning allows students to allocate their mental resources more efficiently and focus on understanding content and problem-solving strategies rather than struggling to find solutions from scratch. Structure learning process supports cognitive processing, especially for novice learners who require support in developing fundamental problem-solving schemas (Andini et al., 2024). Students who have built schemas in these areas will be active in discovering additional knowledge to extend the structure of their prior knowledge, thus supporting long-term memory (Orón & Lizasoain, 2023; Santosa & Filiz, 2025). Schema building makes it possible for the student to work on solving new problems. The results of the study answered the proposed objectives, indicating that the implementation of the example-based learning model significantly reduced students' cognitive load at each stage of problem-solving. Cognitive load in the example-based learning group was consistently lower in the first to third steps compared to the problem-solving group, which was directly asked to solve problems without initial examples.

Retention and near-transfer tests

Based on the prerequisite test with a significance level of $\alpha = 0.05$, it shows that the retention and near transfer test data are normal distributed and homogeneous. The significance value of the normality test on the retention test is 0.097 (example-based learning) and 0.288 (problem-solving), while on the near transfer test it is 0.240 (example-based learning) and 0.414 (problem-solving). The significance value of the homogeneity test for both groups was 0.132 (retention) and 0.334 (near-transfer). Descriptive statistical analysis of students' retention and near transfer tests is presented in Table 8.

Table 8. *Descriptive analysis of retention and near transfer test data*

Cognitive load	Learning model	N	Mean	Standard deviation
Retention	Example-based learning	39	83,333	19,118
	Problem-solving	39	62,607	21,364
Near transfer	Example-based learning	39	69,871	20,379
	Problem-solving	39	37,820	23,246

Table 8 presents the descriptive statistics for students' performance on retention and near transfer tests based on the learning model applied. The retention mean score for the example-based learning group was 83.333 ($SD = 19.118$), considerably higher than the score of 62.607 ($SD = 21.364$) recorded by the problem-solving group. A similar pattern was observed in the near transfer test, where the example-based group achieved a mean of 69.871 ($SD = 20.379$), while the problem-solving group had a lower mean of 37.820 ($SD = 23.246$).

The next step is hypothesis testing using repeated measures ANOVA. To determine the effect of the learning model on students' knowledge transfer, a repeated measures ANOVA 2 (Example-based learning vs Problem-solving) x 3 (step 1, step 2, and step 3) test was conducted. The results of the hypothesis test for students' retention and near transfer tests are presented in Table 9.

Table 9. *The results of the hypothesis test of student knowledge transfer*

Repeated measures ANOVA		df	f	p	η^2
Between subject effect	Learning model	1	37.740	< .001	0.246
Within subject effect	Knowledge transfer	1	84.328	< .001	0.129
	Knowledge transfer and Learning Models	1	7.392	0.008	0.011
Simple effect	Retention	1	20,385	< .001	
	Near transfer	1	41,924	< .001	

The main effect of knowledge transfer showed significant results, $F(1, 76) = 37.740,\ p < .001$, $\eta^2 = 0.246$, indicating that over all the example-based learning model reports knowledge transfer. which is significantly better than the problem-solving model. The effect of the type of test conducted on knowledge transfer was also significant $F(2, 152) = 17.708,\ p < .001,\ \eta^2 = 0.060$. Next is the result of a simple effect analysis of two different tests, retention and near transfer tests. The example-based learning group reported significantly higher levels of knowledge transfer on each test compared to the problem-solving group. Retention: $F(1,76) = 41.924, p < 0.001$. Near transfer: $F(1,76) = 27.837, p < .001$. Interaction between test types on students' knowledge transfer $F(1,76) = 7.392, p = 0.008, \eta^2 = 0.011$. After a significant interaction was found, each test type was analyzed using the Holm Test. The example-based learning group reported significantly higher levels of knowledge transfer on all types of tests compared to the problem-solving group. Retention: $t(76) = 4.515, p < .001$. Near transfer: $t(76) = 6.475, p < ,001$.

Students who engaged in learning through the example-based learning model demonstrated higher retention test scores than those taught using the problem-solving model. The positive impact of the example-based learning approach on retention is explained by several cognitive mechanisms that function throughout the learning process. First, example-based learning provides a structured instructional format that helps organize information and encourages their successful incorporation into long-term memory. Secondly, the use of worked examples has been effective in reducing extraneous cognitive load, allowing learners to concentrate on the essential elements of the task. Third, the depth and quality of cognitive elaboration play a critical role in influencing retention. Rather than passively imitating solutions, students actively engage with the material by analyzing example problems, comparing alternative strategies, and reflecting on the reasoning processes involved.

Example-based learning facilitates students' understanding by encouraging active engagement as they analyze and reflect on the provided examples. Students indirectly form new cognitive schemas based on the patterns found in the worked example (Paas & van Merriënboer, 2020). With the problem-solving scheme in the System of Linear Equation in two-variables material, students are able to remember and apply those concepts to similar tasks easily. This research also shows that the problem-solving model, which requires students to solve problems independently without any initial examples, can hinder retention. Students tend to focus on finding a solution, thus not having enough time to build up a thorough knowledge of the whole process. As a result, the information acquired is not effectively stored in their long-term memory. The study supports the results of Valderama and Oligo (2021) who assert that retention results from a systematic and structured learning process. Similarly, Chen et al., (2023) found that students who received examples exhibited improved retention, as learning from modeled solutions enabled them to internalize strategies more effectively.

The effect of example-based learning in improving near-transfer ability is that students understand the problem-solving process well. Such guidance facilitates the development of a well-structured knowledge framework that can be retrieved and adapted to novel problem contexts. Engagement with the example-based learning model fosters students' ability to recognize solution patterns and apply analogous strategies to problems exhibiting similar structural features. Observations during the research indicated that when students encountered slightly modified problems, they relied not solely on memory but also demonstrated the ability to identify structural similarities and adapt previously acquired problem-solving strategies accordingly. Meanwhile, learning through problem-solving from the beginning can cause cognitive overload that inhibits the formation of schemas. Without a well-established schema, students struggle to identify analogies between learned and novel problems (Santosa et al., 2019). The higher near-transfer test scores in the example-based learning group highlight the model's potential to foster reusable and adaptable strategies.

The findings help fill a gap in the literature on how example-based learning supports knowledge retention and the development of transferable problem-solving schemas, an area often overlooked as research focuses on reducing cognitive load. By integrating assessments of retention and near-transfer, this study offers a to a greater extent perspectives on exactly those ways in which students internalize and adapt solution strategies. The novelty of this study rests on its enhancement of multiple learning outcomes and its focus on cognitive processing at the micro level, specifically in solving systems of linear equations, where learning is organized into a sequence of procedural steps. This structured approach serves to reduce unnecessary cognitive load while encouraging schema construction, thus fostering greater strategic awareness.

Although the effect on near-transfer performance was not as strong as on retention tasks, the example-based learning model still outperformed the problem-solving approach. As noted by Dixon and Brown (2012), optimal transfer requires students to apply learned knowledge automatically and efficiently in novel contexts. When instructional phases are too brief, learners may not have sufficient time to reinforce the necessary schemas. Therefore, while the findings of this study underscore the advantages of the example-based learning model, they also highlight the need to strengthen practice and application phases. Doing so will better support students in developing higher-order transfer skills, especially when confronted with more complex and unfamiliar problem variations.

The second research objective was met through higher retention and near-transfer performance in the example-based learning group, demonstrating the effectivity of this model in supporting schema construction. The findings suggest that this model effectively enhances students' retention ability and supports the transfer of knowledge to a similar new situation. This research provides an important contribution in furthering the understanding of the effectivity of example-based learning in terms of cognitive efficiency as well as in transfer and retention, which are often underdeveloped in previous studies.

Conclusion

Drawing from the results, the study suggests example-based learning model has a significant influence on students' cognitive load at the micro level and on the ability of knowledge transfer in learning mathematics. Students who take part in learning with an example-based learning model experience lower cognitive load at each step of problem solving. This shows that example-based learning is effective in helping students understand information gradually through examples. In addition, students who received learning through the example-based learning model obtained higher results on the retention and near transfer tests compared to students who learned using the problem solving model, which indicates that worked examples not only facilitate concept understanding, but also improve students' ability to transfer knowledge to new similar situations.

Grounded in the findings of this research, it is advised that educators and researchers consider incorporating the example-based learning model into mathematics instruction. The integration of this model can be especially beneficial in contexts where cognitive efficiency and skill acquisition are critical. Future studies may examine its application at various educational levels, involve more advanced mathematical concepts, or explore its combination with other pedagogical strategies, such as self-explanation prompts. Additionally, further research could expand the scope of assessment by including measures of far transfer, thereby providing a more nuanced understanding of the model's impact on broader learning outcomes.

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