Exploration of Cognitive Engagement Patterns in Online Environments with Multiple External Representations

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Abstract: This study investigates learners' cognitive engagement patterns in an online, self-directed learning environment enriched with multiple external representations. Participants interacted with scaffolded online modules with prompt questions designed based on the Interactive, Constructive, Active, and Passive (ICAP) framework. Data was collected through students' responses to knowledge tests, question prompts, and student-module interaction videos. A diversity in students' engagement patterns was observed which led to different learning outcomes. Findings reveal that constructive responses to prompt questions are associated with improved learning outcomes. Video analyses show that high achievers also engage in careful reading of instructional texts and purposeful simulation manipulation. This study contributes to understanding the nature and diversity of student engagement patterns and informs the effective design of self-directed online environments with multiple representations.

Introduction

The surge in online education, predominantly catalyzed by the COVID-19 pandemic, has brought to the pressing need to establish efficient instructional approaches for teaching intricate STEM subjects in self-directed online environments (AI Mamun et al., 2022). One direction of research in this burgeoning field is the investigation of the design of online environments to support science learning with multiple external representations (e.g., visual representations) in the absence of teachers (Pan et al., 2023; Rau et al., 2021). Specifically, the investigation focused on how embedded instruction facilitates students' interactions with online multimedia contents and thereby influences their engagement and approaches to learning (Su et al., 2023). Earlier studies have extensively investigated various facets of online education. However, there is a lack of research that probes student engagement patterns within online learning environments supported by multiple external representations (MERs), especially when learning complex scientific concepts (Ainsworth, 2006; Kozma, 2003). When presenting MERs which encompass texts, pictures, animations, simulations, and/or videos, learners' cognitive functions are distributed across diverse mediums, fostering a multifaceted understanding of a complex concept (Wu & Puntambekar, 2012). However, challenges arise in leveraging the use of MERs since they can induce external cognitive load which may hinder students from developing deeper understanding (Rau et al., 2015).

Grounded in this context, the current study aims to identify pivotal patterns as learners grapple with the frequently misconceived concept of natural selection within a MERs-supported online learning environment. With the further intent to decipher students' learning trajectories in the online module, we probed into the differential engagement patterns displayed by high achievers and low achievers. Employing the Interactive-Constructive-Active-Passive (ICAP) framework (Chi & Wylie, 2018), we objectively identified learners' cognitive engagement patterns throughout the learning process. The research questions are as follows:

1. What are the common cognitive engagement patterns exhibited by learners when responding to *prompt questions* in an online environment?
2. How do these identified *engagement patterns* correlate with and potentially influence students' *learning outcomes* in an online environment?
3. In what ways do individual learner engagement patterns differ or converge when interacting with *multiple external representations* in an online environment?

Theoretical framework

The Interactive Constructive Active Passive (ICAP) framework

The ICAP framework categorizes students' learning processes into four distinct modes: passive, active, constructive, and interactive. This framework enables researchers to map learning behavior to these modes and gain insights into how the learner's knowledge evolves. *Passive* learning involves learners receiving information from instructional materials without any overt action. *Active* learning, on the other hand, requires learners to exhibit visible behavior or physical manipulation, such as adjusting simulation parameters to observe changes and pausing or rewinding instructional videos. *Constructive* learning involves learners generating or producing additional outputs beyond what is provided in the learning materials, such as explaining reasons for the observed changes in the simulation and reflecting on the instructional materials while identifying what was important and missed in their understanding. *Interactive* learning requires two peers or a small group to collaboratively co-generate knowledge. When learners expand upon, justify, or critique each other's ideas, they introduce new information and constructively respond to each other's input.

The ICAP framework depicts student learning as involving various knowledge-changing stages: passive, active, constructive, and interactive. Each phase is foundational for the next, with interactive building on constructive, which in turn builds on active and passive. The focus is not about minimizing the passive phase or maximizing the constructive phase; it is stressing the importance of understanding the interdependence of these stages and developing opportunities for deep cognitive engagement. Due to its nuanced descriptions of learner engagement modes, the framework has become an objective measure for comprehending and assessing students' learning processes (Hsiao et al., 2022).

Method

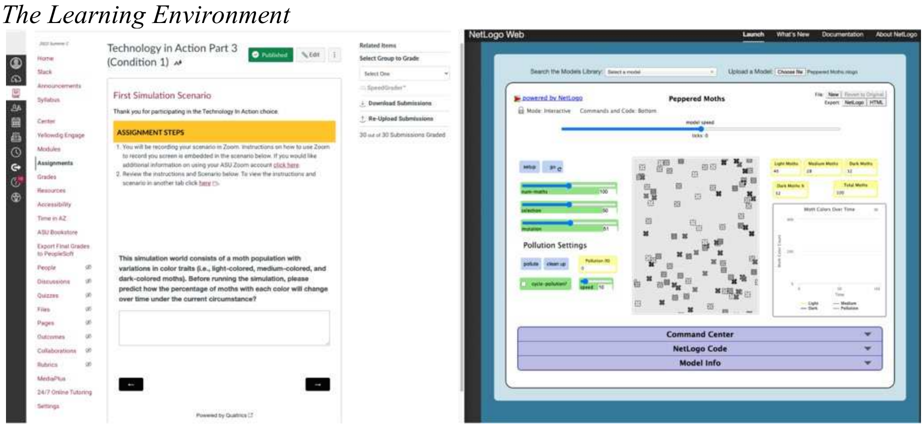
Participants

Recruitment was conducted in an online course for undergraduate students at a public university in the Southwestern United States. A total of 50 students in this course consented to participate and completed all the tasks required in this study. They were assigned to Control (n = 26) or Intervention (n = 24) groups based on pretest results using randomized block sampling approach. Among them, 22% were male, 76% were female, and 2% were non-binary. The average age was 27.4 years (SD = 8.91), reflecting a trend of diverse age groups enrolling in online courses. Ethnicity distribution was: White (68%), Hispanic/Latino (14%), Asian (6%), Black (6%), Native American (2%), and Other (4%). More than half of the participants were juniors (52%) and majoring in Education (58%). Most (86%) took 1-2 biology classes in high school, and only two participants had prior experience with NetLogo simulation (which we used as our online learning environment; see below).

The learning environment

The study was integrated into a seven-week asynchronous online course, overseen by five instructors, each managing a distinct student cluster. The first author coordinated assigning students to conditions and introducing them to learning modules via the Canvas platform (Figure 1, left). Within this environment, students accessed materials and interacted with two simulation models - the Peppered Moths and Rock Pocket Mice models through NetLogo Web, a free browser environment with interactive simulations (Figure 1, right) to learn the concept of natural selection. The course Canvas shell also contained a Qualtrics-based instructional page to supplement their learning (see Figure 1 middle part of the left side). Technical support was available through the course Slack channel and direct contact with the researcher.

Figure 1
The Learning Environment



Both study conditions shared the same learning environment, with each containing eight activities and 40 prompt questions across two modules. These activities aimed to bolster students' comprehension of natural selection via interactions with MERs in the forms of texts, dynamic simulations, pictures, and videos. Participants in both conditions engaged with the content by reading instructional texts, observing, and manipulating simulations, images, or videos, answering prompt questions, and drawing inferences.

While the overarching learning goals remained consistent across the two conditions, the instructional approaches exhibited variations. The control group used a traditional approach and delved into Darwinian principles and the functionality of simulation parameters, while the intervention group adopted a new approach by focusing on illustrating the pattern, agents, interactions, relations, and causal relationship using the simulation. Despite the differences in the instructional approaches, participants in both conditions received identical prompt questions designed based on the ICAP framework to not only help students elicit understandings but also gauging their cognitive engagement modes during the self-directed online learning environment. Sample prompt questions used in the Peppered Moth module were listed in Table 1. The study was initially conceived to examine the impacts of two distinct instructional approaches. However, this paper does not distinguish between the two conditions in relation to the research questions. To address the research questions associated with this paper, we treat both conditions equally, as each provides a self-directed online learning environment where students can engage with MERs.

Table 1
Sample Prompt Questions in the Peppered Moths Module

Activity	Sample Prompt Questions	ICAP
Activity 2 Explore the simulation and learn about the influence of selection pressures	1. *Observe* the simulation and *describe what you observed* in the simulation world from tick 1 to tick 100.	A
	2. *Select* the diagram below that best describes what will happen in terms of the distribution of color variations among moths over 100 ticks?	A
	3. *Run* the simulation and *explain* how the distribution change of color variations is influenced by selection pressures.	C

Data collection procedure

The study employed a pretest-posttest randomized block design approach. Specifically, students were ranked by pretest scores and divided into two groups, with members then randomly assigned to two conditions, ensuring reduced error variance and increased experiment validity (Wickens & Keppel, 2004). At the beginning of the experiment, participants were introduced to the project via a preparatory video and were given an overview, consent form, and pretest. The pretest contained 15 True or False questions and 4 open-ended questions which assessed both factual and deep understanding of natural selection and other emergent concepts. After two weeks of regular online instruction on topics of technology literacy, participants accessed the first Peppered Moths module. After a week of regular instruction, the second module was provided, focusing on Rock Pocket Mice. Right after the second module, participants were given the posttest and survey, which also included an invitation for follow-up interviews. During this procedure, main data sources were collected including: 1) pre-posttest (required); 2) open-ended responses to question prompts (required); 3) video recordings of student interactions with the modules (voluntary). There was a larger study with different research questions that incorporated more data sources, including pre-post study questionnaires and interviews, which were not discussed in this paper.

Data analytical approach

The analytical approach of this study was multifaceted and rigorous, ensuring a nuanced understanding of participants' learning trajectories. Initially, participants' knowledge enhancement was quantified using pretest-posttest scores. More importantly, the study classified pretest-posttest items into deep questions and shallow questions and later calculated scores for deep questions as a measure for deeper conceptual understanding.

Students' prompt responses were scored based on off-task ("0"), passive ("1"), active ("2"), or constructive ("3") mode, where larger numbers indicate higher cognitive engagement. This coding, influenced by the nature and depth of their response to prompts, yielded cumulative engagement scores (summing total scores for all prompt responses) for each student. Half of student prompt responses were scored by two experienced researchers for inter-rater reliability (Kappa was 0.78, $p < 0.001$). Engagement levels were subsequently quantified using ICAP percentages, where specific engagement types were normalized by the total engagement counts. The coding scheme can be found in the third column of Table 2. Based on the ICAP coding, t-tests were conducted to examine the differences in cognitive engagement scores between the two conditions when responding to prompt questions. The study further probed the correlation between cognitive engagement scores and learning outcomes. Pearson's correlation was deployed to establish this relationship.

Additionally, video recordings of four students provided qualitative insights on student interactions with the modules; these were subjected to ICAP coding using V-note (Bremig LLC, 2022; see Figure 2). The ICAP coding scheme for the video recordings was presented in the fourth column of Table 2. The first author later conducted video analysis on four students' engagement patterns during the first Peppered Moths module based on existing practices (Ha, 2022; Stump, 2017). These four students were selected based on specific criteria, including successful video recordings of module interactions, correct screen sharing during these recordings, and equal representation from both the control and intervention groups with high and low learning gains. This multimodal analytical approach ensured a comprehensive and in-depth understanding of participants' learning trajectory during the online environment. It also helps identify emergent themes related to students' experiences, challenges, and suggestions on instructional design for future online learning environments with MERs.

Figure 2
Visualization of V-note Coding Interface.

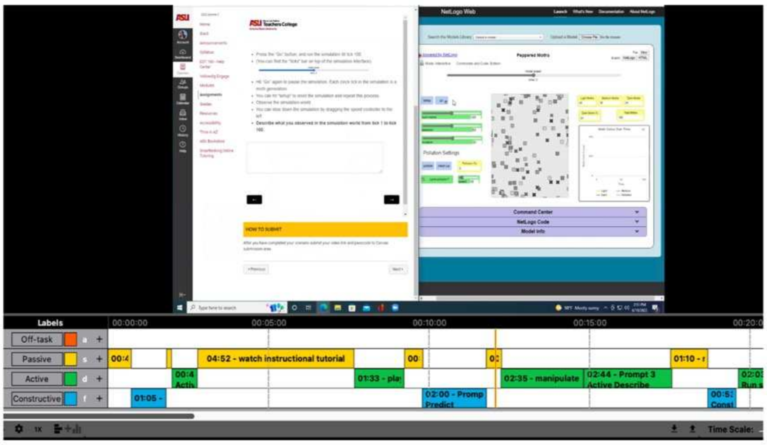


Table 2
Student ICAP Engagement Coding Scheme

Indicator	Definition	Learning Behaviors	
		Prompt Question Response	Simulation Module Interaction
Passive	Learners receiving information from instructional materials without any overt action	• Not sure how to respond • Not sure what the question means • Response too short, such as "all of it"	• Watch simulation videos • Read texts on PAIR-C features or Darwinian Principles
Active	Learners exhibit visible behavior or physical manipulation	• Describe the simulation environment • Describe the changes based on observations • Paraphrase the instructional texts	• Pause, or replay simulation video • Adjust simulation parameters and observe changes • Answer prompt questions actively
Constructive	Learners generate or produce additional outputs beyond what is provided in the learning materials	• Predict changes based on initial condition • Explain why changes happen • Reflect on the instructional materials • Elaborate the observation using PAIR-C features or Darwinian Principles	• Ask questions after reading texts • Check predictions and explain discrepancies • Compare the recorded simulation video with the actual simulation model • Answer prompt questions constructively
Off-task	Learners were not engaged in the learning activity	• No response	• No action

Results and discussion

Overview of common engagement patterns

We first examine RQ1: *What are the common cognitive engagement patterns exhibited by learners when responding to prompt questions in an online environment?* Participants in both conditions encountered an identical number of MERs and prompt questions. Given the uniform exposure to MERs and the consistency in prompt questions across both groups, it is plausible to deduce that the two conditions would not require distinct cognitive efforts or significantly alter their engagement. Empirical findings supported this, revealing no significant difference in cognitive engagement scores (total sum scores) between the two groups. The control group had an average engagement score of 89.46 [Min: 51, Max: 109], while the intervention group scored an average of 87.83 [Min: 72, Max: 107] (t = -.481, p = .633). This engagement score was broken down into approximately 33% *Constructive* engagement, 61% *Active* engagement, and 6% *Passive* engagement when responding to the prompts. Ideally though, given the design of the prompt questions, students should have exhibited around 65% *Constructive* and 35% *Active* engagement based on the way that the materials were designed. This deviation might influence the effectiveness of the experimental materials.

Engagement patterns and learning outcomes

To explore RQ2 (*How do these identified engagement patterns correlate with and potentially influence students' learning outcomes in an online environment?*), Pearson's correlational analysis was conducted. We found significant positive correlations between *Constructive* engagement and the total posttest score (r = .562, p < .001), and deep question posttest score (r = .549, p < .001) (Table 3). However, *Active* engagement negatively correlated with both total question scores (r = -.433, p < .01) and deep question scores (r = -.458, p < .001). Similarly, *Passive* engagement negatively correlated with these scores (total score: r = -.365, p < .01; deep question score: r = -.304, p < .05).

Table 3
Correlation Coefficient Between ICAP Percentage and Learning Outcomes

	Passive	Active	Constructive	Total Score	Deep Score
Passive	-				
Active	.003	-			
Constructive	$-.557^{***}$	$-.832^{***}$	-		
Total Score	$-.365^{**}$	$-.433^{**}$	$.562^{***}$	-	
Deep Score	$-.304^{*}$	$-.458^{***}$	$.549^{***}$	$.901^{***}$	-

*Note. *p < .05, **p < .01, ***p < .001*

To understand these dynamics better, participants were divided based on their gain scores from pretest to posttest using mean split: half were classified as high-achievers (n = 21) and half as low-achievers (n = 29). Analyses indicate significant differences between these groups in their passive, active, and constructive engagement levels, suggesting a strong link between the level of engagement and learning outcomes. As shown in Table 4, there were significant differences in ICAP percentage for *Passive* (t = -1.96, p = .028), *Active* (t = -3.33, p < .001), and *Constructive* (t = 4.49, p < .001) engagement level, respectively indicating that high-achievers exhibited higher percentage of constructive engagement, whereas lower-achievers exhibited higher percentage of active and passive engagement.

Table 4
Differences Between High and Low Learning Performance Groups

	Group	M	SD	t
Passive	High	5.49%	11.66%	$\mathbf{-1.96}^{**}$
	Low	11.36%	9.38%	
Active	High	57.03%	13.70%	$\mathbf{-3.33}^{***}$
	Low	68.28%	9.84%	
Constructive	High	37.48%	15.31%	$\mathbf{4.49}^{***}$
	Low	20.36%	11.38%	

*Note. **p < .01, ***p < .001*

Table 5 and Table 6 further elucidate the relationship between the ICAP percentage and test scores within the low and high achievers' groups (see highlighted parts). For the low achievers, there was no significant correlation between test scores and any of the engagement modes. For the high achievers, significant correlations were primarily with *Active* and *Constructive* engagement levels. Note that the correlation between total test score and the *Active* engagement was negative (r = -.46, p = .037) whereas the correlation between total test score and *Constructive* engagement was positive (r = .443, p = .045).

Table 5
Relationship Between ICAP% and Test Scores in Low-Performance Group.

	Passive	Active	Constructive	Total Score	Deep Score
Passive	-				
Active	-.364	-			
Constructive	-.568**	-.560**	-		
Total Score	-.110	.101	.008	-	
Deep Score	-.004	.077	-.064	.767***	-

Note. $^{**}p < .01$, $^{***}p < .001$

Table 6
Relationship Between ICAP% and Test Scores in High-Performance Group.

	Passive	Active	Constructive	Total Score	Deep Score
Passive	-				
Active	.252	-			
Constructive	-.462*	-.975***	-		
Total Score	-.103	-.457*	.443*	-	
Deep Score	.034	-.497*	.448*	.684***	-

Note. $^{*}p < .05$, $^{***}p < .001$

The ICAP framework posits that students engaging constructively should achieve better learning outcomes. Regression analysis of post-test scores on constructive engagement percentage validated this, with the constructive percentage explaining 67.9% of the variance in post-test scores (F [2, 47] = 20.10, $p < .001$). This supports the ICAP hypothesis and indicates that students who had a higher percentage of constructive engagement during the learning processes would have better learning outcomes. This finding implies that, when responding to the simulation prompt questions, if students put more cognitive effort into providing an explanation, a prediction, or a reflection instead of merely describing, copying information, or manipulating the simulations, they would achieve better learning outcomes.

Comparing learner engagement patterns

To answer RQ3 (*In what ways do individual learner engagement patterns differ or converge when interacting with multiple external representations in an online environment?*), we conducted a more comprehensive exploration into student engagement patterns based on their interaction behaviors during online modules. A subset of four students was selected for a comparative video analysis during their interaction with the Peppered Moths simulation scenario. Table 7 provides a comparative profile of these selected students, identified by pseudonyms.

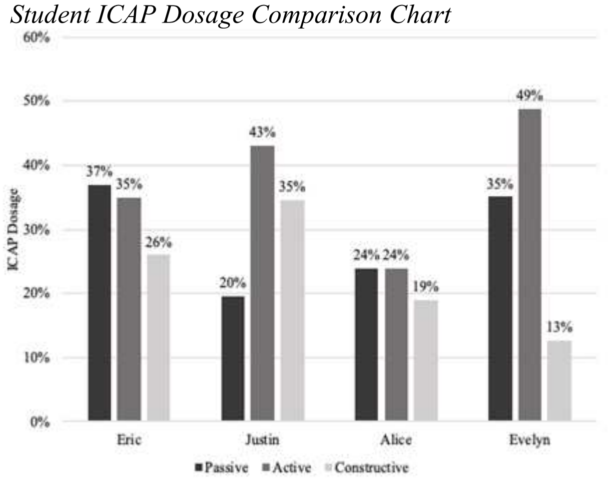
To compare learner engagement patterns among these students, Figure 3 depicts each student's ICAP dosage based on their behavioral interaction with the online module. Notably, Eric and Alice displayed similar passive and active engagement patterns, while Justin and Evelyn had distinct discrepancies in their engagement patterns. For instance, both Justin (43% active) and Evelyn (49% active) spent almost half of their learning time conducting active engagement activities (i.e., manipulating simulations and describing changes).

Insightful observations can be made from the interaction videos of these students. For instance, Evelyn's interaction revealed a tendency to simultaneously adjust various simulation parameters (i.e., selection pressure, mutation, pollution level), leading to potentially convoluted results for interpreting the simulation. Ideally, she should follow the instructions by only manipulating one parameter at a time. Conversely, both Eric and Alice were observed frequently referencing the instructional text, indicating a more informed approach to understanding the simulation. They would even pause the videos, go back to the previous instructional page, and re-read relevant texts before answering prompt questions. In contrast, Justin appeared to prioritize video content over textual information. He sometimes skipped reading the instructional text and provided explanations or reflections without incorporating new ideas.

Table 7
Student Profile Comparison

Name	Group	Learning Gains	Other Demographic Information
Eric	Intervention	High	• Male, 35yrs, other ethnicities • Junior, History major • Took 3 biology courses in high school • Heard about and used NetLogo simulation before
Justin	Intervention	Low	• Male, 19yrs, white • Junior, Education major • Took 2 biology courses in high school • Never heard about NetLogo before
Alice	Control	High	• Female, 21yrs, white • Freshman, Early Childhood Education • Took 1 biology course in high school • Never heard about NetLogo before
Evelyn	Control	Low	• Female, 33yrs, American Indian/Alaska Native • Sophomore, Educational Studies • Took 2 biology courses in high school • Never heard about NetLogo before

Figure 3
Student ICAP Dosage Comparison Chart



These findings suggest that high achievers, as seen with Eric and Alice, do not necessarily possess the highest dosage for constructive engagement in a self-directed online learning environment. Their engagement patterns were characterized by thorough reading of instructional texts and purposeful simulation manipulations, which then informed their constructive responses of the prompt questions. Conversely, for low achievers (i.e., Evelyn and Justin), it appears that a lack of clear scaffolding or explicit monitoring in the self-paced online environment might negatively impact their learning outcomes, leading to potential cognitive fatigue and overload when learning with multiple external representations.

Design principles for self-directed online environments with MERs

Based on our observations, we offer the following principles to guide the effective design of online learning environments with MERs: 1) Integrate Multi-Channel Instructional Content: Given that low achievers might frequently skip over instructional texts, a blend of various instructional channels (e.g., audios, animations, videos) can be more engaging and effective. 2) Limit or Monitor Simulation Parameter Manipulations: Over-manipulation can be counterproductive and potentially lead to confusion. Hence, designers should consider constraining or monitoring parameter changes when using dynamic simulations. 3) Segment Content to Prevent Cognitive Overload: Lengthy modules can be overwhelming for learners. It's recommended to break down the content into shorter, manageable segments for better comprehension and retention.

Conclusion

In this study, we explored how student cognitive engagement relates to the learning outcomes in self-directed online environments with multiple external representations. Findings revealed that constructive responses to prompt questions directly correlate with enhanced learning outcomes, while passive and active responses have less favorable effects. This upholds the ICAP hypotheses (Chi, 2014) about the importance of progressing from passive to active, then constructive. Higher learning performance is achieved when students respond to prompt questions constructively, elaborating and explaining rather than merely describing or paraphrasing content. Analyses of prompt responses showed lower-than-expected cognitive engagement among all students, prompting a detailed review of four students' interaction videos to compare their engagement patterns when interacting with multiple external representations in online modules. The video analysis was a preliminary attempt, but it depicts distinctive learner engagement patterns based on different learner profiles, which could inform future design of online learning environments with multiple external representations for diverse learners.

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