Jurnal Pendidikan Progresif
e-ISSN: 2550-1313 | p-ISSN: 2087-9849
URL: https://jpp.fkip.unila.ac.id/index.php/jpp
Jounal's DOI: http://doi.org/10.23960/jpp

Vol. 16, No. 2, 2026
Article ID: 1741
Pages: 1156-1180

The Example-Based Cognitive Load Control Learning Model to Improve the Effectiveness of Biotechnology Learning

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Received: 24 April 2026 *Accepted: 09 June 2026* *Published: 27 June 2026*

Abstract: Biotechnology learning is often perceived as abstract, complex, and cognitively demanding, which may increase students' cognitive load and hinder meaningful learning. This study aimed to develop, validate, and evaluate the effectiveness of the Example-Based Cognitive Load Control (EBCLC) Learning Model as an instructional model designed to regulate cognitive load and improve biotechnology learning among prospective biology teachers. This study employed a mixed-methods approach within a research and development (R&D) framework. The qualitative phase involved observations, interviews, and document analysis to identify learning difficulties and instructional needs in biotechnology education. The findings informed the development of the EBCLC model. Subsequently, the model was validated by experts and evaluated through a quantitative pre-experimental one-group pretest–posttest design involving 22 prospective biology teachers. Effectiveness was assessed using mental effort ratings and information-processing performance. Data were analyzed using descriptive statistics and paired-sample t-tests. The results showed that the EBCLC model effectively reduced extraneous cognitive load, as indicated by consistently low mental effort scores across 11 biotechnology topics (mean range: 1.33–1.63). Information-processing performance remained high (mean range: 70.30–92.40), indicating effective engagement with complex biotechnology concepts. Furthermore, posttest scores ($M = 78.27$) were significantly higher than pretest scores ($M = 71.27$), indicating an average gain of 7.00 points. The paired-samples t-test revealed a statistically significant improvement, $t(21) = 9.92$, $p < .001$, with a very large effect size (Cohen's $d = 2.12$). The EBCLC model offers a novel instructional synthesis that integrates worked-example principles, guided cognitive processing, and multimodal representations into a structured learning sequence explicitly designed to regulate cognitive load. Unlike conventional worked-example approaches that primarily focus on schema acquisition, the EBCLC model incorporates progressive cognitive guidance and staged information processing to support conceptual understanding of complex biotechnology topics. These findings contribute to the refinement of Cognitive Load Theory and provide an innovative framework for biotechnology instruction in higher education.

Keywords: biotechnology learning, cognitive load, EBCLC, modeling examples, prospective biology teachers.

Article's DOI: https://doi.org/10.23960/jpp.v16i2.pp1156-1180

INTRODUCTION

Biotechnology has become one of the most rapidly advancing scientific fields of the twenty-first century, contributing significantly to developments in healthcare, agriculture, environmental sustainability, food production, and industrial innovation (Joseph et al., 2023; Treanor et al., 2021). As biotechnology continues to influence modern society, educational institutions are increasingly expected to prepare scientifically literate graduates capable of understanding, evaluating, and communicating about biotechnology-related issues. Consequently, biotechnology has become an essential component of biology teacher education programs because prospective biology teachers must not only master biotechnology concepts but also facilitate students' understanding of contemporary scientific developments and their societal implications (Riandi et al., 2022; Sparks et al., 2020).

The importance of biotechnology education is further strengthened by its interdisciplinary nature. Biotechnology integrates concepts from genetics, molecular biology, microbiology, biochemistry, environmental science, and technological innovation, enabling learners to understand how biological knowledge can be applied to solve real-world problems (Wells & Van de Velde, 2020; Riandi et al., 2022). Recent educational trends have emphasized the importance of integrating science, technology, engineering, and mathematics (STEM) perspectives into biotechnology learning to foster scientific literacy, critical thinking, and problem-solving skills required in the twenty-first century (Kulshreshtha et al., 2022; Bardoe et al., 2023; Nurdin et al., 2025). Bibliometric evidence also indicates a growing international interest in biotechnology education and its integration into science teaching practices, highlighting the need for effective instructional approaches that support meaningful learning and conceptual understanding (Riandi et al., 2022; Gürkan & Kahraman, 2022).

Despite its importance, biotechnology remains one of the most challenging topics in biology education. Many biotechnology concepts involve abstract mechanisms and processes occurring at molecular and cellular levels that cannot be directly observed. Students are often required to interpret symbolic representations, visualize microscopic phenomena, and integrate information from multiple biological domains simultaneously. These characteristics make learning biotechnology cognitively demanding and often lead to difficulties in conceptual understanding (Mercado & Picardal, 2023; Sparks et al., 2020). A systematic review by Mercado and Picardal (2023) found that biotechnology learning often requires extensive visualization support, as students struggle to understand abstract biological processes that are inaccessible through direct observation. Similar findings have been reported across science education research, where conceptual complexity, multiple representations, and interdisciplinary knowledge integration are recognized as major barriers to meaningful learning (Costa et al., 2020; Bauer et al., 2020).

These challenges become even more significant in teacher education programs because prospective biology teachers are expected not only to understand biotechnology concepts but also to transform them into meaningful learning experiences for future students. Effective teaching requires integrating content mastery, pedagogical competence, scientific reasoning, and the ability to facilitate students' conceptual development (Shulman, 1986; Bauer et al., 2020). Therefore, difficulties in understanding biotechnology concepts during teacher preparation may negatively affect future instructional quality and students' opportunities to develop scientific literacy.

Given these challenges, improving the quality of biotechnology instruction has become an important concern in biology education research. Effective learning environments should facilitate conceptual understanding, support knowledge construction, and provide appropriate scaffolding for processing complex information. Consequently, there is a growing need for instructional approaches that can help prospective biology teachers learn biotechnology concepts more effectively while promoting deeper understanding, critical thinking, and long-term knowledge retention (Wells & Van de Velde, 2020; Nurdin et al., 2025; Costa et al., 2020).

The complexity of biotechnology learning highlights the importance of understanding how learners process information during instruction. Learning complex scientific concepts requires students to simultaneously process multiple sources of information, integrate prior knowledge with new information, and construct coherent mental representations. When instructional demands exceed the capacity of working memory, learning efficiency may decline, resulting in increased cognitive burden and reduced conceptual understanding (Sweller et al., 2019; Sweller, 2020; Kalyuga & Plass, 2025).

Cognitive Load Theory (CLT) has emerged as one of the most influential theoretical frameworks for explaining the relationship between instructional design and learning effectiveness. Originally developed by Sweller, the theory is grounded in the assumption that human cognitive architecture consists of a limited working memory and a virtually unlimited long-term memory. Learning occurs when information is successfully processed in working memory and organized into schemas stored in long-term memory (van Merriënboer & Sweller, 2005; Plass et al., 2010; Sweller, 2023). Consequently, instructional designs that fail to consider cognitive limitations may hinder learning by imposing excessive cognitive demands on learners (Kirschner, 2002; Ayres & Paas, 2012).

According to Cognitive Load Theory, learners experience different sources of cognitive demand during learning activities. Among these, extraneous cognitive load is particularly influenced by instructional design and can be reduced through well-structured learning materials and appropriate instructional support. Therefore, instructional approaches that minimize unnecessary cognitive demands are expected to facilitate more efficient learning processes. Extraneous cognitive load arises from ineffective instructional design and unnecessary cognitive activities that do not directly contribute to learning. Germane cognitive processing refers to the cognitive effort devoted to schema construction and meaningful learning (Plass et al., 2010; Sweller et al., 2019; Kalyuga, 2022). Among these components, extraneous cognitive load is considered particularly important because it can be reduced through appropriate instructional interventions, thereby allowing learners to allocate more cognitive resources to meaningful information processing (Leppink & Hanham, 2019; Sweller, 2020).

Recent developments in Cognitive Load Theory have emphasized that effective instructional design should not merely present information but should actively regulate cognitive demands placed on learners. Studies across various educational domains, including online learning, mathematics education, computing education, and multimedia learning, have demonstrated that excessive cognitive load negatively affects learning performance, conceptual understanding, and knowledge retention (Kalyuga, 2022; Duran et al., 2022; Adhikari & Anbuchelvan, 2025). Conversely, instructional approaches aligned with CLT principles have been shown to improve learning efficiency by reducing unnecessary cognitive processing while supporting schema acquisition and knowledge integration (Sweller, 2020; Chen & Kalyuga, 2019; Maharana & Binjha, 2025).

The relevance of Cognitive Load Theory becomes particularly evident in biotechnology education. Biotechnology concepts often involve abstract molecular mechanisms, multiple levels of biological organization, symbolic representations, and the integration of interdisciplinary knowledge. These characteristics require learners to process substantial amounts of information simultaneously, increasing the likelihood of cognitive overload. Furthermore, when biotechnology concepts are presented through fragmented explanations, disconnected visualizations, or poorly structured instructional materials, students may experience increased extraneous cognitive load that interferes with conceptual understanding (Mercado & Picardal, 2023; Nurdin et al., 2025).

For prospective biology teachers, managing cognitive load is especially important because they must not only understand biotechnology concepts but also develop pedagogical knowledge to teach them effectively. Therefore, instructional models designed for biotechnology education should explicitly consider cognitive load regulation as a central design principle. Such models should minimize unnecessary cognitive burden while supporting students in constructing meaningful conceptual understanding of complex phenomena in biotechnology.

One instructional approach consistently associated with cognitive load reduction is example-based learning. Within the framework of Cognitive Load Theory, worked and modeling examples are instructional strategies that demonstrate how to solve a problem or perform a task through explicit, structured guidance. Rather than requiring learners to engage immediately in independent problem solving, example-based instruction provides step-by-step demonstrations that allow students to observe expert reasoning processes and develop appropriate cognitive schemas before attempting tasks independently (Renkl et al., 2009; van Merriënboer & Sweller, 2005).

The effectiveness of worked examples has been extensively documented across various educational contexts. Research has shown that example-based learning can reduce unnecessary cognitive processing, improve conceptual understanding, facilitate schema acquisition, and enhance learning efficiency, particularly among novice learners who possess limited prior knowledge (Sweller et al., 2019; Sweller, 2020; Renkl et al., 2009). By reducing the need for trial-and-error problem-solving activities, worked examples allow learners to devote more cognitive resources to understanding underlying concepts and relationships among information elements (Ayres & Paas, 2012; Kalyuga, 2011). Empirical studies in science education have demonstrated that worked examples support students' acquisition of scientific concepts, inquiry skills, and scientific reasoning in domains such as biology, chemistry, and science process learning (Meier et al., 2008; Yu & Klein, 2014; Solé-Llussà et al., 2020; Mara et al., 2021). Recent evidence further suggests that worked examples can positively influence learning performance while reducing unnecessary cognitive load during complex learning tasks.

Recent developments in instructional design have extended traditional worked examples into more dynamic forms of modeling examples. In this approach, learners are not only presented with completed solutions but are also exposed to the cognitive processes, reasoning strategies, and decision-making procedures demonstrated by experts. Such instructional support has been found to facilitate deeper understanding, improve learning transfer, and strengthen learners' ability to construct meaningful knowledge structures (Renkl et al., 2009; Sweller, 2023). For example, video-worked examples have been shown to support the development of science process skills through guided observation and modeling of scientific reasoning, while scaffolded worked examples can improve students' understanding of size, scale, and scientific reasoning in secondary science learning. These advantages are particularly relevant for biotechnology education, where students must integrate complex conceptual information and understand relationships among multiple biological processes.

Despite these advantages, previous studies have generally focused on examining the effectiveness of worked examples or modeling examples as isolated instructional strategies. Most investigations have evaluated their impact on learning outcomes, conceptual understanding, problem-solving skills, or cognitive load in specific learning situations (Renkl et al., 2009; Sweller et al., 2019; Solé-Llussà et al., 2020; Mara et al., 2021). More recent studies have also explored variations, such as erroneous and technology-supported worked examples, demonstrating their potential to enhance learning and regulate cognitive load. However, relatively few studies have developed a comprehensive instructional model that systematically integrates example-based learning with explicit cognitive load regulation throughout the entire learning process.

Furthermore, existing worked-example approaches primarily emphasize schema acquisition through observation and imitation of solution procedures. Although these approaches effectively reduce cognitive load, they often offer limited guidance on how learners should progressively process information, construct conceptual understanding, and transition from guided learning to independent knowledge construction. This limitation is particularly relevant in biotechnology education, where conceptual complexity requires sustained cognitive support that goes beyond mere observation of examples. Therefore, the present study proposes the Example-Based Cognitive Load Control (EBCLC) Learning Model, which systematically combines example-based instruction with explicit cognitive load regulation strategies throughout the learning process.

Therefore, there is a need for a more comprehensive instructional framework that not only utilizes examples as learning resources but also systematically regulates cognitive load throughout the learning process. Such a framework should integrate example observation, guided cognitive processing, knowledge construction, and reflective reinforcement within a coherent sequence of learning activities. Through this integration, cognitive load regulation becomes an explicit design principle rather than merely an indirect consequence of example-based instruction.

Although previous studies have demonstrated the effectiveness of biotechnology-related instructional innovations, important gaps remain in the literature. Research in biotechnology education has primarily focused on integrating technology-enhanced learning environments, virtual laboratories, STEM-based instruction, differentiated learning approaches, and innovative pedagogical practices to improve conceptual understanding and scientific literacy (Mercado & Picardal, 2023; Kulshreshtha et al., 2022; Nurdin et al., 2025). At the same time, studies grounded in Cognitive Load Theory have consistently shown that instructional design plays a critical role in regulating learners' cognitive processing and improving learning effectiveness (Sweller et al., 2019; Kalyuga, 2022; Sweller, 2020). However, these two streams of research have largely developed independently.

Similarly, research on worked examples and modeling examples has reported positive effects on conceptual understanding, problem-solving performance, and cognitive load reduction across various educational domains (Renkl et al., 2009; Sweller et al., 2019). Nevertheless, most of these studies have examined example-based learning as a specific instructional strategy rather than as a comprehensive instructional model. Existing studies generally focus on the effectiveness of examples in supporting schema acquisition and learning performance, while providing limited attention to how cognitive load can be systematically regulated throughout an entire learning sequence. As a result, there remains a lack of instructional models that explicitly integrate example-based learning with cognitive load control principles within a coherent and structured pedagogical framework.

This limitation is particularly evident in biotechnology education. Although learning in biotechnology is characterized by conceptual complexity, multiple representations, and substantial cognitive demands, few studies have developed instructional models specifically designed to manage learners' cognitive load while supporting conceptual understanding in biotechnology contexts. Furthermore, the literature provides limited evidence on how example-based instructional principles can be operationalized across sequential learning stages that guide learners from observing examples to independent knowledge construction while maintaining optimal cognitive processing.

To address these gaps, this study develops the Example-Based Cognitive Load Control (EBCLC) Learning Model. The novelty of the EBCLC model does not lie solely in the use of worked examples, since example-based instruction has long been recognized as an important component of Cognitive Load Theory. Rather, the model introduces a structured instructional framework that systematically integrates example observation, guided cognitive processing, learner-generated model construction, and reflective reinforcement into a unified learning sequence explicitly designed to regulate cognitive load. Through this design, cognitive load regulation becomes a central instructional principle embedded across all learning stages, rather than an incidental outcome of exposure to examples.

Accordingly, this study aims to: (1) develop and validate the EBCLC Learning Model for biotechnology learning; (2) examine students' extraneous cognitive load during the implementation of the EBCLC Learning Model; and (3) evaluate the effectiveness of the EBCLC model in improving biotechnology learning among prospective biology teachers.

Based on these objectives, the study addresses the following research questions: RQ1: How can the Example-Based Cognitive Load Control (EBCLC) Learning Model be developed and validated for biotechnology learning?; RQ2: To what extent does the EBCLC model reduce students' extraneous cognitive load during biotechnology learning?; RQ3: How effective is the EBCLC model in improving learning outcomes among prospective biology teachers?

Based on the theoretical assumptions of Cognitive Load Theory and example-based learning, the study proposes the following hypothesis: H1: The implementation of the EBCLC Learning Model significantly reduces extraneous cognitive load during biotechnology learning. H2: The implementation of the EBCLC Learning Model significantly improves students' biotechnology learning outcomes.

■ METHOD

Participants

This study involved prospective biology teachers enrolled in a Biotechnology course at a university in Indonesia during the 2025/2026 academic year. The population consisted of all students registered in the Biotechnology course. A purposive sampling technique was employed because the participants met the specific criteria required to implement and evaluate the Example-Based Cognitive Load Control (EBCLC) Learning Model. The inclusion criteria were: (1) enrollment in the Biotechnology course during the study period, (2) attendance in all intervention sessions, and (3) completion of both pretest and posttest assessments. Based on these criteria, 22 prospective biology teachers were selected as research participants.

All participants were enrolled in the same Biotechnology course and had previously

Table 1. Demographic characteristics of participants (n=22)

Variable	Category	n	%
Gender	Female	18	81.8
	Male	4	18.2
Academic Year	3rd Year	22	100
Completed Basic Genetics	Yes	22	100
Completed Cell Biology	Yes	22	100

completed Genetics and Cell Biology courses, ensuring comparable prior knowledge before the intervention.

For the qualitative phase, participants included students enrolled in the Biotechnology course and lecturers who taught it. These participants were purposively selected to provide in-depth information on learning difficulties, instructional challenges, and learning needs related to biotechnology. The qualitative findings served as the foundation for developing the EBCLC learning model.

Research Design and Procedures

This study employed a mixed-methods approach within a Research and Development (R&D) framework. The integration of qualitative and quantitative approaches was intended to support both the development and preliminary evaluation of the Example-Based Cognitive Load Control (EBCLC) Learning Model. The study was conducted over three months, from October to December 2025.The research was carried out through four sequential phases.

Phase 1: Needs analysis

The first phase aimed to identify learning difficulties and instructional needs in biotechnology education. Data were collected through classroom observations, semi-structured interviews with students and lecturers, and analysis of course-related documents. The findings from this phase were analyzed to identify challenges associated with biotechnology learning, particularly those related to conceptual complexity and students' learning experiences.

Phase 2: Model development

Based on the findings of the needs analysis, the Example-Based Cognitive Load Control (EBCLC) Learning Model was developed. The model design was informed by Cognitive Load Theory and principles of example-based learning. The resulting model consisted of four instructional stages: (1) Model Observation, (2) Guided Processing, (3) Model Construction, and (4) Reflection and Reinforcement.

Phase 3: Expert validation

The developed model was subsequently evaluated by experts in biology education and instructional design. Expert validation focused on assessing the theoretical relevance, internal consistency, instructional feasibility, clarity of syntax, social system, reaction principles, and expected instructional impacts of the model. Feedback from the validators was used to refine and improve the model prior to implementation.

Phase 4: Model implementation and evaluation

The validated EBCLC model was implemented in biotechnology education across 11 topics. A pre-experimental one-group pretest–posttest design was employed to conduct a preliminary evaluation of the model's effectiveness. Prior to the intervention, students completed a pretest to assess their initial understanding of biotechnology concepts. Following the implementation of the EBCLC model, students completed a posttest, mental effort assessments, and learning performance tasks. Data from these measures were used to evaluate the model's effectiveness in supporting learning and regulating students' cognitive processing.

Although the one-group pretest–posttest design has limitations in controlling potential confounding variables and does not provide the same level of internal validity as experimental or quasi-experimental designs, it was considered appropriate for the preliminary evaluation of a newly developed instructional model. Therefore, causal interpretations of the findings should be made cautiously, and further studies employing comparison or control groups are recommended.

Instruments

Four instruments were employed in this study to collect qualitative and quantitative data.

Learning needs analysis instruments

The qualitative phase utilized classroom observation sheets, semi-structured interview protocols, and document analysis forms. These instruments were developed to identify students' learning difficulties, instructional challenges, and learning needs in biotechnology education. The interview protocol included questions related to conceptual difficulties, learning experiences, instructional strategies, and students' perceptions of biotechnology learning.

Mental effort scale (extraneous cognitive load)

Extraneous cognitive load was measured using a Mental Effort Rating Scale adapted from Paas (1992). The instrument consists of a single-item subjective rating scale ranging from 1 to 10, where higher scores indicate greater mental effort required to understand the learning material. To improve response consistency and minimize ambiguity in interpreting the scale, anchor descriptors were provided at key points: 1 = very low mental effort, 5 = moderate mental effort, and 10 = extremely high mental effort. Students completed the mental effort scale at the end of each biotechnology learning session. In Cognitive Load Theory, mental effort ratings are widely used as indicators of extraneous cognitive load because they reflect the amount of cognitive resources required to process instructional information (Paas, 1992; Sweller et al., 2019).

Information processing performance instrument

Students' information processing performance was assessed using Student Worksheets (LKM) designed for each biotechnology topic. The worksheets measured students' ability to identify, analyze, organize, and apply biotechnology concepts during learning activities. Each worksheet was scored using a detailed analytic rubric with a score range of 0–100, where higher scores indicate better performance in processing and applying biotechnology-related information. All worksheets were evaluated by a single lecturer using the analytic rubric. Prior to scoring, the rubric descriptors were reviewed, refined, and calibrated through pilot assessment sessions to ensure scoring consistency across all student work. The information processing performance score was used as an indicator of students' success in understanding, organizing, and applying biotechnology concepts during learning activities. Higher scores reflected more effective information processing and conceptual understanding during the learning process.

Reflection journal assessment

To evaluate students' engagement in the Reflection and Reinforcement stage of the EBCLC model, students completed a brief reflection journal at the end of each learning session. The journal required students to summarize key concepts learned, identify misconceptions or difficulties encountered during learning, and describe how their understanding had changed following the instructional activities. Reflection journals were evaluated using an analytic rubric that assessed conceptual understanding, identification of misconceptions, and integration of knowledge.

Model validation instrument

The feasibility of the EBCLC Learning Model was evaluated through an expert-validation questionnaire adapted from instructional model development frameworks. The validation instrument assessed: Theoretical

Table 2. Reflection journal assessment rubric

Aspect	Score 1 (Low)	Score 2 (Moderate)	Score 3 (High)
Conceptual Understanding	Demonstrates limited understanding of concepts	Demonstrates adequate understanding of concepts	Demonstrates comprehensive understanding of concepts
Identification of Misconceptions	Unable to identify misconceptions or learning difficulties	Identifies some misconceptions or difficulties	Clearly identifies misconceptions and explains how they were resolved.
Knowledge Integration	Shows weak connections among concepts	Demonstrates partial integration of concepts	Demonstrates strong integration of concepts and learning experiences

relevance, Consistency of model components, Clarity of instructional syntax, Social system, Principle of reaction, Support system, Expected instructional impact, Practicality of implementation.

Experts rated each indicator using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The model was evaluated by three experts, including two senior biology education professors and one instructional design specialist with more than 10 years of experience in curriculum development and higher education teaching. Content validity was quantified using Aiken's V coefficient. The overall Aiken's V value ranged from 0.86 to 0.94 across indicators, indicating high content validity.

Validity and Reliability

Content validity was established through expert judgment involving specialists in biology education and instructional design. Suggestions from validators were incorporated into revisions to the instrument and the EBCLC model. Instrument reliability was assessed using Cronbach's Alpha coefficient. Following Hair et al. (2010), a Cronbach's Alpha value of 0.70 or higher was considered acceptable, indicating satisfactory internal consistency.

Data Analysis

Data analysis was conducted using both qualitative and quantitative techniques in accordance with the mixed-methods research framework.

Qualitative data analysis

Qualitative data obtained from classroom observations, semi-structured interviews, and document analysis were analyzed using thematic analysis procedures proposed by Braun and Clarke (2006). The analysis involved six stages: (1) familiarization with the data, (2) generation of initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the final report. The findings from this phase were used to identify learning difficulties and instructional needs, which subsequently informed the development of the Example-Based Cognitive Load Control (EBCLC) Learning Model.

Quantitative data analysis

Quantitative data consisted of mental effort scores, information processing performance scores, and students' learning outcome scores. Data analysis was performed using descriptive and inferential statistics. Descriptive statistics, including mean, standard deviation, minimum score, and maximum score, were calculated to describe students' cognitive processing and learning performance during the implementation of the EBCLC model. Extraneous cognitive load was analyzed using students' mental effort ratings collected after each biotechnology learning session. The mean mental effort scores were interpreted according to the cognitive load categories proposed by Paas (1992), where lower scores indicate lower extraneous cognitive load.

Information Processing Performance (IPP) was analyzed using students' worksheet (LKM) scores obtained across eleven biotechnology topics. The scores were used to describe students' ability to process, analyze, and apply biotechnology concepts during learning activities. To evaluate the effectiveness of the EBCLC model in improving learning outcomes, a paired-samples t-test was conducted to compare students' pretest and posttest scores. The paired-samples t-test was selected because the study involved repeated measurements of the same participants before and after the intervention (Field, 2013).

Prior to conducting inferential analysis, the normality of the score distribution was examined using the Shapiro–Wilk test. A significance value greater than 0.05 indicated that the assumption of normality was satisfied. In addition to statistical significance testing, effect size analysis was conducted using Cohen's d to determine the magnitude of the intervention effect. The interpretation of Cohen's d followed Cohen (1988): 0.20 = small effect, 0.50 = medium effect, and 0.80 or above = large effect. All statistical analyses were performed at a significance level of á = 0.05.

■ RESULT AND DISCUSSION

Development and Validation of the EBCLC Learning Model (RQ1)

Findings from the needs analysis

The qualitative phase aimed to identify learning difficulties and instructional needs in biotechnology education to inform the development of the Example-Based Cognitive Load Control (EBCLC) Learning Model. Thematic analysis of classroom observations, interviews, and document analysis generated three major themes: (1) difficulties in understanding abstract biotechnology concepts, (2) challenges in integrating information from multiple learning resources, and (3) the need for structured instructional guidance.

Document analysis included course syllabi, previous examination papers, student worksheets, and laboratory reports. The analysis revealed that assessment tasks predominantly emphasized factual recall and procedural knowledge, while opportunities for guided conceptual integration were limited. These findings supported the need for an instructional model that provides structured cognitive support during biotechnology learning.

1. Theme 1: difficulties in understanding abstract biotechnology concepts

The first theme revealed that students had difficulty understanding biotechnology concepts because many topics involve molecular processes, genetic mechanisms, and cellular interactions that cannot be directly observed. Topics such as recombinant DNA technology, tissue culture, and genetic engineering were frequently perceived as abstract and difficult to visualize. Classroom observations indicated that students often required repeated explanations and additional visual representations to understand these concepts.

The interview data further confirmed these findings. One student explained, "I often understand the general idea of genetic engineering, but I find it difficult to visualize what actually happens at the molecular level" (Student 7, Interview Transcript). This statement indicates that although students may grasp the general concepts, they encounter difficulties understanding the underlying molecular mechanisms of biotechnology processes.

Similarly, another student stated, "The biotechnology concepts are connected to many other biology subjects, and sometimes I get confused when trying to combine all the information" (Student 12, Interview Transcript). This finding suggests that students struggle not only with the abstract nature of biotechnology concepts but also with integrating knowledge from multiple biological disciplines, including genetics, microbiology, molecular biology, and biochemistry.

Taken together, these findings indicate that biotechnology learning imposes substantial cognitive demands on learners due to the complexity of the concepts and the need to integrate multiple interconnected knowledge domains. Such challenges highlight the importance of instructional approaches that provide cognitive support and facilitate conceptual visualization.

2. Theme 2: Challenges in integrating information from multiple sources

The second theme concerned students' difficulties in organizing and integrating information obtained from lectures, textbooks, scientific articles, and learning media. Biotechnology learning requires students to connect concepts from genetics, microbiology, molecular biology, and biochemistry simultaneously. Analysis of learning activities showed that students often understood individual concepts but experienced difficulties connecting them into a coherent conceptual framework. This condition potentially increased cognitive demands during learning.

3. Theme 3: Need for structured instructional guidance

The third theme highlighted the importance of structured instructional support in biotechnology learning. Classroom observations showed that students frequently encountered difficulties when asked to independently analyze biotechnology cases or solve complex conceptual problems without prior guidance. Learning activities that provided examples, demonstrations, and step-by-step explanations appeared to facilitate students' understanding and reduce confusion during the learning process.

Evidence from lecturer interviews supported these observations. One lecturer noted, "Students usually perform better when examples are provided first. Without structured guidance, many struggle to analyze biotechnology cases independently" (Lecturer 1, Interview Transcript). This statement suggests that students benefit from instructional approaches that gradually scaffold learning before requiring independent problem-solving and conceptual analysis.

The findings indicate that the absence of structured guidance may increase unnecessary cognitive burden, particularly when students are confronted with complex biotechnology concepts and unfamiliar problem situations. Conversely, instructional support in the form of worked examples, guided explanations, and scaffolded learning activities appears to help students focus on relevant conceptual relationships and reduce confusion during learning.

Based on these findings, it was concluded that learning in biotechnology requires an instructional model that reduces unnecessary cognitive burden while supporting conceptual understanding through systematic guidance. These findings served as the foundation for developing the Example-Based Cognitive Load Control (EBCLC) Learning Model.

Structure and validation of the EBCLC learning model

The findings from the needs analysis informed the development of the Example-Based Cognitive Load Control (EBCLC) Learning Model. The model was designed based on the principles of Cognitive Load Theory (CLT) and example-based learning, with the primary objective of regulating students' cognitive processing during biotechnology learning.

The EBCLC model consists of four sequential instructional stages: (1) Model Observation, (2) Guided Processing, (3) Model Construction, and (4) Reflection and Reinforcement. Unlike conventional example-based instruction, which primarily focuses on presenting worked examples, the EBCLC model integrates cognitive load regulation throughout the learning process. The structure of the EBCLC learning model is illustrated in Figure 1.

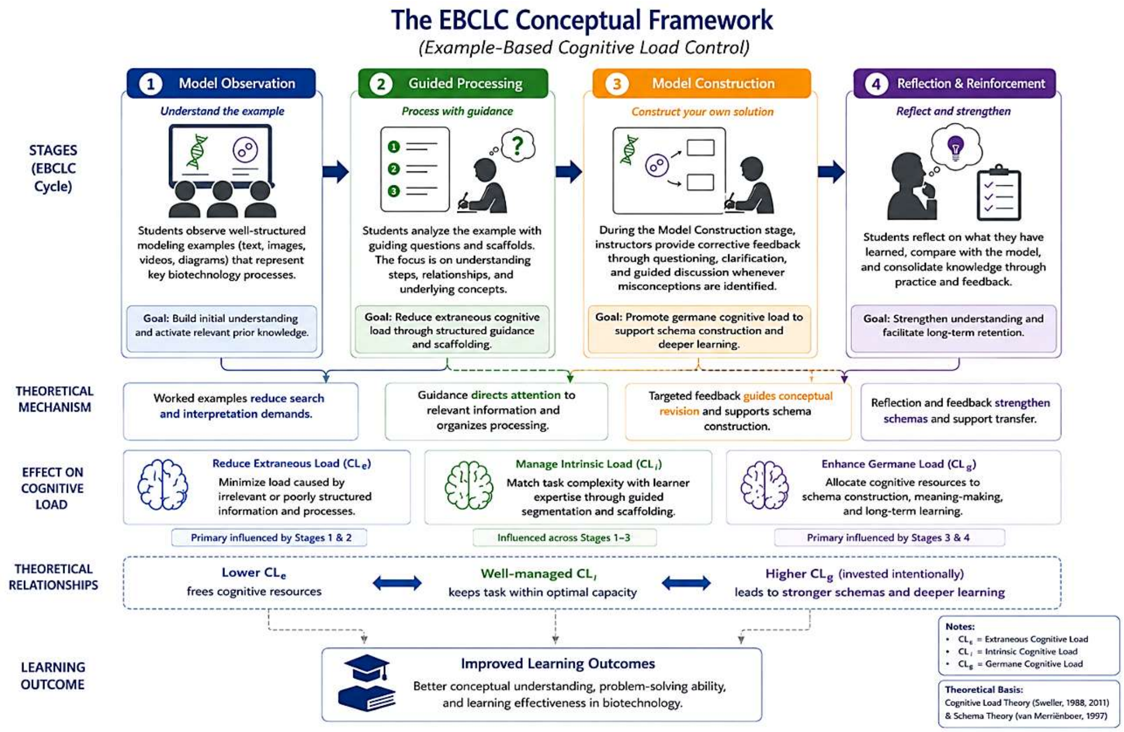

Figure 1. The structure of the EBCLC learning model

In the first stage, Model Observation, students observe structured examples that demonstrate biotechnology concepts, processes, or problem-solving procedures. This stage is intended to reduce extraneous cognitive load by minimizing unnecessary cognitive search processes and providing clear representations of complex concepts. Through structured observati on, students can focus their attention on relevant information rather than expend cognitive resources on determining how to approach a problem.

The second stage, Guided Processing, provides systematic support for students to analyze and interpret the information presented in the examples. At this stage, guiding questions, structured worksheets, and instructor facilitation help students organize information into meaningful conceptual relationships. This stage supports information processing by directing students' cognitive resources toward essential aspects of the learning material.

In the third stage, Model Construction, students actively construct their own explanations, conceptual models, or solutions to problems based on previously studied examples. This stage encourages deeper cognitive engagement and facilitates the organization of knowledge into coherent conceptual structures. Rather than merely imitating examples, students are required to apply and adapt their understanding to new learning situations.

The final stage, Reflection and Reinforcement, encourages students to evaluate their understanding, identify misconceptions, and strengthen conceptual connections. Reflection activities help consolidate learning outcomes and reinforce the knowledge structures developed during previous stages.

From a theoretical perspective, the four stages operate as an integrated cognitive support system. Model Observation primarily functions to reduce extraneous cognitive load through structured example presentation. Guided Processing facilitates efficient information organization and processing. Model Construction promotes active knowledge development and conceptual integration, while Reflection and Reinforcement strengthen understanding and support long-term retention. Consequently, cognitive load regulation is embedded throughout the learning sequence rather than being limited to a single instructional activity.

The developed model was subsequently evaluated by experts in biology education and instructional design. The validation results indicated that the EBCLC model was considered theoretically sound, pedagogically relevant, and feasible for implementation in biotechnology learning. Experts particularly highlighted the systematic integration of example-based learning principles and cognitive load regulation strategies across all instructional stages. Suggestions provided during the validation process were incorporated into the final revision of the model prior to classroom implementation.

Students' Cognitive Processing Performance During the Implementation of the EBCLC Model

Extraneous cognitive load (mental effort)

The influence of the EBCLC model on students' extraneous cognitive load was examined through mental effort ratings collected after each biotechnology learning session. Mental effort was used as an indicator of the cognitive resources students required to understand instructional materials and complete learning tasks. Lower mental effort scores indicate lower levels of extraneous cognitive load and more efficient instructional design. Table 3 presents the average mental effort scores across eleven biotechnology topics.

Table 3. Average mental effort scores across biotechnology topics

No.	Material	Extraneous Cognitive Load Score(scale 1-10)
1.	Totipotency & Tissue Culture	1.41
2.	Secondary Metabolites	1.59
3.	Recombinant DNA Part I	1.64
4.	Recombinant DNA Part II	1.50
5.	Biotechnology Applications (White, Blue, Green, Red Biotechnology)	1.59
6.	Bioethics	1.45
7.	Food Biotechnology Applications	1.59
8.	Health Biotechnology Applications	1.41
9.	Agricultural Biotechnology Applications	1.36
10.	Environmental Biotechnology Applications	1.32
11.	Energy Biotechnology Applications	1.36

To further examine the validity of the mental effort ratings, a Pearson correlation analysis was conducted between students' average mental effort scores and posttest learning outcomes. The analysis revealed a weak positive correlation that was not statistically significant ($r = 0.104$, $p = .645$). Similarly, the correlation between mental effort scores and learning gains was not significant ($r = 0.159$, $p = .481$). These findings suggest that the low mental effort ratings observed across biotechnology topics were not systematically associated with students' learning outcomes. Therefore, the mental effort scores should be interpreted cautiously and may reflect factors beyond instructional effectiveness alone.

The results showed that mental effort scores remained consistently low across all biotechnology topics, ranging from 1.32 to 1.64 on a ten-point scale. These findings suggest that students experienced relatively low levels of extraneous cognitive load throughout the implementation of the EBCLC model.

Although all scores were within the low category, variations were observed across topics. The highest mental effort score was found in Recombinant DNA Part I (M = 1.64), whereas the lowest score was observed in Environmental Biotechnology (M = 1.32). This variation appears to reflect differences in conceptual complexity among biotechnology topics.

Recombinant DNA technology requires students to understand multiple interconnected concepts, including gene isolation, restriction enzymes, DNA ligation, cloning vectors, and gene expression mechanisms. These concepts involve microscopic and abstract biological processes that are difficult to visualize directly. Consequently, students were required to allocate greater cognitive resources to process the information presented during learning.

Despite the topic's inherent complexity, the mental effort score remained relatively low. This finding suggests that the instructional features embedded within the EBCLC model successfully prevented excessive cognitive burden. In particular, the Model Observation stage provided structured examples that demonstrated each step of the recombinant DNA process, while the Guided Processing stage directed students' attention toward essential conceptual relation ships. These instructional supports likely reduced unnecessary cognitive search processes and facilitated more efficient information processing.

Conversely, lower mental effort scores observed in Environmental Biotechnology and Agricultural Biotechnology may be attributed to students' greater familiarity with real-world applications of these topics. Biotechnology applications related to environmental management, waste treatment, and agricultural production are more easily connected to students' prior experiences, thereby reducing the cognitive effort required for comprehension.

These findings support Cognitive Load Theory, which posits that instructional design plays a crucial role in reducing extraneous cognitive load by organizing information in a structured, cognitively efficient manner (Sweller et al., 2019; Sweller, 2020). The findings are also consistent with studies demonstrating that example-based learning reduces unnecessary cognitive processing by providing learners with explicit solution procedures and conceptual guidance (Renkl et al., 2009; Van Gog & Rummel, 2010).

More importantly, the findings suggest that the effectiveness of the EBCLC model lies not merely in the use of examples themselves, but in the systematic sequencing of instructional stages. The integration of Model Observation, Guided Processing, Model Construction, and Reflection and Reinforcement appears to provide continuous cognitive support throughout the learning process, thereby minimizing unnecessary cognitive demands while maintaining engagement with complex biotechnology content.

Information processing performance

Students' information-processing performance was examined using scores from student worksheets (LKM) completed during 11 biotechnology learning sessions. The worksheets were designed to assess students' ability to identify relevant information, analyze biological processes, establish conceptual relationships, and apply biotechnology concepts to solve learning tasks.

Higher scores indicate better information processing performance during learning activities.

Table 4 presents students' information processing performance across the eleven biotechnology topics.

Table 4. Students' information processing performance across biotechnology topics

No.	Material	Score
1.	Totipotency & Tissue Culture	80.3
2.	Secondary Metabolites	76.6
3.	Recombinant DNA Part I	70.3
4.	Recombinant DNA Part II	76.7
5.	Biotechnology Applications (White, Blue, Green, Red Biotechnology)	72.7
6.	Bioethics	74.5
7.	Food Biotechnology Applications	74.5
8.	Health Biotechnology Applications	77.2
9.	Agricultural Biotechnology Applications	91.6
10.	Environmental Biotechnology Applications	92.4
11.	Energy Biotechnology Applications	80.7
12.	Average	78.86

The results showed that students achieved relatively high information-processing performance across all biotechnology topics, with scores ranging from 70.30 to 92.40 and an overall mean of 78.86. These findings indicate that students were generally able to process and organize complex biotechnology information effectively throughout the implementation of the EBCLC model.

Variations in performance were observed across learning topics. The lowest mean score was recorded in Recombinant DNA Part I (M = 70.30), whereas the highest scores were obtained in Agricultural Biotechnology (M = 91.60) and Environmental Biotechnology (M = 92.40). These differences appear to reflect variations in conceptual complexity and students' prior familiarity with the learning content.

The relatively lower score observed in Recombinant DNA Part I may be attributed to the complexity of molecular-level processes involved in genetic engineering. Students were required to understand multiple interconnected concepts simultaneously, including DNA isolation, restriction enzymes, ligation processes, cloning vectors, and gene transfer mechanisms. Such conceptual demands increase the amount of information that must be processed and integrated during learning.

An interesting pattern was observed between Recombinant DNA Part I and Recombinant DNA Part II. Although Part II involved more advanced applications of recombinant DNA technology, students' information processing performance increased from 70.30 to 76.70. This improvement may be explained by the EBCLC model's sequential instructional structure. During Part I, students were introduced to fundamental concepts such as restriction enzymes, DNA ligation, cloning vectors, and gene insertion mechanisms. These concepts constituted the foundational knowledge required for subsequent learning activities. Once these foundational schemas had been established, students were able to process more complex applications in Part II more efficiently. According to Cognitive Load Theory, schema acquisition reduces the cognitive demands of processing new information by enabling learners to integrate new concepts into existing knowledge structures. Therefore, the higher performance observed in Part II may reflect the cumulative effect of prior schema construction and the progressive scaffolding embedded within the EBCLC learning sequence.

Nevertheless, despite being the most challenging topic, students still achieved a satisfactory performance score. This finding suggests that the instructional support provided by the EBCLC model enabled students to process complex information without experiencing substantial learning difficulties. The combination of structured examples, guided information processing activities, and gradual knowledge construction may have facilitated the organization of new information into coherent conceptual structures.

Higher scores observed in Agricultural Biotechnology and Environmental Biotechnology may be explained by the contextual nature of these topics. Students were able to relate the learning materials to familiar real-world applications such as crop improvement, environmental conservation, and waste management. Prior knowledge and contextual relevance likely supported more efficient information processing and conceptual understanding.

These findings are consistent with previous research indicating that example-based learning enhances learners' ability to process complex information by reducing unnecessary cognitive demands and directing attention toward essential conceptual relationships (Renkl et al., 2009; Van Gog et al., 2006). Furthermore, the results support the argument that structured instructional guidance facilitates meaningful learning by helping students organize information into integrated knowledge structures (Sweller et al., 2019).

Importantly, the findings suggest that the EBCLC model not only reduces unnecessary cognitive burden but also supports productive cognitive engagement with complex biotechnology content. The consistently high information processing performance observed across topics indicates that students were able to actively analyze, interpret, and apply biotechnology concepts throughout the learning process. This outcome reflects one of the model's primary objectives: facilitating efficient cognitive processing while maintaining meaningful engagement with challenging subject matter.

Effectiveness of the EBCLC Model on Learning Outcomes

Normality test results

Prior to conducting the paired-samples t-test, the normality assumption was examined using the Shapiro–Wilk test. The results indicated that both pretest and posttest scores were normally distributed. Pretest scores yielded a Shapiro–Wilk statistic of W = 0.957, p = 0.402, whereas posttest scores yielded W = 0.968, p = 0.612. Because both significance values exceeded 0.05, the assumption of normality was satisfied, supporting the use of parametric statistical analysis.

Table 5. Results of the shapiro–wilk normality test

Variable	W	p-value
Pretest	0.957	0.402
Posttest	0.968	0.612

The effectiveness of the EBCLC model was evaluated by comparing students' learning outcomes before and after the intervention. Learning outcomes were measured using pretest and posttest assessments administered to the same group of students. Table 6 presents the results of the paired-samples t-test analysis.

The results revealed a statistically significant increase in students' learning outcomes following

Table 6. Comparison of pretest and posttest scores on information processing performance

Variable	Pretest Mean	Posttest Mean	Mean Difference	95% CI Lower	95% CI Upper	t-value	p-value	Effect Size (Cohen's d)
Information Processing	71.27	78.27	7.00	5.53	8.47	9.92	< 0.001	2.12

the implementation of the EBCLC model. The mean pretest score increased from 71.27 to 78.27, representing an average gain of 7.00 points. The paired-samples t-test indicated that the difference was statistically significant, t(21) = 9.92, p < .001.

Although the calculated effect size was large (Cohen's d = 2.12), this value should be interpreted cautiously because the relatively small standard deviations of the pretest and posttest scores contributed to the magnitude of the effect size estimate. Furthermore, the normalized gain analysis yielded 0.245, which falls in the low category. Therefore, the findings suggest that the EBCLC model was associated with a statistically reliable improvement in learning outcomes; however, the magnitude of improvement relative to th maximum attainable score remained modest.

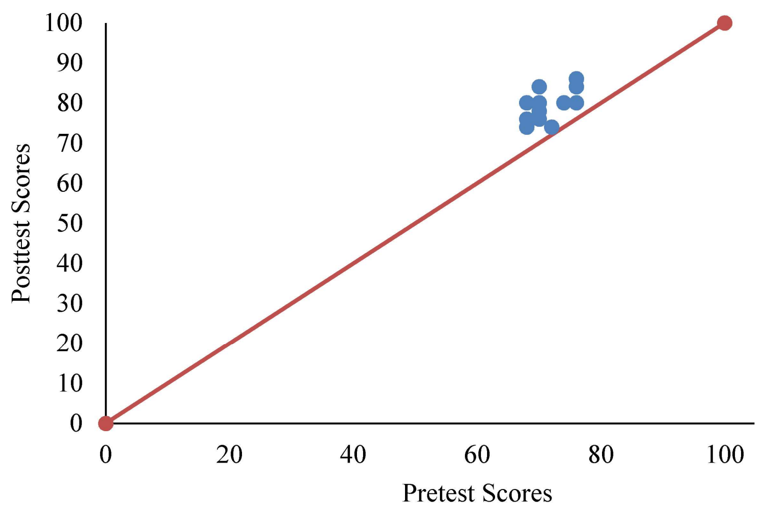

Figure 2. Scatter plot of pretest and posttest scores

As shown in Figure 2, each point represents an individual participant. Points located above the diagonal line indicate improvement from pretest to posttest, whereas points on the line indicate no change. Most participants were positioned above the reference line, suggesting that learning gains occurred across a majority of students. This pattern demonstrates that learning improvement occurred consistently across participants rather th being driven by only a small number of students.

To examine whether extreme cases influenced the observed learning gains, a Mahalanobis distance analysis was conducted using pretest and posttest scores. The maximum Mahalanobis distance observed was 2.60, which was substantially below the critical chi-square value of 13.82 (df = 2, p < .001). Therefore, no multivariate outliers were identified, and all participants were retained for subsequent analyses.

Although several participants entered the study with relatively high pretest scores, all students demonstrated positive learning gains following the intervention. This finding suggests that the EBCLC model remained beneficial for higher-performing students, and no evidence of an expertise reversal effect was observed in the present study.

Normalized gain analysis

To further examine the magnitude of learning improvement and address the limitations associated with a one-group pretest-posttest design, normalized gain (N-gain) scores were calculated using Hake's formula. The analysis yielded a mean N-gain of 0.245, which falls within the low category. This result indicates that students achieved approximately 24.5% of the maximum possible improvement relative to their initial performance levels.

Although the paired-samples t-test showed a statistically significant increase in learning outcomes and a large effect size (Cohen's d = 2.12), the N-gain analysis suggests that the magnitude of improvement relative to the maximum attainable score was modest. This finding may be influenced by the relatively high initial pretest scores, which reduced the available room for improvement.

The low N-gain value should be interpreted in light of the relatively high pretest scores observed among participants. Because students entered the intervention with moderate levels of prior knowledge, the maximum achievable improvement was limited. Consequently, although the absolute gain of seven points was statistically significant and associated with a large effect size, the normalized gain remained within the low category.

The observed improvement may be explained by the instructional design embedded within the EBCLC model. During the Model Observation stage, students were provided with structured examples demonstrating how to approach biotechnology concepts and problems systematically. This instructional support reduced unnecessary cognitive search processes and enabled students to allocate greater cognitive resources to understanding conceptual relationships.

The Guided Processing stage further facilitated learning by directing students' attention toward critical aspects of the material through structured questions and guided analysis activities. Subsequently, the Model Construction stage encouraged students to actively reconstruct and apply their understanding, thereby strengthening conceptual integration and knowledge organization. Finally, Reflection and Reinforcement activities provided opportunities for students to evaluate and consolidate their learning.

These findings are consistent with previous studies demonstrating that example-based learning can enhance conceptual understanding and learning efficiency by reducing unnecessary cognitive demands (Renkl et al., 2009; Van Gog et al., 2006). Similarly, Hoogerheide et al. (2014) reported that modeling examples improves learning performance and reduces cognitive burden by making expert reasoning processes visible to learners.

However, the present study extends previous findings in several important ways. Most earlier studies focused primarily on the effectiveness of worked examples as individual instructional techniques. In contrast, the EBCLC model embeds example-based learning within a structured instructional sequence consisting of observation, guided processing, construction, and reflection. The results suggest that the effectiveness of example-based learning may be enhanced when cognitive support is systematically distributed across multiple learning stages rather than concentrated solely in the presentation of examples.

The findings also contribute to Cognitive Load Theory by providing empirical evidence that instructional models can simultaneously reduce unnecessary cognitive burden and support productive cognitive engagement with complex subject matter. Rather than functioning solely as a worked-example intervention, the EBCLC model operates as a comprehensive instructional framework that integrates cognitive load regulation throughout the learning process.

Taken together, these results indicate that the EBCLC model effectively improves students' learning outcomes while supporting efficient cognitive processing in biotechnology learning.

Theoretical and Practical Contributions of the EBCLC Model

The findings of this study provide both theoretical and practical contributions to biotechnology education and the broader field of instructional design. While the use of worked and modeling examples has been widely discussed in Cognitive Load Theory (CLT), the present study contributes by proposing and empirically evaluating a structured instructional model that systematically integrates these principles into a complete learning sequence.

A key contribution of the EBCLC model lies in its instructional architecture. Previous studies have generally examined worked examples as isolated instructional interventions designed to reduce unnecessary cognitive processing during problem solving (Renkl et al., 2009; Sweller et al., 2019). In contrast, the EBCLC model embeds example-based learning into four interconnected learning stages: Model Observation, Guided Processing, Model Construction, and Reflection and Reinforcement. This sequence distributes cognitive support throughout the learning process rather than concentrating support exclusively during example presentation.

From a Cognitive Load Theory perspective, each stage serves a distinct cognitive function. The Model Observation stage reduces extraneous cognitive load by providing structured examples that direct learners' attention toward relevant information. Guided Processing facilitates the organization and integration of information through instructional scaffolding. Model Construction encourages active knowledge restructuring and schema development, while Reflection and Reinforcement support consolidation and transfer of learning. Together, these stages form a coherent mechanism for regulating cognitive demands during learning.

The present findings also extend previous example-based learning research conducted in the contexts of mathematics, science, engineering, and medical education (Van Gog et al., 2006; Hoogerheide et al., 2014; Duran et al., 2022). Whereas earlier studies primarily focused on improving problem-solving performance, this study demonstrates how example-based instructional principles can be systematically adapted to biotechnology learning, a domain characterized by abstract concepts, microscopic processes, and complex interdisciplinary relationships.

Another important contribution concerns the integration of multimodal learning supports within the cognitive load regulation framework. The EBCLC model combines visual representations, structured worksheets, guided discussions, and example-based activities to facilitate conceptual understanding. This approach aligns with recent developments in Cognitive Load Theory, which emphasize the importance of instructional designs that optimize the interaction between visual and verbal information channels (Sweller, 2020; Kalyuga, 2022).

Practically, the EBCLC model provides educators with a structured framework for teaching complex scientific concepts. The model may be particularly useful in courses involving abstract and cognitively demanding content, where students frequently have difficulty integrating multiple sources of information. By organizing learning activities into sequential stages of cognitive support, the model offers a practical strategy for improving learning effectiveness while minimizing unnecessary cognitive burden.

Overall, the findings suggest that the contribution of the EBCLC model does not lie merely in the use of worked examples, but in the systematic integration of example-based learning, guided cognitive processing, multimodal instructional support, and reflective knowledge construction within a unified instructional framework. This integrated structure represents the model's primary conceptual innovation and distinguishes it from conventional worked-example approaches commonly discussed in the Cognitive Load Theory literature.

Limitations and Future Research Directions

Several limitations should be considered when interpreting the findings of this study. First, the study employed a pre-experimental one-group pretest–posttest design without a control group. Although the results demonstrated statistically significant improvements in learning outcomes following the implementation of the EBCLC model, the absence of a comparison group limits the ability to establish strong causal inferences. Improvements in students' performance may have been influenced by factors other than the intervention itself, such as prior learning experiences, increased familiarity with the assessment format, maturation effects, or external learning resources accessed during the study period. Consequently, the effectiveness findings should be interpreted as evidence of potential instructional benefits rather than definitive proof of causal impact.

Second, the study involved a relatively small sample of 22 prospective biology teachers from a single university. While the sample was appropriate for an initial model evaluation, the limited number of participants restricts the generalizability of the findings. Students from different institutions, educational backgrounds, or cultural contexts may respond differently to the instructional approach implemented in the EBCLC model.

Third, the assessment of cognitive processing in this study relied primarily on self-reported ratings of mental effort and students' information-processing performance recorded on learning worksheets. Although these measures provide valuable insights into students' learning experiences and cognitive engagement, they may not fully capture the complexity of learners' cognitive processes during instruction. The present study focused primarily on extraneous cognitive load, as reflected in students' perceived mental effort, and on information-processing performance during learning activities.

Consequently, the findings should be interpreted as evidence of students' perceived cognitive effort and information-processing performance rather than as a comprehensive evaluation of all dimensions of cognitive load proposed in Cognitive Load Theory. Future studies are encouraged to employ more comprehensive cognitive load instruments, such as the Leppink Cognitive Load Scale, together with complementary measures including physiological indicators, eye-tracking data, or neurocognitive measurements. Such approaches may provide a deeper understanding of how instructional models influence learners' cognitive processes and strengthen the validity of cognitive load assessment.

Fourth, this study was conducted exclusively within the field of biotechnology education. Biotechnology is characterized by abstract concepts, interdisciplinary knowledge structures, and high conceptual complexity. Therefore, the effectiveness of the EBCLC model in other subject areas remains uncertain. Further research is needed to examine whether the model can be successfully adapted and implemented in other disciplines such as genetics, chemistry, physics, engineering, or mathematics education.

Despite these limitations, the findings provide preliminary evidence supporting the potential value of the EBCLC model as an instructional framework for managing cognitive demands in complex learning environments. Future studies should employ more rigorous experimental designs, particularly quasi-experimental or randomized controlled trials, to strengthen internal validity and provide stronger evidence of the model's causal effects.

Future research should also investigate how each stage of the EBCLC model influences the dimensions of cognitive load, including intrinsic, extraneous, and germane. Such investigations would help clarify the mechanisms through which the model facilitates learning and provide opportunities for further refinement of the instructional framework.

In addition, longitudinal studies are recommended to examine the sustainability of learning gains over time and to determine whether the cognitive and conceptual benefits observed during the intervention are maintained after students complete the course. Such evidence would contribute to a deeper understanding of the long-term educational value of the EBCLC model.

CONCLUSION

This study developed and evaluated the Example-Based Cognitive Load Control (EBCLC) Learning Model as an instructional framework designed to support biotechnology learning among prospective biology teachers. The model was developed from qualitative findings on students' learning difficulties and instructional needs, and was subsequently validated and implemented in biotechnology courses.

The findings indicate that the EBCLC model effectively supports cognitive processing during learning. Students reported consistently low levels of mental effort across biotechnology topics, suggesting that the model successfully reduced unnecessary cognitive demands associated with learning complex and abstract concepts. At the same time, students demonstrated relatively high information-processing performance across the learning activities, indicating that they were able to engage meaningfully with biotechnology content.

The effectiveness evaluation revealed statistically significant improvements in students' learning outcomes following the model's implementation. However, the normalized gain analysis indicated that the magnitude of improvement was relatively modest. Therefore, the findings should be interpreted as preliminary evidence that integrating structured examples, guided cognitive processing, model-construction activities, and reflective reinforcement may positively contribute to biotechnology learning, rather than as definitive evidence of high instructional effectiveness.

The primary contribution of this study lies not in the use of worked examples alone, but in the development of a structured instructional framework that systematically integrates example-based learning, guided processing, multimodal instructional support, and reflective knowledge construction within a coherent sequence of learning activities. This instructional architecture extends existing example-based learning approaches by distributing cognitive support across multiple stages of the learning process.

Theoretically, the study contributes to the application and refinement of Cognitive Load Theory in higher education contexts, particularly in learning environments characterized by complex and abstract scientific content. Practically, the EBCLC model offers educators a promising framework for designing instruction that supports efficient cognitive processing and meaningful conceptual understanding. Nevertheless, given the modest normalized gain observed in the present study and the absence of a comparison group, further research is required before stronger conclusions regarding its effectiveness can be drawn.

Given the limitations of the present study, further research with larger samples, comparison groups, and more rigorous experimental designs is recommended to strengthen the evidence for the model's effectiveness and to examine its applicability across disciplines and educational settings.

DECLARATION OF GENERATIVE AI USAGE IN THE WRITING PROCESS

The authors used generative artificial intelligence (AI) tools, specifically ChatGPT (OpenAI), to improve the manuscript's clarity, grammar, and language quality during the writing process. The AI tool was used solely for language editing and drafting support. All conceptualization, research design, data collection, data analysis, interpretation of findings, and final decisions regarding the manuscript content were conducted entirely by the authors. The authors carefully reviewed and edited all AI-assisted outputs and take full responsibility for the accuracy and integrity of the published work.

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