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Worked Example-Based Instruction to Reduce Cognitive Load and Academic Boredom in Mathematics Learning

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ABSTRACT

This study investigates how cognitive load influences learning outcomes by considering the role of academic boredom, while also examining the effectiveness of worked example-based instruction in reducing both cognitive load and academic boredom in mathematics learning. The research employed a quasi-experimental design involving experimental and control groups with a total of 120 participants (n = 120). Data were collected using questionnaires measuring cognitive load and academic boredom, along with tests assessing learning outcomes. The relationships among variables, both direct and indirect, were examined using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results show that an increase in cognitive load tends to be associated with higher levels of academic boredom and a decline in learning outcomes. Academic boredom negatively predicts learning outcomes and acts as a mediating variable between cognitive load and achievement. Worked example-based instruction demonstrates a stronger ability to regulate cognitive and emotional processes compared with traditional instructional approaches. These results underscore the need to maintain an appropriate balance between cognitive demands and students' emotional engagement in mathematics learning. The study offers a contribution by combining cognitive and affective aspects within a unified analytical perspective and presents practical recommendations for developing instructional strategies that foster cognitive-emotional balance.

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1. INTRODUCTION

Cognitive load, a key concept in educational research, describes the mental effort that learners must expend to understand and process new information within working memory. The degree of cognitive load experienced by students is mainly influenced by two factors, namely the intrinsic complexity of the material and the way the information is delivered.

Highly complex tasks delivered without adequate guidance may increase mental effort and hinder students' problem-solving performance [1]. Excessive cognitive load can overwhelm working memory capacity and reduce the effectiveness of learning [2]. These conditions highlight the critical role of instructional design in optimising information processing efficiency, particularly in mathematics, a discipline characterised by hierarchically structured concepts.

Mathematics instruction should support students in developing systematic problem-solving strategies and integrating multiple interconnected concepts. Ill-structured tasks have been shown to significantly increase mental effort [3]. Such heightened cognitive demand affects not only cognitive processing but also students' emotional states. Empirical evidence suggests that the interaction between cognitive load and emotional responses influences learning outcomes [4]. Academic boredom arises when students perceive a mismatch between their abilities and task demands, leading to reduced engagement and diminished interest in learning.

Worked examples are widely recommended as an effective strategy for reducing cognitive load. [5] reported that novice learners demonstrate stronger conceptual understanding when provided with systematically structured solution examples rather than solving problems independently. Well-designed examples support the development of knowledge schemas in long-term memory [6] and enable learners to allocate cognitive resources more efficiently during the learning process [7]. Moreover, structured instructional designs help maintain cognitive load within manageable limits [8].

Learning design is also closely related to students' psychological experiences in the classroom. The quality of the learning environment and the level of instructional support influence how students respond to academic demands [9]. Prior research indicates that clear instructional guidance and well-organised learning structures enhance student engagement and shape their perceptions of assigned tasks [10]. Variations in students' mental effort are strongly affected by task presentation and the clarity of instructions [11]. These findings suggest that instructional delivery influences not only cognitive processing but also the overall quality of the learning experience.

A substantial body of research has examined the direct impact of instructional design on learning outcomes. However, the mechanisms explaining how instructional design operates through cognitive load and academic boredom have not yet been fully clarified [12]. This gap highlights the need for a research model capable of explaining the interplay among worked example-based instructional design, cognitive load, academic boredom, and learning outcomes within an integrated analytical framework. This study is important because it may assist educators in developing more effective mathematics learning experiences. The limitations of this study relate to two factors: the scope of the sample and the context of the instructional materials used. Therefore, the findings of this study need to be interpreted carefully when applied to broader contexts.

The present study aims to analyse the influence of worked example-based instructional design on cognitive load and academic boredom, along with its effect on students' learning outcomes. In addition, this research explores how cognitive load and academic boredom function as mediating variables within this relationship. The study further formulates several hypotheses to be tested.H1: Worked example-based instructional design has a negative and significant effect on cognitive load.

H2: Worked example-based instructional design has a negative and significant effect on academic boredom.

H3: Cognitive load has a positive and significant effect on academic boredom.

H4: Cognitive load has a negative and significant effect on learning outcomes.

H5: Academic boredom has a negative and significant effect on learning outcomes.

H6: Cognitive load mediates the effect of worked example-based instructional design on learning outcomes.

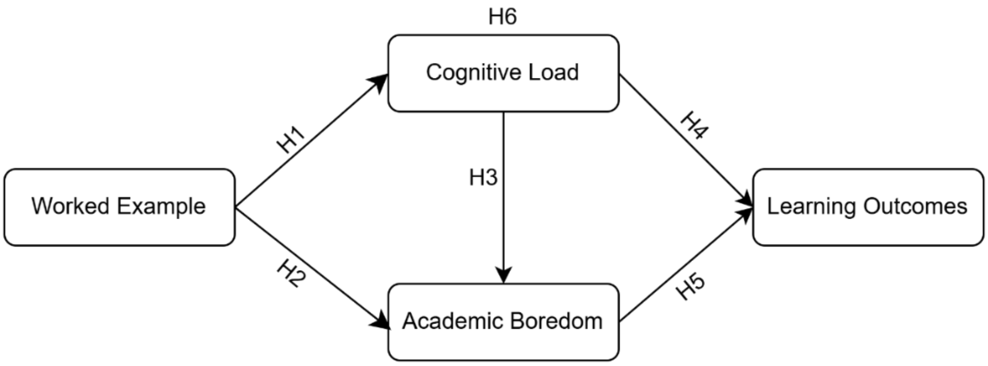

Figure 1. Conceptual model

2. METHOD

2.1. Sample

The present study employed a quasi-experimental design involving two groups: an experimental group and a control group. When complete randomisation is not feasible in a natural school setting, a quasi-experimental design is appropriate for assessing the comparative effects of an intervention across groups [13]. This approach retains naturally formed classroom settings while still allowing a structured evaluation of the treatment effects.

The participants consisted of 120 seventh-grade students enrolled in a junior high school. They were assigned to either the experimental group or the control group based on existing classes (intact groups), without individual randomisation. This nonrandomized group assignment design is commonly used in applied research when full experimental control is difficult to achieve, yet meaningful comparisons between groups can still be made [14].

2.2. Instrument

This study employed three instruments: a cognitive load questionnaire, an academic boredom questionnaire, and a mathematics learning outcomes test focusing specifically on algebraic forms. The cognitive load instrument was adapted from prior studies that distinguish intrinsic, extraneous, and germane cognitive load [15], [16]. It consisted of 10 items rated on a five-point Likert scale. The aspects and corresponding items are presented in Table 1.

Table 1. Aspects and statements of the cognitive load instrument

Aspects	Statements
Intrinsic Cognitive Load	1. The algebraic forms material is difficult for me to understand. 2. The numerous solution steps require me to think intensively. 3. The material requires a high level of concentration.
Extraneous Cognitive Load	4. The presentation of the material is confusing. 5. The explanation makes it difficult for me to understand the concepts. 6. The information is not organised clearly. 7. The way the material is delivered makes it harder for me to follow the lesson.
Germane Cognitive Load	8. I connect new material with my prior knowledge. 9. I seek the most effective strategy to solve the problems. 10. I revise my understanding when I make mistakes.

Academic boredom was measured using an instrument adapted from previous studies on academic boredom [9], [17]. The instrument consisted of 10 items rated on a five-point Likert scale, with higher scores reflecting higher levels of academic boredom. The statements are presented in Table 2.

Table 2. Instrument of Academic Boredom

Construct	Statements
Academic Boredom	1. I feel bored during mathematics lessons. 2. Time seems to pass slowly during class. 3. I am not interested in the material. 4. I feel fatigued while attending the lesson. 5. I feel less enthusiastic when the teacher explains the material. 6. I feel impatient waiting for the lesson to end. 7. I lack motivation to pay attention during the lesson. 8. The lesson feels monotonous. 9. I find it difficult to maintain my attention. 10. I am not enthusiastic about participating in the class.

Mathematics learning outcomes were assessed using a test consisting of multiple-choice and essay questions. The test included 10 items covering algebraic forms, elements of algebraic expressions, algebraic operations, and mathematical modelling. These tasks require both conceptual understanding and procedural skills, making them appropriate for capturing the impact of instructional design on students' cognitive and affective conditions.

2.3. Instrument Validation

Prior to the main study, all instruments were subjected to a validation process. Content validity was established through expert judgment involving two mathematics education specialists and one educational psychology expert. In addition, a pilot test was conducted with 30 students to evaluate item clarity, readability, and overall instrument performance.

The reliability analysis showed that all instruments met acceptable criteria. The cognitive load instrument and the academic boredom instrument each demonstrated satisfactory internal consistency (Cronbach's alpha ≥ 0.70). Item-total correlations and factor loadings were also within acceptable ranges, indicating that the instruments were suitable for measuring the intended constructs.

2.4. Intervention Procedure

The intervention was carried out over several instructional sessions on algebraic forms. The experimental group was taught using a worked example-based approach, whereas the control group received conventional instruction. In the experimental group, students were first exposed to worked examples that clearly demonstrated step-by-step problem-solving procedures.

Each example emphasised key concepts, solution strategies, and underlying reasoning to minimise unnecessary cognitive load and support schema development. After studying the examples, students practised solving similar problems, with guidance gradually reduced to encourage independent problem-solving. In contrast, the control group followed a more traditional approach, where the teacher explained the material and students directly worked on practice problems without structured worked examples.

2.5. Data Analysis

The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4 software. The analysis was conducted in two stages. First, the measurement model (outer model) was evaluated to assess the validity and reliability of the constructs. Convergent validity was examined using outer loadings (≥ 0.70) and Average Variance Extracted (AVE ≥ 0.50), while construct reliability was assessed using Composite Reliability (CR ≥ 0.70) and Cronbach's alpha (≥ 0.70) [18]. Discriminant validity was evaluated using the Heterotrait-Monotrait ratio (HTMT < 0.85) and the Fornell-Larcker criterion [19].

After confirming that the measurement model met the required criteria, the structural model (inner model) was analysed to examine the relationships among variables. The significance of the path coefficients was tested using a bootstrapping procedure with a t-statistic threshold of > 1.96 at the 5% significance level [20]. The coefficient of determination (R^2) was used to indicate the proportion of variance in the endogenous constructs explained by the exogenous constructs. Effect size (f^2) and predictive relevance (Q^2) were calculated to evaluate the model's explanatory power and predictive capability. Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively [21]. Multicollinearity was assessed using the Variance Inflation Factor (VIF ≤ 5) [22]. Model fit was evaluated using the Standardised Root Mean Square Residual (SRMR ≤ 0.08).

3. RESULTS AND DISCUSSION

3.1. Results

The evaluation of models is conducted with the objective of ensuring the validity and reliability of constructs prior to the examination of relationships between variables.

Table 3. Factor Loadings, Reliability, and Validity of the Constructs

Dimension	Code	Loading	α	CR	AVE
Academic Boredom	AB1	0.779	0.938	0.947	0.643
	AB2	0.824			
	AB3	0.762			
	AB4	0.754			
	AB5	0.806			
	AB6	0.837			
	AB7	0.816			
	AB8	0.808			
	AB9	0.803			
	AB10	0.828			
Cognitive Load	CL1	0.834	0.947	0.954	0.677
	CL2	0.823			
	CL3	0.841			
	CL4	0.808			
	CL5	0.875			
	CL6	0.820			
	CL7	0.802			
	CL8	0.752			
	CL9	0.811			
	CL10	0.859			
Learning Outcome	LO1	0.900	0.970	0.974	0.787
	LO2	0.873			
	LO3	0.881			
	LO4	0.889			
	LO5	0.894			
	LO6	0.902			
	LO7	0.905			
	LO8	0.861			
	LO9	0.887			
	LO10	0.876			

All indicators demonstrated outer loading values above 0.70, ranging from 0.752 to 0.905, indicating a strong contribution to their respective constructs. Therefore, no items were removed from the model. The values of Cronbach's alpha and Composite Reliability (CR) exceeded 0.70, and the Average Variance Extracted (AVE) was above 0.50, confirming adequate convergent validity and construct reliability. Discriminant validity, assessed using the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larcker criterion, indicated that each construct was empirically distinct. The detailed results of the discriminant validity assessment are presented in Table 4.

Table 4. Discriminant Validity: HTMT and Fornell-Larcker Criteria

Construct	HTMT			Fornell-Larcker		
	Academic Boredom	Cognitive Load	Learning Outcome	Academic Boredom	Cognitive Load	Learning Outcome
Academic Boredom	-	0.677	0.727	0.802		
Cognitive Load	0.677	-	0.744	0.641	0.823	
Learning Outcome	0.727	0.744	-	-0.699	-0.714	0.887

The HTMT values for all construct pairs were below 0.85, satisfying the criterion for discriminant validity. In addition, the square roots of the AVE values on the diagonal of the Fornell-Larcker matrix exceeded the inter-construct correlations. These results confirm the discriminant validity of all constructs. Subsequently, the structural model was evaluated to examine the relationships among the constructs in this study.

Table 5. Path Coefficients and Significance Testing

Construct Relationship	β (Original Sample)	Standard Error	t-statistic	p-values
Academic boredom → Learning Outcome	-0.410	0.081	5.074	0.000
Cognitive load → Academic Boredom	0.641	0.053	12.176	0.000
Cognitive load → Learning Outcome	-0.451	0.079	5.730	0.000

All hypothesised relationships in the structural model were statistically significant ($t > 1.96$; $p < 0.001$). Cognitive load showed a positive effect on academic boredom ($\beta = 0.641$) and a negative effect on learning outcomes ($\beta = -0.451$). Academic boredom also negatively affected learning outcomes ($\beta = -0.410$). The strongest effect appears in the relationship between cognitive load and academic boredom, indicating that increased cognitive demands are closely linked to students' disengagement during learning. The structural model is illustrated in Figure 2.

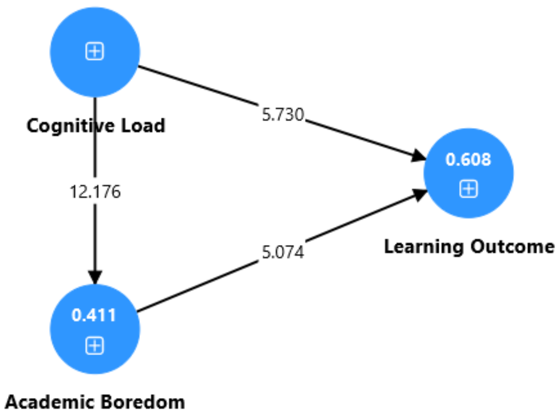

Figure 2. Structural model with t-Statistics

As shown in Figure 2, the structural model presents the t-statistic values for each path, all of which exceed 1.96. The R^2 value of 0.411 indicates that 41.1% of the variance in academic boredom is explained by cognitive load, while 60.8% of the variance in learning outcomes is explained by cognitive load and academic boredom. These findings are further supported by the analysis of indirect and total effects, as reported in Table 6.

Table 6. Results of Indirect and Total Effects

Construct Relationship	Indirect Effect (β)	Standard error	t-statistic	p-value	Total effect (β)	Standard error	t-statistic	p-value
Academic boredom → Learning Outcome	-	-	-	-	-0.410	0.081	5.074	0.000
Cognitive load → Academic Boredom	-	-	-	-	0.641	0.053	12.176	0.000
Cognitive load → Learning Outcome	-0.263	0.059	4.426	0.000	-0.714	0.039	18.191	0.000

The mediation analysis shows that cognitive load has a significant indirect effect on learning outcomes through academic boredom ($\beta = -0.263$; $t = 4.426$; $p < 0.001$). The total effect of cognitive load on learning outcomes is also significant ($\beta = -0.714$; $p < 0.001$). These results indicate that academic boredom functions as a partial mediator, meaning that cognitive load influences learning outcomes both directly and indirectly through students' emotional responses.

Table 7. Result of Coefficient of Determination (R^2), Predictive Relevance (Q^2), Variance Inflation Factor (VIF), and Effect Size (f^2)

Construct	R^2	Q^2	Construct Relationship	VIF	f^2
Academic Boredom	0.411	0.397	Academic boredom → Learning Outcome	1.698	0.253
Cognitive Load	0.608	0.499	Cognitive load → Academic Boredom	1.000	0.698
Learning Outcome	-	-	Cognitive load → Learning Outcome	1.698	0.306

The R^2 values indicate that 41.1% of the variance in academic boredom and 60.8% of the variance in learning outcomes are explained by the model. The Q^2 values are positive, indicating acceptable predictive relevance. VIF values below 5 indicate no multicollinearity issues. The large effect size of cognitive load on academic boredom ($f^2 = 0.698$) shows that cognitive burden is a dominant factor influencing students' emotional experience during learning. The SRMR value of 0.046 (< 0.08) indicates a good model fit.

A comparison between groups shows a consistent pattern in the relationship between cognitive load and academic boredom, as well as between academic boredom and learning outcomes. A key difference appears in the direct relationship between cognitive load and learning outcomes. The effect is not significant in the experimental group, while it remains significant in the control group. This result suggests that worked example-based instruction reduces the direct negative impact of cognitive load on learning outcomes by restructuring how students process information.

Table 8. Comparison of Path Coefficients between Experimental and Control Groups

Worked Example	Construct Relationship	β (Original Sample)	Standard Error	t-statistic	p-values
Experiment	Academic boredom → Learning Outcome	-0.399	0.131	3.043	0.002
	Cognitive load → Academic Boredom	0.467	0.097	4.797	0.000
	Cognitive load → Learning Outcome	-0.270	0.142	1.908	0.056
Control	Academic boredom → Learning Outcome	-0.311	0.130	2.391	0.017
	Cognitive load → Academic Boredom	0.388	0.084	4.631	0.000
	Cognitive load → Learning Outcome	-0.368	0.113	3.263	0.001

Table 9. Comparison of Indirect and Total Effects between Experimental and Control Groups

	Construct Relationship	Indirect Effect (β)	Standard error	t-statistic	p-value	Total effect (β)	Standard error	t-statistic	p-value
Experiment	Academic boredom → Learning Outcome	-	-	-	-	-0.399	0.131	3.043	0.002
	Cognitive load → Academic Boredom	-	-	-	-	0.467	0.097	4.797	0.000
	Cognitive load → Learning Outcome	-0.187	0.084	2.218	0.027	-0.457	0.093	4.922	0.000
Control	Academic boredom → Learning Outcome	-	-	-	-	-0.311	0.130	2.391	0.017
	Cognitive load → Academic Boredom	-	-	-	-	0.388	0.084	4.631	0.000
	Cognitive load → Learning Outcome	-0.120	0.062	1.942	0.052	-0.488	0.077	6.320	0.000

The mediation analysis conducted for each group reveals different mechanisms. The experimental group shows a significant indirect effect through academic boredom, while the direct effect is not significant. The control group shows the opposite pattern, where the direct effect remains significant, and the indirect effect is not. This pattern indicates that worked example-based instruction shifts the influence of cognitive load into an indirect pathway mediated by students' emotional engagement.

44

3.2. Discussion

The first hypothesis, which proposes that cognitive load positively influences academic boredom, is supported by the existing literature. High cognitive load constrains working memory capacity, resulting in less efficient information processing. This mechanism is consistent with Cognitive Load Theory, which suggests that cognitive overload may trigger negative affective responses in learning contexts [5]. Similarly, [12] reported that increased intrinsic load during problem solving is associated with greater cognitive pressure. These findings reinforce the argument that cognitive strain serves as an important antecedent of academic boredom.

52 The second hypothesis, regarding the negative effect of cognitive load on learning outcomes, was also supported by the structural model. Excessive cognitive load hinders the integration of new information into existing knowledge schemas. This pattern is consistent with the findings [23], which emphasised that learning environments characterised by high cognitive demands tend to result in lower problem-solving performance. Furthermore, [1] demonstrated that instructional designs that fail to manage task complexity effectively can weaken students' conceptual representations. Collectively, these findings underscore the importance of optimising cognitive load to enhance mathematics learning outcomes.

40 The third hypothesis, which proposes that academic boredom negatively affects learning outcomes, is also supported. Academic boredom can lead to cognitive disengagement, limiting students' willingness to allocate mental resources to conceptual understanding. These findings are consistent with [24], who reported a relationship between negative affective states in mathematics learning and lower academic achievement. Similarly, [25] argued that monotonous and insufficiently challenging learning experiences are associated with reduced motivation and performance. The present study, therefore, reinforces the view that academic boredom constitutes a significant affective factor in explaining variations in learning outcomes.

29 The fourth hypothesis, concerning the mediating role of academic boredom in the relationship between cognitive load and learning outcomes, was also supported by a significant indirect effect. This mechanism indicates that cognitive load influences learning outcomes not only directly but also indirectly through affective pathways. These findings align with [26], who emphasised the interplay between cognitive and emotional regulation in problem-based learning. Likewise, [27] demonstrated that incorporating emotional dimensions into instructional design enhances learning effectiveness. 9 A key contribution of this study lies in validating the mediation model within the context of worked example-based mathematics instruction.

The fifth hypothesis, concerning the effectiveness of worked examples in the experimental group, is supported by a more stable pattern of relationships compared to the control group. Worked examples provide an initial framework that reduces unstructured problem exploration and facilitates systematic step-by-step processing. These findings are consistent with [5], who demonstrated the worked example effect on mathematics retention and transfer. Similarly, [28] reported that structured examples enhance the cognitive efficiency of secondary school students. This study extends the existing literature by highlighting the structural implications of worked examples within the cognitive-affective pathway.

A deeper examination of the group differences reveals that the structured nature of worked examples plays a critical role in shaping how cognitive load is processed. In the experimental group, students are guided through organised solution steps, which reduces unnecessary cognitive burden and allows cognitive resources to be allocated more efficiently. In contrast, students in the control group rely more heavily on unguided problem-solving, which increases the likelihood of cognitive overload and fragmented understanding. This difference explains why the direct effect of cognitive load on learning outcomes weakens in the experimental group while remaining strong in the control group.

The sixth hypothesis, regarding differences in relationship patterns between the experimental and control groups, also yielded noteworthy results. In the experimental group, the indirect effect became more prominent, whereas in the control group, the direct effect of cognitive load on learning outcomes remained strong. This pattern aligns with [29], who found that non-scaffolded approaches increase reliance on internal cognitive resources. [30] further emphasized that conventional instructional methods often impose higher mental demands without sufficient regulatory support. Collectively, these findings reinforce the role of worked examples as an effective strategy for mitigating cognitive load.

These contrasting patterns indicate that instructional design does not merely reduce cognitive load but also transforms the pathway through which learning occurs. The worked example approach shifts the influence of cognitive load from a direct constraint on performance into an indirect process mediated by students' affective responses. This shift highlights the importance of considering both cognitive efficiency and emotional engagement in explaining learning outcomes.

The worked example design implemented in this study aligns with contemporary perspectives on example-based learning. [12] argued that combining problem-solving activities with direct instruction promotes meaningful conceptual and procedural differentiation. Providing worked examples prior to independent problem exploration allows students to develop more stable mental models. The present findings further support the effectiveness of this approach in mathematics education, a domain that requires both procedural accuracy and deep conceptual understanding.

In the early stages of learning, reducing cognitive load is essential to prevent mental strain. [5] suggested that worked examples decrease cognitive load at each stage of problem-solving, particularly in tasks with high element interactivity. This mechanism helps explain the stronger mediating effect observed in the experimental group compared to the control group. The current study extends Chen's work by incorporating academic boredom as an additional mediator within the structural model.

The affective dimension of mathematics learning often remains overlooked in instructional design. In a study conducted by [31], the impact of high-quality learning experiences on students' emotional engagement was a central focus. Similarly, [32] found that structured instruction enhances self-regulation and motivational stability. The integration of worked examples in the present study demonstrates that cognitive stabilisation can simultaneously promote affective stabilisation.

The novelty of this study lies in the integration of cognitive and affective dimensions within a single structural framework. Unlike previous studies that tend to examine cognitive load or emotional factors separately, this study demonstrates how both dimensions interact dynamically to influence learning outcomes. The findings suggest that the effectiveness of worked examples extends beyond cognitive optimisation, as they also contribute to reducing negative emotional states such as boredom. This integrated perspective provides a more comprehensive explanation of how instructional design impacts student learning.

The theoretical contribution of this study lies in the integration of Cognitive Load Theory, the worked example effect, and academic boredom into a single empirically tested structural model. This model illustrates the dynamic interplay between cognitive and affective variables in shaping mathematics learning outcomes. Previous studies have tended to examine cognitive and affective dimensions separately, as reflected in the works of [33] and [34]. The present findings extend this body of research by demonstrating that instructional effectiveness is achieved through the simultaneous regulation of cognitive demands and emotional experiences, rather than through cognitive mechanisms alone. These findings provide practical guidance for teachers to design mathematics instruction that balances structured guidance with opportunities for independent practice, thereby supporting both cognitive efficiency and students' emotional engagement.

4. CONCLUSION

The present study demonstrates that worked example-based instructional design has an important role in regulating cognitive load and supporting students' emotional experiences in mathematics learning. Cognitive load was shown to have both a direct effect on academic achievement and an indirect effect through emotional factors, especially academic boredom. The findings suggest that learning effectiveness is shaped not only by cognitive aspects but also by the interaction between the management of mental effort and students' affective involvement. The proposed structural model provides a broader perspective on how instructional design can enhance learning by combining cognitive and emotional elements.

This study makes a key contribution by expanding the Cognitive Load Theory framework through the inclusion of academic boredom as a mediating factor in the context of worked example-based learning in mathematics education. From a practical standpoint, the results imply that instructional strategies need to carefully regulate task complexity to avoid excessive cognitive burden and reduced emotional engagement. Further studies are recommended to test this model in various educational contexts and disciplines, as well as to incorporate other affective factors such as anxiety or motivation to deepen the understanding of learning processes based on instructional design.

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