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Interactive Neuroscience: Designing and Implementing Web-Based Simulations to Teach Cognitive Neuroscience Concepts in an Online Classroom A Pilot Study

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Interactive Neuroscience: Designing and Implementing Web-Based Simulations to Teach Cognitive Neuroscience Concepts in an Online Classroom

A Pilot Study

by

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Abstract

While computer simulations are effective tools when learning difficult concepts, little is currently known about the most effective learning environment for the implementation of computer simulations in the classroom. The current study aimed to determine if the effectiveness of simulations depends on the learning environment in which they are implemented. Tested within various passive and active learning environments, this study begins to shed light on the impact of the instructional method in which simulations are implemented on learning outcomes for novice learners. Results from this study suggest that within passive learning environments, simulated animations may be more effective than informationally equivalent static demonstrations. When simulations are used in active learning environments, supplying additional scaffolding to inquiry-based tasks may allow for greater concept mastery than self-directed inquiry alone, and scaffolding may be more successful when the learning materials are simulations over static equivalents.

Keywords: computer simulations, passive learning, active learning, scaffolding, inquiry-based, difficult concepts, self-direct inquiry

Computer simulations have become effective and integral parts of the science classroom (Ruttan, van Joolingen & van der Veen, 2011; Smetana & Bell, 2007; Tundle & Bell, 2009). Thought to facilitate science instruction and learning through improved visualization and interactivity of dynamic processes (de Jong & Van Joolingen, 1998), one argument for the implementation of simulations has been that these simulations help learners succeed in more complex tasks than they could otherwise master (Reiser et al., 2001). Indeed, simulations allow for the exploration of hypothetical situations, interaction with simplified processes and systems, and give space for lower-stake practice in realistic environments (van Berkum & de Jong, 1991). Simulations have been used to improve student learning outcomes and facilitate higher level thinking, critical reasoning, and knowledge retention (Web, 2005; Bish & Schleidt, 2008). For example, Sarabando et al. (2014) found that student understanding of concepts of weight and mass improved with the use of simulations, with or without the addition of a guiding activity.

When used appropriately, computer simulations involve students in authentic science explorations (Smentana, 2012). However, the effectiveness of simulations is closely connected to the pedagogy through which they are employed (Trundle & Bell, 2009). Outside of improper simulation implementation, investigations suggesting computer simulations as less effective than traditional and hands-on instruction remain (Marshall & Young, 2006; Rieber, Boyce, & Assad, 1990, as cited in Trundle & Bell, 2009). Moreover, despite the web-based nature of computer simulations, little is known about the best learning environment for implementing simulations into online classrooms (Blikstein et al., 2017).

The current study therefore aimed to determine whether the effectiveness of simulations to teach complex processes depends on the learning environment in which they are implemented. The simulations investigated here were created to teach students key electroencephalography concepts as part of the NSF-funded initiative PURSUE (Preparing Undergraduates for Research in STEM-related fields Using Electrophysiology) that develops undergraduate training materials for cognitive electrophysiology. Our goal was to create simulations depicting difficult electroencephalography (EEG) concepts and determine a learning environment where implementing such simulations was both effective and engaging for novice learners.

Active Learning Environments

Instructors are turning away from traditional, passive teaching in favor of active learning to promote higher-order thinking and student engagement more successfully (Reed et al., 20; Parappillya et al., 2013; Bonwell, 1991; Sarabando et al., 2014; Ebner & Holzinger, 2007). Stemming from the constructionist learning environment (Papert & Harel, 1991), active learning places a strong emphasis on the learner to be an active agent in the process of knowledge acquisition (De Jong & Van Joolingen, 1998). Active learning is thus generally defined as any instructional method that directly engages students in the learning process, requires students to reflect meaningful about what they are doing and participate in theory revision to achieve concept mastery (Parappillya et al., 2013; May & Silva-Fletcher, 2015; Hmelo-Silver et al., 2007). Within the realm of active learning, highly scaffolded and inquiry-based learning are becoming increasingly popular as methods of conveying complex scientific processes. This is largely due to the common emphasis on engaging in knowledge construction practices in science instruction (Resier et al., 2001), as both learning environments require direct student engagement with the learning materials. As such, we selected these two popular active learning environments as the focus of our study.

Inquiry-based learning is centered on posing questions, gathering and analyzing data, and constructing evidence-based arguments. An inquiry-based learning environment requires self-driven engagement with the material, as well as students to draw their own conclusions, and determine if these conclusions align with the concepts. Inquiry can foster deep and meaningful learning (Hmelo-Silver et al., 2007), and increase conceptual knowledge, engagement, and mastery (Lynch et al., 2005; Scheinder et al., 2013). For example, Parappilly et al. (2013) found that students who participated in inquiry-based physics laboratories not only performed better on assessments, but also reported greater engagement and critical thinking than students who participated in traditionally based laboratories.

Highly scaffolded learning environments provide students support by suppling direct guidance to allow accomplishment of ambitious tasks. Scaffolding is a key strategy in *cognitive apprenticeship*, in which students can learn by taking increasing responsibility and ownership for their role in complex problem solving with the structure and guidance of more knowledgeable mentors or teachers (Resier et al., 2001). As such, key tenants of scaffolding are that learning is aided via the assistance of a mentor, and that the agency of the learner increases throughout the intervention (i.e., requires fewer instances of assistance from a mentor). In this way, scaffolding assists learners in accomplishing tasks while simultaneously facilitating learning from experience (Resier et al., 2001; Mamun et al., 2020). Scaffolding assists in sense making, manages student investigations and problem-solving process, and requires students to engage with key concepts meaningfully (Reiser, 2004; Quintana et al., 2004). While scaffolding necessitates intervention of an individual (mentor; teacher; expert), results from Mamun et al. (2020) suggest scaffolding can be successfully implementing in an online environment. Mamun et al. (2020) posited that the addition of external representations, guiding questions, and instructional guidance mitigates the need of immediate intervention of another individual in an online environment.

While these two learning environments offer learners different amount of agency and information when it comes to problem solving, they are not mutually exclusive. In fact, the success of inquiry-based approaches may depend on how much scaffolding is supplied throughout the learning process. A truly inquiry-based approach involves self-discovery and increased agency; thus, key information is withheld, guidance is limited, and students must also work more independently to figure out how to solve a problem. Minimization of guidance is a marked downfall of inquiry-based learning, contributing dramatically to the presence of literature in opposition to its effectiveness (Hmelo-Silver et al., 2017; van Berkum & de Jong, 1991). Striking a balance between inquiry and scaffolding does in fact produce desire learning outcomes; Adbi (2014) speaks to the improved scores on assessments for students who were instructed through inquiry-based learning compared to their traditionally taught peers. Students in this inquiry-based condition were provided questions, suggestions, and feedback— inherent components of a scaffolded approach. A purely scaffolded approach is also difficult to construct, particularly in the sciences, where heavy emphasis is placed on knowledge construction practices (Reiser et al., 2001). Moreover, the acquisition of reasoning strategies and knowledge throughout scaffolded learning inherently lends to inquiry-based learning strategies toward the end of intervention (Reiser at al., 2001; Mamun et al., 2020). Scaffolded learning, more frequently as an active learning style, is facilitated by providing core knowledge through lecture and context-related problem-solving and supported through directed and self-directed learning (May & Silver-Fletcher, 2015). This allows for the integrated knowledge construction in a way that is move effective than pure inquiry-based learning (May & Silver-Fletcher, 2015).

The complementary nature of these active learning environments recognizable within simulations themselves. Simulations inherently place emphasis on the learner as an active agent in knowledge acquisition, allowing for authentic inquiry (e.g., forming questions, developing hypotheses, collecting data, revising theory) (de Jonng & van Joolingen, 1998). Simultaneously, simulations structure learning of difficult concepts by functioning as simplified, artificial models of complex processes. Failure to consider and provide learning support (e.g., directed, guiding instruction) will not produce desired instructional gains (Trundle & Bell, 2009).

PURSUE Simulations

Due to the ability for simulations to improve student learning outcomes when dealing with difficult concepts, the PURSUE initiative designed four web-based interactive simulations portraying key EEG concepts. Electroencephalography (EEG) is a direct and continuous measure of brain activity recorded by electrodes on the scalp, and it is a method commonly used in cognitive neuroscience experiments. While EEG has many advantages in undergraduate education, including its relatively low cost, its direct ability to measure neural activity that corresponds to cognitive progressing, and its real-time recording precision (Bukach et al., 2019), it is a difficult concept to teach at the undergraduate level. Roadblocks in undergraduate EEG education primarily include the conceptually complex nature of EEG, and the time required to appropriately train students in data collection and analysis techniques. Because EEG typically requires a great deal of background and hands-on, attentive practice to master, the typical classroom setting tends to compound effective learning.

The PURSUE initiative's aim is to facilitate training of undergraduates in electrophysiology. To combat the difficulties of teaching EEG to undergraduates in the traditional classroom, the PURSUE project developed four web-based, interactive simulations explaining the factors that influence the EEG signal measured at each electrode. Simulation One portrays how the orientation of an electrode can affect the directionality of an EEG waveform. Simulation Two portrays how the distance of the neural source from the scalp impacts the distribution of electrical potential at different scalp locations. Simulation Three portrays how the orientation of the neural source from the scalp impacts the distribution of electrical potential and the EEG waveforms recorded at different scalp locations. Simulation Four combines principles from the previous three.

While an investigation is still needed examining the effectiveness of all four PURSUE simulations, the current study only involved Simulation Two. Specifically, this simulation displayed how the distance of the neural source with respect to the scalp electrode impacts the strength of the signal recorded by the electrode and associated waveform produced.

We have yet to test the impact of online learning environment on learning outcomes directly using the simulations developed for PURSUE. Pilot data collected on from a Cognitive Neuroscience class who used Simulation One revealed that students who were able to use the simulation out-performed baseline students when predicting the impact of electrode location on polarity and orientation (Jackson et al., 2018). This is consistent with the current literature, where interactive, web-based learning is seen to improve student learning outcomes, facilitate higher thinking, and knowledge retention (Bish & Schleidt, 2008; Mehlenbacher et al., 2000; Blikstein et al., 2017).

Simulation Design

Before testing the simulations in various learning environments, we redesigned the PURSUE simulations to maximize their effectiveness as learning tools. Taking key considerations in the design of effective multimedia tools into account, this project involved a complete alternation of simulations from versions one to versions two (Figure One). Primarily, multimedia design considerations require recognition of the limitations in human information processing systems (Reed et al., 2021). The theory of multimedia learning is based on the assumptions that humans possess separate processing systems for visual and verbal information, and that each of these systems are limited in the amount of information that can be processed at a given time (Mayer & Monero, 2003). In addition, humans possess a limited capacity of what can be stored in working memory: a component of the memory system involved in the temporary storage and manipulation of information for complex cognitive tasks (e.g., learning) (Baddeley, 1992).

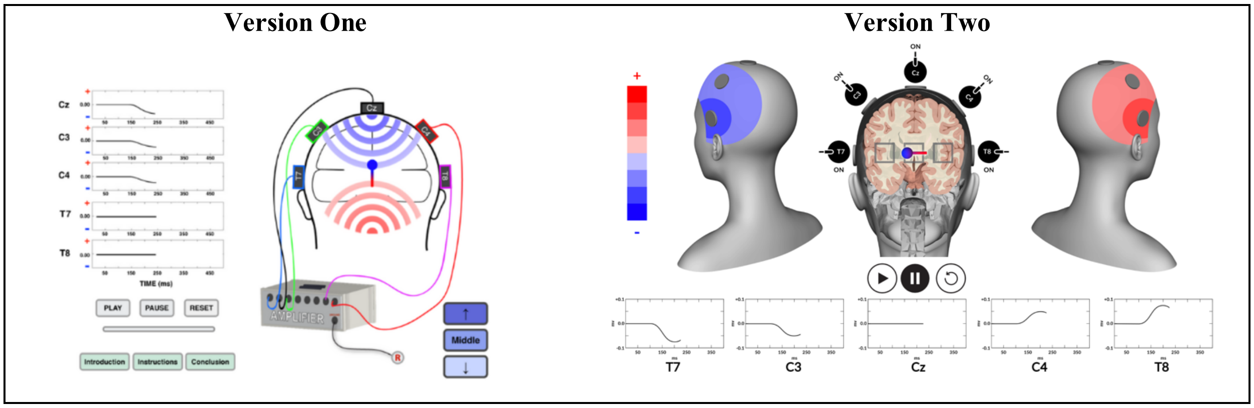
Multimedia learning involves the integration of multi-sensory information to help learners create *mental models* (the internal representation of an external phenomenon) (Mayer & Monero, 2003; Mayer 2014). The construction of a mental model is a requirement for meaningful learning— however, the substantial cognitive processing required during meaningful learning limits the learner's cognitive processing capacity. Therefore, improperly designed multimedia learning tools makes learners more susceptible to exceeding their information-processing capacities, increasing the potential for *cognitive overload* (learner's intended cognitive processing exceeds the learner's available cognitive capacity) (Mayer & Monero, 2003). The proper implementation of multimedia learning tools allows for a reduced risk of cognitive overload in learners (Mayer, 2012; 2014c; Mayer & Moreno, 2003).

One outlined multimedia implementation principle involves the reduction in extraneous processing in order to focus attention of relevant information (Mayer, 2014b). Irrelevant information should be minimized, and images should be simplified (Reed et al., 2021; Mayer & Johnson, 2008; Mayer & Moreno, 2003). Text use should be limited, and replaced with narration if possible (Mayer, 2003; Mayer 2012; Mayer & Moreno, 2003), as to separate concurrent information processing by visual vs auditory system. To create maximally attention and engagement of learner, a conversational style of language should be utilized during narration (Mayer, 2008).

We concentrated on these multimedia learning principles when designing the simulations used in this experiment. In the most recent version, all simulations were simplified to the most essential components. Simulations were created by the primary investigator of this project, the PURSUE research coordinator, undergraduate research assistants, and a graphic designer to ensure that their learning goals were portrayed well and easily understood. In addition, when experimental materials were created for this study, a heavy emphasis was placed on reducing cognitive load via increased narration and limited text (see Materials).

Figure 1

Version History: PURSUE Simulation Two



The Current Study

The goal of the current study was to determine the most effective online learning environment for the implementation of an interactive simulation displaying key EEG concepts. EEG is conceptually complex, difficult to teach, and difficult to understand. Computer simulations relating to EEG exists as a favorable learning tool to overcome these challenges. However, despite the increasing employment of active learning techniques to teach difficult scientific concepts, and the effective nature of computer simulations to facilitate scientific instruction, a considerable gap in the literature exists regarding how to effectively implement simulations. Therefore, the current study investigated the following questions: (1) Are simulations effective in a traditional demonstration? (2) Are simulations effective in an inquiry-based environment? (3) Does the effectiveness of inquiry-based environments depend on level of scaffolding?

To explore these questions, we compared two different learning environments: demonstrations conditions, which mirrored a passive learning environment, and active conditions, which required meaningful engagement with the simulation materials. Within the demonstration conditions, there were two experimental groups: a simulation demonstration, or an informationally equivalent static demonstration. In the demo conditions, participants passively viewed a recorded demonstration. Comparison of learning outcomes and engagement between the two demonstrations provides insight to if the simulations are effective teaching tools. Within the active conditions, there were three groups: a highly scaffolded simulation demonstration, a highly scaffolded static demonstration, or self-directed simulation inquiry. Highly scaffolded learning tasked participants with making predictions, while self-directed inquiry required participants to engage in self-discovery of the simulation concepts. Comparisons between these groups allows for a direct investigation of differences between learning outcomes and engagements of these popularly deployed active learning environments.

Due to the complex nature of the experimental materials required to investigate these questions, the present study is a pilot investigation of the research questions. Results from this study justify employing this experimental design in future studies.

Materials and Methods

Design

A random assignment pilot study was conducted investigating passive versus active learning environments for simulation implementation. Five different experimental groups were tested: Passive Static Demonstration, Passive Simulation Demonstration, Highly Scaffolded Demonstration, Highly Scaffolded Simulation, Self-Directed Simulation Inquiry (Table One).

Table One

Experimental Conditions

	Learning Environment				
	Active		Passive		
Experimental Condition	Highly scaffolded demonstration	Highly Scaffolded Simulation	Self-Directed Simulation Inquiry	Simulation Demonstration	Static Demonstration
n	10	15	6	10	11

Online learning environment. Online learning environment was manipulated via simulation presentation. Demonstration learning environments included a single narrated video where components of the simulation were explained to participants by a narrator. Highly Scaffolded learning environments were operationalized as presentation of the simulation materials (identical to the demonstration for the appropriate condition) segmented by guiding prediction questions. The inquiry-based learning environment tasked participants will self-direct discovery of the simulation's key concept without external support.

Simulation Presentation. The organization in simulation presentation did not vary for any groups aside from the self-directed inquiry condition. The exact presentation order of dipole location and electrode activation for the experimentally manipulated conditions can be found in Supplemental Materials 3.

Static Demonstration.

Participants in this group watched a narrated video recording of informationally equivalent, static images of the simulation. In this video recording, participants were unable to see the dynamic process of neural activity. Participants merely saw the scalp distribution associated with each active dipole's location, and the final EEG waveform recorded by electrodes. Participants were unable to follow the timecourse relationship of the dipole's activity to the produced scalp distribution and the recorded EEG waveform. The recorded video was approximately five minutes long and included a voice-over explaining the scalp distribution formation and EEG signal recording at each dipole location for each electrode.

Simulation Demonstration.

The simulation demonstration was identical to the static demonstration in organization and narration; however, participants viewed a narrated recording of the simulation itself. Because of this, participants watched the dipole's activity peak, and saw how this related to the EEG recordings' peak amplitude, as well as the strength and organization of the scalp distribution. The recorded video was approximately five minutes long and included a voice-over explaining the scalp distribution formation and EEG signal recording at each dipole location for each electrode.

Highly Scaffolded Simulation.

Participants in this condition saw equivalent recorded videos to that of the simulation demonstration condition. However, the presentation of the simulation materials was unique: instead of watching a single narrated recording of the simulation, participants viewed the recording in five different segments, divided by four prediction questions. The first segment demonstrated the dipole in one location and explained the recorded signal from three of the five electrodes. This segment ended by asking participants to predict the recorded signal from the remaining two electrodes. This pattern of explanation then prediction continued for each video segment: the second segment explained the correct answer from their first prediction, and included the second prediction question, where participants were asked to predict the EEG recording from three of the five electrodes in a novel position. They then watched a video segment explaining the correct answer for and were asked to predict the EEG recordings from the remaining two electrodes. In the next segment, participants received an explanation of the correct signal from these two electrodes and were given their final prediction question, where participants were asked to select their prediction of the EEG recording from all five electrodes when the dipole was moved to a novel position.

Highly Scaffolded Demonstration.

The pattern (e.g., explanation then prediction) for this experimental condition was identical to that outlined above. This group varied from the highly scaffolded simulation group by the materials presented: participants in this group saw materials identical to those in the static demonstration condition. Therefore, participants were unable to see the dynamic relationship of dipole activity, scalp distribution, and electrode recordings, watched five video segments and answered four prediction questions.

Self-Directed Simulation Inquiry.

Participants in this group were given direct access to the simulation interface. The simulation was imbedded directly into the experiment and included the following written instructions: *"You will now be asked to interact with the simulation materials. We ask that you explore the simulation at your own pace and try you hardest to identify the key concept of the simulation. It is important that pay attention while interacting with the simulation, as you will be assessed on your understanding of the content"*. Participants did not receive any feedback or explanation of the simulation's learning goal. The visual information included in this condition did not vary from the other conditions, and this condition only differed by the lack of narration and guidance supplied.

Participants.

A total of 94 undergraduates from the University of Richmond campus participated in this study. 15 participants were excluded from analysis because they had reported having learned about EEG in a previous course. 27 participants were excluded from analysis for not completing the study. Therefore, the final sample included 52 participants (39 women; 13 men, M_{age} = 18.0). Seven participants identified as Asian, five identified as Black or African American, 35 identified as White, eight identified as Hispanic or Latino, and one Identified as Arab. Four participants reported being of more than one race. Participants were randomly assigned into the static demonstration (n=11), the simulation demonstration (n=10), the highly scaffolded simulation (n=15), the highly scaffolded demonstration (n=10), or the self-directed inquiry (n=6) conditions (Table One). Participants received a $10 Amazon gift card for their conset to participate.

Materials

Simulation. The simulation was created as part of the PURSUE initiative. The simulation displayed how the distance of the neural source with respect to the scalp electrode impacts the strength of the signal recorded by the electrode and associated waveform produced. The simulation was created in Hype and included a coronal section slice of the head, five standard electrodes with a graph for each electrode, three possible dipole locations, and two external scalp views where scalp distributions were displayed (Figure 2). The simulation can be found on http://pursue.richmond.edu.

Static Images. The static images were screen-captures of the simulation, including the background and instruction sections. The static images were therefore identical to the simulation, however displayed the simulation as a still image, with the scalp distribution and EEG recording outcomes present throughout the entire demonstration.

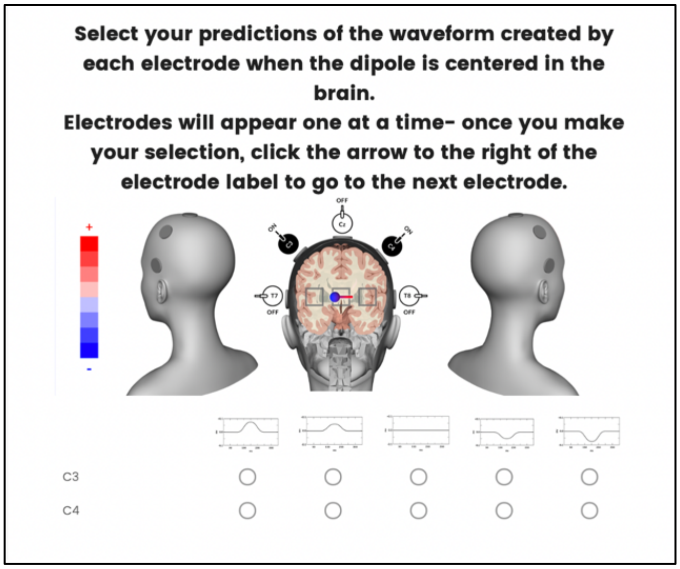
Lecture Recording. All participants viewed a pre-recorded introductory lecture. This lecture included background information on electroencephalography, as well information relating to neural communication and understanding the EEG signal. The lecture was created with specific intent to adhere to multimedia design principles, including the exclusion of irrelevant information; simplification of images; limited text; and concurrent, conversational style voice narration. In addition, the lecture was designed to serve as an opportunity to develop foundational knowledge for simulation use. This was done so that the interaction with simulation materials could be devoted to the understanding the relationship of concepts displayed in the simulation, not defining and/or understanding the concepts themselves. Video editing and voice narration was conducted using Camtasia 2019 software. The lecture could be paused at the participants convenience. The lecture recording was approximately 13 minutes.

Guiding Question. Guiding questions were included only in highly scaffolded groups. Guiding questions were present between defined segments of the simulation materials (see Supplemental Materials 1 for all guiding questions). Questions included prediction questions where participants were asked to match the current dipole and electrode configuration to the appropriate

EEG waveform recorded by the electrode. Questions included instructions, as well as an image displaying the dipole location and the active and inactive electrodes (Figure 2).

Figure 2

Sample Guiding Question



Note. Questions appeared as a vertical carousel for participants, where they selected the waveform from a dropdown of images one electrode at a time.

Assessment Questions. Assessment questions were included at the end of the experiment. Participants were asked to answer a variety of question styles, including multiple-choice (ex: *"Which dipole is most likely to create the following scalp distribution?"*), open-ended (ex: *"Explain how the distance of the dipole from the electrode affects the amplitude and polarity of the EEG signal."*), and matching questions (ex: *"Predict the signal at each of the electrodes from the following dipole"*). Images of heads with or without scalp distributions were included in questions when appropriate. When included, the appropriate electrodes for each question were turned on or off. See Supplemental Materials 2 for all assessment questions.

Engagement Questions. After completing the assessment questions, participants answered engagement questions on the survey as a whole, rating their level of agreement on a 5-point Likert scale (Table 2).

Table 2

Engagement Questions

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I found the lecture interesting					
I found the simulation interesting					
I would like to learn more about neuroscience of ERPs methods					
I lack the scientific background to tackle neuroscience/ERP research					

Procedure.

Participants accessed the study via an online link to Qualtrics (http://qualtrics.com). After providing informed consent, participants were first asked to complete a series of questionnaires that collected basic demographic information as well as information on the student's academic history (undergraduate major, year in college). All participants then watched the pre-recorded introductory lecture. After watching the lecture, participants were randomly assigned to one of the five conditions. For all conditions, participants watched or interacted with the simulation or static images and answered the assessment and engagement questions.

For demonstration groups, participants watched a narrated video recording explaining the scalp distribution and EEG recording at each dipole location. There were two demonstration groups: one who viewed a video recording of the simulation as an animation, and one who viewed equivalent static images of the scalp distribution and EEG signal recording outcomes of dipole activity. For both groups, an instructor narrated the key concepts.

For highly scaffolded groups (both static and simulation), the demonstration was broken into five segments with guiding prediction questions between. For each segment, participants viewed a signal dipole location and listened to an explanation of the related waveform created by electrodes. Participants then made predictions of either the waveform from other electrodes in the same location or prediction of the waveform from electrodes in a new location. After making a prediction, the beginning of the next segment displayed the correct answer to the previous prediction question and provided an explanation of the recorded EEG signal at the appropriate electrodes.

For the inquiry group, participants were given direct access to the simulation interface. Participants were instructed to explore the simulation at their own pace to determine the key concept.

Following simulation investigation for all groups, participants were asked to complete assessment questions that targeted concepts taught in both the introductory lecture and simulation materials. After completing the assessment questions, participants answered engagement questions on the study as a whole. In total, the experiment took between 30-45 minutes.

Results

Due to the pilot nature of this study, the low n-size does not provide enough power to statistically test the effectiveness. As a result, all statistical analysis reported below do not reflect the efficaciousness of each experimental group on participant learning outcomes or participant engagement. While the small sample size precludes any conclusions to be drawn, the trends in our data are suggestive that our experimental design shows promise for further investigations.

Learning Outcomes.

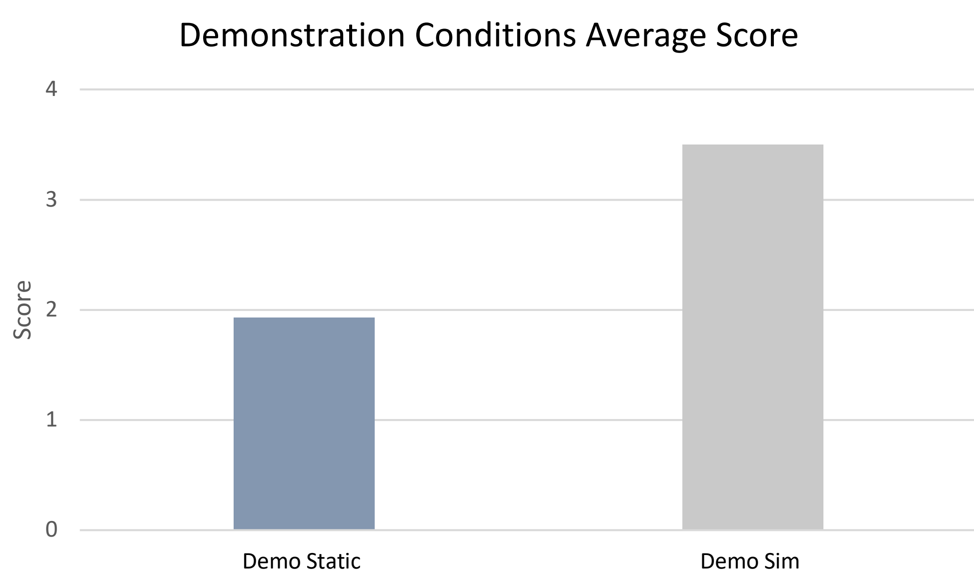
We did not include each assessment question in analysis due to major time restraints of the project. To focus on learning outcomes related to the simulation itself, we investigated mean scores on five questions: one open-ended “identify the concept” question, one multiple-choice “scalp to dipole” question, and three prediction questions. In the open-ended question, participants were asked to explain how the distance of the dipole from the electrode affects the amplitude and polarity of the EEG signal. Scoring for the open-ended question awarded two points for identifying the impact of dipole location on the EEG signal’s amplitude, two points for identifying the impact of dipole location on the EEG signal’s polarity, and two points for acknowledging that when the recording electrode is perpendicular to the dipole, the recorded signal is zero. In the multiple-choice question, participants were required to think about the simulation in reverse and identify the correct dipole location to produce the pictured scalp distribution. In the prediction questions, participants saw a novel dipole arrangement and had to select their prediction of the correct EEG recording for each electrode. These three questions varied in difficulty, where the easiest question included a familiar dipole orientation and the scalp distribution included, the intermediate question had a new dipole orientation and the scalp distribution included, and the most difficult question contained a new dipole orientation and scalp distribution omitted.

Identify the Concept.

An independent samples t-test comparing the mean score on the open-ended question for the static demonstration condition with that for the simulation demonstration condition was conducted. The simulation demonstration group scored significantly higher than the static demonstration group, $t(19) = -2.52$, $p = 0.02$ (Figure 3). In contrast, a One-Way ANOVA with active conditions as between-subjects factors revealed no significant difference on mean score on the open-ended question ($M_{scaffolded\text{-}sim} = 2.2$, $M_{scaffolded\text{-}static} = 1.9$, $M_{inquiry\text{-}sim} = 1.6$), $p = 0.75$ (Figure 4).

Figure 3

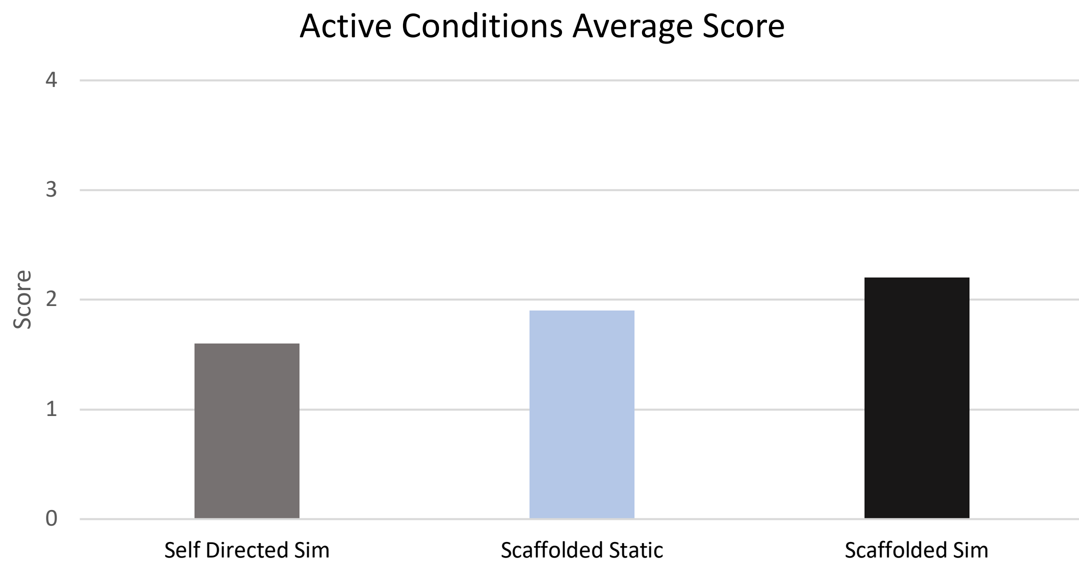
Demonstration Conditions: Identify the Concept



Note. Error Bars not included due the small n-size.

Figure 4

Active Conditions: Identify the Concept



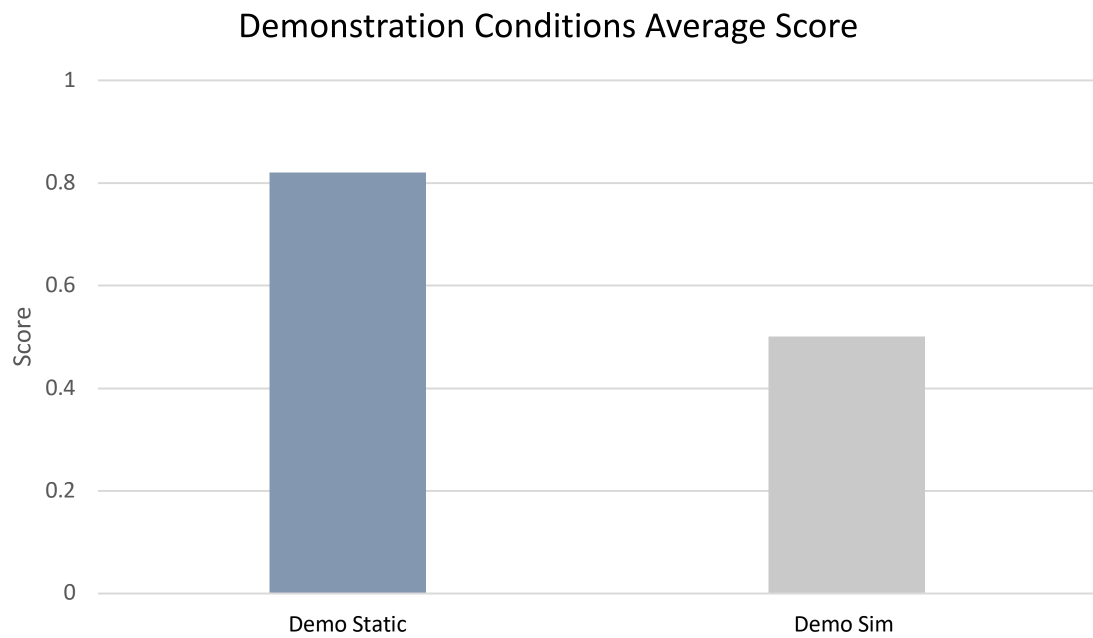
Note. Error Bars not included due to the small n-size.

Scalp to Dipole.

An independent samples t-test comparing the mean score on the multiple-choice question for the static demonstration condition with that for the simulation demonstration condition revealed no significant difference ($M_{simulation} = 0.5$, $M_{static} = 0.82$), p = 0.135. However, the visual pattern of means suggest static demonstration participants were better able to identify the correct dipole location (Figure 5). Similarly, a One-Way ANOVA showed with active conditions as between groups-factors revealed no significant difference for mean score on the open-ended question ($M_{scaffolded\text{-}sim} = 0.73$, $M_{scaffolded\text{-}static} = 0.6$, $M_{inquiry\text{-}sim} = 0.5$), p = 0.58. Trends in performance suggest the highly scaffolded simulation group was best equipped to correctly identify the correct dipole location (Figure 6).

Figure 5

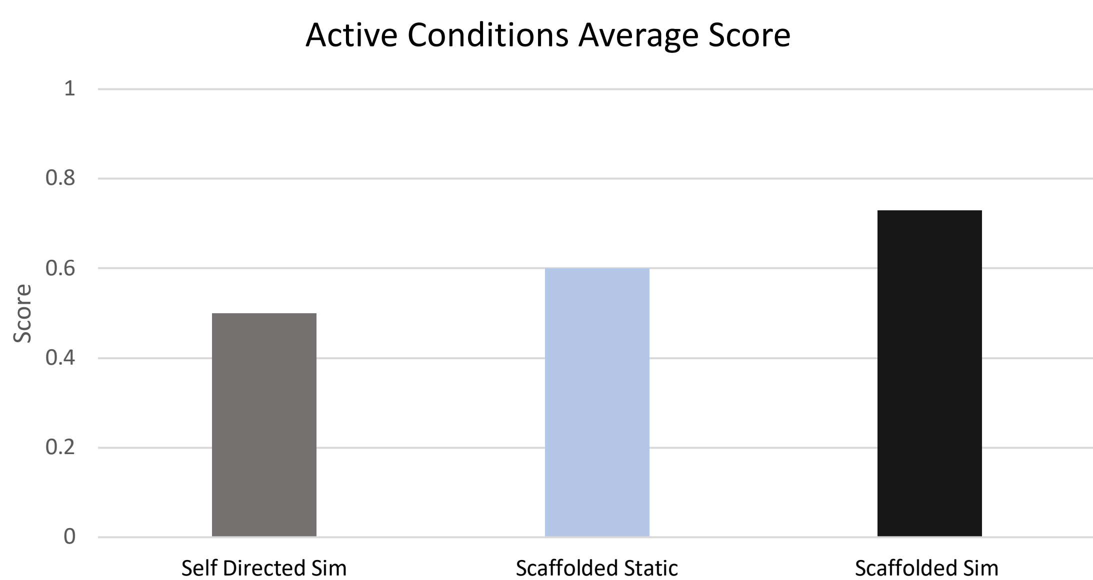
Demonstration Conditions: Scalp to Dipole



Note. Error Bars not included due to small n-size

Figure 6

Active Conditions: Scalp to Dipole



Note. Error Bars not included due to small n-size.

Predicting the Waveform.

A 2 x 3 mixed factorial ANOVA with the between-groups simulation presentation factor (Simulation Demonstration, Static Demonstration) and within-groups prediction question factor (Easy, Intermediate, Difficult) was conducted. Results showed no significant main effects between demonstration groups, $F\ (1,\ 19) = 1.03,\ p = 0.329$, or level of difficulty, $F\ (1,\ 19) = 9.21,\ p = .144$, or interaction $F\ (1,19) = 1.08,\ p = .311$. Visual trends in group performance show that when prediction questions are intermediate or difficult, the simulation demonstration group scored higher (Table 3, Figure 7).

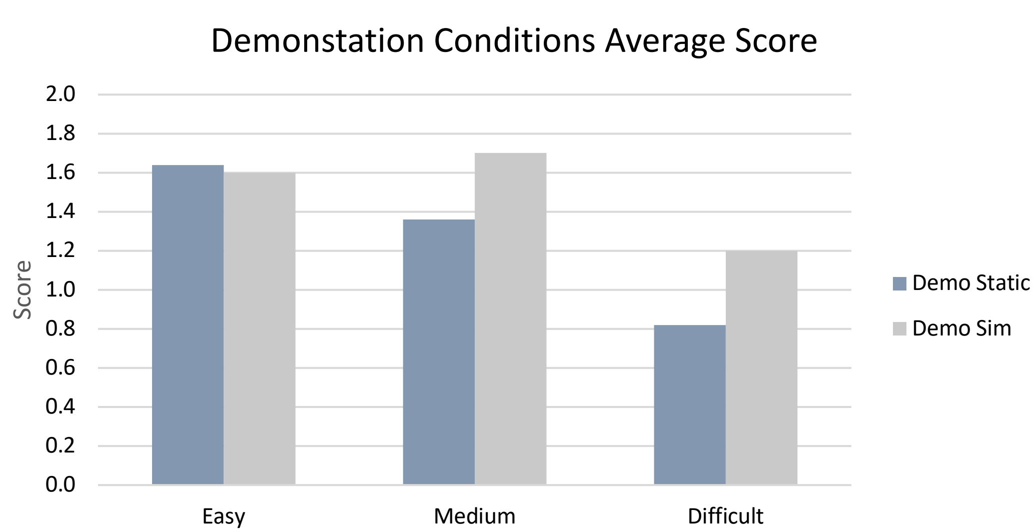
Table 3

Demonstration Groups Average Prediction Question Score.

	Easy	Intermediate	Difficult
Static	1.6	1.4	0.8
Simulation	1.6	1.7	1.2

Figure 7

Demonstration Conditions: Predict the Waveform



Note. Error Bars not included due to small n-size.

A 3 x 3 mixed factorial ANOVA with the between-groups simulation presentation factor (Highly Scaffolded Simulation, Highly Scaffolded Demonstration, Self-Directed Inquiry) and within-groups prediction question factor (Easy, Intermediate, Difficult) was conducted. Results showed no significant main effect of between groups, $F(2, 28) = 0.107, p = 0.899$, or question type $F(2, 28) = .101, p = 0.735$, or interaction $F(2, 28) = .108, p = 0.836$. Trends in group performance show that when prediction questions are easy, the self-directed simulation inquiry conditions scores highest, but when intermediate, the highly scaffolded static demonstration scores highest (Table 4, Figure 8).

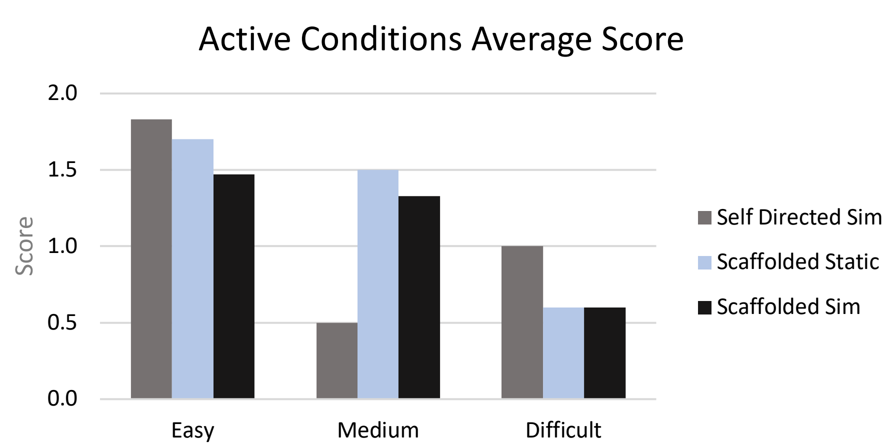
Table 4

Active Groups Mean Prediction Question Score

	Easy	Intermediate	Difficult
Self-Directed Simulation	1.8	0.5	1.0
Scaffolded Static	1.7	1.5	0.6
Scaffolded Simulation	1.5	1.3	0.6

Figure 8.

Active Conditions: Predict the Waveform



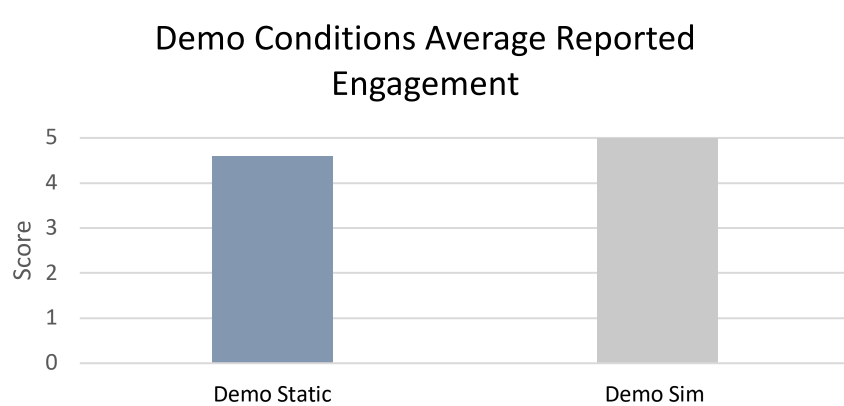
Note. Error Bars not included due to small n-size.

Engagement.

An independent samples t-test comparing the mean engagement score for the static demonstration condition with that for the simulation demonstration condition revealed no significant difference between groups ($M_{simulation} = 5, M_{static} = 4.6), p = 0.64$ (Figure 9). Trends suggest participants experienced marginally greater engagement in the simulation demonstration condition than the static demonstration. Similarly, a One-Way ANOVA with active conditions are the between-groups factor showed no significant difference on mean engagement score ($M_{scaffolded\text{-}sim} = 4.13, M_{scaffolded\text{-}static} = 4.4, M_{inquiry\text{-}sim} = 3.83), p = 0.93$ (Figure 10). Trends suggest within the active conditions, participants experienced the most engagement within the highly scaffolded static demonstration, and the least within the self-directed inquiry condition.

Figure 9

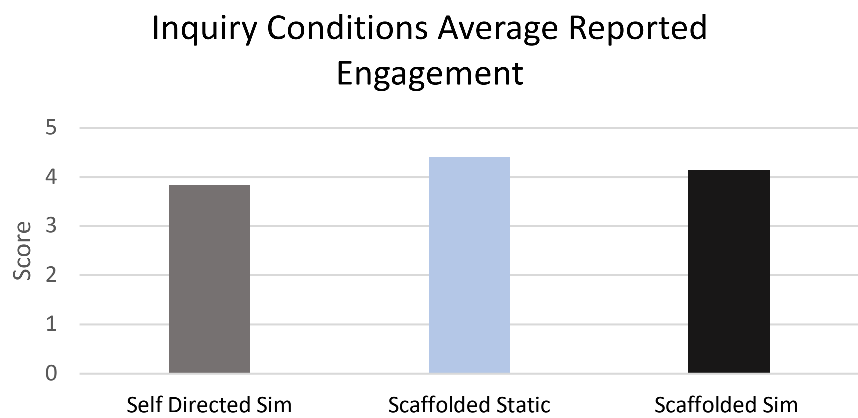
Demonstration Conditions Average Reported Engagement



Note. Error Bars not included due to small n-size.

Figure 10

Active Conditions Average Reported Engagement



Note. Error Bars not included due to small n-size.

General Discussion

Computer simulations are an excellent tool of increasing student understanding in the science classroom: by improving visualization of and interactivity with conceptually complex, dynamic, or intangible processes, simulations allow for concept mastery. Interactive simulations inherently involve students in active learning practices: students are the central agent in their own knowledge acquisition. This differs from demonstrations, where learning is passive, and students are not required at the forefront of concept construction. While interacting with simulations dually requires highly scaffolded and inquiry-based learning mechanisms (i.e., effective instruction and direction; concept testing and discovery), much remains to be known about the most advantageous learning environment for their implement them in the classroom. Due to this paucity, the current study aimed to further the current understanding of the most effective learning environment for simulation implementation.

As a pilot investigation with a small sample size, this study is unable to reliably determine the effectiveness of the investigated learning environments. However, this study sheds lights on the validity of the experimental design and learning environment manipulations. While the sample size (N=52) restricts the ability to find significant differences, from the small number of participants included in analysis we were able to see trends in our data suggestive of disparate learning outcomes between groups.

When the simulation materials were presented as a passive demonstration, participants in the simulation condition scored higher on almost all assessment questions included in analysis (Figure 3, Figure 7). However, participants who were in the static demonstration condition outperformed the simulation demonstration group when asked to correctly identify the correct dipole for a particular scalp distribution (Figure 5). This could have occurred for several reasons: primarily, the static demonstration condition materials were not dynamic, and included the appropriate scalp distribution for each dipole constantly. As such, the static group viewed the dipole and resulting scalp distribution throughout the entire demonstration. This is markedly different from the simulation demonstration group, where participants saw the scalp distribution temporarily as the dipole's activity peaked. And, with all results, differences in group performance cannot be ruled out by inadequate power.

When participants were placed in various active learning environments, participants in the highly scaffolded simulation condition tended to perform better on assessment questions relating to the key concepts displayed (Figure 4, 6). When participants were asked to apply the knowledge gained from the simulation materials to novel situations, however, the self-directed inquiry condition participants were more likely to appropriately predict the correct response when these questions were easy, or intermediately difficult. When novel application was most difficult, participants in the highly scaffolded demonstration performed better than the other active learning groups (Figure 8). Analogous with differences in demonstration group learning outcomes, this is likely due to inadequate power. Due to the large number of participants who did not complete the study, the assignment between groups— particularly active learning groups — was not equal (Table 1).

Limitations.

Despite demonstrated promise in results, a clear limitation of the study is the small sample size. Due to the small size and unequal distribution of the sample, we are unable to report significant effects of learning environment on learning outcomes. Moreover, the assessment approach also limits our results; due to the exploratory nature of the project, this study involved immediate recall of simulation content. A more effective investigation of learning outcomes would include both immediate and long-term retention. Finally, because this study was conducted online with novice learners, the level of performance on assessment questions may not reflect the level of learning in the context of an EEG-focused classroom. Despite this, we expect that patterns of performance between learning environments would remain.

Conclusions and Future Directions.

Trends in the data indicate that the simulation is generally more effective than equivalent, static demonstrations. Fundamentally, having superior understanding and application of concepts when viewing the simulation over a static demonstration supports the use of this simulation for teaching key EEG concepts. Additionally, when participants were placed in various active learning environments, the highly scaffolded groups outperformed the self-directed inquiry group when answering questions related to fundamental understanding of simulation concepts. This indicates that scaffolded learning may be more beneficial than inquiry-based learning for understanding difficult concepts taught within a simulation. Of the highly scaffolded groups, the highly scaffolded simulation condition scored higher than the highly scaffolded demonstration condition, supporting the conclusion that simulations are more effective than demonstrations for teaching EEG concepts. Taken together, results demonstrate that the design of this experiment was sound and will be effective for future investigations.

This study is part of a larger experiment involving all four PURSUE simulations. The research question, aims, and experimental groups will be identical to those in the present study, however, the five experimental groups will either interact with simulations one through three (which build in complexity), or simulation four (which combines the principles of simulations one-three).

Acknowledgements

This work was completed under the advising of Dr. Cindy Bukach. Members of Dr. Bukach's laboratory, including the PURSUE project coordinator, Nadia Bukach, the lab manager, Olivia Stibolt, and the undergraduate research assistants were instrumental in the completion of this project. Contributions of these individuals include developing and revising the PURSUE simulation, programming the online experiment, and recruiting participants. This work was supported by collaborative grants from the National Science Foundation's program for Improving Undergraduate STEM Education: Education and Human Resources (Bukach 1625521 & 1914858; Couperus 1625610 & 1914834; Reed 1626554 & 1914855), the James S. McDonnell Foundation Understanding Human Cognition Scholars Award (Bukach, 2015), and the John Neasmith Memorial Dickinson Award in Psychology (Stewart, 2020).

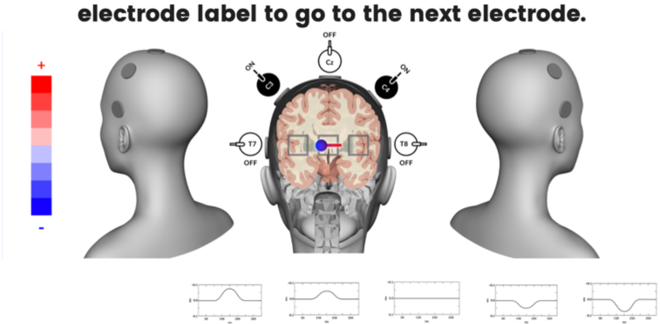
Supplemental Materials

Supplemental Materials 1.

Guiding Questions for Highly Scaffolded Conditions

Inquiry Prediction Question 1

Select your predictions of the waveform created by each electrode when the dipole is centered in the brain.
Electrodes will appear one at a time- once you make your selection, click the arrow to the right of the electrode label to go to the next electrode.

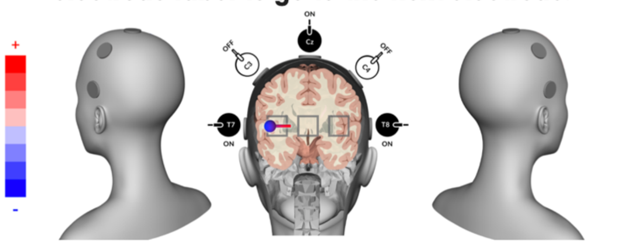


C3

C4

Inquiry Prediction Question 2

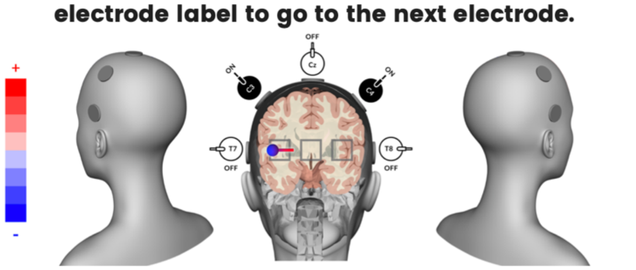
Select your predictions of the waveform created by each electrode when the dipole is moved to the left position in the brain.
Electrodes will appear one at a time- once you make your selection, click the arrow to the right of the electrode label to go to the next electrode.



T7							
T8							
Cz							

Inquiry Prediction Question 3

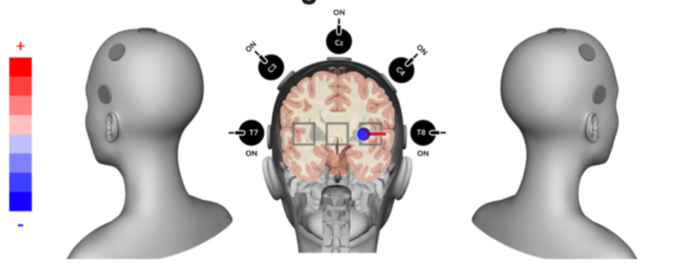
Select your predictions of the waveform created by each electrode when the dipole is moved to the left position in the brain.
Electrodes will appear one at a time- once you make your selection, click the arrow to the right of the electrode label to go to the next electrode.



C3							
C4							

Inquiry Prediction Question 4

Select your predictions of the waveform created by each electrode when the dipole is moved to the right position in the brain.
Electrodes will appear one at a time- once you make your selection, click the arrow to the right of the electrode label to go to the next electrode.



T7	○	○	○	○	○	○	○	○	○
C3	○	○	○	○	○	○	○	○	○
Cz	○	○	○	○	○	○	○	○	○
C4	○	○	○	○	○	○	○	○	○
T8	○	○	○	○	○	○	○	○	○

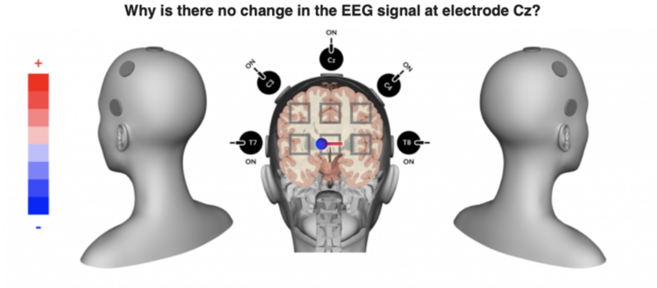
Supplemental Materials 2.

Assessment Questions

Post Test Questions: Open Ended Questions (A)

What is EEG?

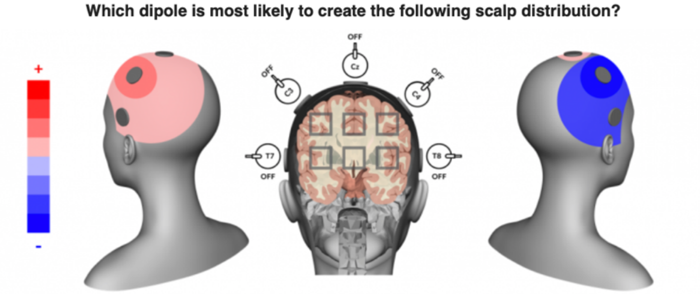
Why is there no change in the EEG signal at electrode Cz?



Explain how the distance of the dipole from the electrode affects the amplitude and polarity of the EEG signal.

Post Test Questions: Multiple Choice Questions (B)

Which dipole is most likely to create the following scalp distribution?



Which of the following are advantages of the EEG/ERP method?

- ○ Good temporal resolution
- ○ Linking brain and behavior
- ○ Less expensive than other neuroimaging methods
- ○ All of the above

Where do EEG signals come from?

- ○ The changes in electrical charges outside of the cell during post synaptic potentials
- ○ The changes in electrical charges outside of the cell during action potentials
- ○ The changes in electrical charges inside of the cell during post synaptic potentials
- ○ The changes in electrical charges inside of the cell during action potentials

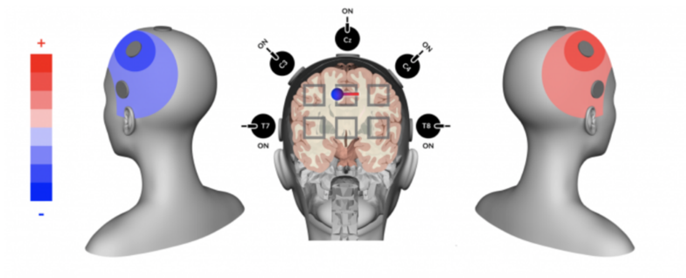
What does an ERP measure?

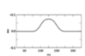
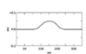
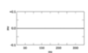
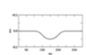
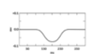
- ○ Blood flow
- ○ Summed neuronal electrical activity
- ○ Individual neuronal electrical activity
- ○ Magnetic fields potentials

Post Test Questions: Matrix Table Questions (C)

Predict the signal at each of the electrodes from the following dipole.

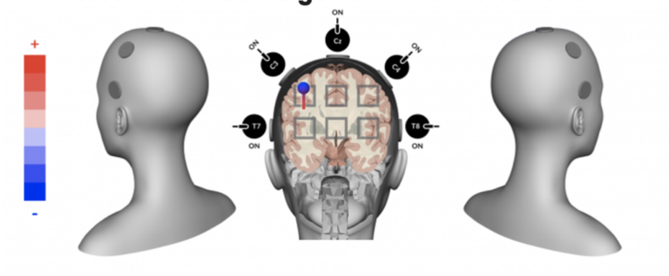
Electrodes are shown one at a time- once you make your selection, click the arrow on the right of the electrode label to go to the next electrode

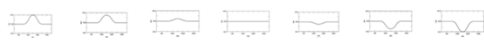


					
T7	○	○	○	○	○
C3	○	○	○	○	○
Cz	○	○	○	○	○
C4	○	○	○	○	○
T8	○	○	○	○	○

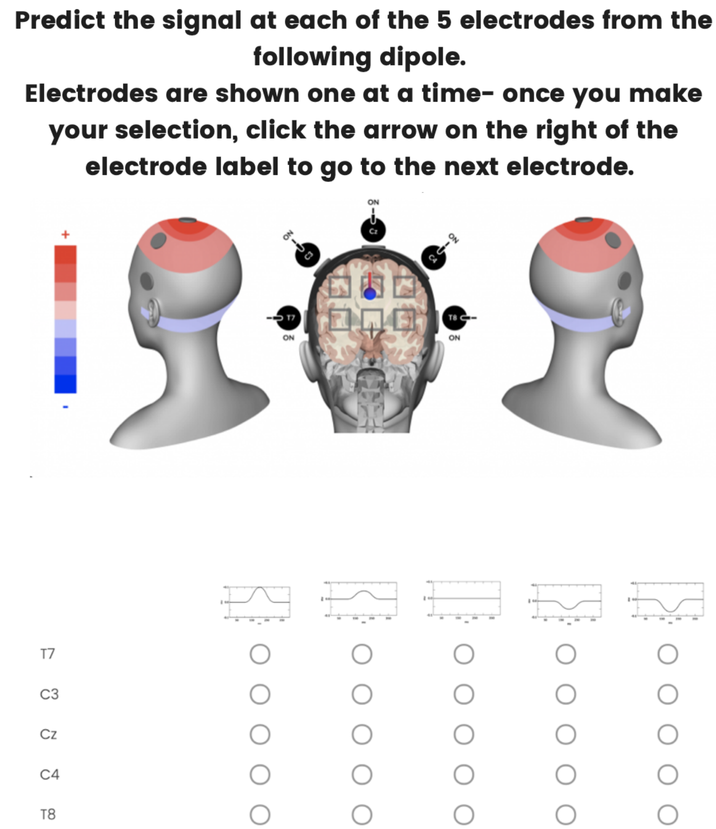
Predict the signal at each of the 5 electrodes from the following dipole.
(the scalp distribution is purposefully not displayed in this question.)

Electrodes are shown one at a time- once you make your selection, click the arrow on the right of the electrode label to go to the next electrode.





T7	○	○	○	○	○	○	○
C3	○	○	○	○	○	○	○
Cz	○	○	○	○	○	○	○
C4	○	○	○	○	○	○	○
T8	○	○	○	○	○	○	○



Supplemental Materials 3.

Organization of Simulation Presentation

	Presentation Order				
	1	2	3	4	5
Dipole Position	Middle	Middle	Left	Left	Right
Active Electrodes	T7, T8, Cz	C3, C4	T7, T8, Cz	C3, C4	T7, T8, Cz, C3, C4

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