Simulated Computational Module Improves Student Knowledge about Cellular Respiration System

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Introduction

Thinking about biological phenomena from a systems perspective has been defined as essential for undergraduate biology students[1]. Unfortunately, it is difficult for learners new to thinking about systems to consider the components, relationships, and processes within a system[2]. One such system is cellular respiration. Cellular respiration is an important topic of study because it is a foundational topic for understanding 1) core concepts like matter and energy transformation and conservation[3-5] and 2) larger-scale biological activities such as digestion and food webs[6,7]. Additionally, cellular respiration is ubiquitously taught in secondary and undergraduate biology courses and remains a difficult topic for learners[7,8].

We have developed a learning approach where students learn about biological systems through guided investigations using simulated computational models. These computational modeling interventions (CMI) have been purposefully designed with evidence-based best practices to facilitate conceptual understanding and enhance systems thinking skills.

Research Question

How does the computational modeling intervention (CMI) affect student knowledge about cellular respiration?

Methods

The study population consisted of students enrolled in the first of two introductory biology lectures and laboratories that introduced students to life at the cellular level. During a dry lab on cellular respiration, students engaged in our learning module. The learning module was comprised of several parts (Figure 1) including pre-lab assignments and in-lab activities.

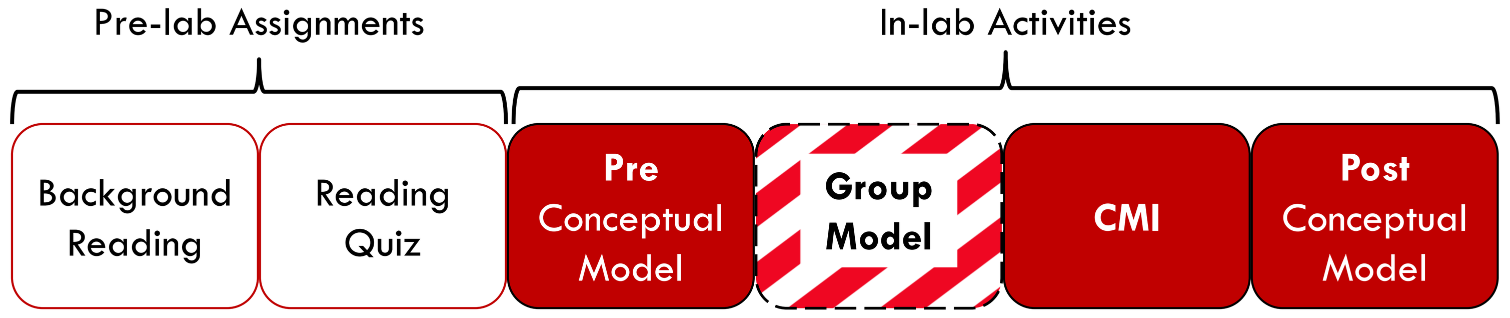


Figure 1. Learning Module

Conceptual Modeling Assessment

We assessed student knowledge of cellular respiration with conceptual models before (Pre) and after (Post) the CMI. Conceptual models are external representations of cognitive structures[9,10]. Students generated models in the box and arrow format informed by Structure-Behavior-Function theory,[2,9,10]. Students were instructed to construct a model to show the events of cellular respiration and fermentation.

Students were provided with 27 relevant structures and required to use at least 10. Students were encouraged to use all of the provided structures and include more if necessary. Half of the lab sections also did a group modeling activity.

We analyzed a stratified sample (n=142) of student models by sampling up to four consenting students per lab section. All student-generated data were collected with institutional review board approval.

The conceptual modeling assessments were used to examine how knowledge changed after students engaged with the CMI on cellular respiration. The CMI was purposefully designed to guide students through cellular respiration using simulations of a computational model.

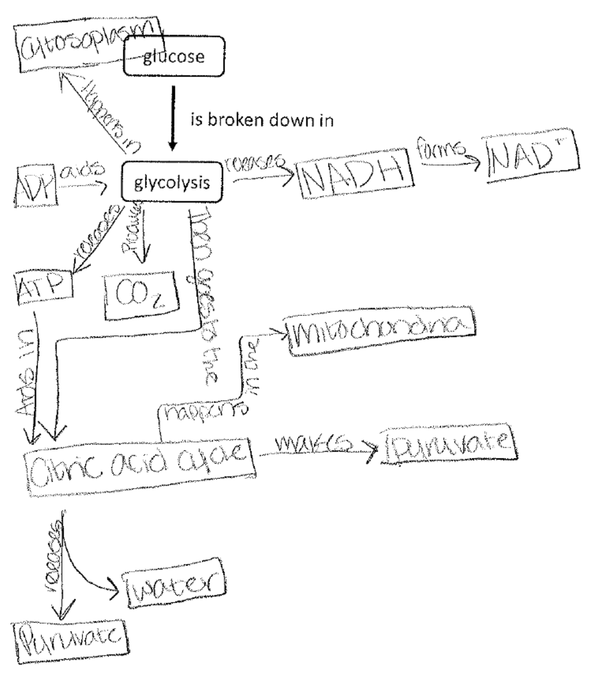


Figure 2. Example of a student-generated conceptual model

Computational Modeling Intervention

Computational Model

It can be difficult for students to learn the dynamics of biological systems from static figures[11]. We have created a computational model of cellular respiration (Figure 3) for students to learn about the dynamics of cellular respiration.

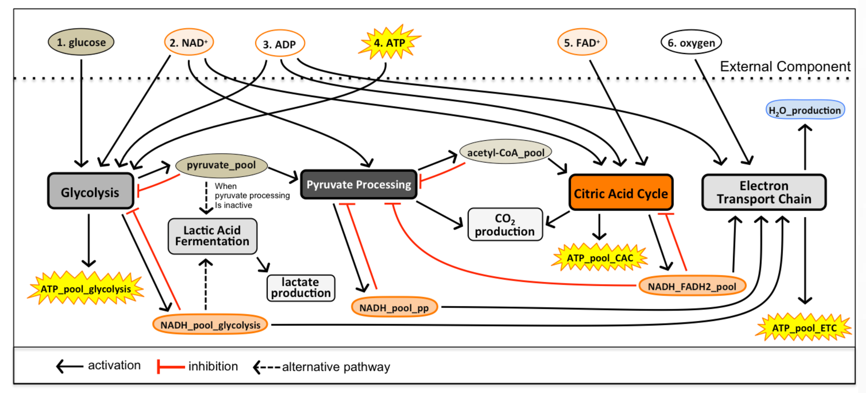


Figure 3. Computational Model of Cellular Respiration

Learn.CellCollective.org

Students simulate the computational model with the web-based learning platform (Figure 4). Here, students can manipulate cellular conditions (e.g., nutrient availability, genetic mutations) and monitor the effects on the components of cellular respiration.

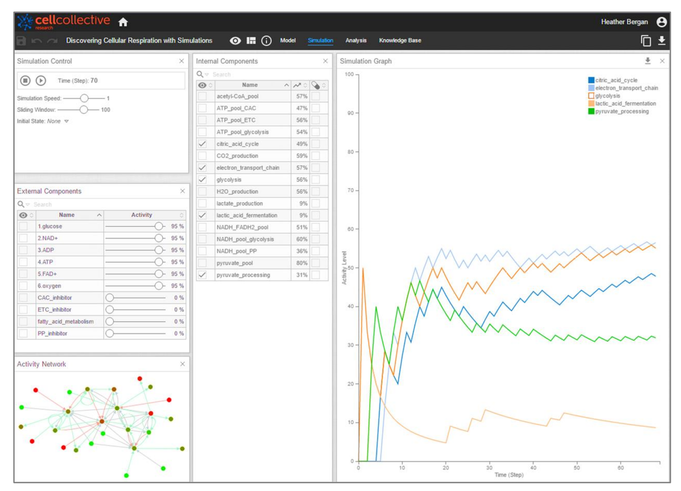


Figure 4. Simulation Platform

Investigations

Students are presented with scenarios to investigate cellular respiration with simulations of a computation model. They explore each scenario by completing the objectives.

Scenarios

1. How are brain cells affected by low glucose availability?
2. How can fatty acids contribute to cellular energy production?
3. How does an inhibitor of the citric acid cycle affect production of carbon dioxide?
4. How does inhibition of pyruvate processing affect the other processes of CR?
5. How does the absence of oxygen affect the processes of CR?

Objectives

A. Make a prediction.
B. Support your prediction with a mechanism.
C. Test your prediction.
D. Report simulations results.
E. Evaluate your prediction.
F. Accurately describe the mechanism.

Results

Setting Slightly Affected Post Models

Multiple regression analysis revealed some significant ($p < 0.05$) differences among student performance on Post conceptual model metrics (i.e., quantity of structures, relationships, and described relationships, connectivity, and correctness) based on setting (i.e., time of lab, teaching assistant, week of lab, day of lab, and lecturer).

- Students in the 11:30AM sections created smaller, less connected Post models than students in the sections at other times of the day.
- TAs contributed 20-31% of the variability in Post model size and interconnectedness, but only 6% in correctness.
- Students in the second week created more correct models than students in the first week.

All Students Benefited from the CMI

Student demographics and background (i.e., sex, age, ethnicity/race, class, composite ACT score, weighted high school GPA) were not significant predictors of any of the Post conceptual model metrics.

Group Modeling Didn't Affect Post Models

For all Post conceptual model metrics, students who did the group modeling did not differ significantly ($p > 0.05$) from students who did not do the group modeling. Therefore, we pooled data from students who did and did not do the group modeling.

Results Continued

Students Improved Conceptual Models after CMI

- Students significantly increased the size, interconnectedness, and correctness of conceptual models after the CMI (Figure 5).
- The largest effect was seen in interconnectedness of models (as measured by WCI[12]).

* represents a significant difference ($p < 0.05$) when comparing between Pre and Post models within each metric.

Numbers above bars represent effect size (Hedge's g_{av}).

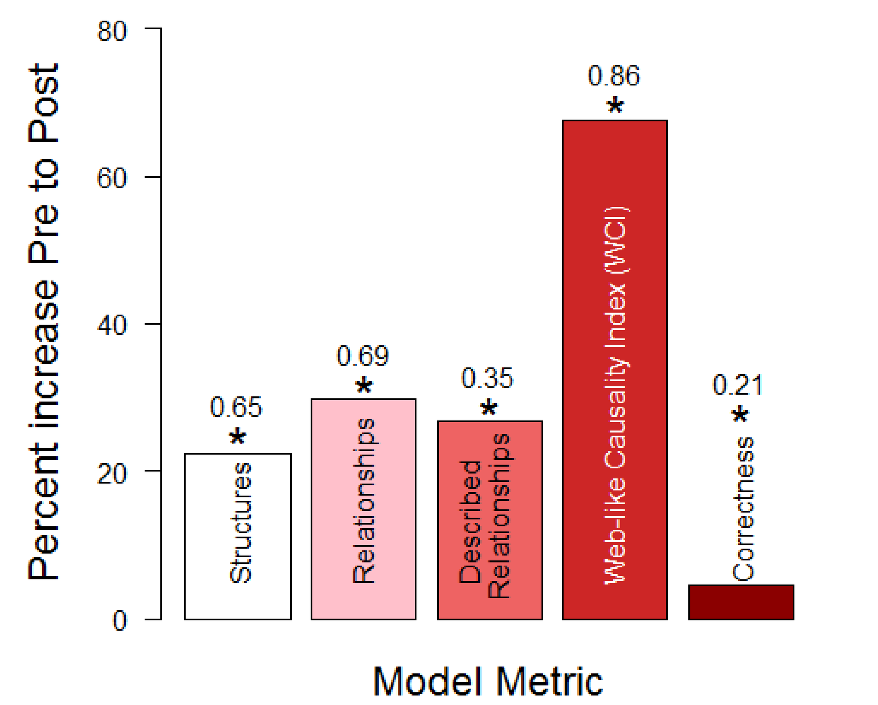
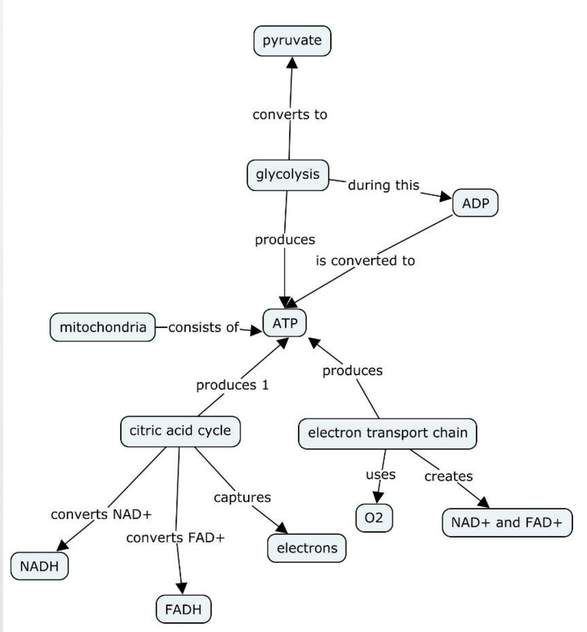


Figure 5. Changes in student-generated conceptual model metrics from Pre to Post

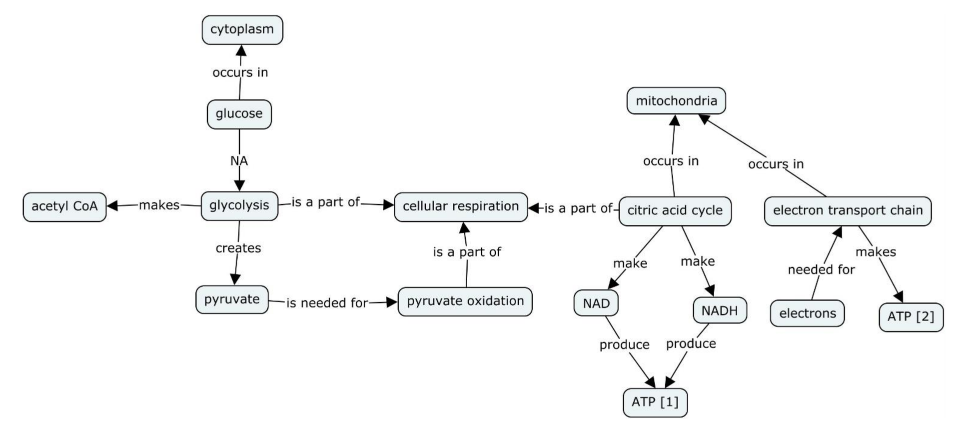
Exemplary Models

Pre



Post

- More structures, relationships, and described relationships
- More interconnected
- More accurate relationships



Summary & Conclusions

- Pre and Post conceptual models revealed that the computational modeling intervention (CMI) improves student knowledge about cellular respiration regardless of variability in setting and student background and demographics.
- Changes in conceptual models reflect changes in student cognitive structures[9] of cellular respiration. Increased size, integration, and accuracy of cognitive structures should improve retrieval of knowledge of cellular respiration.
- Instructors can implement the computational modeling intervention (CMI) to improve student knowledge of cellular respiration.

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Acknowledgements

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