Using NeuroIS Tools to Understand How Individual Characteristics Relate to Cognitive Behaviors of Students

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Abstract. NeuroIS tools have increasingly been used to examine cognitive behaviors in educational settings. Here we present results of ongoing work applying neurophysiological tools to examine the cognitive load of student learners in the context of chemistry education. In particular, we investigate how individual characteristics relate to the Pope Engagement Index for students interacting with an information system for visualizing molecules. Characteristics such as meditation, levels of athleticism, and medication affecting alertness were found to significantly and positively correlate with cognitive load.

Keywords: Cognitive load · individual characteristics · Pope Engagement Index · EEG · chemistry student learners.

1 Introduction

Increasingly, neuroIS tools are being used in "neuro-education" to better understand student learners and their cognitive processes [1-3]. Researchers are able to use tools such as electroencephalography (EEG) in conjunction with traditional psychometric tools to describe a learner's full-body experience, including their feelings and levels of engagement, that may otherwise be difficult to articulate. In fact, neuroIS tools may be able to help better pinpoint when such mental changes take place and thus offer more clarity on what to change in a learning environment [3].

Within neuroIS, cognitive load has received particular focus as a construct of interest and has been measured using EEG and eye-tracking tools [4, 5]. Here, we also focus on cognitive load, as measured using the popular Pope Engagement Index (PEI) calculated from surface EEG recordings [6]. In particular, we investigate the relationship of cognitive load with the individual characteristics of chemistry students from a university in a metropolitan midwestern city as part of a federally-funded grant project[1] in the United States.

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2 Methodology

At the start of the session, students completed a survey about their individual characteristics that was adopted from brain-computer interfacing, a sub-area of neuroIS [7]. These individual characteristics were not limited to age, gender, and race, but also included differences in self-perceived levels of athleticism, hand dexterity, medication intake, smoking status, prior biometric tool use, and video game experience. We also obtained cognitive measures of spatial ability using the Purdue Visual Rotation Test (PVRoT) [8] and the Hidden Figures Test (HFT) [9].

Then, students engaged in a simulated learning environment where an instructor was present to explain the lesson and then remained while the student worked through exercises on their personal laptop. The students engaged in six different activities using PyRx, an opensource tool for visualizing chemical molecules [10]. This tool was purported to have an "easy-to-use user interface" (https://pyrx.sourceforge.io/home) yet some students still experienced difficulty with its setup. Students used PyRx to visualize proteins and match different ligands to the protein sites, much like finding the right key for a lock.

A 16-channel, research-grade BioSemi ActiveTwo[2] bioamplifier system recorded students' electrical brain activity during the activities. This system was run on a Windows laptop. The electrode cap was configured according to the widely used 10-20 system of electrode placement [11]. Active electrodes were placed on the cap to allow for the recording of brain activations down-sampled to 256 Hz using a Common Average Reference (CAR). The sixteen recorded channels were: 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).

The recorded data was later analyzed using using the EEGLab plugin (https://sccn.ucsd.edu/eeglab/index.php) to Matlab to ascertain band powers and calculate cognitive load according to the PEI best represented by the calculation of (combined beta power) / (combined alpha power + combined theta power) [6]. A separate PEI was calculated for each of the six activities performed. RStudio Cloud (https://rstudio.cloud.com) was then used to find correlations between the student learners' individual characteristics and their PEI per activity.

3 Preliminary Results

Results for two of the six activities are presented here where we could compare the same students across both activities. Out of the original ten participants, the same six students completed both of these activities. The average age was 21 (ranged 20-22 years) with 2 males and 4 females. Correlations were found significant at the level where alpha equaled 0.05.

Activity 1: Docking the Ligand. This activity entailed students selecting the ligands and isolating the possible binding sites of the protein in the software. For this activity,

[2] https://cortechsolutions.com/product-category/eeg-ecg-emg-systems/eeg-ecg-emg-systems-activetwo/

we found strong positive correlations to the PEI with Meditation and Athleticism. Table 1 summarizes the correlations found for this activity. This indicates that a student who regularly engaged in meditation and had higher levels of self-rated athleticism experienced higher cognitive load.

Table 1. Significant correlations of individual characteristics to the Pope Engagement Index for the Docking the Ligand activity.

	Correlation	P-Value
Meditation	1.0000	0.0000
Athleticism	0.9147	0.0106

Activity 2: Visualizing the Docked Ligand. This activity entailed selecting and viewing a particular ligand bound to the protein in PyRx and zooming in to see more detail. For this activity, we found a strong positive correlation only with AffectiveMeds to the cognitive load experienced by the student as measured by their PEI. This indicates that taking medication that made the student more alert correlated with higher levels of cognitive load experienced for this activity. Particularly, the correlation coefficient was 0.8832 with a p-value of 0.0197.

Summary. Meditation, Athleticism, and AffectiveMeds were the three characteristics found with strong positive correlations to students' PEI for the two different activities. Common convention implies that individuals would translate the calm and focus often gained from meditating, engaging in athletic activities, and from stimulating medication to achieve lower cognitive load; it seems something more is yet to be revealed. Through scatterplot analysis, one participant may be dominating the results, however we felt it more important to retain all data points due to the distinctly small sample size of six students. Although a definite conclusion is impossible at this stage, we are encouraged to seek understanding of the full picture of our students when pairing them with such learning activities. These results indicate that some individual characteristics may have more influence than others on a student's cognitive load experienced in this setting.

4 Conclusion

This study provides an example of how neuroIS tools may be used in an educational setting to better understand the cognitive processes of students. In particular, we investigated the relationship between individual characteristics and the cognitive load of chemistry students as measured by the Pope Engagement Index calculated from EEG recordings. This work-in-progress paper presents a snapshot from a larger study that spans three years and is still under analysis.

Although results cannot be generalized to a wider population due to low sample size, these efforts indicate the importance of gaining a comprehensive view of students to better understand the impacts on their learning environment. Certainly, more data should better reveal which characteristics have particular saliency in this setting. Further, we may find distinction in our future results by dissecting our reliance on the original calculation of the PEI as a measure for cognitive load. Lastly, we will seek to delineate the nature of the tasks as having external and internal attentional components in line with newer research examining the relationship of alpha waves to cognitive load, where alpha is a key component of PEI calculations.

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