Application of NeuroIS Tools to Understand Cognitive Behaviors of Student Learners in Biochemistry

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Abstract Cognitive load has received increased focus as an area that can be more richly explored using neuroIS tools. This research study presents the application of electroencephalography and eye tracking technologies to examine cognitive load of student learners in biochemistry. In addition to leveraging the Pope Engagement Index and eye tracking analysis techniques, we seek better understanding of the relationship that various individual characteristics have with the level of cognitive load experienced. While this study focuses on a particular STEM student population as they manipulate various learning models, it has implications for further studies in human-computer interaction and other learning environments.

Keywords Cognitive load · EEG · Eye tracking · Student learners · Individual characteristics

1 Introduction

In recent years, cognitive load has received increased focus as a construct of distinct interest that may be more richly explored using neuroIS tools [1, 2]. In particular, others have used neuroIS tools to examine the importance of engagement and cog-

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nitive load in the areas of training and education [3] and shown their usefulness in understanding someone's full-body experience as they engage with technology [4]. Resulting, is a growing area of "neuro-education" [5, 6] to which we hope to contribute with our efforts.

In our ongoing study that is taking place as part of a federally-funded grant project in the United States, we use electroencephalography (EEG) and eye tracking technologies to assess cognitive load of student learners in biochemistry. Overall, the goals of this project are:

- to understand cognitive load as it impacts the development of undergraduate students' conceptual understanding of structure-function relationships in chemistry and biochemistry, and to
- refine the process for more effectively collecting and analyzing biometric data for mock classroom activities.

Use of neurophysiological tools such as EEG and eye tracking has been touted as complementary to traditional psychometric tools of survey and observation by providing increased understanding of human behavior [7], and we have found that to be the case here, as well. Further, although brain-computer interface (BCI) tools have typically been used to provide communication and environmental control to people with severe motor disabilities [8], they have also been used to more richly assess cognitive states such as cognitive load [9]. Here, we seek to use the concept of a passive BCI [10] to allow for enrichment of classroom-based interactions while students engage in various modeling exercises in support of learning biochemistry concepts. Passive BCI models have incorporated an EEG-based engagement index [11, 12] into their classifiers and we seek to do the same. A passive BCI represents a downline goal for this current three-year effort to collect and refine measurements of cognitive load.

In addition to measuring cognitive load, we are interested in how it relates to individual human characteristics. Understanding the relationship that various individual characteristics have with experienced cognitive load could help us better understand the pipeline for students engaging in science, technology, engineering and math (STEM) fields—of which information systems is considered a subset—and better provide support for students. While this study focuses on a particular STEM student population in biochemistry as they manipulate various learning models, it has implications for further studies with various student populations. Further, we may have more confidence when applying neuroIS tools to understand human-computer interaction phenomena, such as cognitive load, in seeing this case.

2 Methodology

The objective of the study is to evaluate the learning process and conceptual understanding of students in order to decrease their cognitive load. In the first year of this three-year study, more than sixty (60) students from a university in a metropolitan midwestestern city who are in the chemistry field have participated. Participants of the study were subdivided based on their stage of school year and four stages of curriculum. The classification categories included fall and spring General Chemistry, Organic Chemistry, and Biochemistry curriculum. Even though the potential study population consists of freshman to senior students, many of the actual participants in the first exercise were freshman students.

Students were asked to fill out a survey about their individual characteristics ranging from gender to level of athleticism. Individual characteristics of the study population were not limited to gender, race, and ethnicity, but also included differences in self-perceived levels of athleticism, dexterity, medication intake, smoking status, biometric tool use, and video game experience. This project is part of a larger study that will analyze the relationship between individual characteristics and various cognitive measures of spatial ability such as obtained using a Purdue Visual Rotation Test [13] and Hidden Figures Test [14].

The study is being conducted in a simulated learning environment where an instructor is present to explain the lesson and while the student works through exercises. Students' electrical brain activity is being measured using a 16-channel research-grade BioSemi ActiveTwo bioamplifier system (http://www.cortechsolutions.com/Products/Physiological-data-acquisition/Systems/ActiveTwo.aspx) running on a laptop. The electrode cap is configured according to the widely used 10–20 system of electrode placement [15]. Active electrodes are placed on the cap to allow for the recording of brain activations downsampled to 256 Hz using a Common Average Reference (CAR). The sixteen recorded channels are: frontal-polar (Fp1, Fp2), frontal-central (FC3, FCz, FC4), central (C3, Cz, C4), temporal-parietal (TP7, TP8), parietal (P3, Pz, P4), and occipital (O1, Oz, O2). Eye tracking data is being recorded using Tobii eye tracking glasses (www.tobii.com) while students are manipulating 2D, 3D, and virtual objects.

Afterward, data is being analyzed using the EEGLab plugin (https://sccn.ucsd.edu/eeglab/index.php) to Matlab to ascertain band powers and calculate cognitive load according to the Pope Engagement Index best represented by the calculation of (combined beta power)/(combined alpha power + combined theta power) [11].

3 Preliminary Results

Presently, data has been transcribed for the first year and cleaned with some initial analysis conducted. Statistical analysis will be used to assess the relationship between individual characteristics, spatial ability measures, and cognitive load as reflected by the Pope Engagement Index. The initial data indicates that the students are predominantly freshman, white females, and traditionally-aged ranging from 19 to 21 years.

Figure 1 starts to tell an interesting story of seven different student experiences based on EEG data that was able to be reliably captured and analyzed out of thirteen students in the first field visit. The y-axis in the figure represents the calculated

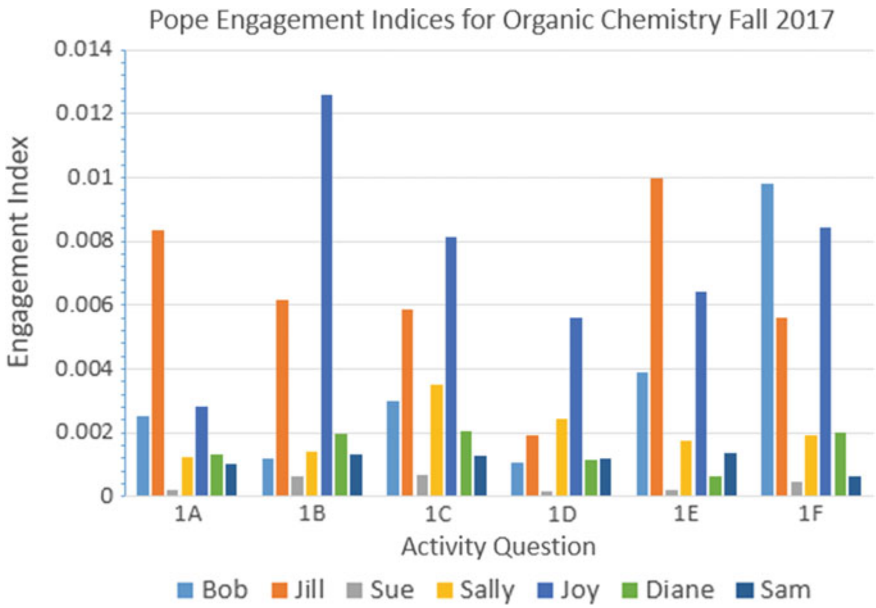

Fig. 1 Bar graph of Pope Engagement Indices calculated for Organic Chemistry students (Pseudonyms used to protect identities) across six classroom exercise questions

values of the Pope Engagement Index per question per student and serves as a reflection of cognitive load. It appears that Jill and Joy had a particularly difficult time with the classroom exercises whereas Sue and Diane did not necessarily have the same experience. This difference in cognitive load indicates that gender may not be the determining factor here. Data will be further analyzed to assess the relationship of individual characteristics, various spatial abilities, and cognitive measures to more fully understand student experiences. Already, later classroom exercises were modified based on preliminary understanding gained by reviewing general neurophysiological data, and there is early indication that cognitive load was able to be reduced for harder problems by providing better structure and scaffolding to solve these problems.

4 Conclusion

NeuroIS tools may be used to assess cognitive load of students while engaging in classroom learning activities and manipulating biochemistry models of varying types. There is a growing area of "neuro-education" research and use of neuroIS tools to assess training. Although the population of focus here is a student one in a particular subject area, this study has greater implications for future work and understanding the impact of individual characteristics on cognitive abilities. Further, this study presents an example of how we may inform passive BCI technologies and use them outside of a clinical setting typically reserved for patients with severe motor disabilities; hence, we may expand their use to a real-world, classroom-based setting to better understand cognitive ability.

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