USE OF EEG TO UNDERSTAND BRAIN INTENSITY IN ENGINEERING STUDENTS USING A STEM EDUCATIONAL MOBILE APPLICATION

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science in Engineering

By

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2016
Wright State University

WRIGHT STATE UNIVERSITY

GRADUATE SCHOOL

April 18, 2016

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Kevin Hatcher ENTITLED Use of EEG to Understand Brain Intensity In Engineering Students Using a Stem Educational Mobile Application BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering.

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ABSTRACT

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In the first two years of undergraduate work in engineering, students are taught concepts such as physics, electronics, and most importantly calculus. It is especially important for students to get a better grasp on foundational math concepts, such as calculus in the beginning or they will be overwhelmed by the workload to come. The focus of this research was to understand how students learning calculus, could benefit from an augmented-educational mobile application. In the study students were measured with electroencephalography (EEG) measurements utilized by the Emotive EPOC® as they attempted to solve different limit themed problems in order to determine if learning with an augmented educational mobile application had an impact on brain intensity. Results indicated that mobile learners showed increased intensity in selected brain regions when compared to non-mobile learners. This study will aid in better understanding the impact that an augmented-education mobile application can have on learning.

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1. BACKGROUND

This section provides a literature review into the challenges of learning engineering concepts, brain plasticity, as well as, how the understanding of brain functions has been incorporated into the educational training process. Additionally, the imaging technique of electroencephalogram (EEG) is examined, and the perception of traditional learning and mobile learning are explained.

1.1 Engineering Challenges

The impact that engineering education has on aspiring undergraduate engineering students is designed to cultivate the practice of applied concepts so that they can be prosperous upon graduation. However, persistence in the engineering curriculum is lower, when compared to other majors in higher education and because of this engineering students are more prone to drop out of college or transfer into a different major which they perceive as being less difficult than engineering. It has been reported that students are seeking engineering degrees, but according to the National Science Board, of the total 7.5 % of engineering students surveyed in 2007 only 4.5% of those students reached graduation (National Science Board, 2016; M. Meyers and S. Marx, 2014). This occurs when students intend on applying to engineering but do not have the required study skills to continue in the major; and for professors who feel that students should know how to study this combination only ends in disaster for the students (L. Bernold, J. Spurlin, C. Anson, 2007). The decision to persist in engineering changes once students realize how difficult the major is. Some of the reasons for students leaving include: challenging coursework, inadequate academic advising, and poor preparation for college after graduating high school (M. Meyers and S. Marx, 2014). The challenging coursework is one of the primary reasons for engineering dropouts and the inefficiency in mathematics skills is a big factor in this (P. Tolley, 2012). Even for some students, completing courses such as calculus does not guarantee completion of engineering; especially if the course was not thoroughly learned by the student. Simple mistakes and the inability to transfer mathematical knowledge to engineering courses can impact engineering students' success in their major. (P. Tolley, 2012). For students who were interested in engineering courses, research has shown that the interest decreases once students feel that their instructors are not adequately teaching them (M. Ohland, 2008). When students feel that they are not adequately prepared, then their self-confidence and self-efficacy can decline and this has been reported as two of the broad factors driving students to no longer persist in engineering (B. Geisinger, R. Raman, 2013). However, there are ways to improve retention and it starts with addressing declines in self-confidence and self-efficacy, as well as, grades, conceptual understanding, classroom climate, and academic climate (B. Geisinger, R. Raman, 2013). There have been strides in improving retention through curriculum changes, such as creating courses where required calculus, physics and other abstract courses are taught to students in the beginning of their engineering career (N. Klingbeil et al, 2009). By changing the curriculum and addressing the academic climate change, improvements can be seen in engineering retention and also impact knowledge acquisition and knowledge retention in students.

1.2 Learning – Traditional and Mobile Learning

Learning is defined as the processes of memorization, gaining understanding, having an insight, and even changing behavior, but what is most important is learning to make sense of something (G. Caine and R. Caine, 2006). Learning is something that is essential and is the foundation of education. Typically, learning has been about the instructor and what they feel is important for the student to learn. Although traditional learning offers students the opportunity to receive direct feedback from the instructor it is still set at the instructor's pace of teaching, rather than the student's pace of learning. With mobile technology (tablets and mobile phones) learning can be improved upon and offer advantages that traditional teaching methods possibly cannot. In general, mobile augmented learning differs from traditional learning because it allows learners to essentially always have digital content on hand, as well as the ability to embed information within links so that students can potentially have additional information within a learning tool (D. West, 2013). A mobile-based learning study looked at the positive perceptions that students had for mobile devices in the classroom and the results showed that students felt it was useful for note-taking, useful for its search capabilities, accessibility when trying to get class material, accessibility when trying to view PowerPoint's, and the option of portability as a potential substitute to carrying textbooks (L. Jackson and S. Obispo, 2013). Another way at addressing the academic climate is to get a better understanding of neuroanatomy and neurophysiology of the brain functions in order to inform and understand knowledge acquisition and the impact of using augmented learning tools to improve knowledge acquisition.

1.3 Neuron and Brain Development

Neuroscience in education focuses on the concepts of neuroplasticity and how this occurrence can be related to learning (V. Knowland and M. Thomas, 2014). With neuroplasticity, brain cells show a lasting change in development and growth based off of some learning experiences. The surface of the brain is known as the cortex and it has an outer layer known as the gray matter; just below the surface of the gray matter is the white matter, which houses the mylelinated axons (J. Webster, 2010).

Growth in the white matter means changes for the axons such as: an increase in axon diameter, the increase in the number of axons, and an increase in myelination surrounding the axons (R. Zatorre, R. Fields and H. Johansen-Berg, 2012). In addition to changes in the white matter, neuroplasticity also affects the gray matter through growth of new cells (neurogenesis), the growth of new synaptic connections (synaptogenesis) as well as general changes in neurons themselves (R. Zatorre, R. Fields and H. Johansen-Berg, 2012). Some examples of cited neurogenesis were seen in the hippocampus area of the brain after learning occurred (R. Zatorre, R. Fields and H. Johansen-Berg, 2012). Learning has been shown to accelerate growth in the hippocampus area and evidence has been seen in the larger than average hippocampal volumes, area most associated with memory, of expert London taxi cab drivers who have learned and memorized the layout of the city (R. Zatorre, R. Fields and H. Johansen-Berg, 2012).

The development of the brain happens in stages beginning with the birth of the nerve or glial cell and ending with the formation of myelin (B. Kolb and R. Gibb, 2011). During the process of cell maturation, dendrites begin to grow more, which allows more surface area for synapses and the extension of axons, which assist in the formation of synapses (B. Kolb and R. Gibb, 2011). In addition to the growth and development of neurons, there is also the occurrence of neuronal cell death or a pruning process that occurs because of changes in the brain based on experiences or even stress. The last stage of brain development involves glial cells, which help with the process of myelin formation. The regions of the prefrontal cortex, posterior parietal cortex, and anterior temporal cortex are affected the most by this final stage of development (B. Kolb and R. Gibb, 2011). When it comes to the experiences that affect the plasticity in our brain, the changes that occur are localized changes based on what regions of the brain are affected by the experience (B. Kolb and R. Gibb, 2011).

In addition to explaining how the brain can grow, incorporating neuroscience into education can help educators understand what areas of the brain function affect learning. For example, in previous studies the posterior parietal cortex has been related to number processing and fact retrieval, while the prefrontal cortex has been related to decision making, working memory, and attention (V. Menon, 2010; F. Rocha et. al, 2004). In Menon's study the left and right posterior parietal cortex was the focus for number processing and fact retrieval (2010). Meanwhile, the prefrontal cortex was involved with decision making and working memory. It has also been studied that in the case of increasing difficulty in arithmetic problems (increased difficulty meant increase in the number of operands used and the number of stimuli) additional regions of the brain were activated such as the caudate and the cerebellum (V. Menon, 2010). Additional studies have looked at how the brain waves changed as task became more difficult, in particular arithmetic tasks. These waves included the beta, theta, and alpha waves for the parietal area and the beta waves for the medial-frontal area of the brain. (J. Chun-Ling Lin et al, 2012). The frontal area and parietal area of the brain are the main areas that have shown activation in studies involving arithmetic and number processing. For simple problems the parietal area (specifically the left portion) has played a prominent role and for more complex problems the frontal area has also shown increased activation (L. Zamarian, A. Ischebeck, M. Delazer, 2009). The combination of mobile technology and learning will give students an advantage to learning and can support the way their brains learn. This is why concepts such as Brain-Based Learning, which allow the integration of neuroscience and education, can be helpful for students.

1.4 Brain-Based Learning

Brain-Based Learning (BBL) is a theory of education that is based on the idea of incorporating teaching methods that are designed for students to learn in a way that their brain processes new information as well as understanding how the learner best acquires knowledge (R. Caine and G. Caine, 1990). This theory gets its foundation from the principles of neuroplasticity, which is when a neuron begins to develop lasting new growth which occurs because of learned experiences. (J. Roberts, 2002). The changes that BBL focuses on are changes that occur due to learning information and are driven by the principle that studies in neuroscience should develop the learning process (M. Gulpinar, 2005). It is a theory that is based on the concept of constructivism, which is when a learner takes an experience and transforms it into a way that they can understand rather than interpreting the topic based off of prior knowledge (G. Caine and R. Caine, 2006).

Brain based learning is composed of principles that were first developed by Renate Caine and Geoffrey Caine. The twelve principles include: (R. Caine and G. Caine, 1990; M. Gulpinar, 2005)

1. All learning engages the entire physiology
2. The brain is a parallel processor
3. The search for meaning is a natural process
4. Searching for meaning occurs through patterning
5. Emotions are critical to patterning
6. The brain is capable of processing parts as well as whole topics simultaneously
7. Learning needs both focused attention as well as peripheral perception
8. Learning is both conscious and unconscious (explicit as well as implicit)
9. Memory has two approaches: rote learning system or spatial memory system
10. The brain understands and remembers best when facts and skills are embedded in natural spatial memory.
11. Complex learning is enhanced by challenge and inhibited by fear connected with helplessness and fatigue
12. Each brain is uniquely organized

From these principles, elements of optimum learning were derived and they included: Relaxed Alertness, Orchestrated Immersion in Complex Experiences, and Active Processing of Experiences (E. Gozuyesil and A. Dikici, 2014; M. Gulpinar, 2005). Relaxed Alertness relates to creating an environment that is not stressful for a student but also gives the student a challenge when it comes to learning. Orchestrated Immersion in Complex Experiences is about creating experiential learning for students so that they can reflect on their experiences and better understand the subject matter. Finally, Active Processing of Experiences is about consolidating learning and allowing students to create mental models and form their own patterns through the consolidation of experiences that they go through with learning (E. Gozuyesil and A. Dikici, 2014), (M. Gulpinar, 2005).

These optimum elements of learning were previously utilized in a study by Duman (2010) where, learning styles and BBL were incorporated together to determine if BBL had an impact on student learning success. In the study students were recruited to learn about concepts related to measurements and evaluation of measurements. The study incorporated the elements of Relaxed Alertness by teaching engaging material in a relaxed environment. The Orchestrated Immersion of Complex Experiences was implemented when students introduced to different topics, which were not only explained but included examples with the explanations. Finally, the Active Processing of Experiences was met when students of different learning styles were allowed to learn based on their learning style (B. Duman, 2010). From the study it was found that BBL allowed students to perform significantly better than students who were taught in the traditional learning style, which consisted of typical direct feedback from educators and the inability for students to learn using their own learning style.

The process of BBL is part of the area of executive functioning, which includes our decision making area (G. Caine and R. Caine, 2006). This executive functioning area is located near the frontal and prefrontal cortex of the brain. Since this area is so connected with decision making and learning it is also a focal point for problem solving. With the executive functioning areas students can maintain effective performance and maintain attention and memory (G. Caine and R. Caine, 2006). To better view the executive functioning areas, as well as other areas of interest, neuroimaging techniques could be used. For the purpose of this research, electroencephalography was considered.

1.5 Electroencephalography

Electroencephalography (EEG) is a brain measuring technique that can measure the electrical activity of the brain. EEG measurements can be recorded both invasively and noninvasively and it is primarily useful for its temporal resolution. For the purposes of our experiment scalp measurements were utilized to record event related potentials of participants so that analysis of their thought latency (thinking period before making a response) and actual response could be determined. EEG was used as an effective method for studying the parietal and prefrontal areas of the brain; since the areas were associated with number processing and fact retrieval. (M. Duvinage, 2013).

When performing scalp EEG, measurements must be taken beyond the scalp, skull, the meninges (which consist of the dura mater, arachnoid mater and pia mater), and the cerebral spinal fluid (J.G. Webster, 2010). The cells that contribute the most to the surface electrodes of the EEG include cortical pyramidal cells which run parallel to one another and produce a cortical field potential. (J.G. Webster, 2010). The flow of current to and from the synaptic nerves produces a wavelike pattern (J.G. Webster, 2010). With EEG certain measurements have been designated based on these wavelike patterns or oscillations. These oscillations are known as brain waves and these brain waves are divided into types which can include: alpha waves, beta waves, theta waves, and delta waves (J.G. Webster, 2010). These brain waves are important because they indicate whether activity is occurring or not and when learning is occurring brain activity is occurring.

The EEG was measured using the Emotive EPOC ®, which is a wireless device that can be used to perform EEG measurements, is easy to use, and is portable. By using the Emotive EPOC ® the goal was to measure brain intensity in the areas of focus and determine if an augmented-educational mobile application would have an impact.

2. RESEARCH OBJECTIVES

The focus of this research was to understand whether using an augmented educational mobile application (AEMA) display would have a greater intensity in activating specific brain areas during an event related potential (ERP). In addition the research was done to understand whether using an AEMA would have an impact on post-test achievement, when it came to answering questions correctly as well as whether AEMA users would perceive it as a useful learning tool. Some of the key research related questions included:

1. Is there a visual difference in brain heat maps between mobile learners and non-mobile learners as it pertains to brain area intensity when answering limit based questions?
2. Does learning with different learning modalities, mobile or non-mobile, have an effect on brain intensity while answering limit based questions?
3. Does learning with a mobile device have an effect on the latency time and the amount of correct responses as it pertains to answering limit based questions?

H_o: There is no significant difference between mobile learners and non-mobile learners as it pertains to latency time

H_1: There will be a significant difference between mobile learners and non-mobile learners as it pertains to latency time

4. Does GPA have an effect on the latency time and the amount of correct responses as it pertains to answering limit based questions?

    H_o: There is no significant difference between high GPA and low GPA as it pertains to latency time

    H_1: There will be a significant difference between high GPA and low GPA as it pertains to latency time

5. Does problem difficulty have an effect on the latency time and the amount of correct responses as it pertains to answering limit based questions?

    H_o: There is no significant difference between simple and complex problems as it pertains to latency time

    H_1: There will be a significant difference between simple and complex problems as it pertains to latency time

In order to address the research question an empirical evaluation was conducted. The details of the research methods are presented in the next chapter.

3. METHODOLOGY

3.1 Methods Overview

The experiment was designed to test whether or not an AMEA could be utilized to solve limit based questions during a post-test assessment. The independent variables included the GPA, problem difficulty and the type of learning modality used. While the dependent variables examined were the response time from the participants as well as the number of correct responses given by the participants. The experiment included measuring applications to test the AMEA's effects on the brain activity as well as its perceived use from participants who used it.

3.1.1 GPA

The GPA was divided into two groups of high and low, where high was 3.3 and greater and low was 3.29 and lower. The GPAs were based on their cumulative GPAs and were selected based off of the previous participant selection from Abhyankar and Ganapathy's (2013) research over learning calculus and physics through the means of mobile learning. GPA was examined as a means of testing how students who were considered high achievers would compare to students who were low achievers when learning under a specific learning modality.

3.1.2 Problem difficulty

The problems were divided into two types, simple and complex and were designed as additional factors that could be tested with the GPA as well as the learning modality. The simple and complex problems contained 6 multiple choices, where only one choice was the correct choice. The problems were identified by the number of missing variables as well as the level of mathematical manipulation involved in solving the problem.

3.1.3 Learning Modality

Participants were also asked to learn material with either the AMEA (mobile learner) or without it (non-mobile learner). The section below describes in more detail the distinct difference between the two learning modalities.

3.2 Recruitment

The experiment was designed to test whether or not a mobile AMEA had an effect on solving limit based problems. Wright State undergraduate engineering students who had completed calculus 1, within the last year, were recruited for the experiment. The experiment excluded participants who suffered from any attention or hyperactivity disorders because their disorders would have caused biasing in the results. The recruits, total of 32, were divided into two groups of 16 and they included mobile and non-mobile learners. Within each of these groups there was further division of high and low GPA participants, GPA distribution shown in Figure 1, of 8 for low and 8 for high GPA participants.

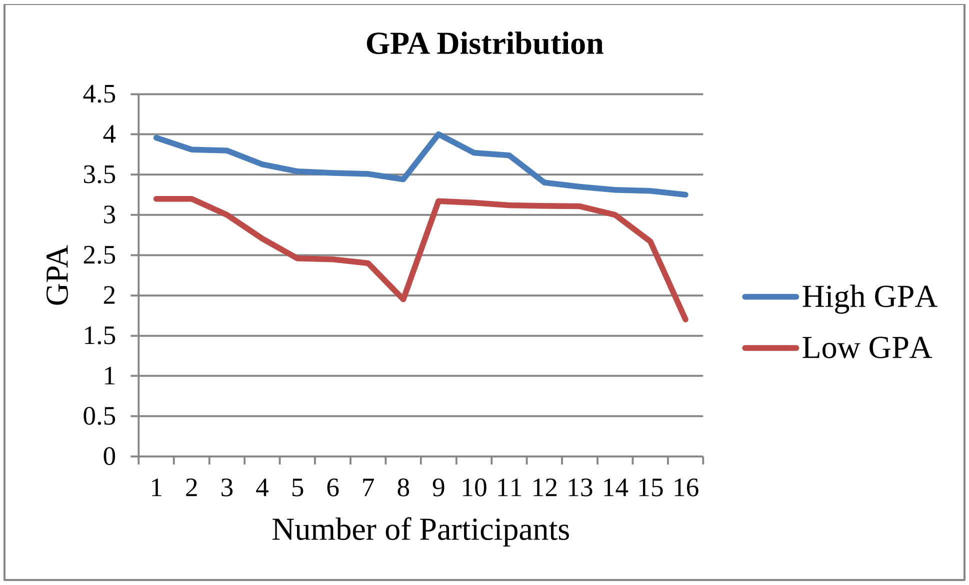


Figure 1: GPA distribution of all participants

Each recruit was presented with material to refresh their knowledge over limits in calculus. The learning modality that a participant received was based on if they were a mobile learner or non-mobile learner. Non-mobile learners were given a print out of material that they could look over before taking the limit based test, while mobile learners were instructed to learn from an AMEA. The learning methods were restrained in a manner where participants were teaching themselves and could not use a writing tool to take notes. Mobile learners were allowed to interact with the AEMA and could take notes but notes were limited to the area of screen for the mobile application while non-mobile learners could not take notes at all.

3.3 Stimuli - Mobile Learning Application

For the experiment, the lab designed mobile application known as *AugmentED* (shown in Figure 2) was utilized for testing purposes. This AEMA was designed to be utilized on a larger scale to improve student retention by assisting in the knowledge retention and knowledge acquisition of physics and calculus. (K. Abhyankar and S. Ganapathy, 2013). For the purpose of this study only the limit based calculus portion of the application was used. Mobile learners used the application to refresh their knowledge of the concept of limits in calculus based mathematics. The material that mobile learners had available to study from was identical to what the non-mobile learners had, with the only difference being that mobile learners learned with a mobile device and had the option to interact with the learning material. Mobile learners, like non-mobile learners, were allowed 10 minutes to study the material and during this time they could utilize the AEMA to its full extent. The mobile device, that used the AEMA, was a Samsung Galaxy Tab ™ tablet with a 10” screen display. Unlike the non-mobile learners, mobile learners were allowed interaction with the learning material and could make drawings and notes on the screen, there was also the option to include additional information with the use of embedded links and interaction with real time graphs; with the AEMA learners could visually see what happened as they changed inputs in the graphs.

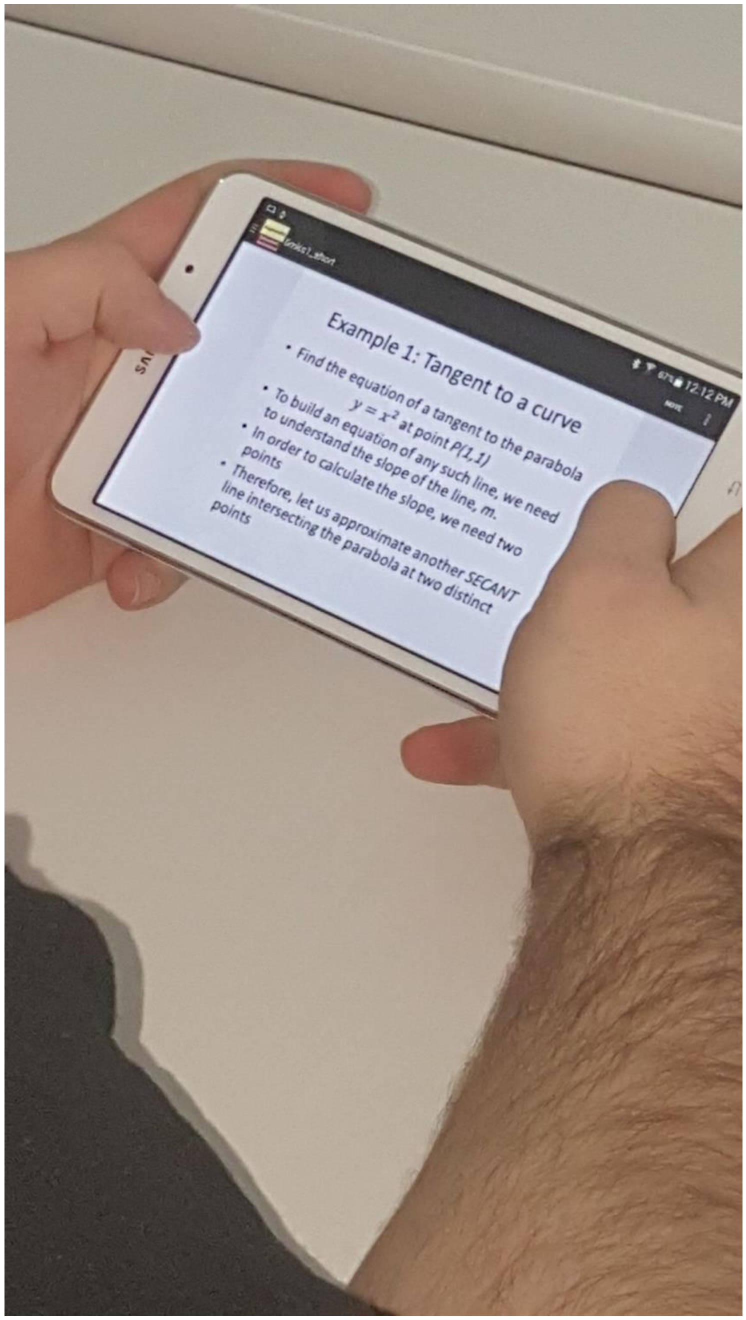


Figure 2: Augmented-Education Mobile Application (AEMA) in Use

After the learning session of 10 minutes both mobile and non-mobile learners were instructed to play the puzzle game Tetris. The game Tetris was chosen because of its ability to work visual spatial memory. In a past study there was evidence shown that by working on visual spatial memory other factors of memory could be reduced. Evidence was seen in the results where participants who suffered from post-traumatic stress disorder were able to temporarily forget startling images that were normally triggers for their disorder, after playing the game of Tetris ®. (E. Holmes, 2009). By having the participant play Tetris ® for 10 minutes the goal was to test the participant's retention of what they just learned, whether it was through a mobile or non-mobile modality.

3.4 Testing

The stimuli presentation and experiment control program Presentation ® (seen in Figure 3) was used during the testing phase and it was developed by Neurobehavioral Systems (Neurobehavioral Systems, 2016). With this system, stimuli (problems) were presented to learners and remained on the monitor for a maximum of 70 seconds. The stimuli would change once a button response was made or once the maximum time of 70 seconds had passed.

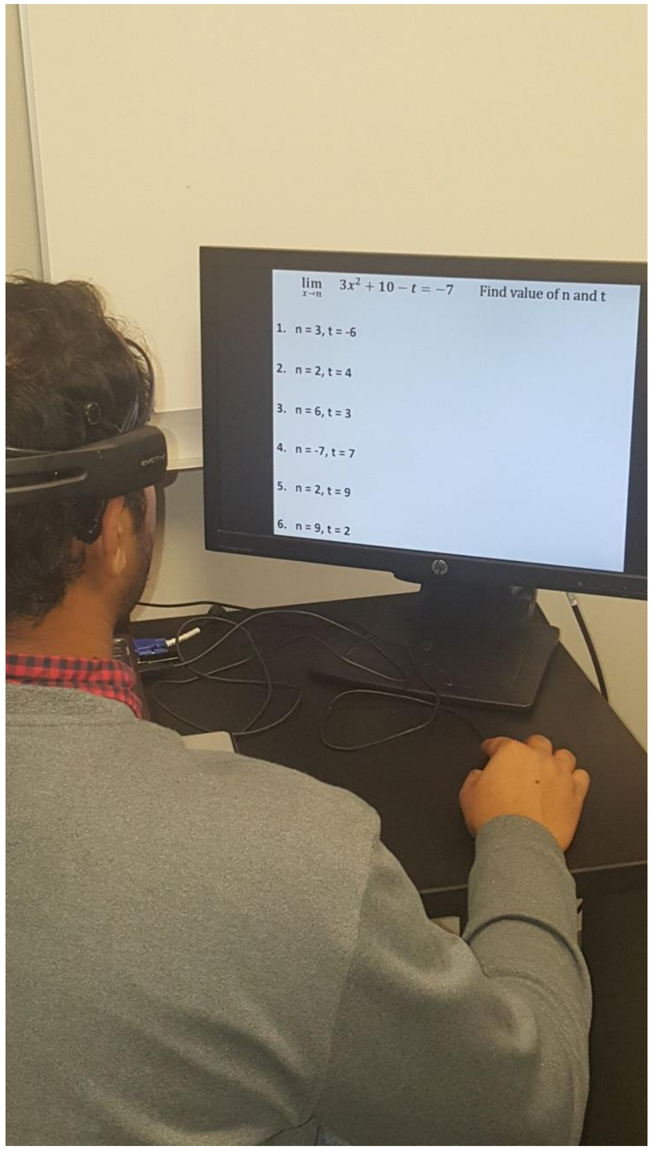


Figure 3: Testing Stimuli in Use

The stimuli included limit based questions which were either simple or complex (shown in Figures 4 and 5 respectively) in nature.

$$\lim_{x \to n} 4 + 3x + t = -1$$

Find value of n and t

1) n = 3, t = 6 2) n = 2, t = 1 3) n = -1, t = -1

4) n = 8, t = 7 5) n = 2, t = -1 6) n = -2, t = 1

Figure 4: Simple Problem

$$\lim_{x \to 2} \frac{x^2 - 4}{x - 2} = z$$

Find value of z

1)z=3 2)z=-4 3)z=4 4)z=-6 5)z=-2 6)z=6

Figure 5: Complex Problem

Complex problems were missing the final solution, but the limit was included. Complex problems included: some form of complex conjugate solution, binomial, and even trinomial type problems. While simple problems were typically simple binomial problems that could be solved easily. The final difference between simple and complex problems were that with simple problems substitution could be utilized by plugging in the limit and with complex this was not possible. All problems were paired with a list of 6 answers with only one answer being correct. Learners were instructed to press a choice of either 1 through 6 on the keyboard; and once pressed the stimuli or problem would change. In total the test consisted of 15 simple and 15 complex limit based problems, which were randomized. For the testing procedures learners were not permitted to use a writing tool or paper. This was done in order to reduce the amount of muscle movements which would create muscle noise in the EEG measurement signals. When the experiment concluded non-mobile learners could leave but mobile learners were asked to fill out a survey which was based on the unified theory of acceptance and use of technology (UTAUT). The UTAUT theory looks at why individuals utilize technology and what are some factors that can influence their use of it (V. Venkatesh et al., 2003). It is based on several different models which are individually utilized to predict the acceptance and usability that a participant has on technology. These different models look at behavior, values, attitudes, usefulness and other factors which help in determining the role that technology plays when it is being utilized. (V. Venkatesh et al., 2003). To measure the different learners' brain intensity the Emotiv EPOC ® was also utilized.

3.5 EEG Analysis

The wireless EEG, known as Emotiv EPOC ®, device contains 14 channels and two reference channels and has a sampling rate of 128 Hz (Emotiv EPOC ®, 2014). The channels are presoaked with a saline solution to ensure conductivity for the leads as well as to sterilize the leads.

The signals measured by the Emotiv EPOC ® were processed using the MATLAB toolbox EEGLAB. EEGLAB is an open source tool which can process EEG signals once they have been measured and recorded (A. Delorme and S. Makeig, 2004). This processing tool works with different EEG devices on the market and is compatible with the Emotiv EPOC ®. It also works with different stimuli presentation systems including Presentation ®, which was used in the experiment. EEG data was first processed using the features within EEGLAB and for this study a high pass filter was used to remove the trendlines within the EEG data. Independent Component Analysis (ICA) was then used for further analysis of the EEG data. ICA is an analysis technique that reduces the summation of the cortical potentials detected by the EEG sensor into simpler signals for the sensors to process (A. Delorme and S. Makeig, 2004). This analysis technique is useful for reducing eye blink noise as well as some muscle noise. Additional noise was removed manually from the continuous EEG data and from there EEG events were extracted from the Presentation ® system logfiles. In the case of this experiment the logfiles consisted of the latency times for the stimuli. Epochs or time locked events around a designated time were created in EEGLAB and were averaged across the different learner types, mobile or non-mobile, to create average event related potentials (ERP) around the time of response. The ERPs gave a visual image of what occurred in the brain during the event, or when the response was made, which was shown at zero millisecond.

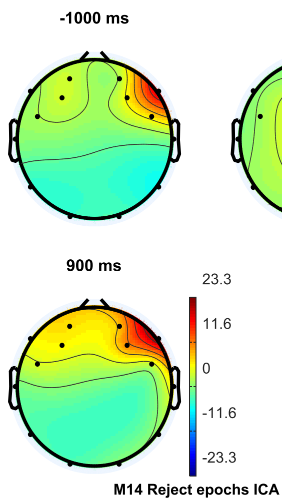
3.6 Statistics

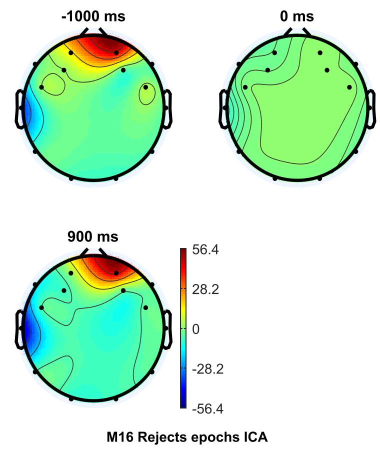
To analyze the significance of the factors of GPA, problem difficulty, and learner type an F-test was used with the statistical software JMP. Statistics labeled as F(n, dF), p<value; where the n represented the number of factors as well as their represented interactions, dF is the number of inputs tested across, and the p-values are tested with an α level that is 0.05.

4. RESULTS

4.1 Results

The results analyzed included data from the brain signals as well as the significance between the learners, problem difficulty and GPA as it related to either latency time or amount of correct responses. From the results of the analyzed brain signals topographical maps of the scalps show the intensity of activation in different areas of the brain. In the figure below the areas of interest were the prefrontal cortex and the parietal cortex. The colors on the heat maps ranged from green (0 μV) to red (positive μV) and blue (negative μV). The heat maps were visual representations of the measured electrical activity detected by the EEG. In addition to the heat maps; the ERPs were compared across the participants and the selected time frame before, during and after the response were examined. As seen below in Figure 6 there was more intensity occurring in mobile learners who had a higher GPA than those who had a lower GPA in the prefrontal cortex and parietal cortex.



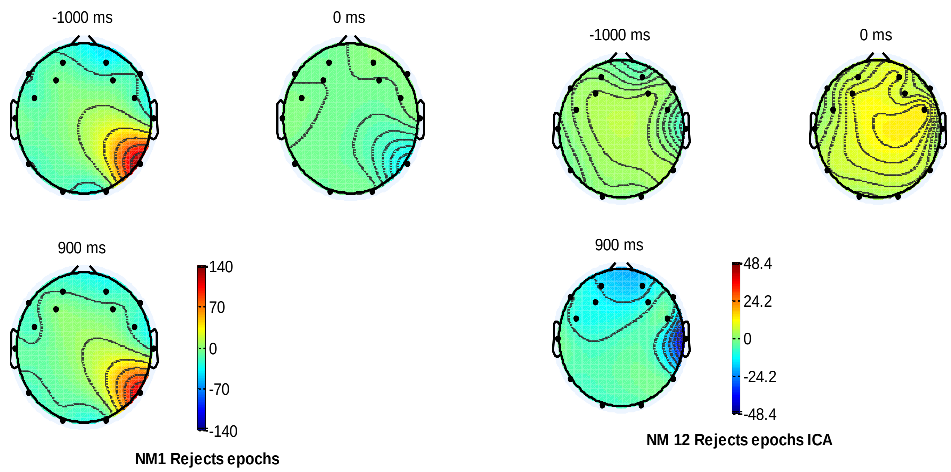


High GPA Mobile Learner (M14)

Low GPA Mobile Learner (M16)

Figure 6: Example of Mobile Learners (high and low GPA)

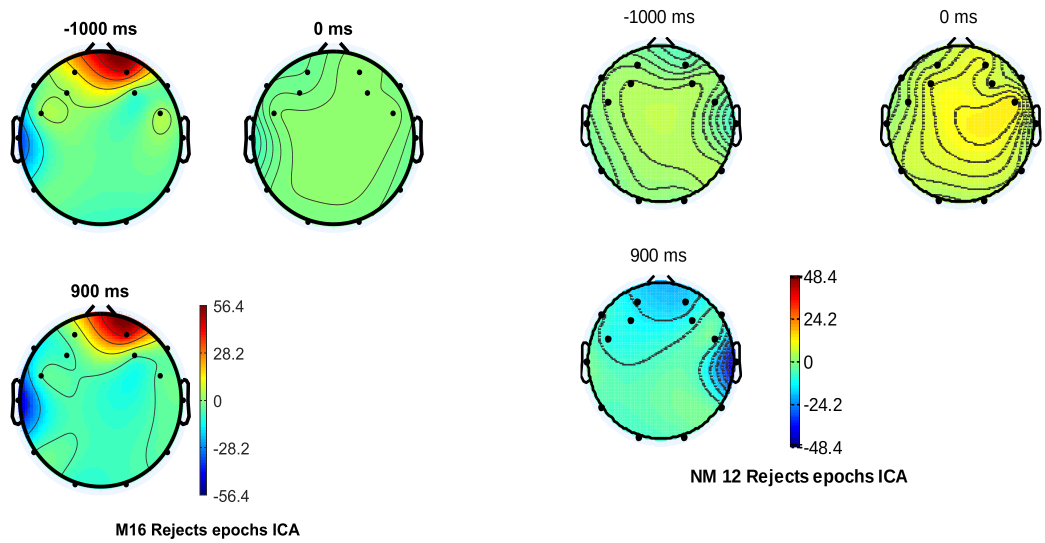
The same type of comparison can be seen with non-mobile learners but instead of high intensity in the prefrontal cortex, greater intensity is seen in the temporal cortex (shown in Figure 7). While Figure 8 shows the comparison between low GPA mobile and non-mobile learners.



High GPA Non-Mobile Learner (NM 1)

Low GPA Non-Mobile Learner (NM 12)

Figure 7: Example of Non-Mobile Learners (high and low GPA)



Low GPA Mobile Learner (M16) Low GPA Non-Mobile Learner (NM 12)

Figure 8: Mobile Learner compared with Non-Mobile Learner (low GPA)

Examining the ERPs, the difference between the mobile and non-mobile learners can be seen while questions were responded to (responses occurred at zero millisecond) in Figures 9 and 10 below.

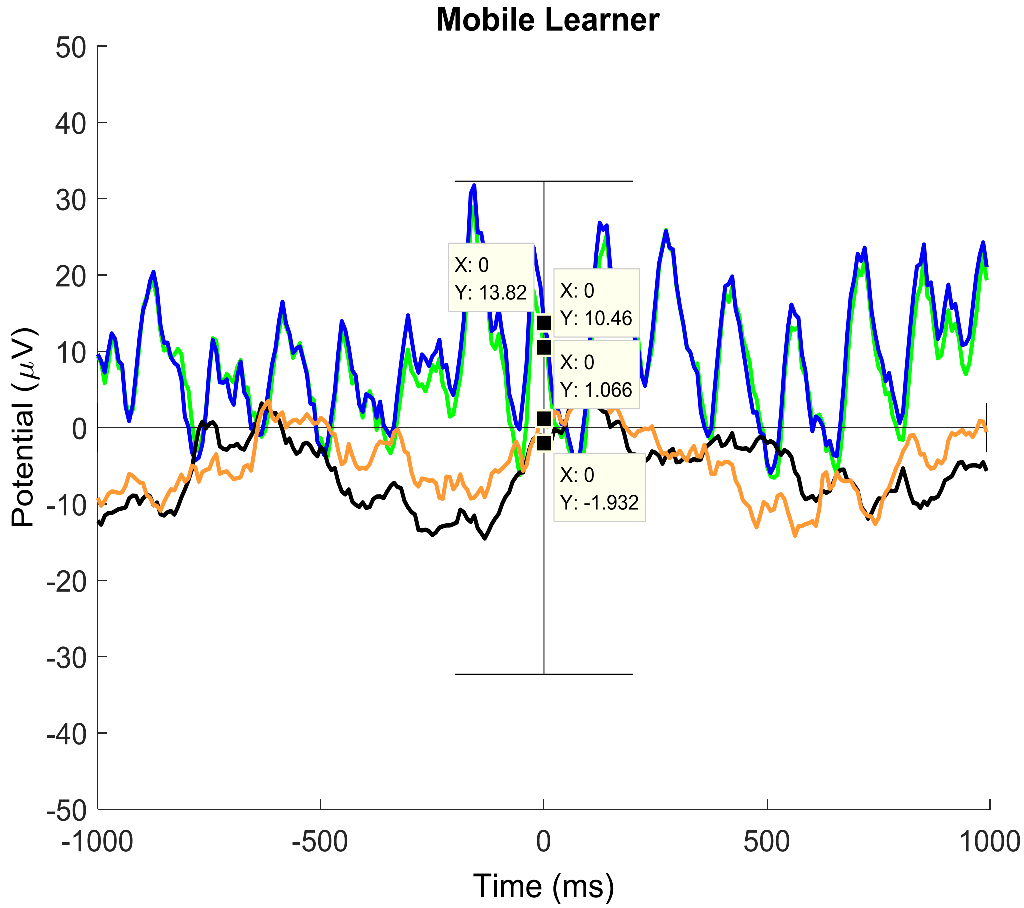


Figure 9: Examples of mobile learners' event related potential for both low and high GPA. Blue is prefrontal high GPA (10.46 μV), green is parietal high GPA (13.82 μV), orange is prefrontal low GPA (1.066 μV), and black is parietal low GPA (-1.932 μV)

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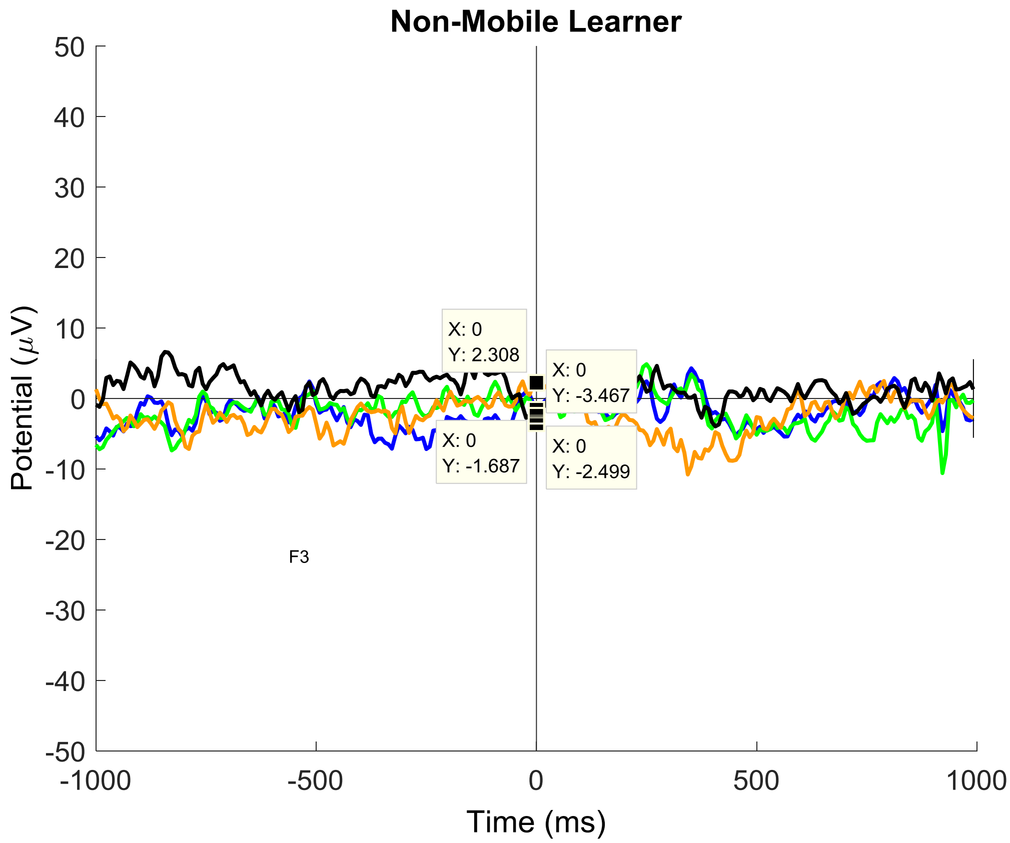

Figure 10: Examples of non- mobile learners' event related potential for both low and high GPA. Blue is prefrontal high GPA (-1.687 μV), green is parietal high GPA (-3.467 μV), orange is prefrontal low GPA (2.308 μV), and black is parietal low GPA (2.499 μV)

The graphs showed that high GPA mobile learners had a more positive voltage potential for the prefrontal cortex and the parietal cortex when compared to low GPA mobile learners.

Finally, when comparing the low GPA mobile learner and the low GPA non-mobile; the low GPA mobile learner had a higher intensity in the parietal cortex but a lower intensity in the prefrontal cortex when compared to low GPA non-mobile learner.

4.2 Responses

The results indicated that the type of learner and the GPA did not have a significant difference when it came to the latency time. However, the results indicated that problem difficulty had a significant difference when it came to latency time, (F (1,816), p-value < 0.001). There was an interaction effect seen from the results, from the combination of the three factors (problem difficulty, GPA, and the type of learner). The results indicated that the combination of all three factors showed significance as it pertained to response time (F (7,816), p-value < 0.001). Additionally, the interaction of problem difficulty and GPA also had a significant difference when it came to response time (F (7,816), p-value < 0.003). The effect details as well as the interaction graphs can be seen in the figures 12-17 of the Appendix.

The analysis of responses from learners was also examined, and was based on the number of correct, incorrect, and no responses relating to the complexity of the questions (simple and complex). Figure 11 below shows the breakdown based on learner, GPA, correct response, incorrect response, and no response.

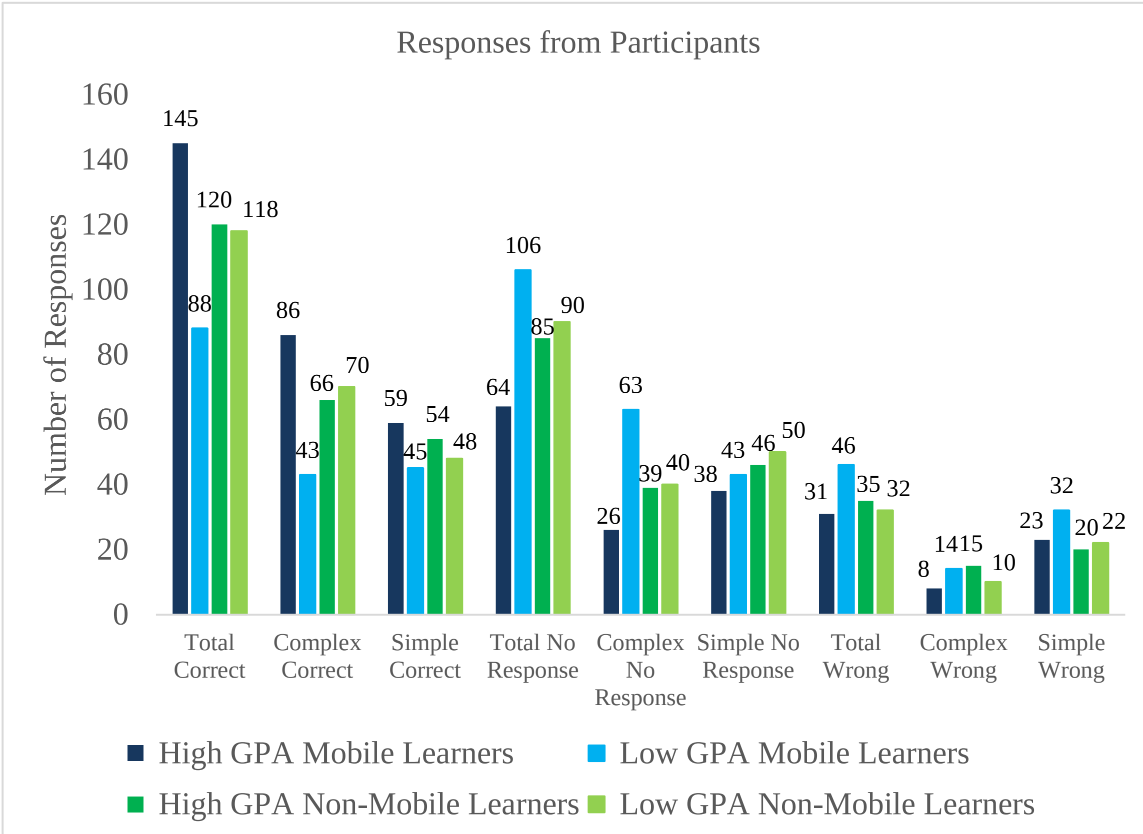

Figure 11: Shows the number of response made by different learners using different learning modalities

4.3 Perception of Mobile Application

The acceptance of the AEMA was also analyzed, using the UTAUT questionnaire amongst mobile learners to determine how acceptable it was to them. In the table below (Table 1), the average scores for the constructs from the UTAUT can be seen. The scores were based on a likert scale of 5, where 5 was considered most likely and 1 was least likely.

Table 1: UTAUT Scores for constructs.

UTAUT Constructs	Average Score
Ease of Use	4.3
Perceived Ease of Use	3.9
Facilitating Conditions	3.9
Effort Expectancy	3.8
Attitude toward Behavior	3.8
Self-Efficacy	3.8
Compatibility	3.6
Mobility	3.6
Intrinsic Motivation	3.5

According to Venkatesh these constructs came from theories of behavior (2003). The ease of use and perceived ease of use were based on whether the user of the technology felt that utilization of the mobile device would be free of effort and was based on the model of technology acceptance. This model was designed to predict the usage of technology by users at a job (V. Venkatesh et al., 2003). Facilitating conditions examined whether users felt that they could obtain assistance with the technology if they needed it; while effort expectancy looks at the degree of ease associated with participants' use of the AEMA (V. Venkatesh et al., 2003; V. Venkatesh, J. Thong, X. Hu, 2012). Attitude toward behavior indicated the positive or negative feelings that a participant had with the technology. The remaining constructs looked at how participants felt the mobile technology would help them in succeeding (self-efficacy), whether participants could see themselves carrying the device just for the purposes of it being used (mobility), whether the AEMA was compatible with their learning preferences (compatibility), and finally whether the participants found the AEMA enjoyable to use without being told to enjoy the device (V. Venkatesh et al., 2003; V. Venkatesh, J. Thong, X. Hu, 2012).

5. DISCUSSION

5.1 Discussion

In the topographic maps of the mobile learners (Figure 6) the parietal cortex and prefrontal cortex show consistent intensities, and when comparing the intensities at the response time, the low GPA mobile learner has a smaller intensity. This showed that the high GPA learner was able to benefit from the technology intervention because the participant was able to continue to process numbers as well as incorporate their working memory. Unlike the low GPA mobile learner who shows attention, indicated by the high intensity in the prefrontal cortex, before and after the response; during the response the high GPA mobile learner shows that they benefitted from the AEMA when compared to the low GPA mobile learner. The conclusions drawn from the high and low non-mobile learners (Figure 7) were that the intensities in the prefrontal and parietal cortex were low which indicated that learners did not have strong number processing skills and they were not as attentive to the problems when compared to the mobile learner. Additionally the conclusions drawn from the non-mobile learner were that utilization of an AEMA assist with working memory and fact retrieval and ultimately can allow students to perform better. This was inferred to be due to the lack of assistance from the AEMA. Additional conclusions drawn from the topographic maps (Figure 8) showed that there was more intensity in the prefrontal cortex before and after the response in the low GPA mobile learner than when compared to the low GPA non-mobile learner. The conclusions drawn were that without the intervention of technology in low GPA non-mobile learners, the working memory and decision making before the response are not accessed. An additional implication is the temporal cortex activation. Since the temporal cortex is associated with visual memory and since this learner did not get the opportunity to interact with the mobile application they are forced to try to recall the visual images that they previously studied (M. Carreiras, 2015). It was also inferred that since the first time non-mobile learners used technology was when they were playing Tetris ®, it may have had an effect on working their visual spatial memory. This showed that between the low GPA mobile and non-mobile learners that an AEMA not only assisted in keeping attention before the task but also helped the learner visually remember the task.

The conclusions drawn from the graphical results showed that with an AEMA number processing and fact retrieval were assisted and evidence of this can be seen from the results when the parietal cortex voltage potential was greater with mobile learners than with non-mobile learners. The results showed a discrepancy, in that low GPA mobile learners had a lower intensity than low GPA non-mobile learners for the prefrontal cortex. This means that the AEMA did not play a significant role in affecting working memory and attention for every learner, especially when focusing on the relationship between the low GPA mobile learners and low GPA non-mobile learners.

The responses made by mobile and non-mobile learners were calculated and displayed base on the number of correct, no responses, and incorrect responses. The analysis showed that high GPA mobile learners out performed non-mobile learners when it came to answering correctly. The conclusions drawn relate back to the fact that the parietal cortex is being intensified the most as evident from Figures 9 and 10. This means that fact retrieval and number processing are being activated and therefore more correct questions can be answered by high GPA mobile learners when compared to low GPA mobile learners. For non-mobile leaners the difference between the total correct responses between low and high GPA non-mobile learners is smaller than when compared to the difference between high and low mobile learners. Evidence from Figures 9 and 10 show that the difference between parietal cortex intensity in high and low GPA non-mobile learners is small so therefore the number processing and fact retrieval needed for mathematics would be closer in activation and the differences between correct responses would be small.

Overall the perception of acceptance in the constructs for UTAUT (Table 2) was generally acceptable and mostly neutral in responses. Mobile learners felt that the AEMA was easy to use and not much effort was required on their part to work it. Mobile learners also felt that the AEMA was a tool that had benefits to helping them improve and better achieve in limit based mathematics.

5.2 Strengths

AEMAs have shown for this study their benefit as it pertains to increasing brain activity. The perception of it being a useful learning tool was high among the participant who used it in the study. AEMAs offered its users the opportunity to learn in an interactive way that engaged their areas of learning more effectively as it pertained to number processing.

5.3 Limitations

Some possible difficulties with the study can be seen in the recruitment as well as seen between the mobile learners and non-mobile learners. The students that were recruited were split into GPA groups where low GPA was 3.29 and lower and high GPA was 3.3 and higher. The GPA however only considered overall GPA and not exclusively engineering GPA. In addition the GPAs were seen as broad and in the future these can be broken down further with the addition of more recruits for the study. By recruiting more participants the GPAs could be broken down into three groups that could include high achievers, average achievers, and low achievers. In addition to the GPA, the mobile and non-mobile learners may have had a bias, due to the fact that mobile learners were able to write notes on the mobile device but non-mobile learners were not allowed to take notes. By eliminating this criterion, the true difference seen between the two learning modalities would only be the interactivity between them.

5.4 Future Work

Future work in this area would be seen in increasing the recruitment size of the study and addressing the limitations mentioned as it pertains to GPA and restrictions associated with non-mobile learning. The study could also examine the effects that an AMEA would have with participants for other courses such as integral calculus or physics. The study utilized EEG as an imaging technique but other imaging techniques with better spatial resolution such as fMRI could be used in the future.

6. IMPLICATIONS

6.1 Research Implications

In this research BBL was used to determine whether there was a difference between learners who utilized technology or not. For both learners the learning environment was relaxed, so that the optimum element of Relaxed Alertness was met. Orchestrated Immersion was done through an enriched environment where definitions and examples of limit based calculus was provided. Finally, Active Processing was done when students consolidated their learning experiences (mobile or non-mobile) through the interactions that they had with either learning modality.

The research implications showed that an AEMA has some potential in moving the area of education forward because it has shown that it can increase the intensity within the parietal cortex which is a key area in number processing and fact retrieval. The research showed that students with high GPAs and users of the AEMAs were able to outperform non-mobile learners. With an AEMA, researchers can learn more about neuroplasticity by examining whether the intensity in the parietal cortex grows more intense through continued use of the AEMA. With this gained knowledge, research in improving knowledge retention and knowledge acquisition can better be achieved for students and the impact of technology can better be understood.

6.2 Teaching Implications

The research can aid in moving education and teaching forward by giving more evidence to the area of BBL. Through utilization of AEMA students can learn and shape Knowledge at their own pace. Additional learning capabilities can also be included such as: embedded links, textbook, videos and even interactive graphs and figures. Since BBL is based on how a student incorporates learning into their own way, mobile technology complements this well and assists in understanding how an AEMA affects a learner's brain. When educators understand better how their material is learned by students then they can shift their way of teaching to meet the needs of the students more easily.

7. CONCLUSION

The conclusions drawn from the study were that an AMEA was beneficial when it came to increasing parietal cortex activity. This increase inferred that the AMEA was responsible for assisting with number processing and therefore could be used as a tool to help when it came to processing numbers when solving limit based problems. The study also concluded that students that were high GPA mobile learners benefitted the most since these students were able to answer the most questions correctly during a post-test assessment. There are no other studies available which examine how an AMEA impacts student learning and continued research on this study can further advance the area of engineering education.

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9. APPENDIX

Effect Tests					
Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Problem Difficulty	1	1	1.7744e+10	68.2285	<.0001*
Learner	1	1	305346767	1.1741	0.2789
Problem Difficulty*Learner	1	1	230335603	0.8857	0.3469
GPA	1	1	220861675	0.8492	0.3570
Problem Difficulty*GPA	1	1	2307347074	8.8721	0.0030*
Learner*GPA	1	1	610092787	2.3459	0.1260
Problem Difficulty*Learner*GPA	1	1	2517142700	9.6788	0.0019*

Figure 12: Shows the effects test of the factors within the study

Problem Difficulty*GPA

Least Squares Means Table

Level	Least Sq Mean	Std Error
Complex,HGPA	31020.175	1095.3182
Complex,LGPA	35435.650	1097.4676
Simple,HGPA	43743.808	1149.1093
Simple,LGPA	41414.950	1184.1759

Figure 13: Effects details of interaction between problem difficulty and GPA

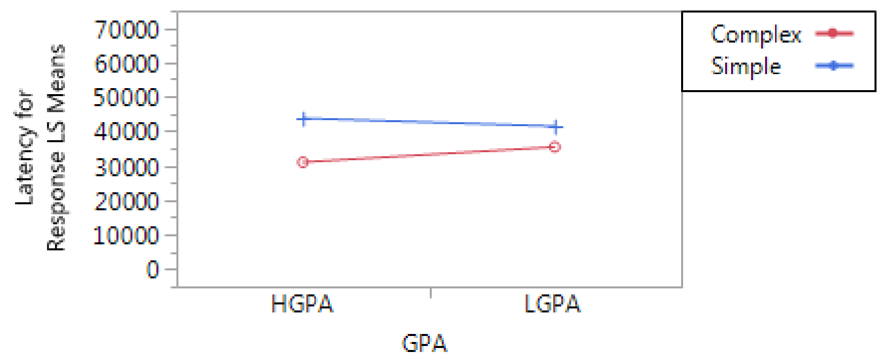
Problem Difficulty*Learner*GPA

Least Squares Means Table

Level	Least Sq Mean	Std Error
Complex,Mobile,HGPA	28311.462	1523.8250
Complex,Mobile,LGPA	37983.082	1566.3585
Complex,NonMobile,HGPA	33728.888	1573.7997
Complex,NonMobile,LGPA	32888.218	1537.6155
Simple,Mobile,HGPA	43491.785	1637.4130
Simple,Mobile,LGPA	39374.793	1719.1064
Simple,NonMobile,HGPA	43995.832	1612.6648
Simple,NonMobile,LGPA	43455.107	1629.0374

Figure 14: Effect details for interaction of all three factors

LS Means Plot



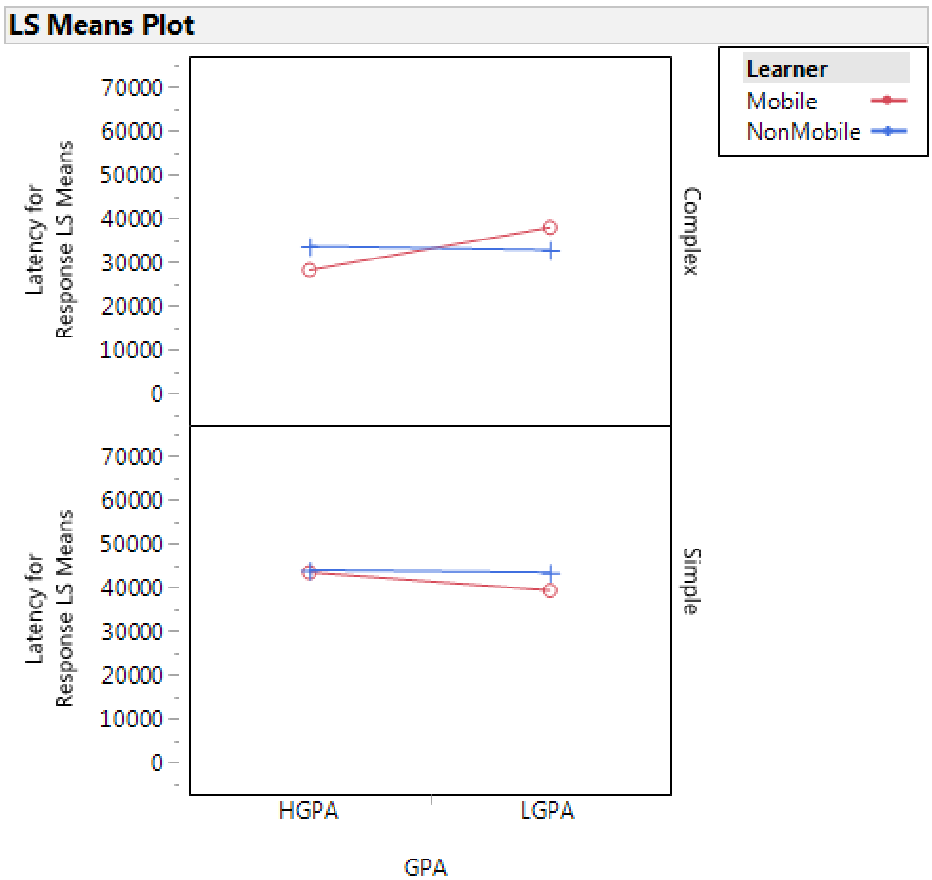
LSMeans Differences Student's t

α= 0.050 t= 1.9629

Level				Least Sq Mean
Simple,HGPA	A			43743.808
Simple,LGPA	A			41414.950
Complex,LGPA		B		35435.650
Complex,HGPA			C	31020.175

Levels not connected by same letter are significantly different.

Figure 15: Shows the interaction of problem and GPA with connecting letters report



LSMeans Differences Student's t

α= 0.050 t= 1.9629

Level						Least Sq Mean
Simple,NonMobile,HGPA	A					43995.832
Simple,Mobile,HGPA	A					43491.785
Simple,NonMobile,LGPA	A					43455.107
Simple,Mobile,LGPA	A	B				39374.793
Complex,Mobile,LGPA		B	C			37983.082
Complex,NonMobile,HGPA			C	D		33728.888
Complex,NonMobile,LGPA				D		32888.218
Complex,Mobile,HGPA					E	28311.462

Levels not connected by same letter are significantly different.

Figure 16: Shows the interaction between all the factors as well as their connecting letters report

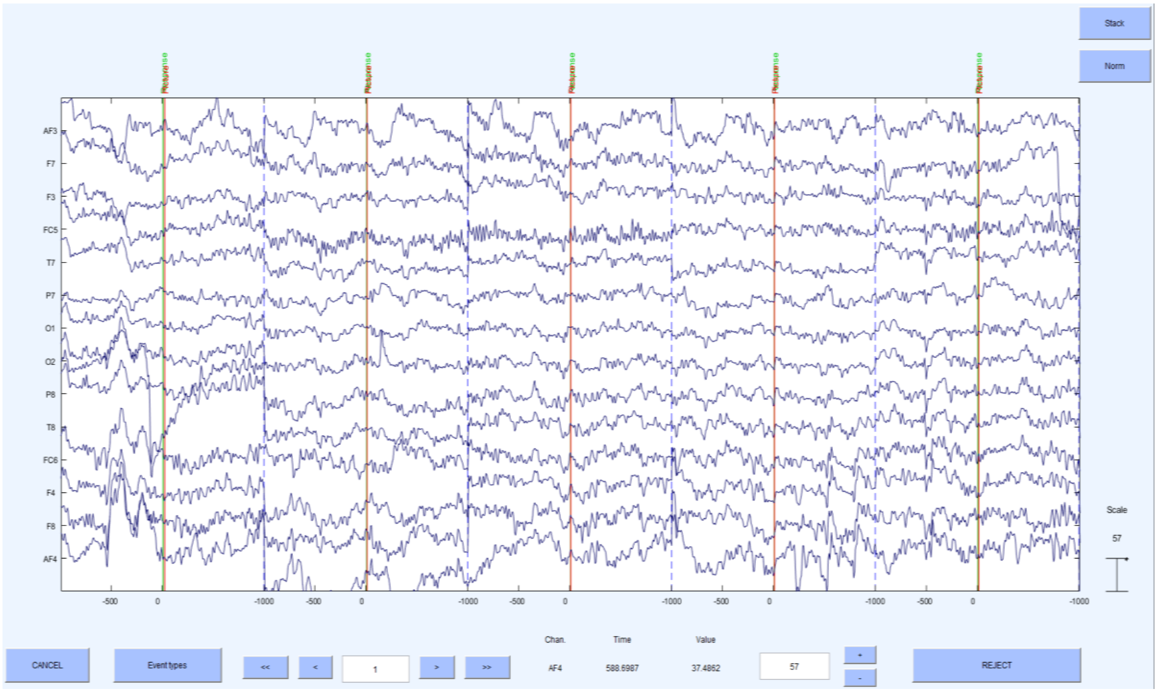


Figure 17: Example of events that have been extracted to form epochs for ERPs