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 cognitive 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[1] in the United States, we use electroencephalography (EEG) and eye tracking

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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 down-sampled 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 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.

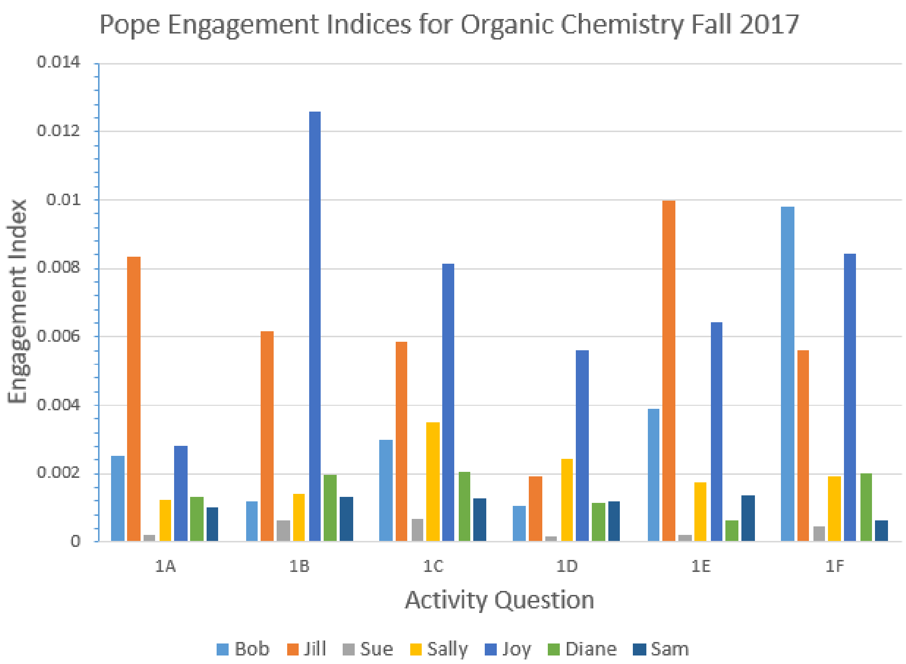

Fig. 1. Bar graph of Pope Engagement Indices calculated for Organic Chemistry students[2] across six classroom exercise questions

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,

[2] Pseudonyms used to protect identities.

we may expand their use to a real-world, classroom-based setting to better understand cognitive ability.

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Task Switching and Visual Discrimination in Pedestrian Mobile Multitasking: Influence of IT Mobile Task Type

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Abstract. With the growing use of smartphones in our daily life, mobile multitasking has become a widespread (and often dangerous) behavior. Research on mobile multitasking thus far only focuses on a limited number of IT tasks that can be performed with a smartphone: talking, listening to music, and texting. Thus, we do not know the extent to which these results generalize to other types of mobile multitasking behaviors such as reading while walking and gaming while walking. Also, we do not know the extent to which motor movement through physical space (i.e., walking vs. only standing) affects this phenomena. The current paper reports on an ongoing research that explores these questions. Our preliminary results suggest that mobile and standing multitasking leads to the inability to perceive incoming stimuli. Gaming appears to be the most dangerous mobile multitasking task for pedestrians.

Keywords: Multitasking, pedestrian, EEG, texting while walking, gaming while walking

1 Introduction

With the growing use of smartphones in our daily life, mobile multitasking has become a widespread (and often dangerous) behavior. We define *mobile multitasking* as the concurrent performance of one or more information technology (IT) tasks with a small computerized device (in most cases, a smartphone) while doing a motor movement such as walking. The behavior is increasingly common and can be seen almost anywhere. People are commuting to and from work, navigating the corridors of an office building, and even walking the halls of shopping malls, all while using their smartphone [1, 2].

While public safety research shows that mobile multitaskers are more cognitively distracted than non-mobile pedestrians [3] our team's recent work specifically measured this distraction using electroencephalography (EEG) and it is, to our knowledge, the first of its kind [4, 5]. Our results suggest that the influence of task-set inhibition on switch cost is more important when subjects are texting while walking. In other words, the more participants engage cognitively in texting while walking, the less attentional resources are available to attend to external (and potentially dangerous) stimuli.

Research on mobile multitasking thus far only focuses on a limited number of IT tasks that can be performed with a smartphone: talking, listening to music, and texting [3, 4, 6-9]. Thus, we do not know the extent to which these results generalize to other types of mobile multitasking behaviors such as reading while walking and gaming while walking. Also, we do not know the extent to which motor movement through physical space (i.e., walking vs. only standing) affects this phenomena. The current paper reports on an ongoing research program that explores these questions.

2 Related Work

Humans generally experience performance problems when multitasking [10]. *Multitasking* is defined as the concurrent performance of two or more distinct tasks [11]. Research clearly demonstrates that multitasking deteriorates performance as compared to performing tasks one at a time [11]. This deterioration is explained by theories underlying divided attention and dual-task performance, which have asserted that limitations in human multitasking are attributed to competition for processing resources (i.e., Multiple-resource theory), as well as to competition for processing mechanisms (i.e., Structural theory) [12].

Mobile multitasking is cognitively and perceptually complex [13]. While most dual-task research has been conducted in laboratory settings (e.g., [3], mobile multitasking is a daily activity which is arguably more complex than the experimental paradigms typically used to study the attentional mechanisms involved in dual-task interference. First, mobile multitasking involves one or more IT tasks on a smartphone, which require focused attention and fine motor control. Also, it involves gross motor control (during walking, cycling, and other physical activities involving motor movement through physical space). The mobile multitasker must divide his attention between the IT tasks and the dynamic visual scenes which necessitate a sustained vigilance to the external environment. Mobile multitasking in urban areas is even more demanding as it involves making spatial decisions in complex dynamic visual scenes (e.g., walking in a crowd where others are also moving, crossing streets, using public transit, and climbing stairs). Finally, the opportunity to become immersed in the IT task while walking is greater than for similar activities such as driving since individuals can engage in: 1) more numerous and complex range of IT tasks, 2) which may be sustained for longer periods of time (imagine a pedestrian slowly wandering through a crowd while staring at a mobile device, whereas the same person driving may quickly produce an accident or have other cars honking at them).

Recent studies confirm a significant increase in pedestrian injuries due to mobile phone usage between 2004 and 2010 [14], which coincides with the massive adoption of smartphones in urban areas. Numerous accidents involving pedestrians using phones have been reported with the majority of victims being less than 30 years of age [3]. Several articles on public safety report the unsafe and risky behaviour of mobile multitaskers [3, 6, 8, 9, 13, 14]. An observation study conducted at multiple high risk intersections in a metropolitan area revealed that more than 7% of pedestrians were mobile multitasking, and these individuals took significantly longer to cross the intersections [9]. Experimental studies using a virtual environment also show the prevalence of unsafe and risky behaviors [15]. In a virtual pedestrian environment, mobile multitaskers took more time to cross the street, missed several safe opportunities to cross, took longer to initiate crossing when a safe gap was available, looked left and right less often, spent more time looking away from the road, and were more likely to be hit or almost hit by an oncoming vehicle [3, 6]. This is not just an outdoor phenomena as mobile multitaskers are also at risk of accidents in an office environment [16]. Indeed, accidents are also increasing on work premises (e.g., falling down the stairs) and some organizations, such as General Motor, are now even prohibiting mobile multitasking inside company buildings [17].

Current research mostly focuses on texting while walking and we have little knowledge on the effect of other mobile multitasking behaviors. The device enables tasks with different levels of interactivity. Reading news on a mobile phone is unidirectional while texting is bidirectional. Writing an email usually entails slower communication speed than exchanging a short text message (SMS) which typically involve faster interactions. Some application like games may impose time constraints on the player (such as limited time to answer a question), which may have a consequence on the task switching behavior. Finally, some IT tasks are under the control of the user (such as scrolling through Facebook posts), while other events or alerts are not controlled by the user (e.g., pop-ups indicating new emails).

3 Methodology

Experimental design: We conducted a 2-factor within-subject experiment: Position (Standing vs Walking) and Task type. Due to the complexity of the design, we conducted the project in two phases. In Phase 1 (standing condition only), we used 4 mobile tasks: A) reading a document, B) writing an email, C) playing Tetris, and D) group texting (i.e., texting with 2 individuals in the same conversation). In the second phase (walking condition only), 3 mobile tasks were used: (C) playing Tetris, D) group texting and E) individual texting (with one person)[1]. In both phases, we also had a control group in which participants were only attending to the stimuli (F).

Participants: Thirty people (14 males, 16 females; ages 21-43, M = 25.6 years, SD = 5.9 years) participated in Phase 1 (standing) and 48 participated in Phase 2 (walking)

[1] In order to keep the number of conditions at a manageable level, two tasks which exhibited the smallest levels of dual task interference in Phase 1 (Tasks A and B) were excluded from Phase 2.

(20 males, 28 females; ages 18-46, M=25.5 years, SD=5.5 years). All participants had normal or corrected-to-normal vision and were pre-screened for glasses, epilepsy, as well as health, neurological, and psychiatric diagnoses. This study was approved by the ethics committee of our institution. Participants provided written consent before participating and received a 40$ gift certificate as compensation upon experiment completion.

Stimuli and Apparatus: A dynamic point-light walker representation of a walking human form composed of 15 black dots was used as a biological motion stimulus. The dots, representing the head, shoulders, hips, elbows, wrists, knees, and ankles, were presented on a white background walking either leftward or rightward with a deviation angle of 3.0° (or -3.0°) from the participant. The point-light walker figure was displayed for 1000 ms with a resolution of 1280 x 1024 pixels using a projector (ViewSonic, Brea, California, United States). The walker stimulus had a height of 1.80 m and was displayed 4 m from participants, giving a 25 degree visual angle. Two speakers were located in front of participants which played a 1000 ms auditory stimulus cue with a random delay of +/- 500 ms before the presentation of the walker. Performance on point-like walker direction identification is strongly affected by divided attention in a dual-task paradigm, and the walker has ecological value in pedestrian safety research [4]. Thus, point-like walker stimulus is a suitable task for evaluating the switch cost of mobile multitasking in an authentic context. Mobile phone tasks were performed using an iPhone 6s (Apple, USA). In phase 2, the threadmill used was the iMov iMovR's ThermoTread GT (iMovR, USA).

Instrumentation and Measures: EEG data was recorded from 32 Ag-AgCl preamplified electrodes mounted on the actiCap and with a brainAmp amplifier (Brainvision, Morrisville). The EEG signal was recorded using 32 electrodes with an acquisition sampling rate of 1,000 Hz and analyzed with EEGLAB (San Diego, USA) and Brainvision (Morrisville, USA).

Procedure: While participants were standing (Phase 1) or walking (Phase 2), the point-like figure walker was presented shortly after the auditory cue stimulus. Participants were then asked to verbally identify the walker's direction by answering "left" or "right" according to the side on which they perceived the walker would pass them. Participants were also performing different mobile tasks for approximately 16-18 seconds per task. The experiment was composed of 5 blocks in Phase 1, one for each mobile tasks conditions and a control condition (5 x 22 trials), and 4 blocks in Phase 2, one for each tasks and a control condition (4 x 40 trials). The order of the blocks was counterbalanced and they were separated by a two-minute pause in which participants could sit on a chair while completing a short questionnaire. Prior to the first block, participants had a two-minute practice period to get used to the walker stimulus.

4 Preliminary Results and Ongoing Work

We recently completed the data collection for this project and the EEG analysis is currently underway. However, the behavioral results have already been analyzed. Linear regression with mixed model was performed to compare the least squares means (LSM) of performance across tasks. LSM was calculated using the model where we control for age, sex, and level of social use. Table 1 presents the performance (i.e,, the proportion of walker directions correctly indicated by participants) by task. Unsurprisingly, the results show that mobile multitasking is risky.

In the standing position, there are significant differences between playing Tetris and the control task ($t(116)=-5.64$, $p<.0001$, Table 1) and between engaging in group texting and the control task ($t(116)=-4.26$, $p = 0.0003$) after adjustment for multiple comparisons [18].

	Task name	Phase 1 Standing	Phase 2 Walking
A	Reading document	80,6%	-
B	Writing an email	76,6%	-
C	Playing tetris	66,6%†	80,8%† ‡
D	Group texting	70,4%†	84,0%†
E	Individual texting	-	85,4%
F	Control	82,1%	89,1%

Table. 1. Behavioral results (Least Squares Means of Performance by Task)
†: significantly lower than the control task;
‡: significantly lower than the individual texting task.

In the walking condition, there are significant differences between playing Tetris and the control task ($t(141)=-5.11$, $p<.0001$, Table 1) and between engaging in group texting and the control task ($p = 0.0003$) with the same adjustment. In the walking condition, we even find that performance of playing Tetris is lower that individual texting ($t(141)=-2.85$, $p=0.02$) after adjustment for multiple comparisons (Holm, 1979).

5 Discussion and Concluding Comments

Our preliminary results suggest that mobile and standing multitasking leads to the inability to perceive incoming stimuli. While the impacts on behavioral performance might seems small percentage wise, in real life only a single instance of not attending to an external stimuli can lead to physical injuries or have life threatening consequences. Our results also suggest that walking might not be the main contributor in reducing the behavioral performance. Even in the standing position, some tasks like playing a game and engaging in a group text might prevent people from noticing external events in a public environment. Finally, gaming appears to be the most dangerous mobile multitasking task for pedestrians.

This research contributes to a better understanding of the impact of mobile multitasking on user behaviors. It contributes to the literature by exploring and comparing a larger number of IT tasks performed on smartphones. Preliminary results suggest that playing a game and engaging in group texting (tasks that were absent from the mobile multitasking literature) diminish individuals' performance compared to individuals not using a smartphone.

These preliminary findings suggest that smartphone application designers and smartphone manufacturers should be careful in developing mobile apps, especially those related to games and group texting, by considering features related to user security. Given that some smartphone games are especially designed for mobility (e.g., Pokemon Go), we believe that these results should raise awareness of this very dangerous behavior in a pedestrian context.

As with any experimental studies, our research has limitations. We used a relatively young sample, so potentially very good at multitasking and do have the cognitive performance declines of older adults (e.g. [19]). Thus, research might not be representative for the whole population, especially an issue as large-scale adoption of devices such as smartphones spreads to older age groups. Also, the walker required attention, but the impact of errors is not near as significant as in real life (imagine an oncoming car). Thus, it is conceivable that a pedestrian in a real-world situation may perform differently.

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