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The Effects of Working Memory on Brain-Computer Interface Performance

A thesis

presented to

the faculty of the Department of Psychology

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Master of Arts in Psychology

by

Samantha A. Sprague

August 2014

Eric W. Sellers, Ph.D., Chair

Matthew McBee, Ph.D.

Russell Brown, Ph.D.

Shannon Ross-Sheehy, Ph.D.

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ABSTRACT

The Effects of Working Memory on Brain-Computer Interface Performance

by

Samantha A. Sprague

Amyotrophic lateral sclerosis and other neurodegenerative disorders can cause individuals to lose control of their muscles until they are unable to move or communicate. The development of brain-computer interface (BCI) technology has provided these individuals with an alternative method of communication that does not require muscle movement. Recent research has shown the impact psychological factors have on BCI performance and has highlighted the need for further research. Working memory is one psychological factor that could influence BCI performance. The purpose of the present study is to evaluate the relationship between working memory and brain-computer interface performance. The results indicate that both working memory and general intelligence are significant predictors of BCI performance. This suggests that working memory training could be used to improve performance on a BCI task.

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CHAPTER 1

INTRODUCTION

Approximately 30,000 people are living with amyotrophic lateral sclerosis (ALS) in the United States and 5,000 additional people are diagnosed annually (Brownlee & Palovcak, 2007). It is a progressive neuromuscular disease that eventually renders its victims unable to interact with their environment. Amyotrophic lateral sclerosis is commonly known as Lou Gehrig's disease and can cause locked-in syndrome. The term "locked-in" refers to a condition in which an individual has lost all neuromuscular control except for eye movements while cognitive functioning remains mostly intact (Vallabhaneni, Wang, & He, 2005). The loss of motor control causes those with ALS to become completely dependent upon family members and caregivers to meet their daily needs. Ultimately they lose the ability to communicate. As a progressive disease these deteriorations occur over time, and ALS patients are required to use many forms of augmentative and alternative communication (AAC) techniques. AAC devices include any method of communication that does not require speech (Brownlee & Palovcak, 2007). Examples of these include writing, typing, letter and picture boards, eye blinks, and eye tracking devices (Brownlee & Palovcak, 2007). As the disease progresses to its final stages, a nonmuscular form of communication may become the only possible option.

Brain-computer interfaces (BCIs) are an alternative form of communication that, unlike the majority of AAC devices, require no muscular movement or control. Brain-computer interfaces use brain signals for the purpose of controlling a computer. Not only is this a potential method of communication for individuals with ALS, people with other forms of locked-in syndrome (LIS) can also benefit from the technology (e.g., brainstem stroke, spinal cord injury).

Locked-in syndrome is a condition defined by damage to the ventral pons resulting in a loss of muscle control (Patterson & Grabois, 1986).

In the time since Hans Berger discovered the electroencephalogram, researchers have been trying to harness brain signals to control external devices (Vallabhaneni et al., 2005). Electroencephalogram is one of the most common methods for recording input. This is because it is less expensive and more convenient than other methods (e.g., invasive methods). There are a number of components essential to the successful operation of any BCI. These include the input of the user's brain activity, the output that controls the BCI, the process of turning input into output, and the specific parameters that dictate the details of the interaction between the BCI and the end user (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). The output that controls the BCI is the device command. These commands change based on the processes that the BCI is designed to carry out. BCI technology has been used to perform a number of tasks. Examples of some of these tasks include virtual typing (Popescu, Badower, Fazli, Dornhege, & Muller, 2006), moving a cursor (Wilson, Schalk, Walton, & Williams, 2009), controlling robotic arms (McFarland & Wolpaw, 2008), virtual reality navigation (Lécuyer, Lotte, Reilly, Hirose, & Slater, 2008), controlling vehicles (Galán et al., 2008), and videogames (Lécuyer et al., 2008). Regardless of the task and the specific algorithms that produce control, the technology used to realize the BCI is very similar. One of the most important experimental challenges of BCI research is to improve the speed and accuracy of the system (Vallabhaneni et al., 2005). Brain-computer interface users need efficient systems because they need to communicate as quickly as possible (Nijboer et al., 2008). Currently it is difficult for users to keep up with normal conversation rates due to slow systems and errors (Sellers & Donchin, 2006).

General Types of BCI

Invasive BCIs

Noninvasive BCIs place electrodes on the surface of the scalp, whereas invasive BCIs require the implantation of electrodes beneath the skull. Electrodes can be placed on top of the dura mater, on the surface of the cortex, or into the cortex (i.e., single unit recordings). The majority of research involving single unit recordings has been conducted using animal models due to the risks associated with the procedure (Birbaumer, 2006b). Many fewer studies have used invasive methods in the human population (Birbaumer, 2006a; Lal et al., 2005; Leuthardt, Schalk, Wolpaw, Ojemann, & Moran, 2004). This can be attributed to possible risks and uncertainty as to the added value invasive BCIs bring (Wolpaw et al., 2000). The physical risks associated with invasive BCIs include infection, discomfort, brain damage, and in some cases, death (Wolpaw & McFarland, 2004). In addition, the longevity of the implanted electrodes is questionable and may lead to a decrease in signal strength over time (Vallabhaneni et al., 2005). In the case of paralysis as a result of a spinal cord injury, neural plasticity leading to restructuring of areas within the motor cortex may also reduce the efficacy of invasive forms of BCI (Brouwer & Hopkins-Rosseel, 1997).

A major limitation of studies that have used invasive BCIs is that the participants are typically epileptic patients because they routinely have electrodes implanted to monitor seizure activity (Krusienski & Shih, 2011; Lal et al., 2005). This can be problematic because these findings may not generalize to other populations, specifically those with neuromuscular disability. In order for an individual to be able to use an invasive BCI, brain signals associated with movement must still be present in the cortex. The individual must also be able to activate these signals through the intent to move (Hochberg et al., 2006). This can be challenging, especially in individuals who have not had muscular control for some time.

Electrocorticography (ECoG) places epidural or subdural electrode grids, or strips, beneath the skull (Schalk, 2012). Some researchers claim that there are possible benefits to using ECoG instead of EEG, which include higher spatial resolution, higher signal bandwidth, and increased signal amplitude (Wilson, Felton, Garell, Schalk, & Williams, 2006). Despite claims made that ECoG-based BCIs provide an increased signal-to-noise ratio, there is not yet sufficient evidence to warrant the claim of invasive BCIs being superior to noninvasive BCIs (Krusienski & Shih, 2011; Speier, Fried, & Pouratian, 2013). McFarland, Sarnacki, and Wolpaw (2010) showed that high signal resolution is not necessary in order to conduct three-dimensional movement. They further hypothesized that pending additional advances in research, it may eventually become feasible for operation of external devices such as a robotic limb or wheelchair.

Noninvasive BCIs

Noninvasive BCIs are operated through the use of brain activity that is recorded from the scalp using an EEG (Wolpaw et al., 2000). The brain waves that are recorded with the EEG have multiple components that can be used to control the BCI (Birbaumer, 2006b; Birbaumer et al., 2000; McFarland, Lefkowicz, & Wolpaw, 1997). Two of the most studied components are event-related potentials (ERPs) such as the P300 (Sellers, Arbel, & Donchin, 2012) and event-related desynchronization/synchronization (ERD/ERS; Pfurtscheller, 2001). These components represent fluctuations in the EEG and occur in response to cognitive processing and other forms of brain activity (Pfurtscheller, 2001). Event-related potentials are discussed in detail below. Both ERD and ERS refer to a change in sensorimotor rhythms. Event-related desynchronization refers to a decrease in amplitude, whereas event-related synchronization refers to an increase in amplitude (Graimann, Huggins, Levine, & Pfurtscheller, 2004; Pfurtscheller, 2001). Although the amount of training required to use a BCI varies from individual to individual, the average training time for a user to operate a P300-based BCI is minimal compared to BCIs operated by other components (Guger et al., 2009). This substantial decrease in training time makes the P300-based BCI desirable because those in need of assistive methods of communication can start using the BCI sooner.

Event-Related Potentials

Event-related potentials (ERPs) are brain activity representing psychological phenomenon elicited by some internal or external event and can be found within EEG recordings (Vallabhaneni et al., 2005). Event-related potentials are realized by time-locking the EEG with a specific event, meaning each ERP corresponds to an eliciting stimulus (Fabiani, Gratton, & Coles, 2000). Event-related potential components consist of both positive and negative waves labeled “P” for positive and “N” for negative. The latency of each component is sometimes contained in the label (i.e., P300; Kayser & Tenke, 2003). There are also exogenous and endogenous components of an ERP. Exogenous components represent a response to the physical aspects of a stimulus (e.g., a flash), whereas endogenous components occur after an exogenous component and represent cognitive activity occurring in response to a stimulus (Horst, Johnson, & Donchin, 1980; Vallabhaneni et al., 2005).

A low signal-to-noise ratio is typically observed in ERPs. This is because the ongoing EEG is substantially larger in amplitude than ERP components, making it difficult to extract ERPs from the EEG (Fabiani et al., 2000). Thus, several ERPs must be averaged for components to be observed. In addition, because of the low signal-to-noise ratio, artifacts can obscure or mimic ERP signals; thus, they are a source of error that must be corrected for in many cases. The artifacts can come from biological sources (e.g., eye blinks, heartbeats) or nonbiological sources (e.g., 60Hz line noise, medical equipment; Coles & Rugg, 1996). The waveforms created by these artifacts can resemble ERP waveforms because they may occur at similar frequencies. Relevant to BCIs, artifacts are a problem because they inhibit classification by obscuring or mimicking the components that are being used for BCI operation. There are certain precautions that can be taken to limit artifacts and other outside noise. For example, instructing participants to remain as still and calm as possible can reduce the number of biological artifacts.

Amplifiers contain filters that can eliminate artifacts. A low-pass filter reduces the number of high frequency signals, whereas a high-pass filter reduces the number of signals produced at a frequency that is lower than the signal of interest. The use of filters can be problematic and researchers should be aware of these potential pitfalls when using filters. For example, filtering out high frequency signals can make it more difficult to recognize leftover artifacts in the EEG due to muscle movement. Although the majority of artifacts caused by muscle movement occur at frequencies above 60 Hz, some can occur at lower frequencies (e.g., 8-30 Hz). Without the high frequency signals marking these muscle movements, the leftover artifacts may be mistaken for signals of interest (Srinivasan, 2012).

The P300 ERP Component

The P300 ERP Component was first discovered by Samuel Sutton and colleagues in 1965 (Sutton, Braren, Zubini, & John, 1965). The P300 is one of several components observed in an ERP. It is a waveform with a positive peak around 300ms, and it occurs in response to some meaningful internal or external event. . The amplitude of the P300 is partially dependent upon the amount of time that passes between stimulus presentations. The more time that passes before the next stimulus is presented, the greater the amplitude the P300 will have (Gonsalvez & Polich, 2002). On the other hand, the amplitude decreases when the target stimulus is presented frequently and rapidly, one after another (Sellers et al., 2012). Herrmann and Knight (2001) have shown that attention has been found to be an important component in the elicitation of a P300 response. Participants must pay attention to the task at hand in order to elicit a P300 response. As a result, when a task is highly complicated, or more than one task is being conducted at once, the P300 amplitude decreases (Hohnsbein, Falkenstein, & Hoormann, 1995). As defined by Donchin and Coles (1988), the P300 ERP reflects a process known as context-updating. This is a process that takes place while the participant is evaluating the stimuli he or she is presented with. Whenever the presentation of stimuli becomes inconsistent with the current model (i.e., an unexpected presentation occurs), the participant will have to update the model in order to adjust it so that it is again consistent.

The P300 is often studied using what is known as an oddball paradigm. According to Donchin and Coles (1988) four requirements must be met in order to constitute an oddball paradigm. The first is that a participant must be presented with two categories of stimuli and each stimulus must fall into only one of the categories. The second is that one type of stimuli must be presented far less frequently than the other. Thus, when that type of stimulus is presented to the participant it constitutes a rare response. The third requirement is that the participant is instructed to perform a task that entails placing each stimulus into one of the categories. The final requirement is that the stimuli must be presented in a random order. Often times the task involves paying attention to the rare stimulus and ignoring the frequent stimulus (Fichtenholtz et al., 2004). This usually involves instructing the participant to silently count the number of times the rare stimulus is presented (Farwell & Donchin, 1988). The task may also require the participant to perform a movement or action such as pressing a button or lever (Huettel & McCarthy, 2004). It is interesting to note that a P300 ERP response can be elicited by the absence of a stimulus if the participant was expecting a stimulus to be presented (Sutton, Tueting, Zubin, & John, 1967), this exemplifies the endogenous nature of the component.

The reliability of the P300 response has been established a variety of times within studies, which makes it a dependable measure (Fabiani, Gratton, Karis, & Donchin, 1987). The P300 response is amiable to BCI use for a variety of reasons. It can be obtained through noninvasive means, it requires minimal training to successfully elicit, the classifier can be customized to the user relatively quickly, and the majority of people are able to use it (Guger et al., 2009). Additionally, the P300 response can be elicited without movement. This is particularly beneficial because many of the disabled BCI users have limited or no motor control (Piccione et al., 2006).

The P300-BCI

There are three main types of P300-BCI paradigms: visual, auditory, and tactile. Auditory and tactile oddball paradigms must also follow the same rules as the visual oddball paradigm (Donchin & Coles, 1988); however, the type of stimuli the participant is presented with differs. Auditory oddball paradigms can use tones at two different frequencies and the participant's task is to discriminate between them (Stevens, Skudlarski, Gatenby, & Gore, 2000). Other options for auditory stimuli include words, sounds, and music. Tactile oddball paradigms require a stimulus that involves touch, such as applying a stimulus to the hand or wrist (Aloise et al., 2007). Aloise et al. (2007) set out to examine the effects of different types of stimuli on performance accuracy. They found that visual stimuli provided the highest accuracy with 93%, followed by auditory with 70%, and tactile with 68%. As all three provided accuracy rates above chance, the type of oddball paradigm used should be determined on a case-by-case basis.

The visual P300-BCI paradigm has consistently performed better than any other modality in terms of speed and accuracy. Thus, the design of the current study employs a visual presentation. The canonical oddball task presents two stimuli, one is attended to and the other is not. In contrast, the “P300 Speller” uses many stimuli that are presented in a row/column arrangement (see Figure 1).

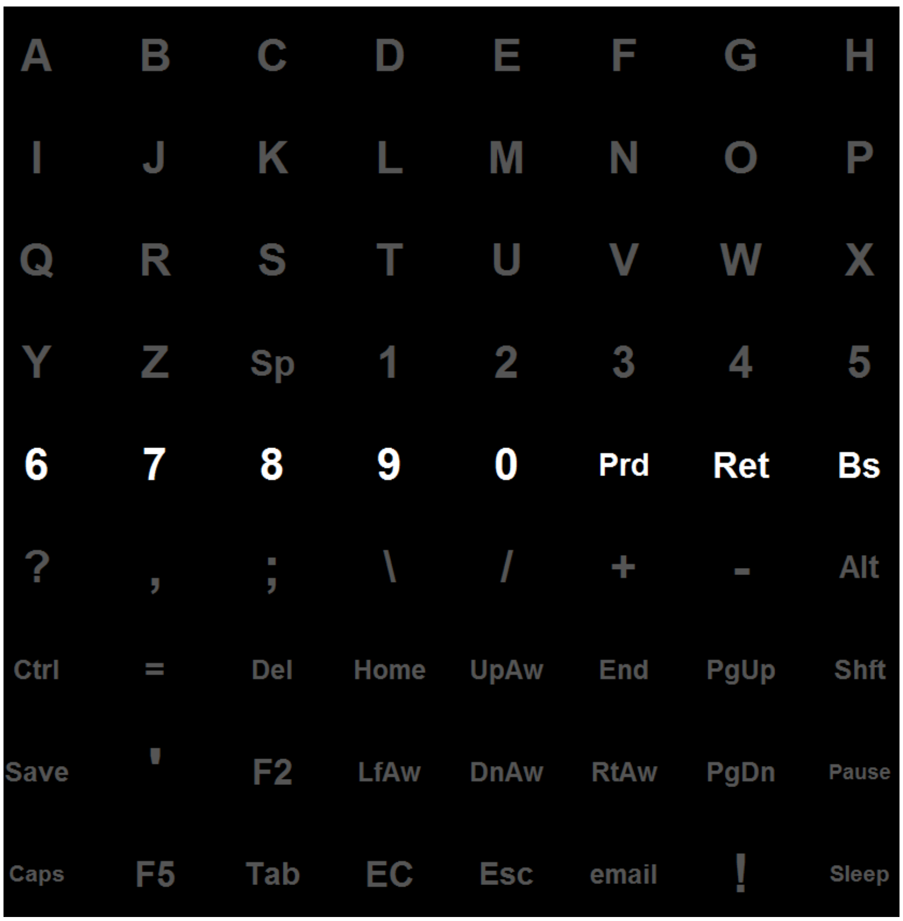

Figure 1. Example 8x9 matrix row-column paradigm

The first P300-BCI study arranged the letters of the alphabet and some commands in a 6x6 matrix. The six rows and six columns flashed rapidly and the participants’ attentional task was to count each flash of the letter they wished to select. Thus, the desired letter was located in one column and in one row. The row and column that contained the desired item should elicit a larger P300 response than the other five rows and the other five columns (Farwell & Donchin, 1988). After the rows and columns of the matrix stop flashing, an algorithm (see Classification section) is used to determine the row and column with the largest P300s. The letter contained at the intersection of the row and column is then presented to the participant as feedback. As shown in Figure 2, each cell corresponds to a character of a 6x6 matrix.

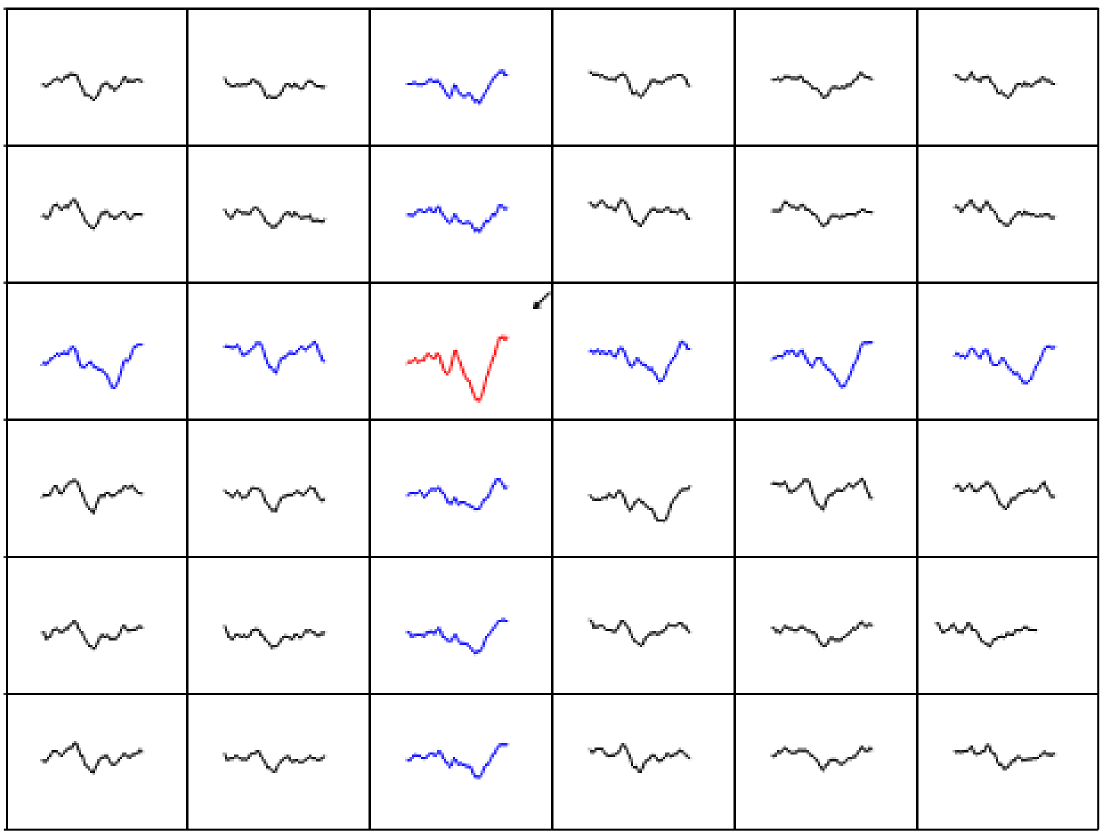

Figure 2. Waveforms of the ERPs elicited by character flashes in a 6x6 matrix

The waveforms in each cell represent the ERP elicited by the flash of each character. In this case, the red waveform in column 3 and row 3 corresponds to the cell that contained the character that the participant attended to, and, as expected, the waveform shown in this cell exhibited the largest P300. Figure 3 shows an overlay of the waveforms corresponding to the 36 cells in Figure 2. The ERP to the attended character is shown in red. The ERPs to the characters in the rows and columns that contained the item that was attended to are shown in blue; the higher amplitude responses to these items is due to the fact that they flash at the same time as the desired character (Frye, Hauser, Townsend, & Sellers, 2011). ERPs to all other characters are shown in black.

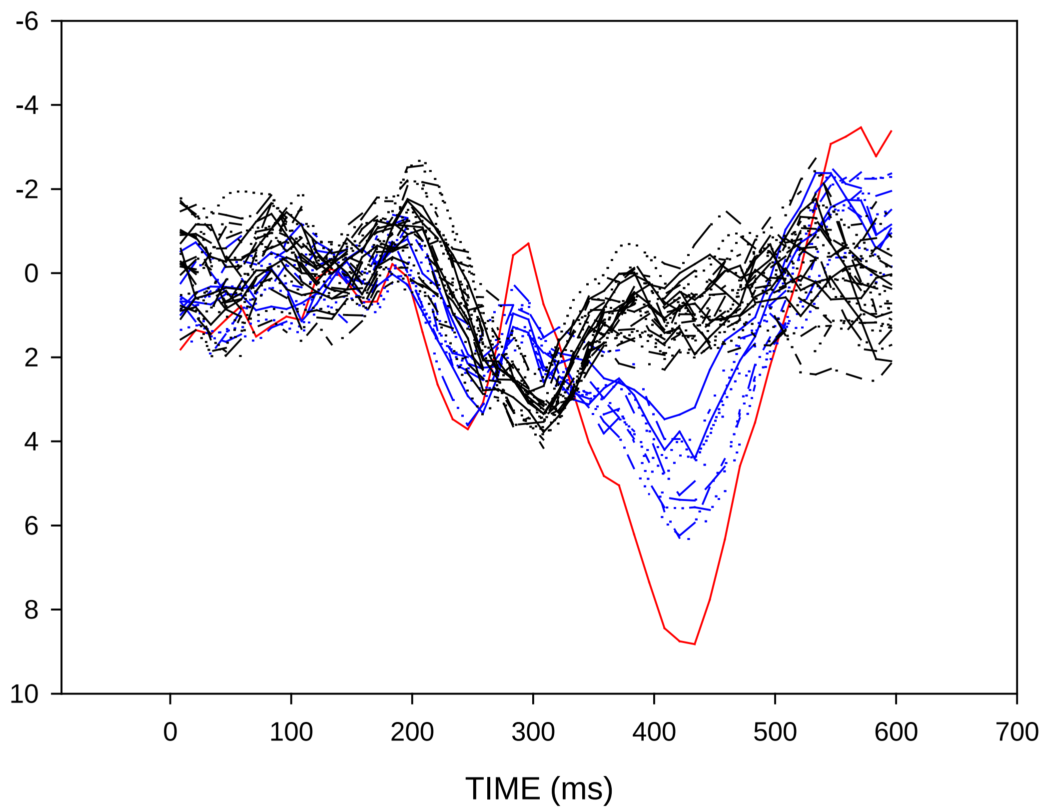

Figure 3. An overlay of the waveforms corresponding to the 36 cells in Figure 2

Subsequent to the introduction of the P300-BCI by Farwell and Donchin (1988), many paradigmatic manipulations have been studied. A limitation of the row-column paradigm (RCP) is that incorrect selections typically occur in a row or column that contains the target (see Figure 2). A major improvement was achieved by dissociating the row and columns of the matrix. Townsend et al. (2010) flashed items in quasi-random groups; this paradigm is referred to as the checkerboard paradigm (CBP) and was able to significantly improve speed and accuracy of the BCI (Figure 4). Therefore, the current study employed the checkerboard paradigm.

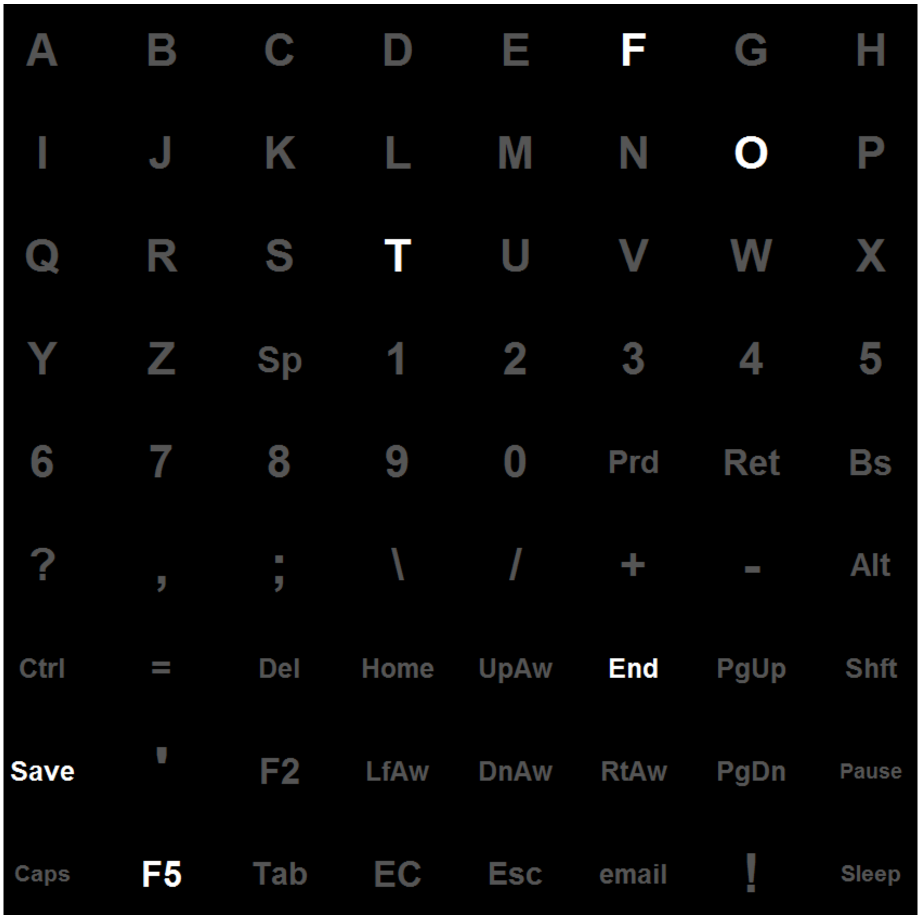

Figure 4. Example 8x9 matrix checkerboard paradigm

<u>Potential Psychological Predictors of BCI Performance</u>

There has been much progress and success in the field of BCI; however, there are some shortcomings to be addressed. One problem involves the individual differences in BCI performance (Kleih, Nijboer, Halder, & Kübler, 2010). For example, some people find the BCI very difficult to use and others are unable to use the system at all. Recent research has examined the relationship between psychological factors and BCI use. For example, Kübler et al. (2001) have found that restrictions to BCI use exist as a result of the patient’s psychological situation in addition to technological and physical restraints. Johnson (1986) developed a triarchic model of

P300 amplitude showing that psychological variables have an influence on the P300 amplitude. Kleih et al. (2010) extended Johnson's research and showed that motivation also impacts the P300 amplitude. Leeb et al. (2007) conducted an experiment that showed highly motivated participants were more successful at navigating a 3D environment than their counterparts. Kübler et al. (2001) went so far as to predict the failure of the field of BCI if researchers do not begin to implement more psychological theory and experimentation into their research instead of focusing solely on the technological aspects of BCI. Additional research should be conducted to examine the variability in BCI performance related to psychological factors and how these factors can be used to improve and predict subsequent performance (Nijboer, Birbaumer, & Kübler, 2010).

Working memory is a factor that may account for inter-individual differences in BCI performance. Conducting studies that compare working memory with performance on BCI tasks can help create methods that can assist in accounting for individual differences in BCI use, potentially leading to an increase in BCI implementation and performance. The current study examined executive function, general intelligence, and working memory prior to conducting the BCI task. These measurements were taken in order to compare the relationship between them and an individual's performance on a BCI task. The focus of the current study is working memory; however, executive function and general intelligence are correlated with working memory and could also affect BCI performance. Therefore, these measurements were taken in order to account for this possibility and to determine what portion of BCI task performance is due to working.

Executive Function

Weintraub et al. (2013) define executive function as "the top-down cognitive modulation of goal-directed activity" (p. S55). Executive function changes throughout the life span; it gradually increases during childhood and begins to decline in old age (Zelazo, Craik, & Booth, 2004). From a physiological standpoint, processes of executive function are primarily carried out in the frontal lobes of the brain (Craik & Bialystok, 2006). Executive function as a whole can be measured generally to obtain an average estimate of an individual's ability to conduct these high-level processes. There are several components within executive function that can be controlled and measured in order to obtain a more detailed analysis of an individual's cognitive abilities. These include mechanisms such as cognitive flexibility, problem solving, working memory, general intelligence ("*g*"), and response inhibition and selection (Alvarez & Emory, 2006). For the purpose of this study, executive function was measured using the Dimensional Change Card Sort Test (DCCS). Further details on the DCCS are discussed below.

General Intelligence

Gottfredson (1994) defines intelligence as "a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience" (p. 13). Charles Spearman (1904) originally developed the concept of general intelligence, also known as "*g*" or the "g-factor." He described it as representing a general measure of cognitive ability that could be applied to various kinds of cognitive tasks (Deary, Penke, & Johnson, 2010; Spearman, 1904). The "g-factor" is responsible for a large portion of the individual differences in cognitive ability and is a major source of the predictive power of cognitive measures (Deary et al., 2010).

General intelligence is a component of executive function that has been found to be highly correlated with working memory (Ackerman, Beier, & Boyle, 2005). This makes it an important component to measure in the current study in order to ensure the individual differences in BCI performance are due to working memory and not general intelligence. In order to measure general intelligence, the Picture Vocabulary Test (TPVT) was administered. The TPVT is a single-word vocabulary comprehension test used to measure the vocabulary portion of language (Weintraub et al., 2013). Additional aspects of the TPVT are discussed below.

Working Memory

Over the years there have been several debates over the best model of memory. One previously popular view was that of a dichotomous model with a long-term memory and a short-term memory component. Long-term memory is dependent on neuronal growth, whereas short-term memory is a result of brief electrical activation (Baddeley, 2003). The short-term memory component was meant to comprise working memory. As additional research examined the model, flaws began to arise within the idea that short-term memory included working memory (Baddeley, 1992). This gave rise to new theories that accounted for working memory being more independent from short-term memory.

The term "working memory" was first used more than 40 years ago by Miller, Galanter, and Pribram (1970). It was originally defined as a cognitive system designed to temporarily store and manipulate information (Baddeley & Hitch, 1975). Baddeley's original model of working memory contained three subcomponents: the central executive, the visuospatial sketch pad, and the phonological loop. The central executive subcomponent controls the way an individual's attention is divided. The visuospatial sketch pad is considered to be one of two "slave systems." It is in charge of remembering and manipulating visual stimuli. The phonological loop is the other "slave system" and it operates in a similar way to the visuospatial sketch pad but with auditory, speech stimuli (Baddeley, 1992). Baddeley later added an additional component to working memory, the episodic buffer. This component is able to take information from the other three components as well as from long-term memory and create a single episodic representation that can be temporarily stored in the buffer (Baddeley, 2000). The original model continues to remain at the core of working memory theories today. Recent theories have expanded the model to include multiple components such as attentional control (Cowan, 1988; Logie, 2011) and individual differences (Just & Carpenter, 1992; Jarrold & Towse, 2006; Unsworth & Engle, 2007).

Working memory is thought to control interactions between perception, long-term memory, and action (Baddeley & Hitch, 1975). It holds information for a short period of time and allows the individual to manipulate that information if necessary. Working memory differs between individuals and some individuals are able to retain more and manipulate information more effectively than others (Baddeley, 2003; Baddeley & Hitch, 1994). Working memory span is one area in which individuals differ. It is defined as the number of items that can be held in one's mind at once (Baddeley & Hitch, 1975). In a task designed to assess working memory span, participants are read a series of words or numbers and instructed to repeat as many words or numbers back as they can remember. The List Sorting Working Memory Task (LSWM) was used to measure working memory in the current study. In this task individuals are required to remember a series of words and then recall them in a specific order (Weintraub et al., 2013).

By examining the relationship between working memory and BCI performance in healthy participants, further insight can be obtained on ways to improve BCI performance in our target population. If working memory has a significantly large impact on accuracy, this information can be used to develop new methods to improve BCI performance. This would be particularly beneficial for individuals who have amyotrophic lateral sclerosis (ALS), which can leave cognitive ability relatively unharmed in comparison to other neurodegenerative diseases. Individuals with ALS do, however, show some deterioration in working memory (Hammer, Vielhaber, Rodriguez-Fornells, Mohammadi, & Münte, 2011). Thus, methods that can improve working memory may be especially important for this group.

CHAPTER 2

CURRENT STUDY

A primary objective of brain-computer interface (BCI) research is to restore the ability to communicate to individuals that are unable to do so on their own. Research conducted over the past 30 years has demonstrated that electroencephalographic (EEG) signals can be used to allow people to move a cursor on a computer screen, control a robotic arm, or emulate typing. BCI systems represent a major advance over conventional augmentative communication methods, all of which depend on muscle control and may not be viable communication options for severely paralyzed people.

The primary purpose of the current study is to identify factors that are related to BCI performance that can potentially be used to improve performance. The study was an examination of executive function, general intelligence ("*g*"), and working memory in order to determine which construct is most important to BCI performance. The main hypothesis of the study is that participants with high levels of working memory capacity will show higher accuracy on a BCI task. Specifically, it was hypothesized that working memory would have a medium (~0.5), positive, significant effect size and that this effect size would be the largest of the three components.

CHAPTER 3

METHODS

Participants

The study involved a sample of 34 healthy participants obtained using the online participant pool at ETSU. The study was approved by the ETSU Institutional Review Board.

Stimuli and Materials

Each participant took part in two sessions conducted on different days. Upon arriving at the first session, the participant read and signed the informed consent document. The first session consisted of three computerized measures. The order the measures were predetermined using a Latin square design. In the second session, participants operated a BCI.

Measuring Psychological Factors

The three instruments used in this study were selected from the NIH (National Institute of Health) Toolbox Cognition Battery, a component of the NIH Toolbox for the Assessment of Neurological and Behavioral Function (Gershon et al., 2013). The NIH consulted with 102 experts in the field of cognition in order to select or develop instruments to be included in the battery. The resulting collection of instruments was then tested using a sample of 476 participants ages 3 to 85. The sample included participants from three different ethnic categories and three levels of education (Weintraub et al., 2013). The instruments were validated in English and tested for age effects on performance, convergent and discriminant construct validity, and test-retest reliability. Gold standard measures of the same construct were used to test the convergent construct validity of each measure. To confirm test-retest reliability, one third of participants were randomly selected and contacted 7 to 21 days later to complete the measures a second time. Age effects on performance for each measure showed validity for indicating the expected amount of cognitive decline during adulthood. Finally, test-retest reliability was successfully established (Weintraub et al., 2013).

The three measures selected for this study were the List Sorting Working Memory Test (LSWM), the Dimensional Change Card Sort Test (DCCS), and the Picture Vocabulary Test (TPVT). For each measure the researcher read aloud the instructions displayed on the researcher's monitor. The participant had a copy of the instructions on a separate monitor set up in front of the participant for clarity. The researcher started and stopped the test using a mouse. Once the test began, the participant responded in one of three ways: verbally (LSWM), using the left and right arrow keys on the keyboard (DCCS), or the mouse (TPVT). Accuracy was recorded for all three measures and timing was recorded for the DCCS. The scoring for all three measures provides a computed score and an age-adjusted score for easier comparison. All measures were distributed in the same way.

The TPVT measures receptive vocabulary, which is considered to be a good representation of general intelligence ("g"). The test takes approximately 4 minutes to administer and is completely computerized. After the researcher read the participant the instructions, the test began by presenting the participant with an audio recording of a word paired with a display of four pictures on the monitor. For this test, the mouse was used to respond. An example of a stimulus is shown in Figure 5.

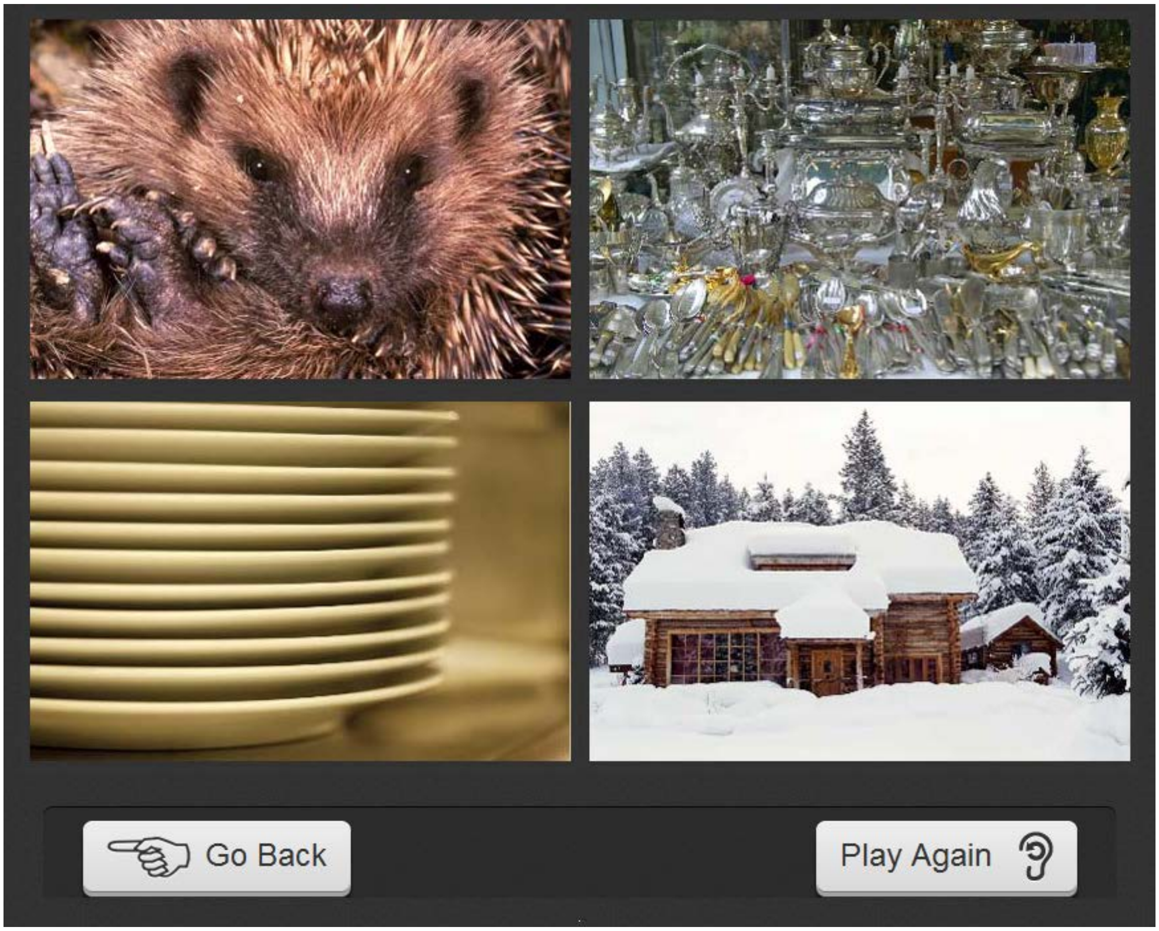

Figure 5. Example of a Picture Vocabulary Test (TPVT) trial of the word “hodgepodge”

In this test participants were presented with an auditory word and four pictures on the screen. They were required to click on the picture that best matched the meaning of the word that was said.

The DCCS measures executive function by determining cognitive flexibility. The DCCS is also computerized and takes 4 minutes to administer. There are 40 trials and each trial takes approximately 6 seconds to complete. There are two types of tasks included in the DCCS. Both tasks require the participant to choose between two target pictures that differ on one or two levels. The first task entails choosing the picture that matches the same shape as the stimulus. The second task involves matching the color of the stimulus. The first two sets of trials contain all of the same type of task. The third trial mixes the two tasks and requires the participant to quickly match either the shape or color of the stimulus based on a word (e.g., “shape,” “color”) that flashes before the two pictures are presented. An example of a stimulus is shown in Figure 6.

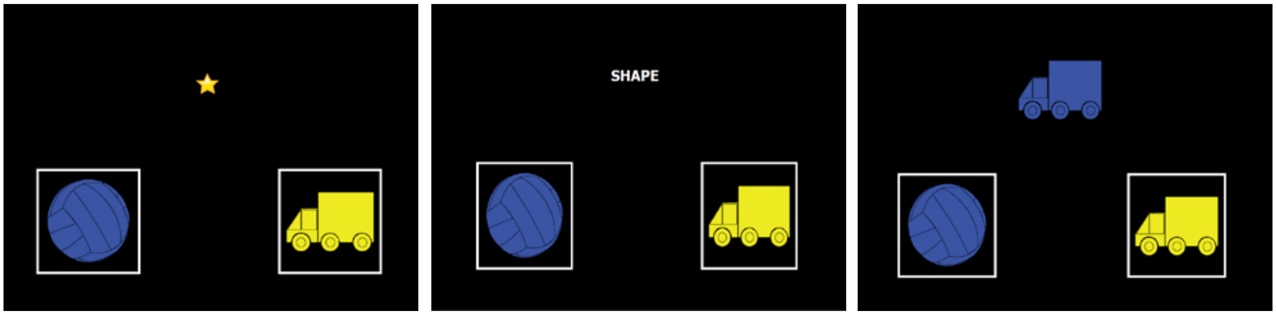

Figure 6. Example of a Dimensional Card Sort Test (DCCS) trial

In this test participants saw a star, which they were instructed to focus on. This was followed by the word shape or color, indicating whether they would be matching by shape or color for the present trial. They were then presented with a picture in the middle of the screen and were instructed to press the left or right arrow key to select the picture that matched the color or shape of the picture in the middle of the screen.

The LSWM measures working memory by evaluating both information processing and storage. This computerized test takes 7 minutes to administer and consists of two parts. For each trial in the first portion of the task, the participant was presented with an audio recording of a list of all animals or all food items. Participants were shown pictures of the animals or food items on their monitor with the name of the animal or food item printed under each picture. Participants were then asked to repeat the list of animals or food items to the researcher in increasing size order. For trials in the second portion of the task, participants were presented with a list containing both food and animals. They were then instructed to repeat the list to the researcher in size order from smallest to largest, naming the food items first and then the animals. The researcher recorded responses to both portions on the researcher’s monitor and was provided with instructions on how to proceed based on the participant's response. An example of a stimulus is shown in Figure 7.

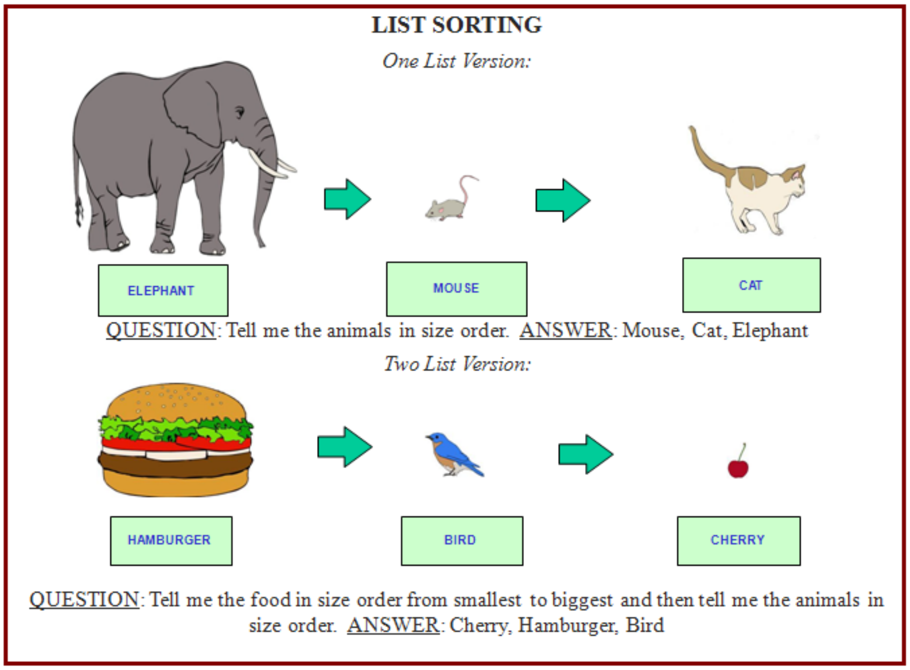

Figure 7. Description of the List Sorting Working Memory Test (LSWM)

For the first portion of the test participants were presented with a list of animals or food items. They were then instructed to repeat the list to the researcher in increasing size order. For the second portion of the test participants were presented with both food and animals in a set of pictures. They then had to repeat the food items first in increasing size order, followed by the animals in increasing size order.

Brain-Computer Interface Task

The second session began with the participant being seated in front of a monitor to the right of the researcher. Each participant was given a series of surveys in order to measure his or her current levels of fatigue, hunger, caffeine, motivation, and mood. These were collected so they could be controlled for in the statistical analyses by including them as covariates. The

Stanford Sleepiness Scale (SSS) was used to measure fatigue. Three visual analog scales were created for this study; measures of hunger, motivation, and mood. Caffeine use was also measured. A second measure of motivation was also used, the Questionnaire for Current Motivation for BCI2000 (QCMBCI2000), which was designed to measure motivation specific to the BCI task. All measures, except for the QCMBCI2000, were given to the participants to fill out during the first session as well. Participants were then shown an informational PowerPoint about the BCI while they were measured and fitted with an EEG cap. The researcher filled the electrodes in the cap with a water-soluble conductive gel using a blunted needle. Next, the participant was presented with an 8x9 matrix on the participant's monitor.

The first portion of the session was used to obtain data for the calibration of the BCI. At the top of the screen a six-letter word was displayed and the participant's task was to "copy-spell" the word. Figure 8 presents an example, the word DRAGON is initially displayed at the top of the screen.

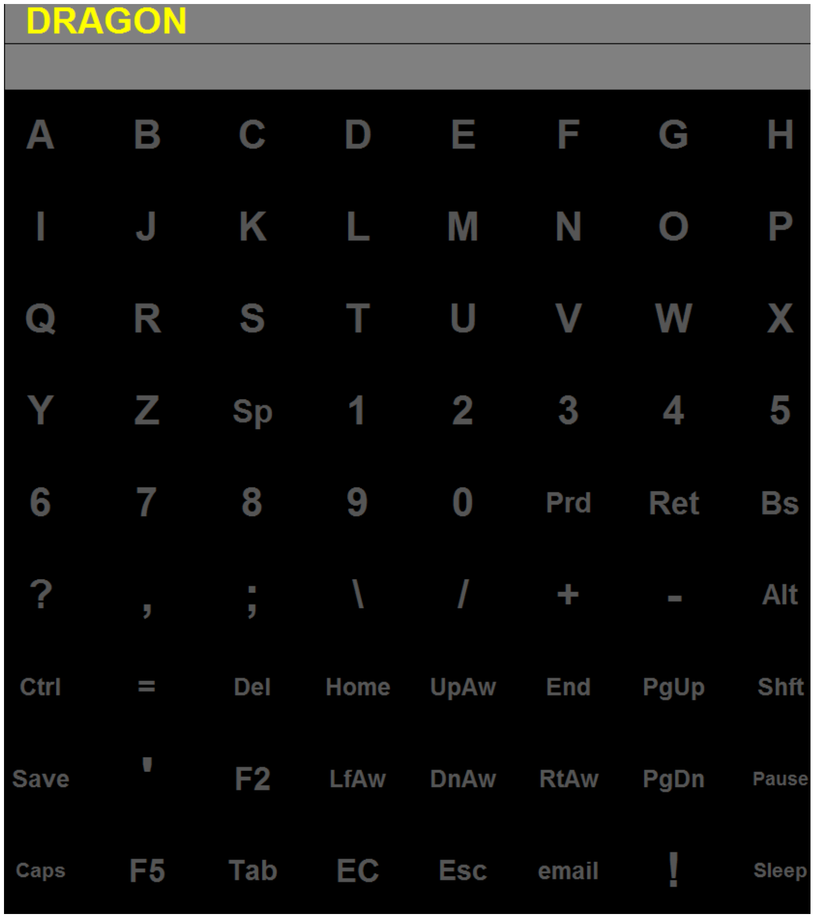

Figure 8. Example of calibration word

When the matrix starts to flash, the word DRAGON(D) replaces DRAGON as an indicator of which letter the participant is supposed to attend to in the matrix (Figure 9). Participants were required to spell three, six-letter words selected from a random word generator for the calibration portion. Prior to calibration the task was explained and a practice trial was performed. Each group of stimuli was presented for 62.5ms, followed by an inter-stimulus interval (ISI) of 62.5ms; thus, stimulus onset asynchrony (SOA) was 125ms. After spelling all three words, the data were processed offline using SWLDA (discussed in detail below) to produce a classifier that was used during the second portion of the session, which provided “online feedback” regarding the accuracy of the BCI selection. In this task the participant spelled three predetermined sentences: THE_CAT_IN_THE_HAT, THE_QUICK_BROWN_FOX, and MARY_HAD_A_LITTLE_LAMB.

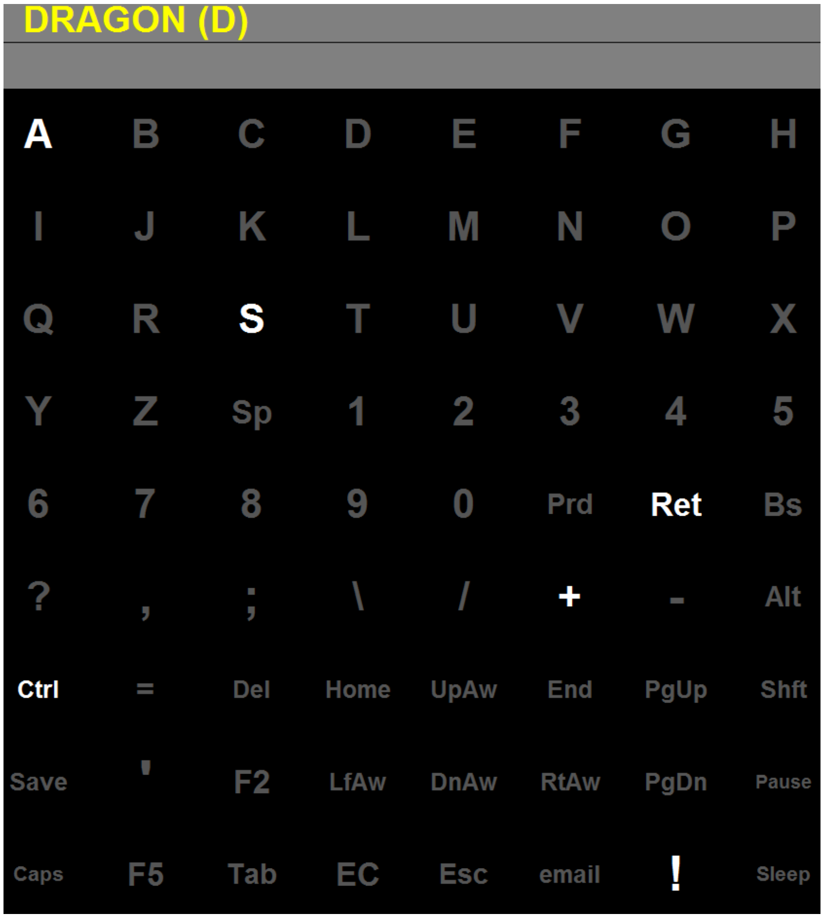

Figure 9. Example of system flashing during calibration

During this portion of the session the sentence was not displayed at the top of the screen. The researcher read a sentence to the participant and he or she was required to spell it from memory using the BCI. This was done to increase cognitive load during the task to make it more similar to how the BCI would be used in a practical application. An example of feedback provided by the BCI is shown in Figure 10. Participants were instructed not to attempt to correct mistakes and to move on to the next letter in the sentence if a mistake was made.

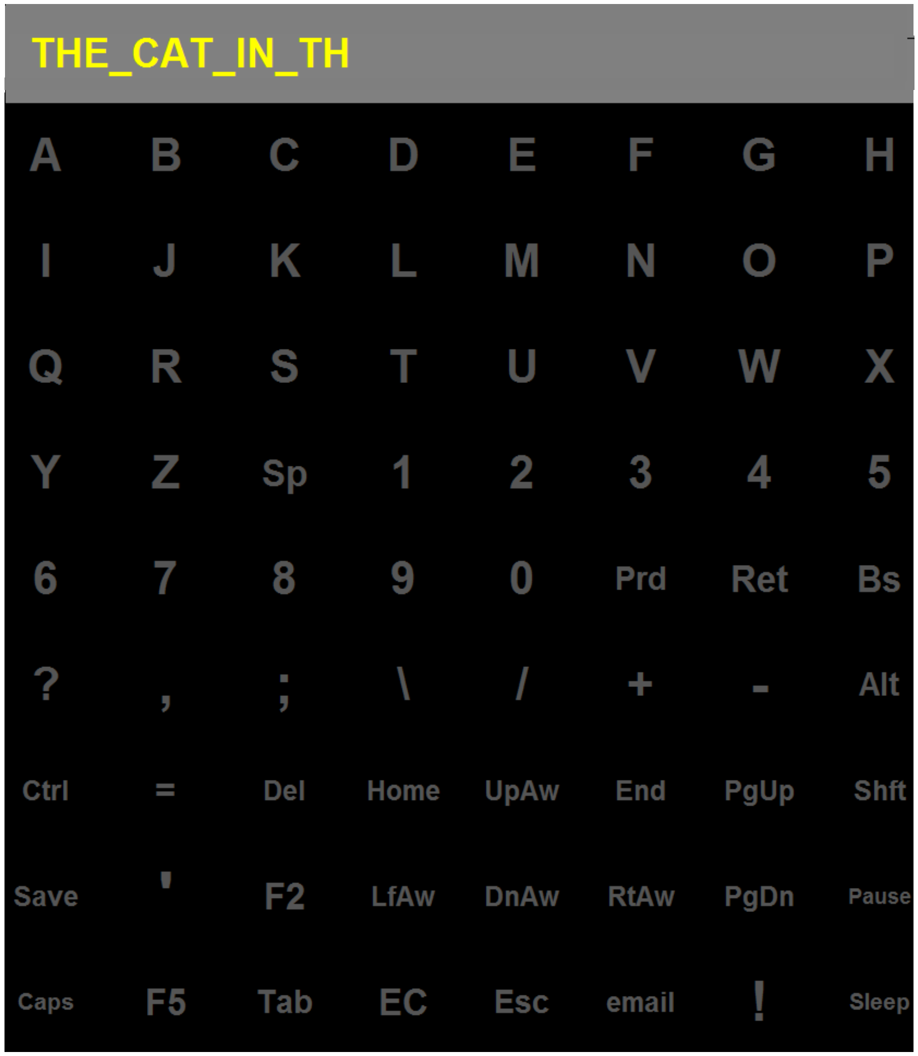

Figure 10. Example of feedback during online portion

<u>EEG Acquisition and Processing</u>

A 32-channel EEG cap (tin electrodes; Electro-Cap International, Inc.) was used to record the EEG. The left mastoid electrode acted as the ground and the right mastoid electrode acted as the reference. Two 16-channel USB biosignal amplifiers from Guger Techniologies (g.tec) were used in order to increase the amplitude of the electrical activity from the scalp being recorded. The electrical activity was then amplified (+/- 2V before ADC) before being digitized at 256 Hz. The data were filtered using a 0.50Hz to 30.0Hz bandpass filter. Although the EEG cap consists of 32 channels, only eight electrodes were used for BCI operation: Fz, Cz, Pz, P3, P4, P07, P08, and Oz. Previous research has shown that these eight electrodes are optimal for accuracy (Krusienski et al., 2006). BCI2000 software was used to control stimulus presentation, data collection, and online processing (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004). The researcher ensured impedance values were below 30.0 kΩ before proceeding with the session.

Classification

Stepwise linear discriminate analysis (SWLDA) has proven to be one of the more successful classification techniques, making it widely used across BCI studies (Krusienski et al., 2006). SWLDA uses a forward and backward stepwise regression analysis as well as ordinary least-squares regression in order to choose which features the discriminant function should contain (Krusienski et al., 2006). The most statistically significant features are added to the discriminant function one-by-one. Features are labeled as statistically significant if they meet the criterion of predicting the target variable with a p-value of less than 0.10. Every time a new feature is added, features with p-values greater than 0.15 are removed from the model (Krusienski et al., 2006; Krusienski, Sellers, McFarland, Vaughan, & Wolpaw, 2008). Features continue to be added and subtracted from the discriminant function until no additional features meet the inclusion or exclusion criteria or a specific number of features are included in the model. In this study the maximum features that could be included in the model was set to 60, based on prior research (Krusienski et al., 2006; Krusienski et al., 2008).

CHAPTER 4

RESULTS

Data from 27 out of the original 34 participants were included in the above mentioned statistical analyses. Participants who were excluded from the analyses were taken out for the following reasons: failure to complete both sessions, not a native English speaker, and issues with the technology. NIH toolbox scores and BCI performance accuracy for the participants that were included in the analysis are listed in Table 1.

Table 1: *Data for NIH Toolbox tasks and BCI performance accuracy*

	NIH Toolbox Tasks			BCI Performance Accuracy
Subject ID	LSWM	DCCS	TPVT	Percent Correct
ExStudy_009	103.57	119.15	102.31	94.92
ExStudy_010	80.70	87.13	88.07	6.78
ExStudy_011	140.86	97.57	128.70	100.00
ExStudy_012	97.60	111.36	117.52	94.92
ExStudy_014	118.14	109.94	113.75	79.66
ExStudy_015	89.14	101.53	100.16	71.19
ExStudy_016	128.24	107.80	108.53	76.27
ExStudy_017	118.14	105.00	92.84	10.17
ExStudy_018	108.26	113.55	130.95	50.85
ExStudy_019	89.14	119.65	114.80	89.83
ExStudy_021	94.33	105.35	99.41	74.58
ExStudy_022	102.63	122.65	117.02	91.53
ExStudy_023	103.57	117.95	94.94	91.53
ExStudy_025	108.26	116.57	91.69	91.53
ExStudy_026	113.85	111.64	120.21	91.53
ExStudy_027	113.85	105.00	97.13	91.53
ExStudy_029	98.44	110.89	117.54	86.44
ExStudy_031	103.57	100.84	77.91	55.93
ExStudy_033	89.14	114.71	100.89	44.07
ExStudy_034	122.75	120.42	116.61	66.10
ExStudy_036	84.92	105.02	112.23	35.59
ExStudy_037	108.26	119.65	102.94	45.76
ExStudy_038	98.44	103.46	117.03	44.07
ExStudy_039	98.44	116.31	120.21	55.93

Table 1 (continued)

ExStudy_040	94.33	95.84	89.39	25.42
ExStudy_041	98.44	101.79	103.96	5.08
ExStudy_042	108.01	124.21	114.88	72.88
Mean	104.26	109.81	107.10	64.60

Descriptive Statistics

Figure 11 shows mean scores on all three NIH toolbox tasks and the BCI task. The mean score for the List Sorting Working Memory Test (LSWM) was 104.26 (SE=5.62). The mean score for the Dimensional Change Card Sort Test (DCCS) was 109.81 (SE=1.76). The Picture Vocabulary Test (TPVT) had a mean score of 107.10 (SE=2.53). The mean scores for all three measures were within one standard deviation of the normative data (mean=100; SD=15).

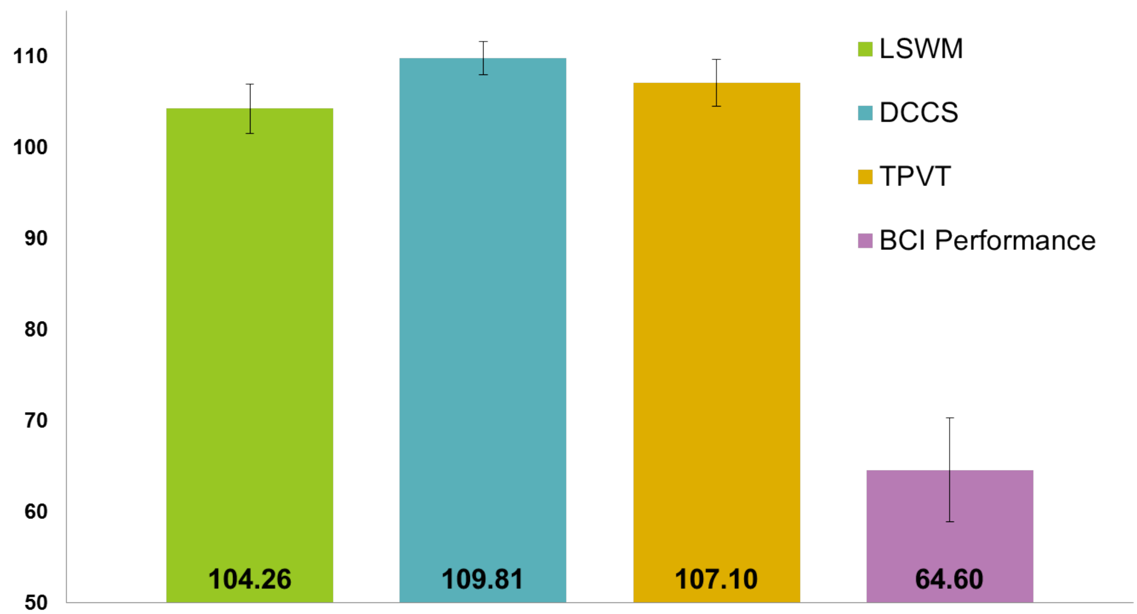

Figure 11. Average scores for NIH Toolbox tasks and BCI performance accuracy

Means, standard deviations, and standard errors from the measures collected in the first session are shown in Table 2.

Table 2: *Means, standard deviations, and standard errors for first session*

	LSWM	DCCS	TPVT	VAS Mot	VAS Mood	Hunger	Caffeine	Fatigue
Mean	104.26	109.81	107.10	7.49	7.72	3.11	53.79	1.96
SD	13.71	9.14	13.14	1.86	1.52	2.45	89.66	0.76
SE	2.64	1.76	2.53	0.36	0.29	0.47	17.26	0.15

Similarly, Table 3 presents measures collected in the second session. Correlations between all measures are presented in Table 4 (first session) and 5 (second session). Table 6 provides the significance of variables with mediators excluded and included. Table 7 shows the model fit R^2 for mediators excluded and included.

Table 3: *Means, standard deviations, and standard errors for second session*

							QCMBCI2000			
	BCI Acc	VAS Mood	VAS Mot	Hunger	Caffeine	Fatigue	IF	I	C	MC
Mean	0.65	7.61	7.47	3.56	47.24	2.11	2.36	5.42	5.16	5.57
SD	0.29	2.06	2.37	2.75	69.73	0.89	1.13	1.21	0.68	0.99
SE	0.06	0.40	0.46	0.53	13.42	0.17	0.22	0.23	0.13	0.19

Abbreviations:

IF = incompetence fear
I = interest
C = challenge
MC = mastery confidence

Table 4: *Table of correlations between all measures for the first session*

	LSWM	*DCCS*	*TPVT*	*VAS Mot*	*VAS Mood*	*Hunger*	*Caffeine*	*Fatigue*
LSWM		.140	.304	.066	.192	.325	.242	.204
DCCS	.140		.366	-.061	-.236	.152	.074	-.010
TPVT	.304	.366		.282	.169	.089	.618**	-.323
VAS Mot	.066	-.061	.282		.389*	-.173	.255	-.363
VAS Mood	.192	-.236	.169	.389*		.071	.281	-.111
Hunger	.325	.152	.089	-.173	.071		-.170	.130
Caffeine	.242	.074	.618**	.255	.281	-.170		-.082
Fatigue	.204	-.010	-.323	-.363	-.111	.130	-.082	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 5: *Table of correlations between all measures for the second session*

	BCI Acc	*MC*	*IF*	*I*	*C*	*Vas Mot*	*VAS Mood*	*Hunger*	*Caffeine*	*Fatigue*
BCI Acc		.241	-.299	.117	-.081	-.106	.212	.287	.021	.021
MC	.241		-.639**	.657**	.220	.362	.448*	-.146	.323	-.281
IF	-.299	-.639**		-.391*	.141	-.230	-.445*	-.084	-.134	.370
I	.117	.657**	-.391*		.681**	.651**	.636**	-.292	.476*	-.423*
C	-.081	.220	.141	.681**		.486*	.351	-.342	.259	-.030
Vas Mot	-.106	.362	-.230	.651**	.486*		.729**	-.453*	.312	-.576**
Vas Mood	.212	.448*	-.445*	.636**	.073	.729**		-.447*	.341	-.627**
Hunger	.287	-.146	-.084	-.292	.081	-.453*	-.447*		-.131	.212
Caffeine	.021	.323	-.134	.476*	.192	.312	.341	-.131		-.228
Fatigue	.021	-.281	.370	-.423*	.883	-.576**	-.627**	.212	-.228	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 6: *Significance of variables with mediators excluded and included*

Model	Unstandardized Coefficients		Standard Coefficients		
	B	*SE B*	*β*	*t*	*p*
(Constant)	-4.139	2.873		-1.440	.166
EF_Minus_WM_and_G	.071	.042	.300	1.695	.106
G_Minus_WM_and_EF	.110	.035	.643	3.168	.005
WM with G and EF	.069	.028	.444	2.446	.024
P2_Hunger	.355	.131	.483	2.708	.014
P2_Mood	.388	.242	.397	1.606	.125
P2_Caffeine	-.008	.005	-.280	-1.614	.123
P2_Fatigue	.590	.505	.260	1.169	.257
(Constant)	-4.906	4.848		-1.012	.329
EF_Minus_WM_and_G	.054	.072	.226	.744	.469
G_Minus_WM_and_EF	.108	.042	.627	2.590	.021
WM with G and EF	.070	.049	.454	1.442	.171
P2_Hunger	.349	.154	.476	2.265	.040
P2_Mood	.516	.418	.528	1.235	.237
P2_Caffeine	-.009	.006	-.317	-1.418	.178
P2_Fatigue	.519	.810	.229	.641	.532
P2_Mastery_Confidence	-.014	.598	-.007	-.023	.982
P2_Incompetence_Fear	.254	.530	.143	.480	.638
P2_Interest	.439	.735	.263	.598	.559
P2_Challenge	-.189	1.187	-.064	-.159	.876
P2_Motivation	-.257	.306	-.302	-.840	.415
Dependent Variable: logit_BCI					

Table 7: *Model fit R^2 for mediators excluded and included*

Model	*R*	R^2	Adjusted R^2	*SE*
1	.752[a]	.565	.405	1.558
2	.776[b]	.602	.261	1.736

Notes:

a. Predictors: (Constant), P2_Fatigue, WM with G and EF, P2_Hunger, P2_Caffeine, EF_Minus_WM_and_G, G_Minus_WM_and_EF, P2_Mood

b. Predictors: (Constant), P2_Fatigue, WM with G and EF, P2_Hunger, P2_Caffeine, EF_Minus_WM_and_G, G_Minus_WM_and_EF, P2_Mood, P2_Mastery_Confidence, P2_Challenge, P2_Incompetence_Fear, P2_Motivation, P2_Interest

The relationship between BCI accuracy and each of the three measures are presented in Figures 12, 13, and 14. As shown in the figures, there was a positive relationship between accuracy and each of the three measures.

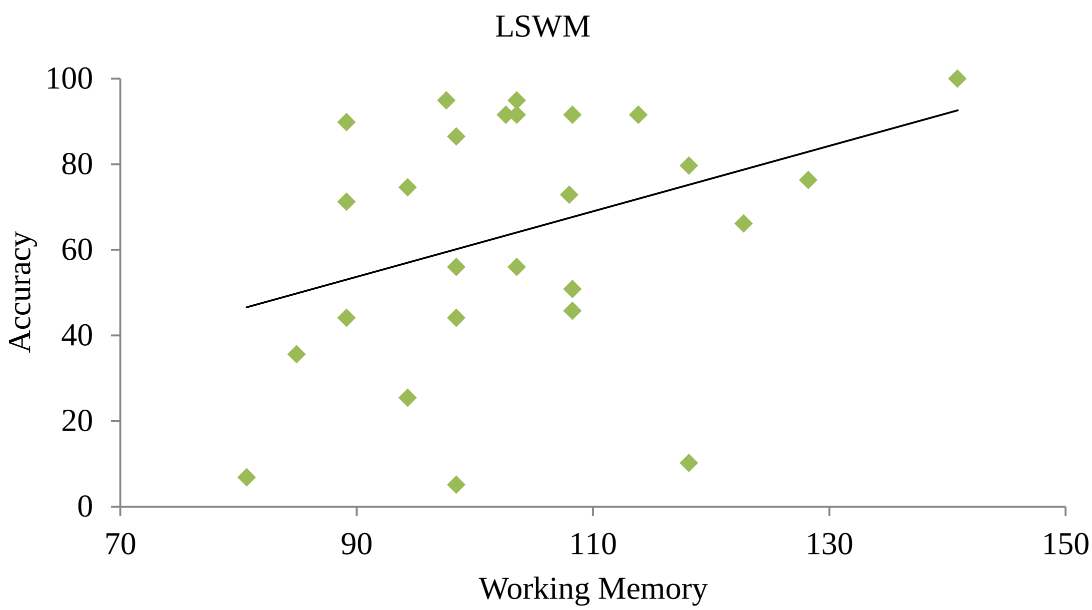

Figure 12. Scatterplot of working memory and BCI accuracy

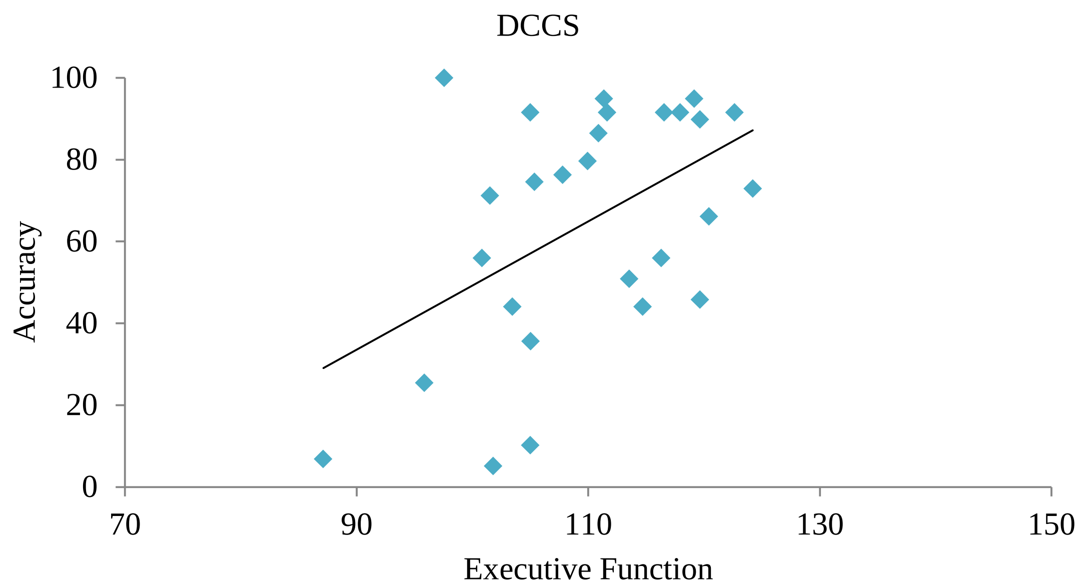

Figure 13. Scatterplot of executive function and BCI accuracy

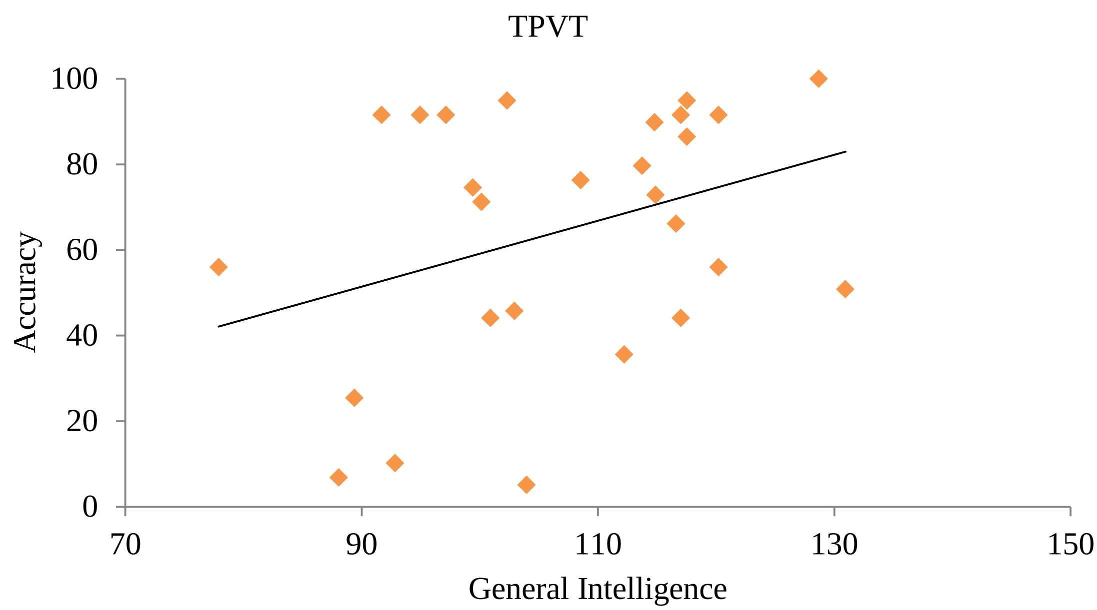

Figure 14. Scatterplot of general intelligence and BCI accuracy

Regression Analyses

To examine the contribution of each of the three measures to BCI accuracy, a simultaneous regression was performed on the data. In the final model BCI performance was regressed on executive function, general intelligence, and working memory. There were three components included in the model. The first component was the regression of working memory on executive function and general intelligence. The unstandardized residuals were saved, representing the variability in working memory that is not due to executive function or general intelligence. The second component involved regressing executive function on working memory and general intelligence; the unstandardized residuals were saved. The third component required the regression of general intelligence on working memory and executive function; the unstandardized residuals were again saved. The following measures were originally included in the final model as covariates: hunger, mood, caffeine, fatigue, mastery confidence, incompetence fear, interest, challenge, and motivation. A covariate is a variable that has an effect on other variables in the model (Aron, Aron, & Coups, 2009). However, some of these covariates were removed from the model because they are strongly correlated with one another, as well as with working memory, general intelligence, and executive function, and may actually be mediators. A mediator is "an intervening variable, a variable that explains the presumed causal relationship between two other variables" (Aron et al., p. 627). In the subsequent model working memory was shown to have a significant effect on BCI performance that was not shown in the previous analysis. This indicates that some of the measures (i.e., mastery confidence, incompetence fear, interest, challenge, and motivation) are likely mediators; unfortunately, the current study design does not possess the power necessary to perform mediation. Therefore, the final model only contained measures that cannot be mediators: hunger, mood, caffeine, and fatigue.

Both general intelligence, $t(26)=3.168$, $p=.005$, and working memory, $t(26)=2.446$, $p<.024$, were found to be significant predictors of BCI performance ($p<.05$). General intelligence was found to be responsible for a larger portion of variance in BCI performance than working memory, with beta values of .643 and .444, respectively. Hunger was also found to be a significant predictor of BCI performance, t(26)=2.708, p=.014, with a beta value of .483.

CHAPTER 5

DISCUSSION

The majority of BCI research focuses on improving the hardware and signal processing methods. Although advancements in technology are necessary to continue progress in the field of BCI, additional research focusing on the users can provide further advancements where the technology falls short. Although individual differences in BCI performance exist, few studies have examined causal mechanisms. By evaluating the impact of psychological factors such as executive function, general intelligence, and working memory on BCI performance, a better understanding of the causal factors behind variation in BCI performance can be achieved.

Both working memory and general intelligence were found to have significant effects on BCI performance; therefore, both can be measured in order to predict BCI performance. General intelligence tends to remain stable throughout the lifespan, whereas working memory is a more malleable construct. Working memory can be increased through training, which should lead to an increase in an individual's BCI performance.

There are a number of possible explanations as to why working memory is related to BCI performance. When a user is using the system to spell out a sentence, he or she must formulate a sentence, remember the sentence while spelling it, and remember which character he or she is currently trying to select. This entire process is aided by working memory and a user with lower working memory is more likely to make mistakes due to forgetting where he or she is at in the sentence. It is well known that there is a strong attentional component in the BCI task and the central executive component assists with attentional control.

Working Memory Training

Working memory capacity has been previously thought to be a stable construct; however, recent research has indicated that there is plasticity in the neural systems underlying working memory that is training-induced (Olesen, Westerberg, & Klingberg, 2003). Studies have shown that taking part in a training program containing working memory tasks can create increased activity in the prefrontal and parietal cortices, leading to improved performance on working memory tasks and increased working memory capacity (Akerlund, Esbjörnsson, Sunnerhagen, & Björkdahl, 2013; Klingberg, 2010; Olesen et al., 2003).

There are several different training procedures that can be implemented in order to improve working memory. The majority of training programs take place over a period of 5 weeks, 5 days per week, for under an hour (Klingberg, 2006; Morrison & Chein, 2010; Olesen et al., 2003). Training tasks involving variations of the n-back task have been shown to significantly increase working memory (Morrison & Chein, 2010; Verhaeghen, Cerella, & Basak, 2004). An n-back task with a four-back condition requires participants to indicate if each new stimulus is the same as the stimulus shown four items back. The n-back task can be distributed as a computerized measure for easy administration and data collection. The response system used to complete the n-back task can be modified to meet the needs of the user. For example, if the user has control over eye movements, he or she may use eye blinks or looking to the left or the right to respond. Improvements on the training task are confounded because increased performance accuracy may be due to task-specific practice. Therefore, performance transfer must be demonstrated using untrained working memory tasks (Shipstead, Hicks, & Engle, 2012), such as BCI, for example. It is also possible that repeated use of the BCI leads to an increase in BCI performance by improving working memory over time. It may be the case that the BCI task itself is a better training method than tasks such as the n-back task for increasing working memory. In order to determine which method provides a larger and/or faster increase in BCI performance, a study including a BCI task group, a n-back task group (or other working memory training task), and a control group should be conducted.

Recent research, such as that of Nijboer et al. (2010), has suggested that psychological factors may offer a significant contribution to the prediction of BCI performance. Understanding which factors contribute to an individual's performance on a BCI task can help inform training procedures in order to allow a greater number of people to successfully operate the BCI as well as improve the BCI performance accuracy of current users. Studies such as that of Kleih et al. (2010) as well as the current study show promising results associated with psychological factors as predictors of BCI performance. Further research on these factors should lead to an overall improvement in BCI performance and allow more people to benefit from the technology.

CHAPTER 6

CONCLUSION

Recently there has been an increased interest in researching psychological factors that have the potential to influence BCI performance. Through the examination of potential contributing factors such as executive function, general intelligence, and working memory, more can be learned about the causation of individual differences in BCI performance. The current study provides promising results indicating that there are additional psychological factors outside of motivation that contribute to a user's BCI performance. Future research should focus on determining other potential psychological factors that are related to BCI performance such as anxiety, personality type, and self-esteem. This increase in knowledge will help to better inform BCI training procedures in order to allow a broader range of individuals to successfully operate and communicate using BCIs.

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APPENDICES

Appendix A: Visual Analogue Scale for Hunger

VAS Hunger

SONA #: ____________
Date: ____________
Study + Condition: __________________________

Dear Participant,

Please answer the following question:

1. Please rate your level of hunger today on the line below. Number 0 indicates that you are not hungry at all while number 10 means that you are extremely hungry. Please draw a vertical bar on the line to mark the position that most accurately represents your level of hunger.

0=
not hungry at all

10=
extremely hungry

Caffeine Questionnaire

Please answer the following question:

1. List any caffeinated beverages you've had today:

Drink	**Amount (oz.)**

Thank you very much for participating in this study!

Stanford Sleepiness Scale

This is a quick way to assess how alert you are feeling. If it is during the day when you go about your business, ideally you would want a rating of a one.

Degree of Sleepiness	**Scale Rating**
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	X

Appendix C: Visual Analogue Scale for Motivation and Mood

VAS Motivation and Mood

SONA #: ____________
Date: ____________
Study + Condition: __________________________

Dear Participant,

Please answer the following two questions:

1. Please rate your motivation to perform the task in this study today on the line below. Number 0 indicates that you are not motivated at all while number 10 means that you are extremely motivated. Please draw a vertical bar on the line to mark the position that most accurately represents your motivation.

0= not motivated at all

10= extremely motivated

2. Please rate your mood regarding the study today on the line below. Number 0 indicates that you are in an extremely negative mood while number 10 means that you are in an extremely positive mood. Please draw a vertical bar on the line to mark the position that most accurately represents your mood.

0= Extremely bad mood

10= extremely good mood

Thank you very much for participating in this study!

Appendix D: Questionnaire for Current Motivation for BCI 2000

QUESTIONNAIRE FOR CURRENT MOTIVATION FOR BCI 2000 (QCMBCI2000)

SONA #: ___________
Date: ___________
Study + Condition: ____________________________

We would like to know about your current attitude regarding using the BCI. Please circle a number to indicate to which extent the statements below currently apply.

	Item statement	Disagree strongly						Agree strongly
1	I look forward to working with the BCI today	1	2	3	4	5	6	7
2	I think I can deal with the difficulties of this task	1	2	3	4	5	6	7
3	I think using the BCI will not go well today	1	2	3	4	5	6	7
4	I like improving my strategies or trying out new strategies for using the BCI	1	2	3	4	5	6	7
5	I feel under pressure to perform well	1	2	3	4	5	6	7
6	Using the BCI is a big challenge for me	1	2	3	4	5	6	7
7	I look forward to using the BCI today	1	2	3	4	5	6	7
8	I am very curious how I will perform today	1	2	3	4	5	6	7
9	I worry a little that I can embarrass myself here	1	2	3	4	5	6	7
10	I am fully determined to give my best during the session	1	2	3	4	5	6	7
11	I don't need a reward using the BCI; I find using the BCI fun on its own	1	2	3	4	5	6	7
12	It's embarrassing for me to fail here	1	2	3	4	5	6	7
13	I think that everyone can control his/her brain activity	1	2	3	4	5	6	7
14	I think I won't be able to accomplish using the BCI today	1	2	3	4	5	6	7
15	When I do well using the BCI today, I will be proud of my achievement	1	2	3	4	5	6	7
16	I am worried when I think about using the BCI	1	2	3	4	5	6	7
17	If possible, I would also practice using the BCI outside of the session	1	2	3	4	5	6	7
18	The training demands are an enormous burden on me	1	2	3	4	5	6	7

VITA

SAMANTHA A. SPRAGUE

Education: Public Schools, Cincinnati, Ohio

B. A. Psychology, University of Tennessee, Knoxville, Tennessee 2012

M. A. Psychology, East Tennessee State University, Johnson City, Tennessee 2014

Professional Experience: Graduate Assistant, East Tennessee State University, College of Arts and Sciences, 2012 – 2014

Honors and Awards: Oral Presentation Award for Society, Behavior and Learning (Doctoral Level) – 2nd Place, Appalachian Student Research Forum

ETSU School of Graduate Studies and Graduate Council Outstanding Teaching Award (Teacher Assistant), East Tennessee State University

The Department of Psychology Teaching Award for Graduate Teacher Assistants, East Tennessee State University

Student Scholarship, The 5th International Brain-Computer Interface Meeting