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Improving the P300-Based Brain-Computer Interface by Examining the Role of Psychological
Factors on Performance

A dissertation

Presented to

the faculty of the Department of Psychology

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Doctor of Philosophy in Psychology

by

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August 2016

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Keywords: Brain-Computer Interface, P300 Event-Related Potential, EEG, Psychological

Factors

ABSTRACT

Improving the P300-Based Brain-Computer Interface by Examining the Role of Psychological Factors on Performance

by

Samantha A. Sprague

The effects of neurodegenerative diseases such as amyotrophic-lateral sclerosis (ALS) eventually render those suffering from the illness unable to communicate, leaving their cognitive function relatively unharmed and causing them to be “locked-in” to their own body. With this primary function compromised there has been an increased need for assistive communication methods such as brain-computer interfaces (BCIs). Unlike several augmentative or alternative communication methods (AACs), BCIs do not require any muscular control, which makes this method ideal for people with ALS. The wealth of BCI research focuses mainly on increasing BCI performance through improving stimulus processing and manipulating paradigms. Recent research has suggested a need for studies focused on harnessing psychological qualities of BCI users, such as motivation, mood, emotion, and depression, in order to increase BCI performance through working with the user. The present studies address important issues related to P300-BCI performance: 1) the impact of mood, emotion, motivation, and depression on BCI performance were examined independently; and 2) pleasant, unpleasant, and neutral emotions were induced in order to determine the influence of emotion on BCI performance. By exploring psychological mechanisms that influence BCI performance, further insight can be gained on the best methods for improving BCI performance and increasing the number of potential BCI users. The results from Study 1 did not reveal a significant relationship between any of the four psychological factors and BCI performance. Since previous research has found a significant impact of

motivation and mood on BCI performance, it may be the case that these factors only impact performance for some individuals. As this is the first study to directly investigate the impact of emotion and depression on BCI performance, future research should continue to explore these relationships. The results from Study 2 were inconclusive for the pleasant condition, since it appears the pleasant emotion manipulation was unsuccessful. The findings indicate that unpleasant emotions do not have a significant impact on BCI performance. This result is promising since it indicates that individuals should still be able to use the BCI system to communicate, even when they are experiencing unpleasant emotions. Future research should further explore the impact of pleasant emotions on BCI performance.

DEDICATION

For my dad.

Thank you for teaching me the value of education, and for believing in me, even when I didn't believe in myself.

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CHAPTER 1

INTRODUCTION

Brain-computer interfaces (BCI) are capable of restoring communication to individuals suffering from a variety of impairments. The primary population that has been shown to benefit from BCIs thus far are individuals with amyotrophic lateral sclerosis (ALS) (Sellers & Donchin, 2006). Amyotrophic lateral sclerosis is a neurodegenerative disease that causes the progressive loss of motor neurons, slowly taking away an individual's ability to control their muscle movement. This loss in muscle control can prevent these individuals from using their primary method of communication (e.g., speech, writing, typing). Although ALS causes physical impairment, cognitive function remains relatively intact. This allows people with ALS to utilize the BCI in order to maintain or regain communication with the outside world. While individuals with ALS have been the primary population to benefit from the BCI, individuals suffering from other forms of severe speech and physical impairments (SSPI) are also capable of benefiting from the system. These include spinal cord injury (SCI) (Ikegami, Takano, Saeki, & Kansaku, 2011), traumatic brain injury (TBI) (Daly & Wolpaw, 2008), and stroke (Sellers, Ryan, & Hauser, 2014). Recently, Sellers et al. (2014) demonstrated that the BCI could be utilized by a man who had suffered a brainstem stroke to restore communication. Advancements in the field of BCI have allowed for the population of potential users to grow. Continued progress in the field will promote the further expansion of the population of potential users and allow for the BCI to restore communication to as many people as possible.

Psychological Factors and BCI Performance

Although BCIs have helped many individuals regain their ability to communicate, there is still a large population of individuals who could benefit from the BCI but are unable to operate

the system. This is a huge concern because many people have exhausted all other augmentative or alternative communication (AAC) options and the P300-BCI is their last hope of regaining communication. There have been several attempts to identify the cause of this discrepancy among potential BCI users. Previous BCI research has primarily focused on improving the system and increasing the number of individuals who can benefit from using the BCI through the manipulation of stimulus presentation (Townsend et al., 2010) and signal processing techniques (Krusienski et al., 2011). While this research has led to much advancement in the field, it has not been able to eliminate the individual differences in BCI performance.

Additional research examining the effects of disease progression and physical disability on BCI performance has also been conducted in order to determine if those factors contribute to individual differences in BCI performance. In a study conducted by Nijboer, Birbaumer, and Kubler (2010), people with ALS were given the ALS Functional Rating Scale (ALS-FRS) to measure disease progression and then completed a BCI task to determine their BCI performance. The study was designed to test the hypothesis that as people with ALS experience disease progression, BCI performance declines. The results of this study revealed that there is no statistically significant relationship between these two measures. Silvoni et al. (2013) conducted a similar study with people with ALS which took place over three years. The researchers were looking for a correlation between BCI communication skill and disease progression, but again, no significant correlation was found. A third study conducted by McCane et al. (2014) examining the relationship between physical disability in people with ALS and BCI performance found that while no significant relationship between the overall physical disability in people with ALS and their BCI performance, visual impairment such as double vision, involuntary eye movements, and eyelid drooping can cause difficulty using the BCI.

Answers to the question of why individual differences exist in BCI performance have been primarily sought among physical causes. These include disease progression as well technological factors such as stimulus presentation (e.g., matrix size, stimulus characteristics, timing), signal acquisition (e.g., electrode placement and materials), and signal processing (e.g., classification algorithms, dynamic stopping methods). However, some researchers have begun to explore psychological factors as potential contributors to this issue.

In order to expand the population of potential BCI users and allow individuals that have previously been unable to operate the system to successfully utilize the BCI to communicate, research beyond examining physical causes is needed. Although it is in its early stages, this line of research has shown promise as a route to solving this issue. Of the research that has been conducted, motivation (Kleih, Nijboer, Halder, & Kubler, 2010), mood (Nijboer et al., 2010), and depression (Kübler, Winter, Ludolph, Hautzinger, & Birbaumer, 2005) have all shown promise as psychological factors that are capable of influencing BCI performance. If the field of BCI continues to focus primarily on advancing the technology alone, only a limited amount of additional progress can be made (Kübler, Kotchoubey, Kaiser, Wolpaw, & Birbaumer, 2001). The current studies will build upon previous research in two ways: (1) the influence of multiple psychological factors (i.e., motivation, mood, emotion, and depression) on BCI performance will be examined simultaneously instead of in isolation; and, (2) the psychological factor of emotion will be manipulated in order to better gauge its impact on BCI performance, instead of simply measuring it. The first study is designed to be more basic in that it is clarifying the relationship between several psychological factors and BCI performance. The second study is designed to be more applied in that it will determine the extent to which different emotional states impact BCI performance. This study has the potential to inform future BCI training procedures by

incorporating emotional elicitation into the process, should the findings from this study be significant. These studies will allow us to better understand how multiple psychological factors interact to influence BCI performance, and to more accurately gauge the impact of different emotions on BCI performance.

CHAPTER 2

THE PROGRESSION OF THE BRAIN-COMPUTER INTERFACE

Brain-computer interfaces (BCI) provide an alternative method of communication by building a bridge between a computer and a functioning brain. In order to understand the current state of the BCI, we must first revisit its progression over the past few decades. Hans Berger invented the electroencephalogram (EEG) in 1929. This invention is monumental for the creation of the BCI, as it allows for the recording of human brain waves. There are two main methods that can be used to record EEG for operation of the BCI: invasive and noninvasive.

Invasive versus Noninvasive BCIs

When deciding whether to use an invasive or noninvasive BCI, one must first weigh the costs and benefits of each option. Invasive BCIs (e.g., Electrocorticography/ ECoG, single unit recordings) require the implantation of electrodes beneath the skull, which requires surgery. Noninvasive BCIs place the electrodes on the surface of the scalp. The issue of surgery is the first point that must be considered when comparing these two methods. When considering surgery for the purpose of operating an invasive BCI, the surgery must be planned and consent must be obtained from the patient, and when necessary, the patient's advocate. The risks associated with undergoing this type of surgery include infection, brain damage, and even death (Wolpaw & McFarland, 2004). As a result of these risks, the majority of research on invasive BCIs has been conducted on animals.

Of the research that has been done in a human population, several additional risks and pitfalls have been identified. After the initial implantation of electrodes, a decrease in signal strength over time has been reported (Vallabhaneni, Wang, & He, 2005). Furthermore, the majority of these studies have used epileptic patients already undergoing surgery to implant

electrodes to monitor their seizures (Krusienski & Shih, 2011; Lal et al., 2004). This is an issue because the size and location of the implant is dictated by seizure activity and is typically not optimal for BCI use. As a result, the findings may not generalize to other user populations such as individuals suffering from ALS, spinal cord injury, traumatic brain injury, or stroke.

Despite these risks, invasive BCIs have been found to offer some benefits over noninvasive systems such as higher spatial and temporal resolution (Vallabhaneni et al., 2005) and increased signal amplitude (Wilson, Felton, Garell, Schalk, & Williams, 2006). Additionally, some patients report a preference for invasive options for aesthetic reasons. Therefore, the decision to use either an invasive or noninvasive BCI should be made on a case-by-case basis by reviewing the requirements of the study being conducted and of the individual users. A noninvasive BCI will be used in the current studies because it has far fewer risks and it is sufficient for the needs of the studies.

Event-Related Potentials

Noninvasive BCIs are operated using brain signals that are recorded from the scalp using an EEG. Within the recorded EEG, specific components can be identified. Many of these components can be elicited through training and harnessed so that the user may utilize them to operate the system. Several of these components fall into a category known as event-related potentials (ERP). Event-related potentials are elicited in response to a specific type of stimulus. As a result, they can be time-locked to the stimulus that elicited them (Fabiani, Gratton, & Coles, 2000). Event-related potentials are labeled based on whether they are positive or negative and their latency (Kayser & Tenke, 2003). For example, the P300 ERP is a positive wave that occurs, on average, 300ms after the presentation of a specific stimulus. In addition to there being positive or negative ERPs, there are also exogenous and endogenous ERP components.

Exogenous components occur in response to the physical properties of the stimulus that elicits them (e.g., a flash of a character). Endogenous components have a longer latency than exogenous components and occur in response to the psychological properties of a stimulus (e.g., stimulus meaning). This will be further explained below in the discussion of the P300 ERP.

Event-related potentials tend to have a low signal-to-noise ratio. This means that ERPs can be difficult to detect among the rest of the EEG. In order to account for this, segments of EEG that have been time-locked to the ERP eliciting stimuli are averaged together across electrodes (Fabiani et al., 2000). This process of averaging multiple ERPs together makes it much easier to detect the ERPs of interest. Another issue in detecting ERPs is the presence of artifacts in the EEG. Artifacts are fluctuations in the EEG that are not due to brain activity. Artifacts can be due to the user or the equipment and it can be difficult to distinguish between artifacts and ERPs. Artifacts created by the user are typically due to movement such as eye blinks, jaw tension, or tapping of the foot. Artifacts created by equipment tend to be in the range of 60Hz that can be found in most electrical outlets. In order to limit the presence of artifacts in the data, participants are instructed to keep as still as possible during BCI tasks. Amplifiers can be used to reduce the presence of artifacts by utilizing filters. There are two main types of filters: low-pass and high-pass. Low-pass filters keep low frequency signals and remove high frequency signals, while high-pass filters keep high frequency signals and remove low frequency signals. Filters can also be labeled as bandpass or notch. Bandpass filters retain signals that fall within a certain range (e.g., 0.5-30 Hz), while notch filters remove signals of a particular frequency (e.g., 60Hz). While these techniques can be used to reduce the number of artifacts, it should still be noted that these methods are not a perfect fix and it is possible to mistake some of the remaining artifacts for signals of interest (Srinivasan, 2012).

The P300 Event-Related Potential

Although there are many different event-related potential (ERP) components that can be utilized to operate the BCI, the ERP component that is being used in the present study is the P300 ERP component. This is a positive peak in brain activity that occurs roughly 300ms after the presentation of a specific stimulus. It was discovered in 1965 by Samuel Sutton. In order to understand the P300 ERP component, one must first understand the type of task that elicits it. The oddball task is traditionally used to elicit the P300 ERP. In order to be considered an oddball task, four stipulations must be met: (1) a minimum of two different types of stimuli must be presented; (2) stimuli from one of the categories must be presented less frequently than the other; (3) stimuli must be presented in a random order; and (4) the participant must perform a task in which they place the stimuli into their appropriate categories (E. Donchin & Coles, 1988).

An example of an oddball task would be presenting a participant with a series of “X’s” and “O’s” in which the “X’s” are presented 20 percent of the time and the “O’s” are presented 80 percent of the time. The stimuli would be presented in a random order so that the participant could not predict whether the next presentation would be an “X” or an “O.” Finally, the participant would be instructed to attend to, or count, the “X’s” and ignore the presentation of the “O’s.” Each time the participant is shown the “X,” it would elicit a P300 ERP response. The P300 ERP is considered to be an endogenous component in that it is elicited as a result of stimulus meaning (Emanuel Donchin, Ritter, & McCallum, 1978). In the example given above, the presentation of the “X” is only meaningful to the participant because they have been instructed to attend to it. Without this instruction, the stimuli would have no meaning to the participant and the P300 ERP would be absent. In a similar way, a modified oddball task can be used to elicit a P300 ERP response and allow the user to type out a sentence using the BCI.

The P300-BCI. The visual P300-BCI is the system utilized in the current study. This system incorporates a modified oddball task to create a BCI task that will elicit a P300 response. In order to operate the system, a user is seated approximately one meter away from a computer monitor on which a matrix filled with letters, numbers, symbols, and commands is displayed. The matrix can be customized based on the needs of the individual user. For example, the matrix may contain a command to open a program to compose an email or open a new webpage. Furthermore, the method in which the stimuli are presented can also be customized. Typical manipulations include the speed, color, and grouping of stimuli presentation.

The row-column paradigm was among the first presentation paradigms to be used with the visual P300-BCI. In this paradigm, an entire row or column flashes at once (see Figure 1).

A	B	C	D	E	F	G	H
I	J	K	L	M	N	O	P
Q	R	S	T	U	V	W	X
Y	Z	Sp	1	2	3	4	5
6	7	8	9	0	Prd	Ret	Bs
?	,	;	\	/	+	-	Alt
Ctrl	=	Del	Home	UpAw	End	PgUp	Shft
Save	'	F2	LfAw	DnAw	RtAw	PgDn	Pause
Caps	F5	Tab	EC	Esc	email	!	Sleep

Figure 1. Example of a row-column paradigm.

In order to operate the BCI using the row-column paradigm, the user must attend to the character they are trying to select by fixating their gaze on the individual character, counting the number of times it flashes, and ignoring the flashing of the other stimuli. Every time the row or column containing the target character flashes, a P300 ERP is generated for every item within the same

row or column. The P300 ERP response should be greatest for the target item, which is located at the intersection of the row and column for which the P300 ERP response was most prominent (see Figure 2).

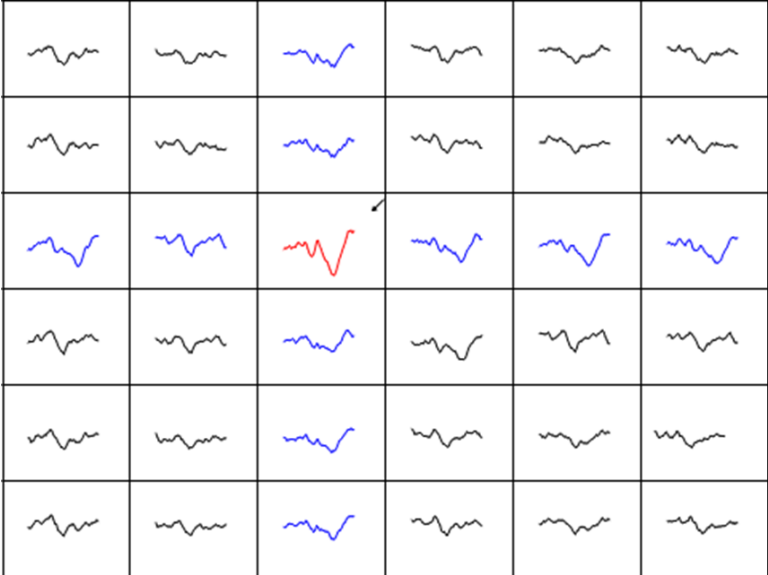


Figure 2. Example of the P300 ERPs generated for each item in a 6x6 matrix.

Although the row-column paradigm remains the most widely used, there are two issues with this paradigm that contribute to high rates of errors (Townsend et al., 2010). The first is that adjacent items, particularly those located in the same row or column as the target item, tend to be the most common incorrect selections. This is due to a P300 ERP response being generated for items other than the target item because they are located in the same row or column, or the user was distracted by the flashing of an adjacent item and attended to it instead of the target item. The second is that the row-column paradigm makes it possible for the target item to flash back-to-back. This is an issue because the user may detect the first flash but miss the second. This would cause a P300 ERP response to occur for the first flash, but not the second, increasing the likelihood that an incorrect selection will be made (Townsend et al., 2010).

In order to reduce the occurrence of these errors, Townsend et al. (2010) compared performance of the row-column paradigm to the “checkerboard paradigm” (see Figure 3). The checkerboard paradigm was created by taking a matrix of items, in this case an 8x9 matrix, and overlaying it with a black and white checkerboard pattern (see Figure 4). Next, all of the white items and all of the black items are grouped together to create two 6x6 matrices. These two matrices determine the order and the groups of items that will flash together. The items in each of the rows in the white matrix will flash together, followed by the items in each of the rows in the black matrix. Then, the items in each of the columns in the white matrix will flash together, followed by the items in each of the columns in the black matrix. This sequencing of flashing is illustrated in Figure 5. When all of the rows and all of the columns in both matrices have flashed once, one sequence has been completed. After each sequence, the items within each matrix are randomized to ensure that the presentation of items remains arbitrary in accordance with the requirements of the oddball paradigm.



Figure 3. Example of a checkerboard paradigm.

A	B	C	D	E	F	G	H
I	J	K	L	M	N	O	P
Q	R	S	T	U	V	W	X
Y	Z	Sp	1	2	3	4	5
6	7	8	9	0	.	Ret	Bs
?	,	;	\	/	+	-	Alt
Ctrl	=	Del	Home	UpAw	End	PgUp	Shft
Save	↑	F2	LFAw	DnAw	RFAw	PgDn	Pause
Caps	F5	Tab	EC	ESC	email	!	Sleep

Figure 4. Checkerboard pattern overlaying a matrix of items.

	13	14	15	16	17	18
	↓	↓	↓	↓	↓	↓
1 →	2	Bs	Shft	H	Sp	EC
2 →	I	R	Y	7	?	=
3 →	Save	F5	M	F2	9	;
4 →	B	K	PgDn	End	email	-
5 →	V	F	Home	.	D	4
6 →	O	T	X	Sleep	/	DnAw
	19	20	21	22	23	24
	↓	↓	↓	↓	↓	↓
7 →	Tab	Del	8	C	1	E
8 →	Del	0	W	3	Ctrl	Z
9 →	Q	J	S	L	,	U
10 →	5	G	N	P	A	+
11 →	LFAw	↑	ESC	6	PgUp	Caps
12 →	UpAw	Pause	Alt	\	!	RFAw

Figure 5. Sequencing of flashing items in a checkerboard paradigm.

It was determined that the checkerboard paradigm led to significantly fewer errors than the row-column paradigm (Townsend et al., 2010). The checkerboard paradigm reduces errors in two ways. By dividing up the items in the matrix and grouping them in this way, the checkerboard paradigm suppresses the flashing of surrounding items in order to reduce the number of incorrectly selected adjacent items to the target. In addition, once an item flashes there is a minimum of six flashes that must occur before the item flashes again. This minimum number is unique to an 8x9 matrix; however, regardless of matrix size back-to-back flashes of an item are

eliminated (Townsend et al., 2010). This decrease in errors makes the checkerboard paradigm a viable alternative option to the traditional row-column paradigm, and therefore will be the paradigm used in the current study. The checkerboard paradigm that will be used in the current study differs from the matrix in Figure 3 in that the items in the matrix will flash different colors instead of flashing white (see Figure 6).

GOBLIN (G)							
A	B	C	D	E	F	G	H
I	J	K	L	M	N	O	P
Q	R	S	T	U	V	W	X
Y	Z	Sp	1	2	3	4	5
6	7	8	9	0	Prd	Ret	Bs
?	,	;	\	/	+	-	Alt
Ctrl	=	Del	Home	UpAw	End	PgUp	Shft
Save	'	F2	LfAw	DnAw	RtAw	PgDn	Pause
Caps	F5	Tab	EC	Esc	email	!	Sleep

Figure 6. Example of color checkerboard paradigm.

The reason this modification was made is that adding different colors to the flashing of items is thought to make the target item easier to focus on and the non-target items less distracting. Now that we have briefly reviewed the history of BCI, we will examine the psychological factors that could potentially impact an individual’s BCI performance.

CHAPTER 3

PSYCHOLOGICAL FACTORS

Brain-computer interface research has primarily focused on improving the system by manipulating technological factors such as stimulus presentation (Townsend et al., 2010) and signal processing techniques (McFarland, Anderson, Muller, Schlogl, & Krusienski, 2006). These types of studies have uncovered several factors that have a significant impact on BCI performance, for example, matrix size and inter stimulus interval (Sellers, Krusienski, McFarland, Vaughan, & Wolpaw, 2006). Although the effects of technological factors on BCI performance have been well-researched, research on the effects of psychological factors on performance is lacking. Some of these factors have been examined individually (Kleih et al., 2010; Kübler et al., 2005; Nijboer et al., 2010), however, it is important to measure all four at once. Designing the first study this way allows us to determine how the factors relate to one another as well as how they impact BCI performance both individually and as a whole. In the second study, emotion will be manipulated prior to the completion of a BCI task in order to investigate the impact of emotion on BCI performance, which has not been examined previously. In this section, several psychological factors that have the potential to impact BCI performance are reviewed. Each psychological factor is described in general, any relevant BCI or basic research is summarized, and the potential impact of the factor on BCI performance is discussed.

Mood

Before we begin our discussion on mood, we must first distinguish mood from emotion. The terms “emotion” and “mood” are often used interchangeably; however, when measuring one or the other it becomes important to determine the construct that is being measured. Although emotion and mood are thought to be related, there are several ways in which they differ; among

these are duration, intensity, cause, and function (Beedie, Terry, & Lane, 2005). When considering differences in duration, moods are described as lasting longer than emotions (Batson, Shaw, & Oleson, 1992; Beedie et al., 2005). By definition, emotion refers to a phasic response to stimuli, while mood refers to a longer-lasting, more graded response to stimuli (Bradley & Lang, 2000). This ties into distinctions regarding intensity; moods are described as being less intense than emotions (Brehm, 1999). Our moods are thought to be caused by our perceptions and expectations of future events, which are derived from our past experiences. The functional purpose of mood is to inform our behavior (Batson et al., 1992). For example, it is common for an individual with ALS to try out several different forms of assistive technology (e.g., eye-tracker, letter board) to restore their ability to communicate prior to using a BCI. If they have been previously unsuccessful at utilizing assistive technology to communicate, they are likely to have doubts about their ability to use the BCI. Their past failed attempts at regaining their ability to communicate could negatively impact their mood and expectations. This can occasionally be detrimental; in the current example, the individual with ALS may choose to avoid attempting to use the BCI altogether if they believe it will not work for them. Again, emotions are more intense and brief than moods and sudden changes in the environment can have a powerful impact on emotion. The cause and function of emotion will be discussed in detail within the emotion section.

In addition to the daily factors that can have an impact on a healthy individual's mood, there are several other factors that a person suffering from a spinal cord injury, brainstem stroke, traumatic brain injury, or ALS may encounter. Some examples of such factors include pain level and ease of breathing. As such, it is crucial that we determine the extent to which mood can impact BCI performance.

Mood can have a powerful impact on human performance on a variety of tasks. For example, in a study conducted by Miner and Glomb (2010), participants experiencing positive mood showed improved task performance as reflected by faster task completion. Therefore, it is not surprising that mood has been shown to impact both BCI training as well as regular BCI use for communication (Nijboer et al., 2008). Specifically, positive mood was shown to lead to better performance (i.e., higher accuracy) on the BCI task (Nijboer et al., 2008). While initial findings on the interaction between mood and BCI performance indicate that a relationship exists, research in this area is still lacking.

In order to inform future research on the relationship between mood and BCI performance, basic research on mood and event-related potentials (ERP) can be examined. In a study conducted by Yuan et al. (2011), mood was manipulated within participants to elicit positive, negative, and neutral moods using sound. Participants then took part in a Stroop color-word interference task. The results revealed that positive mood allowed participants to better ignore task-irrelevant distractions (Yuan et al., 2011). In a second study conducted by Wang et al. (2011), positive, negative, and neutral moods were elicited; however, the moods were elicited using pictures instead of sound. Participants were then tested on their ability to control habitual responses. The results showed that positive mood led to an increase in behavioral inhibitory control while negative mood led to a decrease in behavioral inhibitory control. Additionally, positive mood was associated with more pronounced increased amplitudes of the P300 response (Wang et al., 2011).

Based on the findings from these studies, it can be hypothesized that participants reporting positive mood in the first study will have an increase in P300 amplitude as well as BCI performance. This is because the BCI task requires participants to ignore task-irrelevant

distractions (i.e., the flashing of non-target stimuli) and to inhibit habitual responses (i.e., avoid attending to the flashing of non-target stimuli). Furthermore, increases in the amplitude of the P300 response should also contribute to better BCI performance because the system will be better able to detect the character the participant is trying to select. Furthermore, it can be hypothesized that individuals reporting negative mood will perform worse on the BCI task. One potential reason for this may be that they expect to perform poorly.

Emotion

As described in the previous section, there are several ways in which emotion differs from mood. Emotion is thought of as lasting a shorter period of time than mood; however, emotion tends to be more intense than mood (Batson et al., 1992; Brehm, 1999). Regarding causation and function, emotion is often tied to a specific goal, for example, the goal of regaining the ability to communicate. That is, emotions that increase our expectation of obtaining a goal are typically positive emotions; however, emotions that decrease our expectation of achieving a goal are negative emotions (Batson et al., 1992). For example, if a user makes several mistakes while spelling out a word using the BCI, they may experience negative emotions such as frustration, which are likely to negatively impact BCI performance. Our emotions function by helping us determine progress that we have made in relation to attaining our individual goals (Batson et al., 1992).

According to Osgood, Suci, and Tannenbaum (1957), emotion can be defined as a combination of ratings in multiple dimensions. There are two main dimensions upon which emotion can be rated. The first is affective valence, which ranges from pleasant to unpleasant. The second is arousal, which ranges from calm to excited (Bradley & Lang, 1999). These two dimensions are related in that stimuli receiving an extremely pleasant or unpleasant affective

valence rating are likely to also receive an extremely excited arousal rating. On the other hand, stimuli receiving a moderate affective valence rating (i.e., neither pleasant nor unpleasant) are likely to receive a calm arousal rating. There is also a third dimension that accounts for less variance in ratings as compared to the first two. It is called dominance or control (Bradley & Lang, 1999). For the purposes of the present studies, we will be focusing on the first two dimensions of affective valence and arousal.

Emotions have the potential to significantly impact BCI performance. Negative emotions such as frustration are regularly experienced by BCI users, typically in response to incorrect character selections. Furthermore, the population of BCI users (e.g., individuals with ALS, traumatic brain injury, brainstem stroke, and spinal cord injury) are likely to experience a variety of pleasant and unpleasant emotions on a daily basis due to a multitude of factors that impact their health and lives in general. For example, an ALS patient who has been experiencing trouble breathing is likely to experience a great deal of unpleasant emotions; whereas another ALS patient may be visited by family members and in turn may experience a variety of pleasant emotions. Therefore, it is important to consider the potential impact of emotion on BCI performance.

There have been very few studies conducted on emotion and BCIs, and those that have are primarily focused on emotion detection and translation (Garcia-Molina, Tsoneva, & Nijholt, 2013; Nijboer et al., 2009). Their goal is to successfully detect a range of emotions using a combination of psychophysiological markers (e.g., EEG, heart rate, galvanic skin response, blood pressure) and then translating those emotions. This should increase quality of life for individuals with ALS and their caregivers because it would allow for affect to be expressed along with communication of content (Nijboer et al., 2009). This research is in its early stages

and is not yet ready for use in an ALS population. It is important to note, however, that this research supports the use of the same bi-phasic model of emotion that is the foundation for the battery of pictures (i.e., IAPS) used in the current study to elicit emotion. Additionally, this research shows some of the potential value emotion has in the field of BCI.

Nijboer et al. (2009) conducted a study comparing the emotional processing of people with ALS to the emotional processing of a non-ALS control group of participants. The participants viewed pictures from the International Affective Picture System (IAPS). After the presentation of each picture, they rated their valence and arousal using the self-assessment manikin (SAM). The study revealed that the people with ALS rated pleasant and neutral pictures more positively than the healthy participants, and they also rated unpleasant pictures less negatively. In addition, people with ALS rated calm and neutral pictures higher on arousal than the healthy participants, and highly arousing pictures were rated as less arousing as compared to the healthy participants (Nijboer et al., 2009). The researchers hypothesize that this difference between people with ALS and healthy participants may be due to coping mechanisms, life-sustaining devices, and medication. This should not be an issue for application purposes. If pleasant or unpleasant emotions are found to lead to improved BCI performance in a healthy population, a separate study could be conducted in order to select images that are rated as highly arousing by individuals with ALS. These images could then be used to elicit either pleasant or unpleasant emotions in an ALS population prior to using the BCI.

When inducing emotions, there are three main ways to measure the success of the induction. These include evaluative reports, physiological responses, and overt actions (Bradley & Lang, 2000). Overt actions are typically used in studies with animal models, whereas a combination of evaluative reports and physiological responses are used in studies with humans.

This is beneficial because the findings from the self-report measures can be paired with the findings from the physiological measures in order to confirm that the emotion induction was successful. For example, larger late positive potentials have been found when inducing pleasant and unpleasant emotions as compared to neutral emotions. In addition, as perceived arousal by participants increases, so does the amplitude of the late positive potential (Bradley & Lang, 2000). Therefore, these two measures are able to act as a check for one another.

Since emotion has been mostly excluded from the BCI literature thus far with the exception of the aforementioned studies, a brief review of basic research on emotion and event-related potentials (ERP) will be included. The impact of emotion on ERPs has been examined in a number of studies (Bradley, Hamby, Löw, & Lang, 2007; Codispoti, Ferrari, & Bradley, 2007; Cuthbert, Schupp, Bradley, Birbaumer, & Lang, 2000; Keil et al., 2002; Palomba, Angrilli, & Mini, 1997). In a study conducted by Palomba et al. (1997), participants were shown several images taken from the International Affective Picture System (IAPS) designed to elicit pleasant, unpleasant, and neutral emotions while EEG was recorded. It was determined that images with a high emotional impact (i.e., extremely pleasant or unpleasant) were associated with higher P300 amplitudes than neutral stimuli (Palomba et al., 1997). A similar study conducted by Keil et al. (2002) supported this finding in that emotionally arousing images led to greater P300 amplitude. These findings suggest that showing participants extremely pleasant or unpleasant pictures will result in an increase in BCI performance due to higher P300 amplitudes, making it easier for the system to distinguish between target and non-target items.

The P300 is not the only ERP to have been associated with emotional stimuli. Cuthbert et al. (2000) conducted a similar study which also displayed images from the IAPS to participants while recording EEG. Both pleasant and unpleasant stimuli led to larger slow positive voltage

changes than neutral stimuli. This positive shift was first visible 200-300ms following picture onset with a maximum amplitude occurring 1s after picture onset. This slow positive voltage change was observable for the majority of the 6s display period. The researchers concluded that these late positive waves are reflective of selective processing of emotional stimuli and the activation of motivational systems in the brain (Cuthbert et al., 2000). Bradley et al. (2007) carried out a study examining differences in brain potentials as a result of variations in picture complexity (i.e., figure-ground versus scene pictures) and emotional arousal. Their results supported the findings of the previous study in that pictures that were highly arousing were associated with a larger late positive potential than neutral pictures. During early processing, figure-ground images led to less positivity over posterior regions and less negativity over frontal regions (Bradley et al., 2007). Codispoti et al. (2007) took this research a step further to distinguish between early and late ERPs. It was revealed that early ERPs represent obligatory perceptual processing associated with the participant holding a representation of the image in their short term memory. Additionally, late ERPs were found to correspond with an increase in resource allocation as a result of the motivational relevance of affective cues (Codispoti et al., 2007).

An fMRI study was conducted by Bradley et al. (2003) examining functional activation in the visual cortex during picture viewing. The results showed that as the images increased in emotional arousal there was an increase in functional activation in the occipital cortex as measured by the proportion of active voxels (i.e., the amount of brain volume being measured) and activation strength (i.e., percent signal change; Bradley et al., 2003). Therefore, extremely violent or erotic images led to greater functional activation in the occipital cortex than less violent (e.g., angry faces) or neutral images. Both the extent and strength of this functional

activation were associated with perceived affective arousal. The researchers attribute this increase in the activation of the visual system to motivated attentional processes (Bradley et al., 2003).

Based on the findings from these studies, hypotheses about the current studies can be made. Images with a high emotional impact have been found to lead to higher P300 amplitudes. As such, it can be hypothesized that in the first study, individuals reporting high levels of pleasant or unpleasant emotions will perform better on the BCI task. In the second study, it can be hypothesized that the pleasant and unpleasant conditions will lead to higher peak P300 amplitudes, and as a result, lead to better BCI performance. In addition, we would expect that the pleasant and unpleasant conditions will create a larger slow positive voltage change than the neutral condition. Furthermore, the pleasant and unpleasant conditions should also reveal greater activity in the occipital cortex as a result of motivated attentional processes.

Motivation

Motivation is an important psychological factor to examine in relation to BCI performance because it can have a powerful impact on the amount of effort exhibited by the participant to perform well on the BCI task. Within the realm of BCI research, motivation can be defined as the desire to perform well on a BCI task and/or to use the BCI system to communicate. It is important for healthy participants to exhibit high motivation so that the participants are putting forth every effort to perform well on the BCI tasks so that the best possible data is obtained. Collecting good data will make findings easier to translate to an end-user population and researchers can be more confident that the study was accurate in indicating whether or not an effect exists. It is equally important for disabled participants to be highly motivated in order for the system to have the best chance of working for them.

Thus far, the relationship between motivation and BCI performance has only been briefly studied. In a study conducted by Nijboer et al. (2010) using individuals with ALS, motivational factors were significantly correlated with better BCI performance in some individuals but not in others. Kleih et al. (2010) manipulated extrinsic motivation in healthy participants by providing them with monetary rewards for correct selections. The results indicated that high levels of motivation led to an increase in P300 amplitude as well as in BCI performance (Kleih et al., 2010). A third study including both individuals with ALS and healthy volunteers found a significant, positive relationship between highly motivated individuals and their BCI performance. An experiment carried out by Kleih and Kübler (2013) sought to further investigate the impact of motivation on BCI performance while also taking into consideration the potential impact of empathy on intrinsic motivation in particular. The researchers manipulated intrinsic motivation by reading participants either a boring or interesting paragraph about BCI's potential to help patients (Kleih & Kübler, 2013). Their findings revealed no significant effects. The researchers hypothesized that no effects were found because individuals who are highly empathetic, and therefore intrinsically motivated, may have higher emotional involvement making it more difficult for them to focus and attend to the task at hand (Kleih & Kübler, 2013). Although these results are mixed, it can be concluded that motivation has an impact on BCI performance, at least for some individuals, and further research is needed in order to fully understand this relationship.

Since research on motivation in the field of BCI is limited, basic research on motivation and task performance provides guidance on how motivation may impact BCI performance. There are a number of factors that can influence an individual's motivation level; perhaps among the most powerful of these factors is self-efficacy. Self-efficacy can be defined as an individual's

belief about their competence in completing a task (Schunk, 1995). An individual's self-efficacy is influenced by prior experiences related to the task and is updated based on their performance as they attempt to complete the task (Schunk, 1995). Self-efficacy impacts task performance not only by influencing the individual's motivation to complete the task, but also effort and perseverance (Bandura, 1982). Although individuals with high self-efficacy are expected to perform better on a specific task, without the appropriate level of background knowledge and necessary skills, self-efficacy will not lead to successful task completion (Schunk, 1995). Similarly, if the required amount of attention is not devoted to the task then successful task completion will not be possible. Just as self-efficacy influences motivation, motivation influences attention.

The BCI task requires a great deal of attention and can be taxing on the participant. Attention is thought to be primarily determined by motivation, meaning that a person's attention is more likely to be held by stimuli with motivational significance (Lang, Simons, & Balaban, 2013). For example, if a person is hungry, they are more likely to attend to stimuli related to food than other stimuli. In order to maintain the level of attention necessary to successfully operate the BCI, the participant must be highly motivated. In a study conducted by Engelmann and Pessoa (2014), it was revealed that high levels of motivation lead to an increase in the ability of the participant to engage in exogenous spatial attention. More specifically, high levels of motivation were associated with greater perceptual sensitivity, which in turn made it easier for the participant to detect the target while ignoring distractor stimuli (Engelmann & Pessoa, 2014).

There are two main motive systems that are associated with emotion: appetitive and defensive (Lang & Bradley, 2007). These motive systems are thought to be directly related to the valence and arousal dimensions of emotional expression. The appetitive system is activated in

contexts where survival is promoted (e.g., nutrition, reproduction); this can be thought of as relating to the pleasant portion of valence. The defensive system is activated in contexts where a threat is present (e.g., escape, attack); this can be thought of as relating to the unpleasant portion of valence. Evaluation of affect determines which motivational system is engaged, while evaluation of arousal selects the level of intensity of the motivational system's activation. The strategic demands of the situation may influence affective expression; however, all emotions are structured around motivation (Lang & Bradley, 2007).

The appetitive and defensive motive systems developed in order to help the individual choose the adaptive behavior that is appropriate to meet their immediate needs (Bradley & Lang, 2000). Action is typically required when faced with a stimulus that is either highly pleasant or unpleasant. When a stimulus is considered extremely pleasant or unpleasant, the individual is highly motivated to either interact with or avoid the stimulus (Bradley & Lang, 2000). If a stimulus is neutral, it typically doesn't prompt an action. Motivationally relevant pictures engage the attention of the participant and increase information processing in the visual system as a result. In general, these motivational systems help us to prepare to carry out necessary actions (Bradley & Lang, 2000).

Based on the findings of BCI studies on motivation, it can be concluded that motivation impacts BCI performance for at least some individuals. After conducting a review of basic research on motivation and task performance, it is clear that self-efficacy has a powerful impact on motivation as well as the amount of perseverance and effort that is put forth to successfully complete the task. Furthermore, motivation influences attention, and the BCI task is an attentional task. More specifically, individuals who are highly motivated have an increased ability to engage in exogenous spatial attention, making it easier for them to attend to the target

stimulus and ignore distractor stimuli. Different motivational systems are engaged in response to emotional stimuli, in this case pictures. Motivationally relevant pictures (i.e., pictures that are highly arousing) engage attention and increase information processing in the visual system which should lead to an increase in BCI performance. Therefore, it can be hypothesized that in Study 1, BCI performance should be higher for individuals reporting high levels of motivation. In addition, in Study 2, BCI performance should be higher in the pleasant and unpleasant conditions than in the neutral condition.

Depression

Individuals suffering from severe neurological diseases (e.g., ALS) or other forms of severe speech and physical impairments (SSPI; e.g., spinal cord injury, stroke) often show signs of depression (Hammer, Hacker, Hautzinger, Meyer, & Kubler, 2008; Judd, Stone, Webber, Brown, & Burrows, 1989; Wade, Legh-Smith, & Hewer, 1987). Furthermore, depression often goes undiagnosed and untreated in many patients (Elliott & G., 1996). This may be due to physicians focusing on treating the physical ailments of patients and their limited training in psychological health. Depression has been shown to interfere with effortful cognitive processing and can cause fatigue, both of which can negatively impact attention (Veiel, 1997). As such, depression can negatively impact BCI performance, as BCI tasks require both effortful cognitive processing and high levels of attentional control.

Thus far, the impact of depression on BCI performance has not been examined. Therefore, basic research on depression and task performance will be evaluated. In a study conducted by Farrin, Hull, Unwin, Wykes, and David (2003) a group of men recruited from a group of UK military personnel were placed into a “depressed” or “non-depressed” group based on their scores on the Beck Depression Inventory (Beck & Steer, 1993). It is important to note

that none of the men had received a clinical diagnosis of depression; therefore they were grouped by their levels of depressive symptomology. They were then asked to complete several cognitive tests including the Sustained Attention to Response Task (SART), Paced Auditory Serial Attention Task (PASAT), and Stroop Color-Word Test (SCWT). The men in the depressed group made significantly more errors on the SART, a measure of vigilance, than their non-depressed counterparts, with their reaction time slowing following each error. The researchers report that these errors corresponded with lapses in their sustained attention. Additionally, the men in the depressed group reported more cognitive failures on a standardized questionnaire. This study reveals that depressive symptomology can cause lapses in sustained attention that can lead to an increase in errors and reaction time. Therefore, depressive symptomology could also impair performance on a BCI task because it requires a great deal of sustained attention. Furthermore, if there is an increase in reaction time in the user's ability to detect a target item flash, it may cause the system to have a P300 ERP recorded to an item other than the target item. Further evaluation of the literature revealed that while depression increases reaction time on some tasks, this increase appears to be specific to physical responses such as button pressing. However, stimulus preprocessing and evaluation have been shown to be uninhibited by depression as shown by studies examining P300 latency (Azorin, Benhaim, Hasbroucq, & Possamai, 1995; Giedke, Thier, & Bolz, 1981). Therefore, it is unlikely that depression will negatively impact BCI performance by increasing reaction time to target flashes.

Another avenue through which depression can impact performance is its influence on self-efficacy. Self-efficacy can be defined as a person's belief that they are capable of carrying out the tasks necessary to complete a goal (Bandura, 1977). Not surprisingly, it has been shown that depression can have a detrimental effect on self-efficacy, and individuals suffering from

depression tend to perceive themselves as being incapable of completing many tasks, even those at which they have previously succeeded (Bandura, 1993). Self-efficacy has been found to have an impact on motivation, behavior, and even emotional arousal. If a person believes that they are incapable of successfully completing a task, they are likely to avoid it altogether (Bandura, 1977). Self-efficacy dictates how much effort an individual will put forth in both the preparation and execution phases of task completion, and the extent to which they will continue to persevere in the face of obstacles. For optimal task performance, an individual needs to have a moderate amount of self-efficacy and self-doubt (Bandura, 1982). This is because some self-doubt promotes preparation for learning to occur, but too much can negatively impact the execution of the learned behavior. In addition, too much self-doubt (i.e., too little self-efficacy) can cause an individual to focus on their past failures, potentially hurting task performance by causing their attention to shift away from the task. On the other hand, low levels of self-doubt (i.e., too much self-efficacy) can prevent the individual from putting forth enough effort in preparation to complete the task to the best of their ability (Bandura, 1982). Therefore, for optimal task preparation and performance, some self-doubt is necessary to motivate the individual to effectively prepare to complete the task at hand and execute the task to the best of their ability. In addition, some self-efficacy is required to give the individual enough confidence to attempt the task at all and to persist even when they are faced with obstacles.

It is likely that self-efficacy plays an important role in BCI task performance. Users that have a moderate amount of self-doubt are motivated to attend to the directions given by the researcher for successful operation of the BCI in preparation for attempting the BCI task. They are also motivated to put forth every effort to succeed on the BCI task to the best of their ability. Users that have a moderate amount of self-efficacy have enough confidence to attempt the BCI

task and continue to put forth effort even when they struggle to perform the BCI task, for example, when several errors are made. These factors are extremely important because the BCI task can be both mentally taxing and frustrating since it requires sustaining attention for a long period of time and can become frustrating when several errors are made.

Based on the findings of the aforementioned studies, it can be hypothesized that in Study 1, individuals with higher levels of depressive symptomology will perform worse on the BCI task than individuals with lower levels of depressive symptomology. This is due to the fact that depressive symptomology can cause deficits in sustained attention, making it difficult for the individual to focus on the task at hand. Depression has been found to be associated with low self-efficacy. Individuals with low self-efficacy tend to avoid certain tasks if they feel they will be unsuccessful at completing the task. This may cause them to insufficiently prepare for the task at hand. Low levels of self-efficacy may also cause an individual to become frustrated more easily during the BCI task. Frustration can lead to more errors which has a negative impact on BCI performance. Therefore, participants reporting depressive symptomology are likely to have lower BCI performance as a result.

Relationships Between Mood, Emotion, Motivation, and Depression

These four psychological factors (i.e., mood, emotion, motivation, and depression) are far from distinct and separate constructs. Fluctuations within any of these factors can have a significant impact on the other three factors. There are two main ways in which these factors are linked to one another. The first is through their relationship to depression. Individuals who are depressed often experience low levels of motivation to take part in certain activities or complete specific tasks. This is thought to be partially due to a lack of anticipation of pleasure (Sherdell, Waugh, & Gotlib, 2012). Depression has also been shown to impact mood and emotion.

Depressed individuals tend to experience more negative moods and emotions than their non-depressed counterparts. Furthermore, they have also been shown to have less emotional reactivity to sad stimuli (Rottenberg, 2005).

All four psychological factors also have a relationship to self-efficacy. The experience of positive moods and emotions typically increase self-efficacy while negative moods and emotions decrease self-efficacy (Kavanagh & Bower, 1985). Depression has been shown to decrease an individual's self-efficacy, causing them to perform poorly on some tasks and to avoid certain tasks altogether (Bandura, 1993). Self-efficacy has been found to have a significant effect on motivation. Individuals with high levels of self-efficacy tend to also be highly motivated to complete tasks while low levels of self-efficacy cause individuals to perform worse or avoid certain tasks (Bandura, 1982; Schunk, 1995).

The fact that these four psychological factors have been shown to be related makes it important to examine their influence on BCI performance as a whole, as well as individually. Therefore, in Study 1, both correlation and regression will be used to analyze the data. This will allow us to determine the full impact of these factors on BCI performance.

CHAPTER 4

STUDY 1

Several studies have highlighted the potential impact of a variety of psychological factors (e.g., emotion, mood, motivation, depression) on BCI performance. While a handful of studies have examined the impact of these factors on BCI performance, no single study has measured these factors together. Furthermore, while the impact of mood on BCI performance has been examined, there have not been any studies evaluating the effects of emotion on BCI performance. The present studies aim to further investigate the effects of psychological factors, including motivation, mood, depression, and emotion, on BCI performance by conducting two separate but related studies. In the first study, these four psychological factors were measured along with BCI performance in order to examine possible correlations between them. The second study elicited different types of emotions (e.g., pleasant, neutral, and unpleasant) in participants by having them view a series of images. Participants then completed a BCI task so that the relationship between emotion and BCI performance could be determined. These studies build on the previous research that has been conducted on psychological factors and BCI performance in order to further understand their relationship.

Purpose

The purpose of Study 1 is to evaluate the relationship between BCI performance and the psychological factors of motivation, mood, emotion, and depression. This study builds on previous research in that it is the first study to measure all four factors simultaneously. There are several hypotheses that can be made based on the findings from previous research. Participants reporting positive mood should perform better on the BCI task as a result of being better able to ignore task-irrelevant distractions (i.e., the flashing of non-target stimuli) and should also have

higher P300 amplitudes. Participants experiencing highly pleasant (e.g., joy) or unpleasant emotions (e.g., anger) should also perform better on the BCI task as a result of higher P300 amplitudes and increased attention. Highly motivated participants, specifically participants who are highly motivated to perform well on the BCI task, are expected to perform better on the BCI task as a result of increased attention. This should also lead to higher P300 amplitudes. Finally, participants reporting depressive symptomology are expected to perform more poorly on the BCI task due to deficits in sustained attention, increased reaction time following errors, and lower self-efficacy.

Methods

A total of 39 participants were recruited using East Tennessee State University's undergraduate research participant pool using SONA Systems, Inc. This is software designed to help researchers manage their participants. All participants were required to fill out an informed consent document that was approved by East Tennessee State University's Campus Institutional Review Board. Data collection took place on the campus of East Tennessee State University in the Brain-Computer Interface Laboratory. Participants received course credit in the form of three SONA credits for their participation in this study.

After filling out the informed consent document, each participant was read a paragraph describing the importance of this research, which has been designed to increase the intrinsic motivation of the participant (Brown, Mesa, & Sellers, 2013). At the end of this paragraph, all participants were given the option to leave and receive credit if they feel they cannot give their full attention and effort to the task. If the participant chose to stay, they were given a series of four surveys. These surveys are designed to measure motivation, mood, emotion, and depressive symptom severity. (The aforementioned procedures were followed during data collection of the

first 30 participants. It was then determined that the motivation paragraph should no longer be read to participants in order to promote more variation in motivation scores, see below for additional details.)

The depressive symptom severity measure was given prior to the participant being fitted with an EEG cap; the additional three measures were given after the participant was capped. This is because while depressive symptom severity should remain the same, the capping procedure may influence the participant's responses on the measures of mood, motivation, and emotion. For example, if the participant has a fear of needles, the capping process may cause the participant to experience unpleasant emotions.

The Questionnaire for Current Motivation for BCI2000 (QCM-BCI; Rheinberg et al., 2001) was used to measure motivation. The English version of a subscale of a German measure to assess quality of life, Skalen zur Erfassung der Lebensqualität (SEL; Averbek, 1997), was used to measure mood. The Positive and Negative Affect Schedule (PANAS) was used to measure emotion. The Severity Measure for Depression-Adult, adapted from the Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2010), was used to measure depressive symptom severity. The order in which the participants completed the surveys was counter-balanced to control for potential order effects.

In order to increase the variability in depressive symptomology, the PHQ-9 survey was placed on SONA. Participants who received a score of 10+ were then contacted by email to inquire whether they would be willing to come in to participate in Study 1. Out of the 50 participants who completed the online survey, 17 received a score of 10+ on the PHQ-9. Of the 17 participants that were contacted, only one agreed to participate in Study 1.

After being fitted with an EEG cap and completing the surveys, each participant took part in a BCI task. For this portion of the study, participants were seated in a chair approximately 1m away from the computer monitor. On the monitor, they were presented with an 8x9 matrix filled with letters, numbers, and commands (e.g., pause; see Figure 6). Prior to beginning the BCI task, participants were fitted with a 32-channel EEG cap (Electro-Cap). Once the cap was placed on their head, each of the 32 electrodes were filled with a water-soluble gel using a blunted needle in order to help the cap read the electrical signals from the scalp. The electrodes were adjusted until impedance values were reduced to below 40K Ω (Kappenman & Luck, 2010). Two 16-channel amplifiers (g.tec) were used to digitize the EEG signals recorded from the scalp. Stimulus presentation, signal processing, and classification of EEG data were conducted using BCI2000 software (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004).

After the system was set up, the participant completed a calibration portion in which they copy-spelled three, six-letter words. Copy-spelling refers to the participant being presented with a word at the top of the screen that they must spell out one letter at a time. The three words were selected using a random word generator. This data was used to create a classifier, which was then uploaded to BCI2000 in order to provide the system with information about the participant's unique P300 ERP response. This classifier makes it more likely that the system will be able to correctly determine the selection the participant is attempting to make. Once the classifier was uploaded to the system, the participant took part in an online copy-spelling task for which they received feedback. During this portion, the participant spelled six additional six-letter words, also selected using a random word generator, and their selections were recorded. At the end of the session, the EEG cap was removed from the participant and they were given the option of washing their hair in a sink located in the lab.

Measures and Statistical Analyses. A series of both psychological measures and performance measures were utilized for this study. Data from both types of measures were collected so that the relationship between them can be determined.

Psychological Measures. Four surveys were used to measure motivation, mood, emotion, and depressive symptom severity. The English version of the Questionnaire for Current Motivation for BCI 2000 (QCM-BCI) was used to measure motivation (Rheinberg, Vollmeyer, & Burns, 2001). The QCM-BCI consists of 18 questions, each of which are to be rated on a 7-point Likert-scale (1=disagree strongly, 7=agree strongly). The questionnaire can then be scored in order to derive four separate scores: mastery confidence, incompetence fear, interest, and challenge. Each of these four scores represents an individual factor within motivation.

The English version of a subscale of a German measure to assess quality of life, Skalen zur Erfassung der Lebensqualität (SEL), was used to measure mood (Averbeck, 1997). The mood subscale of the SEL consists of 10 statements that the participant must rate on a 5-point Likert-scale (1=does not apply to my current well-being at all, 5=applies fully to my current well-being) based on their current mood. Five of the items are reversed scored so that higher scores reflect a more positive mood.

The Positive and Negative Affect Schedule (PANAS) was used to measure emotion (Watson, Clark, & Tellegen, 1988). The PANAS consists of 20 words that describe different feelings and emotions. The participant is instructed to rate each word on a 5-point Likert-scale (1=not at all, 5=extremely) in order to indicate the extent to which each word describes how they are presently feeling. Half of the items are summed to create a positive affect score (PAS) and the other half of the items are summed to create a negative affect score (NAS). Higher scores on the PAS indicate higher levels of positive affect such as high energy, concentration, and

pleasurable engagement. Higher scores on the NAS indicate higher levels of negative affect such as distress, fear, and nervousness (Watson et al., 1988).

The Severity Measure for Depression-Adult, adapted from the Patient Health Questionnaire-9 (PHQ-9), was used to measure depressive symptom severity (Kroenke, Spitzer, Williams, & Löwe, 2010). This measure consists of nine items that are rated on a 4-point scale (0=not at all, 3=nearly every day) based on how often they have felt that way in the past week. The participant's responses are summed to obtain a total score that can be interpreted to determine the level of depressive symptom severity as follows: 0-4=none, 5-9=mild depression, 10-14=moderate depression, 15-19=moderately severe depression and 20-27=severe depression. Participants receiving a score of 10+ were emailed with information on the East Tennessee State University Counseling Center.

Performance Measures. In addition to the above psychological measures, three types of performance measures were used. These include accuracy, selections per minute, and information transfer rate (ITR).

There are several different methods that can be used to analyze performance on a BCI task. The traditional measure that is used is calculated by dividing the correct number of selections by the total number of selections made in order to obtain the accuracy of item selection. Another measure that is commonly used is selections per minute, which is calculated by dividing the total number of selections made within a given time period. Bitrate, also known as information transfer rate (ITR), is a performance measure that is calculated using accuracy, selections per minute, and the number of possible selections that can be made (McFarland, Sarnacki, & Wolpaw, 2003). Information transfer rate is influenced by the time between selections, which can change based on the study. In order to account for this and make it easier to

compare ITR across studies, a similar measure known as theoretical ITR can be calculated which removes the time between selections. Lastly, practical ITR is a similar measure that takes into account error correction. Every time an incorrect selection is made, the user must make two additional selections in order to correct their mistake (i.e., they must select 'backspace' and then attempt to make the correct selection). By accounting for error correction, practical ITR creates a more accurate depiction of how the system will work for an end-user. All of these performance measures, with the exception of theoretical ITR, were used in the current study.

In order for a BCI system to be considered an effective form of communication, the system must be able to produce a minimum accuracy of 70% (Kübler et al., 2001). Although 70% accuracy may seem high, an offline analysis performed by Sellers et al. (2006) showed that in order to type out a sentence consisting of 10 correct selections at an accuracy of 70%, a user would need to make a total of 25 selections. The point of this analysis was to show that 70% accuracy may not be as practical as previously believed and perhaps a higher minimum accuracy is necessary for practical BCI use. If the minimum accuracy was raised to 80%, this would mean that in order to obtain 10 correct selections, approximately 17 selections would be required (Sellers et al., 2006). Lastly, if the minimum accuracy was raised to 90%, in order to obtain 10 correct selections, approximately 12 selections would be required (Sellers et al., 2006). Therefore, 90% accuracy allows for successful communication with minimal chances for incorrect selections and appears to be a more practical minimum accuracy for BCI use.

Data collected using a BCI can be analyzed either in online- or offline-mode. In online-mode, the user receives feedback on their performance in real time as they are spelling. The user must first participate in a calibration portion where they spell words without receiving feedback. This data is then used to create a classifier that provides the system with information on the

individual user's unique P300 ERP response. The classifier is tested by having the user complete a subsequent online portion where they spell words while receiving feedback on their performance. In offline-mode, a classifier is created in the same way; however, the classifier is tested without the presence of the user on previously collected data. Online-mode allows for the classifier to be tested in real time and incorporates the variability of human performance, which leads to high external validity. Although offline-mode does not have the same level of external validity, it can still provide a rough estimate of the accuracy of the classifier without requiring the participant to spell additional words. Both online and offline analyses were conducted on the data from Study 1.

Analyses. A power analysis was conducted using G*Power to determine the number of participants that must be collected in order to detect a medium effect size as defined by Cohen's *d*. This analysis revealed that a minimum of 21 participants must be collected. Data collection for Study 1 continued until data collection for Study 2 was complete. Therefore, data was collected from a total of 39 participants.

A principal component analysis was conducted on the three dependent variables (i.e., accuracy, bitrate, and practical bitrate) in order to determine if they could be condensed into one outcome variable. A one-tailed, bivariate, Pearson correlation was conducted in order to examine the relationship between the psychological measures (i.e., emotion, mood, motivation, and depressive symptomology) and the performance measures (i.e., the principal component created using accuracy, bitrate, and practical bitrate). The researchers hypothesized that emotion would be the most highly correlated with BCI performance, followed by motivation, depression, and mood. Regression was then used to determine the amount of variation in BCI performance (i.e., the principal component) due to all of the psychological factors combined. The researchers

hypothesized that the variation in BCI performance due to the psychological factors would be significant.

Scatterplots were created in order to visually inspect the relationship between each of the four psychological factors and P300 peak amplitude. A single scatterplot was made to examine the relationship between P300 peak amplitude and mood as well as depression. However, two scatterplots were made to examine the relationship between emotion and P300 peak amplitude; one for the positive affect score (PAS) and one for the negative affect score (NAS). Additionally, four scatterplots were made to examine the relationship between P300 peak amplitude and each of the four components of motivation measured by the QCM-BCI (i.e., confidence, interest, fear, and challenge). A two-tailed, bivariate, Pearson correlation was conducted to analyze the relationship between the four psychological factors and P300 peak amplitude. The researchers hypothesized that there would be a significant correlation between P300 peak amplitude and all four psychological factors. Specifically, the researchers hypothesized that P300 peak amplitude would be greater for participants reporting high pleasant or unpleasant emotions, high levels of positive mood, high levels of motivation (i.e., high confidence, low fear, high interest, and high challenge), and low depressive symptomology. If any of the correlations were found to be significant, a one-way ANOVA would be conducted in order to identify if there were significant differences in peak amplitude based on group (e.g., participants can be placed into groups based on their depression score using the cutoffs provided by the measure). Post hoc pairwise comparisons would be carried out if any of the one-way ANOVAs revealed a significant difference in P300 peak amplitude based on group. This would be done in order to identify which groups significantly differed from one another.

Target and non-target average waveforms at electrode sites Fz, Cz, and Pz were created using the BCI2000 calibration data for all subjects combined in order to examine overall trends in the data. The calibration data was unedited, meaning it had not been cleaned to remove eye-blinks or other artifacts. Unedited calibration data were used because the BCI system uses these raw data in order to create the classifier for the individual user. Therefore, it is useful to use these raw data to create average waveforms in order to provide an accurate representation. Target waveforms would also be created for any of the aforementioned groups that were found to have significant differences in P300 peak amplitude in order to visualize these differences.

Results

Data from 36 participants were included in the following analyses (24 female, ages 18-25). Three participants were excluded from analyses due to high impedance values.

As mentioned previously, it was determined that the motivation paragraph should no longer be read to participants in order to increase the amount of variation in motivation scores. After the data was analyzed, it was decided that the motivation paragraph may have an impact on the results. Therefore, in order to determine if the motivation paragraph had a significant impact on the results, the data were divided into two groups based on whether the motivation paragraph was read or not. Separate analyses were then conducted on each group. The results revealed that while depression was initially found to correlate significantly with P300 peak amplitude, this was no longer true for the group that was read the motivation paragraph ($r(35) = .323, p = .051$); however, it remained significant for the group that did not receive the motivation paragraph ($r(35) = .548, p < .001$). As this was the only finding that was impacted by whether or not the motivation paragraph was read, the original planned analyses on the data as a whole appear sufficient.

A principal component analysis was conducted in order to determine whether the three dependent variables (i.e., accuracy, bitrate, and practical bitrate) could be combined into one principal component to be used as the outcome variable in the remaining analyses. This analysis revealed that by combining these three factors into one principal component, 91.639% of the variance in those factors is retained. Therefore, this single principal component was used as the outcome variable in all additional analyses.

A one-tailed, bivariate, Pearson correlation was conducted to examine the relationships between each of the four psychological factors and BCI performance (as represented by the single principal component that was created). None of the psychological factors were found to be significantly correlated with BCI performance. The correlation table is provided in Table 1.

Table 1

<i>Correlations Between the Four Psychological Factors and BCI Performance</i>		
<u>Psychological Factor</u>	<u>Pearson Correlation</u>	<u>Significance</u>
PAS	-.018	.458
NAS	.154	.185
Mood	-.166	.167
Confidence	-.015	.466
Fear	.197	.124
Interest	-.170	.160
Challenge	.081	.319
Depression	-.175	.154
*Correlation is significant at the 0.05 level (one-tailed).		

Table 1. Correlation table of a one-tailed, bivariate, Pearson correlation examining the relationships between each of the four psychological factors and BCI performance.

Regression was used to determine the amount of variation in BCI performance that exists due to all psychological factors combined. The results did not indicate that there is a significant amount of variance in BCI performance due to the psychological factors ($R^2=.225$, $F=.978$, $p=.474$).

A total of eight scatterplots were created in order to visually examine the relationship between each of the four psychological factors and P300 peak amplitude. Figure 7 includes a scatterplot of depression and P300 peak amplitude. Figures 8, 9, 10, and 11 include scatterplots for P300 peak amplitude with confidence, fear, interest, and challenge, respectively. Figures 12 and 13 include scatterplots for P300 peak amplitude with PAS and NAS, respectively. Lastly, Figure 14 includes a scatterplot for mood and P300 peak amplitude.

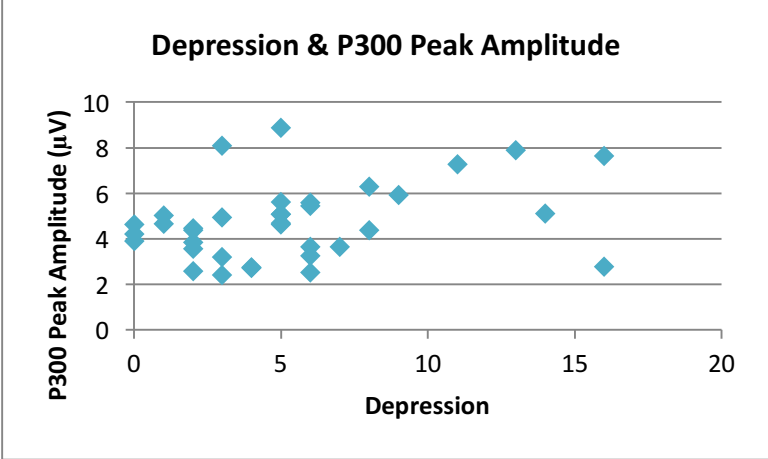


Figure 7. A scatterplot of depression and P300 peak amplitude.

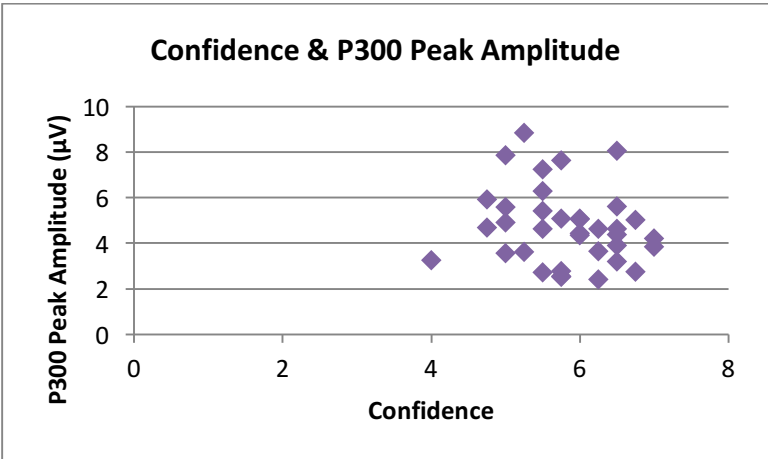


Figure 8. A scatterplot of the confidence component of motivation and P300 peak amplitude.

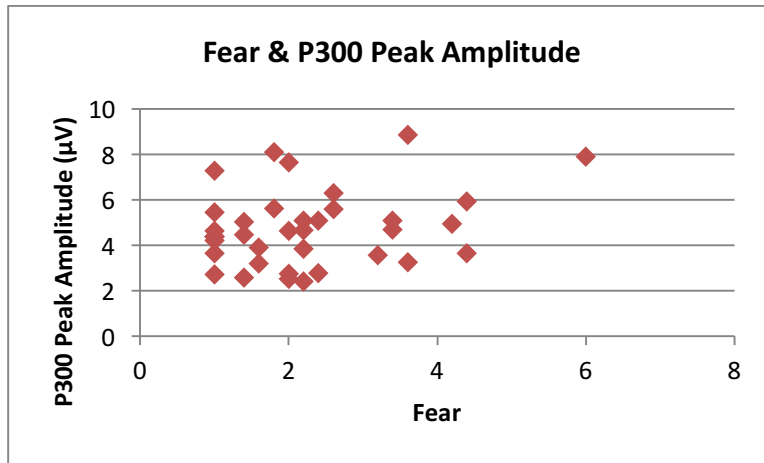


Figure 9. A scatterplot of the fear component of motivation and P300 peak amplitude.

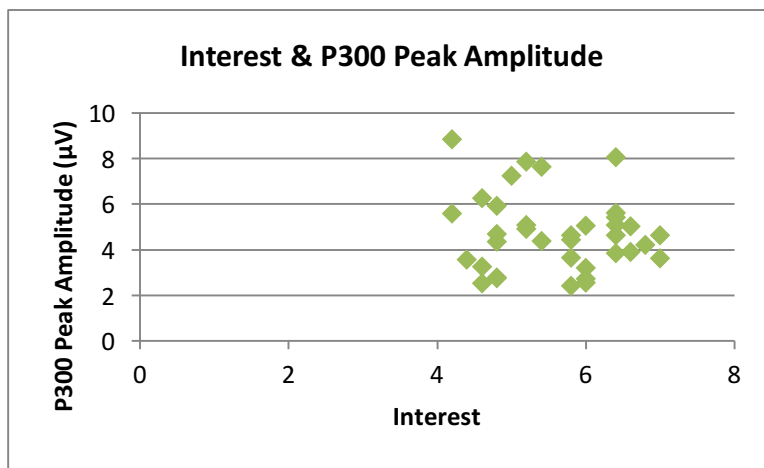


Figure 10. A scatterplot of the interest component of motivation and P300 peak amplitude.

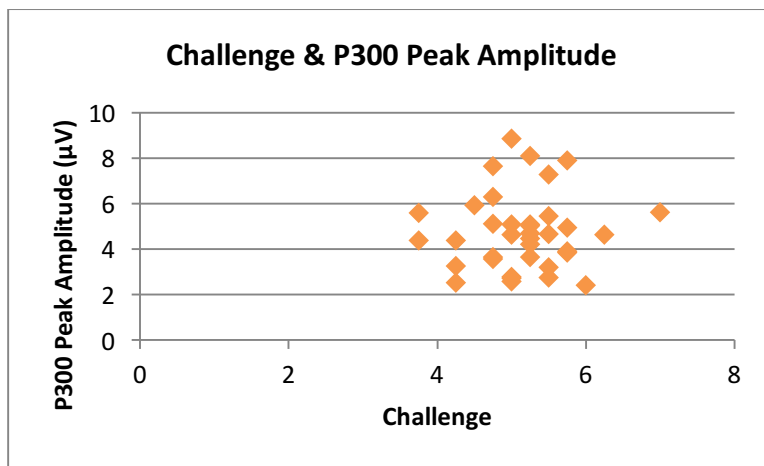


Figure 11. A scatterplot of the challenge component of motivation and P300 peak amplitude.

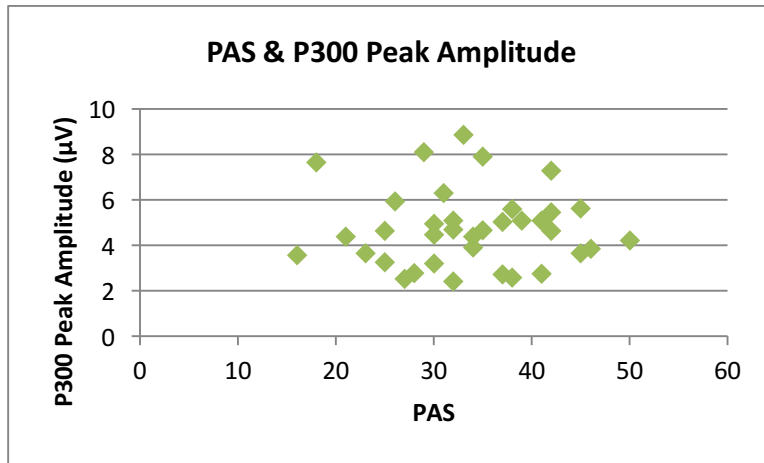


Figure 12. A scatterplot of the positive affect component of emotion and P300 peak amplitude.

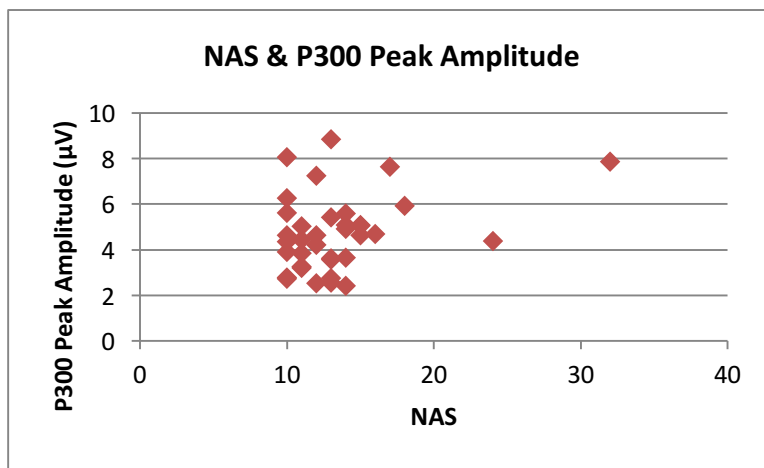


Figure 13. A scatterplot of the negative affect component of emotion and P300 peak amplitude.

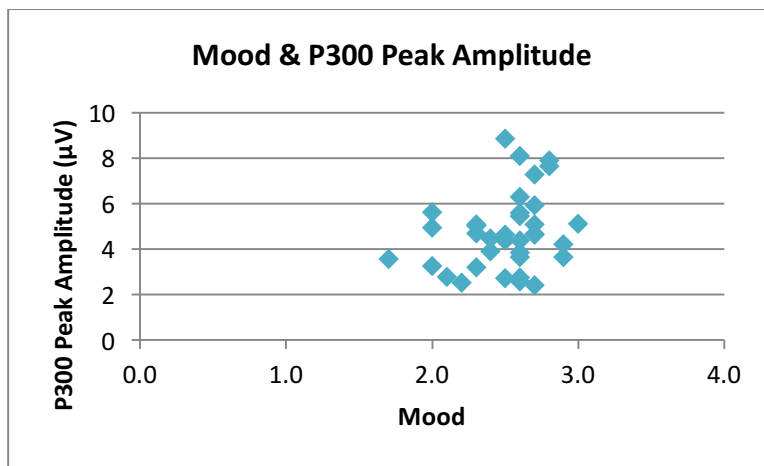


Figure 14. A scatterplot of mood and P300 peak amplitude.

In order to formally analyze the relationship between each of the four psychological factors and P300 peak amplitude, a two-tailed, bivariate, Pearson correlation was conducted (see Table 2). This analysis revealed that depression is significantly correlated with P300 peak amplitude ($r(35)=.335, p=.043$). Next, participants were placed into one of three groups based on their depressive symptomology. Participants receiving a score between 0-4 on the PHQ-9 were placed in the “no depression” group; those receiving a score between 5-9 were placed in the “mild depression” group; participants scoring 10+ were placed into the “moderate to severe depression” group. A one-way ANOVA was then conducted in order to determine if there were significant differences in P300 peak amplitude between groups. The results were statistically significant ($F(2, 33)=3.645, p=.037$). Post hoc pairwise comparisons were conducted in order to determine which of the three depressive symptomology groups were significantly different from one another. This analysis indicated that there was a statistically significant difference in P300 peak amplitude ($p=.014$) between the “no depression” ($M=4.088, SD=1.372$) and “moderate to severe depression” ($M=6.136, SD=2.173$) groups. Interestingly, the “moderate to severe depression” group had a higher average P300 peak amplitude than the “no depression” group, contradictory to the researchers’ hypothesis.

Table 2

<i>Correlations Between the Four Psychological Factors and P300 Peak Amplitude</i>		
<u>Psychological Factor</u>	<u>Pearson Correlation</u>	<u>Significance</u>
PAS	-.012	.947
NAS	.318	.059
Mood	.270	.111
Confidence	-.174	.309
Fear	.275	.104
Interest	-.138	.421
Challenge	.053	.759
Depression	.335*	.043

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

Table 2. Two-tailed, bivariate, Pearson correlation examining the relationship between P300 peak amplitude and the four psychological factors.

Grand mean waveforms, including both target and non-target waveforms, were created at electrode sites Fz (Figure 15), Cz (Figure 16), and Pz (Figure 17) in order to visually examine overall trends in the data. In addition, grand mean target waveforms at electrode site Pz were created for each of the three depressive symptomology groups in order to visually examine the differences in P300 peak amplitude between groups (Figure 18).

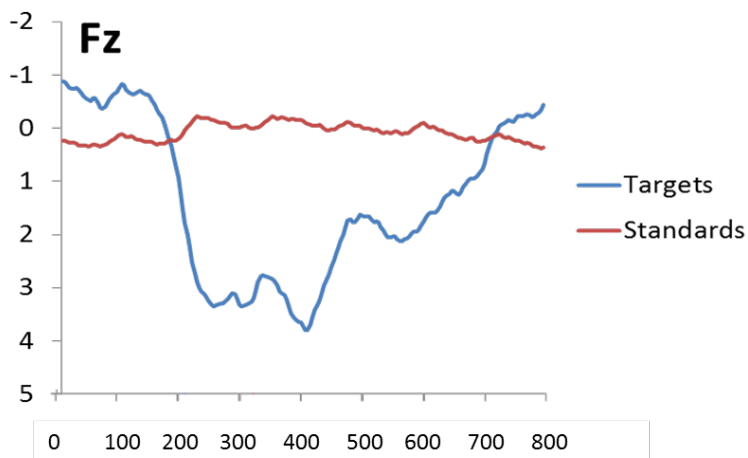


Figure 15. Grand mean target and non-target waveforms at electrode site Fz.

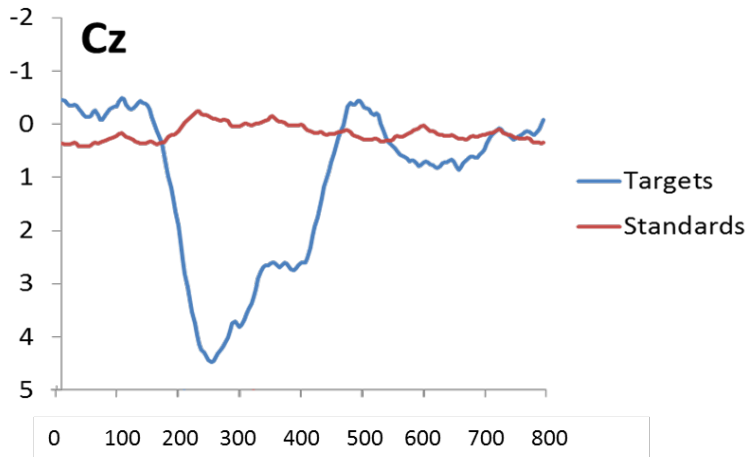


Figure 16. Grand mean target and non-target waveforms at electrode site Cz.

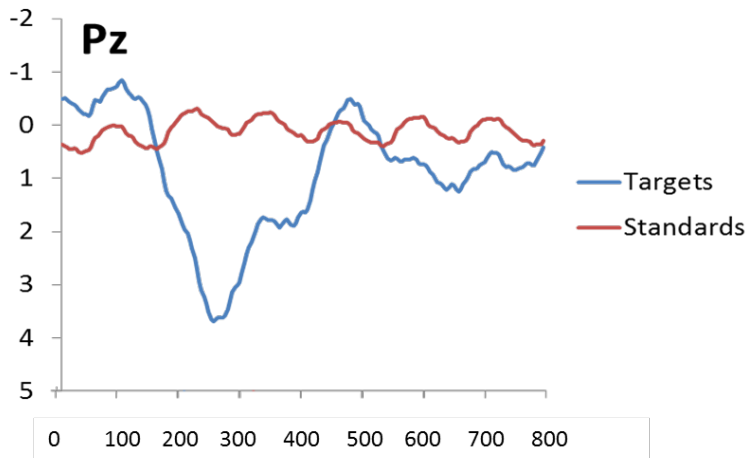


Figure 17. Grand mean target and non-target waveforms at electrode site Pz.

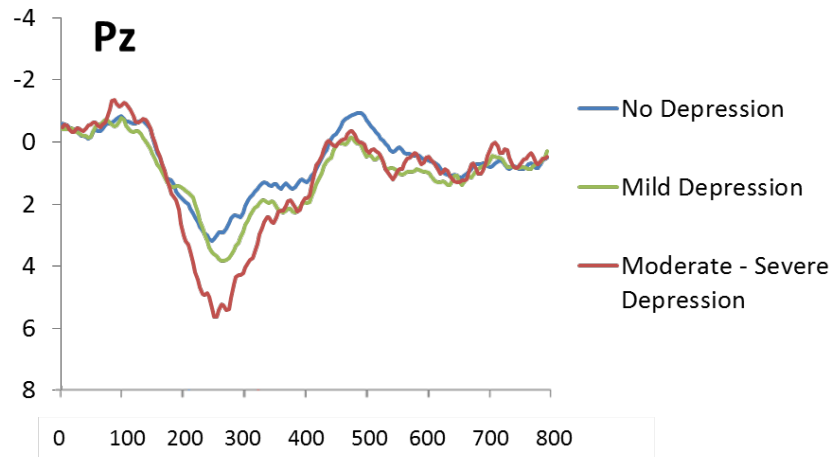


Figure 18. Grand mean target waveforms for each of the three depressive symptomology groups at electrode site Pz.

CHAPTER 5

STUDY 2

Purpose

The purpose of Study 2 is to examine the impact of pleasant, unpleasant, and neutral emotions on BCI performance. Based on the findings of previous studies regarding emotion and event-related potentials, the researchers made several hypotheses. The pleasant and unpleasant conditions were expected to lead to better performance on the BCI task because they should lead to increased attention as compared to the neutral condition. In addition, the researchers expected larger slow positive voltage changes in the pleasant and unpleasant conditions. Furthermore, the peak amplitudes for the P300 and slow positive voltage change were expected to be higher for the pleasant and unpleasant conditions.

Methods

A total of 50 participants were recruited using East Tennessee State University's undergraduate research participant pool using SONA Systems, Inc. All participants took part in three, two-hour sessions conducted on different days. Participants were required to fill out an informed consent document, which has been approved by East Tennessee State University's Campus Institutional Review Board. Data collection took place on the campus of East Tennessee State University in the Brain-Computer Interface Laboratory. Participants received course credit in the form of nine SONA credits (three credits per session) for their participation in this study.

During their first session, after filling out the informed consent document, the participant was read the same motivation paragraph that was described in Study 1, giving them the option to leave and receive credit if they felt they were unable to give their full attention and effort to the task. The motivation paragraph was only read to the first 18 participants. It was then decided, as

in the first study, that the motivation paragraph should no longer be read in order to increase the variation in BCI performance. If the participant agreed to stay, they were read a second paragraph describing the nature of the unpleasant pictures they would be shown during one of the sessions to give them the option of opting out of the study if they were uncomfortable viewing these unpleasant pictures. They were informed that some of the images could include content that may be considered objectionable, such as violent pictures similar to those that can be found on television or in other news outlets. The participant was told that at any point in the study they have the option of closing their eyes or discontinuing the study. If the participant agreed to continue with the study, they were fitted with an EEG cap in the same manner as Study 1. This was done so that the participant's brain activity could be recorded while viewing the pictures. The participant was also fitted with a grounding cuff on their wrist in order to filter out 60Hz noise. After the participant was fitted with an EEG cap, they were given a copy of the Positive and Negative Affect Schedule (PANAS; described in Study 1) to measure their baseline emotional state.

After the participant filled out the PANAS, one of three possible emotions were elicited using the International Affective Picture System (IAPS) (P. J. Lang, Bradley, & Cuthbert, 2008). The IAPS is a normative battery of color photographs that have been rated by a large number of participants on three dimensions: pleasure, arousal, and dominance. These ratings have been used to provide guidelines to categorize each picture based on the emotion it elicits: pleasant, unpleasant, or neutral. The participant was seated approximately 1m away from the computer monitor which was used to display the IAPS pictures. Only one emotion (pleasant, unpleasant, or neutral) was elicited during each session. The order in which the participants completed the conditions was counter-balanced. In order to elicit each emotion, the participant was shown a

total of 18 pictures for a duration of 6s per picture. All participants viewed the same 18 pictures; however, the order in which each participant viewed the pictures was randomized using E-Prime. Participants were first shown a blank slide with a fixation cross for 5 seconds, followed by the IAPS image for 6 seconds. Prior to the start of this portion, participants were instructed to think about how the image made them feel while they were viewing each image. Participants then saw a blank slide with the word “reflection.” Again, prior to beginning this portion, participants were instructed to think about the previous image while they viewed the reflection slide and to also think about how the image made them feel. Lastly, participants took two brief computerized surveys to provide information on their reaction to the previous image. Both surveys were taken from the self-assessment manikin (SAM); the first is designed to measure pleasure and the second is designed to measure arousal (Lang & Bradley, 2007). These surveys are described in detail below. The software program g.Recorder was used for EEG data acquisition during the presentation of the IAPS pictures. Once the participant viewed all 18 pictures, they completed the PANAS for a second time to confirm that the IAPS pictures successfully elicited the intended emotion.

Next, the participant completed a brain-computer interface (BCI) task that is similar to the BCI task described in Study 1. The only difference between the BCI task completed in Study 1 and Study 2 is that the words chosen for the participant to copy-spell were not taken from the random word generator. Instead, the words were selected from the Affective Norms for English Words (ANEW) (Bradley & Lang, 1999). The ANEW is a set of normative emotional ratings for a large number of English words. Each word is rated on the same three dimensions as the IAPS. Nine, six-letter positive, negative, and neutral words were selected from the ANEW to be used in

the calibration and online portions of the BCI task. Each participant spelt the same nine words in a random order for each of the conditions.

At the end of the first session, the researcher confirmed the participant's next appointment to complete their second session, and their third and final session was scheduled. The only difference between sessions was the condition the participant completed (i.e., pleasant, unpleasant, neutral). At the end of each session, the EEG cap was removed from the participant's scalp and they were given the option of washing their hair in the lab sink. The participant was told they would receive their SONA credit for each session by the end of the day.

Measures and Statistical Analysis. The same performance measures that were utilized in Study 1 were used in Study 2. The Positive and Negative Affect Schedule (PANAS) that was used in Study 1 was also used in Study 2.

The International Affective Picture System (IAPS) is an extensive battery of color photographs meant to elicit pleasant, unpleasant, and neutral emotions (Lang et al., 2008). Each picture has been scored on three dimensions using the self-assessment manikin (SAM; described below): pleasure, arousal, and dominance. The first two dimensions account for much more variance than the third dimension (Lang et al., 2008), so only the first two were used in the present study. The IAPS was designed to provide a standardized battery of images that could be used by a variety of researchers to elicit emotion. This battery has been used in a number of studies with adults, college students, children, and even in clinical settings (Codispoti et al., 2007; Cuthbert et al., 2000; Keil et al., 2002). The images contained in the IAPS are very similar to those that can be found on television or in news outlets and there have been no reports of any long-term negative effects as a result of viewing these pictures.

The Affective Norms for English Words (ANEW) is a set of normative emotional ratings for a large number of words in the English language that was designed by the UF Center for Emotion and Attention (CSEA) to supplement the IAPS (Bradley & Lang, 1999). Each word has been rated on the same three dimensions using SAM as the IAPS: pleasure, arousal, and dominance; however, as with the IAPS images, only the first two ratings were used to select the words. The ANEW was also created in an effort to provide standardized materials for researchers attempting to elicit pleasant, unpleasant, and neutral emotions in participants.

The self-assessment manikin (SAM) was first created by Lang (1980). There are several versions of SAM; however, this study used the pleasure and arousal versions of SAM. The pleasure version of SAM ranges from a happy, smiling figure to an unhappy, frowning figure with three other figures in-between. The participant can choose any of the five figures, as well as in-between any two figures, in order to indicate their pleasure. This creates a 9-point Likert scale. The participant is instructed to choose 9 if they felt completely happy while viewing the image and 1 if they felt completely unhappy. The arousal version of SAM ranges from an excited figure to a calm figure with three other figures in-between. This version also has a 9-point Likert scale for the participant to choose from. The participant is instructed to choose 9 if they felt extremely excited while viewing the image and 1 if they felt extremely calm. An example of both of these scales is provided in Figure 19. Although they are shown together in Figure 19, the participant responded to the pleasure version of SAM on one screen and the arousal version of SAM on the following screen. The participant provided their response by pressing a number (1-9) on the keyboard that was placed in front of them.

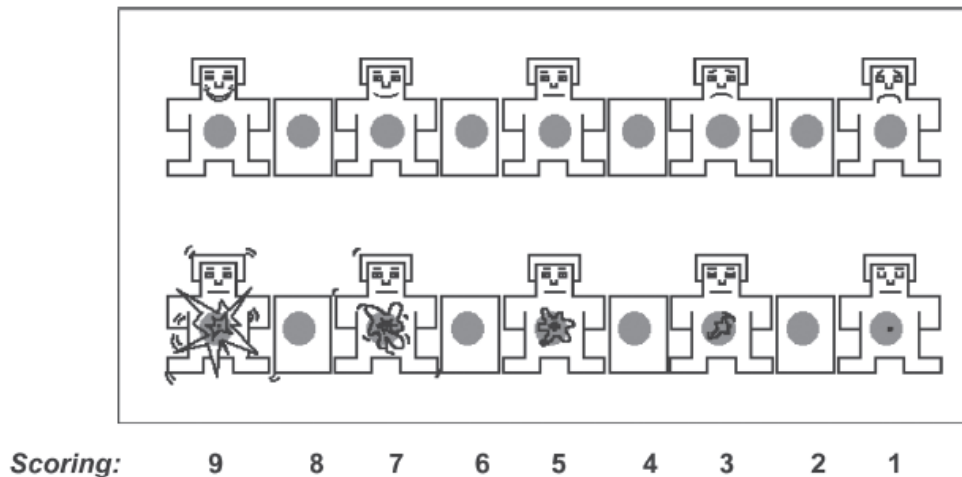


Figure 19. An example of the pleasure (top) and arousal (bottom) version of SAM.

Analyses. A power analysis was conducted using a multilevel model created in R to determine the number of participants that must be collected in order to detect a medium effect size as defined by Cohen’s *d*. This analysis revealed that a minimum of 45 participants must be collected. Again, data from a total of 50 participants was collected, exceeding the minimum requirement.

A paired-samples *t*-test was conducted in order to determine if there is a statistically significant difference in the pre and post PANAS scores by condition. This analysis was done in order to check whether the intended emotional manipulation was successful. The PANAS scores were broken up into positive affect scores (PAS) and negative affect scores (NAS). The researchers hypothesized that in the pleasant condition, the post PAS scores would be significantly higher than the pre PAS scores, and the post NAS scores would be significantly lower than the pre NAS scores. Additionally, the researchers expected that in the neutral condition, there would be no difference in the pre and post PAS or NAS scores. The researchers also hypothesized that in the unpleasant condition, the post PAS scores would be significantly lower than the pre PAS scores, and the post NAS scores would be significantly higher than the

pre NAS scores. If any of our hypotheses for the pleasant or unpleasant conditions were not confirmed, we would conclude that the manipulation was not successful. As a result, we would combine that condition with the neutral condition for future analyses.

A line graph was created in order to visually compare the current study's participants' average pleasure and arousal ratings on the SAM survey to the normative ratings for the images that were shown. No formal analyses were conducted because this is not a manipulation check. Furthermore, the researchers do not expect these ratings to be the same since the present study used a college student population and the normative ratings were collected using a much more diverse sample.

A principal component analysis was conducted, as in Study 1, in order to determine whether the three dependent variables (i.e., accuracy, bitrate, and practical bitrate) could be combined into one outcome variable. A one-way ANOVA was then conducted in order to determine if there is a statistically significant difference in BCI performance by condition (i.e., pleasant, neutral, unpleasant). The researchers hypothesized that participants would be able to spell faster and more accurately in the pleasant and unpleasant conditions than in the neutral condition. This is because the participants should be more aroused in the pleasant and unpleasant conditions, which should lead to increased attention. Post hoc pairwise comparisons would be conducted if the repeated measures ANOVA provided significant results in order to determine which of the three conditions differed from one another.

Grand mean waveforms of the BCI2000 unedited calibration data were created for each of the three conditions at electrode sites Fz, Cz, and Pz in order to visually compare trends in the data. In addition, the same waveforms were created for the g.Recorder data; however, these data were edited using EEGLab. Topography maps were created for the g.Recorder data at the time

point where the slow positive voltage change reached its peak amplitude for each of the three conditions.

Lastly, two one-way ANOVAs were conducted in order to determine if there were significant differences in the peak amplitudes and latencies for specific ERPs between the three condition (i.e., pleasant, unpleasant, and neutral). For the BCI2000 data, the ERPs that were being examined were the P300 and N4 components. For the g.Recorder data, the peak amplitude and latency of the slow-positive voltage change was examined. If any of these findings were found to be significant, post hoc pairwise comparisons were conducted in order to determine which conditions significantly differed from one another.

Results

Data from 50 participants were included in the following analyses (31 female, ages 18-42). Six participants were excluded from analyses involving g.Recorder data due to issues with the system; however, they were included in all other analyses.

As in Study 1, the data in Study 2 were also divided into two groups based on whether the motivation paragraph was read or not. In the motivation paragraph group, the paired samples t-test evaluating the change in negative affect in the neutral condition from pre ($M=12.333$, $SD=3.087$) to post ($M=11.222$, $SD=1.801$) was now found to be significant; $t(49)=2.397$, $p=.020$. As this was the only finding that was impacted, the original planned analyses are considered sufficient.

A paired-samples t-test was conducted in order to determine if there is a significant difference in pre and post PANAS scores by condition. This analysis served as a manipulation check in order to determine if the additional planned analyses could be carried out as intended. The results revealed that in the neutral condition, positive affect significantly decreased from pre

($M=29.340$, $SD=9.940$) to post ($M=25.840$, $SD=10.574$); $t(49)=5.315$, $p<.001$. Although not hypothesized, this is not a surprising finding as the task requires the participant to remain as still as possible with the exception of responding to the SAM survey. In addition, the neutral images are fairly boring so as to not elicit a pleasant or unpleasant emotion. Therefore, this finding will not impact the remaining analyses. There were no significant changes in negative affect in the neutral condition from pre ($M=11.560$, $SD=2.549$) to post ($M=11.500$, $SD=4.390$); $t(49)=.095$, $p=.925$. In the pleasant condition, no significant changes were detected for positive affect from pre ($M=29.340$, $SD=9.657$) to post ($M=28.880$, $SD=9.052$; $t(49)=.632$, $p=.530$), or negative affect from pre ($M=11.420$, $SD=3.326$) to post ($M=11.260$, $SD=4.327$); $t(49)=.224$, $p=.824$. Since no significant results were found for the pleasant condition, our hypotheses were not supported and the pleasant and neutral conditions will be treated as one neutral condition in the remaining analyses. In the unpleasant condition, positive affect significantly decreased from pre ($M=30.800$, $SD=9.105$) to post ($M=25.980$, $SD=9.539$), supporting the researchers' hypothesis; $t(49)=6.069$, $p<.001$. In addition, negative affect significantly increased from pre ($M=11.180$, $SD=1.650$) to post ($M=14.140$, $SD=4.695$), which was also hypothesized by the researchers; $t(49)=-5.193$, $p<.001$.

A line graph was created in order to visually compare the average pleasure and arousal ratings on the SAM survey of the present study's participants to the normative data (see Figures 22 and 23). As mentioned previously, this is not a manipulation check and will not impact the remaining analyses. Furthermore, the researchers expect these average ratings to differ somewhat based on the different populations included in each study.

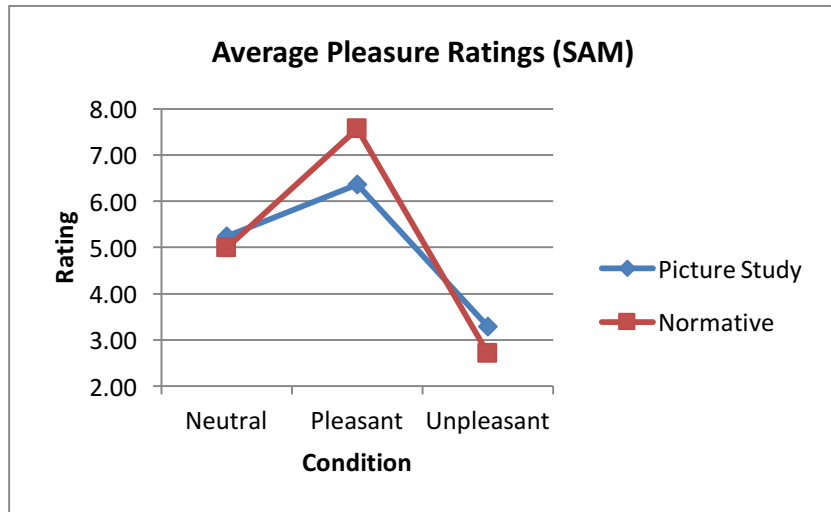


Figure 20. Line graph of average pleasure ratings on SAM measure for present study participants and normative data.

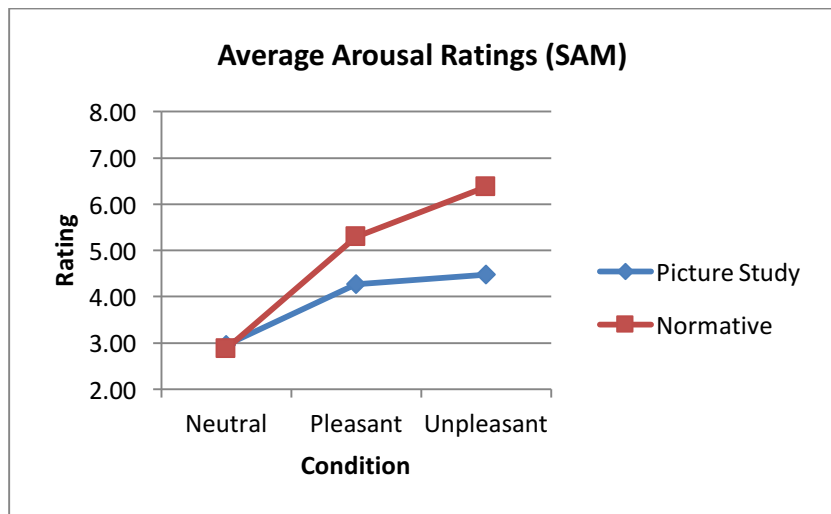


Figure 21. Line graph of average arousal ratings on SAM measure for present study participants and normative data.

A principal component analysis was conducted in order to determine if the three dependent variables (i.e., accuracy, bitrate, and practical bitrate) could be combined into one principal component. The analysis revealed that by combining all three variables into one

principal component, 90.434% of the total variance in the data is retained. Therefore, this principal component will be used as the measure of BCI performance in all additional analyses.

A paired-samples t-test was conducted in order to determine if there is a statistically significant difference in BCI performance between the neutral and unpleasant conditions. Again, the neutral and pleasant conditions were combined and treated as one neutral condition because the paired-samples t-test indicated that the emotional manipulation was unsuccessful. This analysis was originally planned to be a one-way ANOVA; however, since only two groups are being compared instead of three, a paired-samples t-test is sufficient. The results revealed that BCI performance did not significantly differ by condition; $t(49)=-0.144, p=.886$.

Grand mean waveforms were created using the BCI2000, unedited calibration data for each of the three conditions at electrode sites Fz (Figure 22), Cz (Figure 23), and Pz (Figure 24). This was done in order to visually compare peak amplitudes and latencies of the P300 and N4 components. The same waveforms were created for the g.Recorder data with the purpose of visually comparing the peak amplitudes and latencies of the slow positive voltage change for each of the three conditions (Figures 27, 28, and 29).

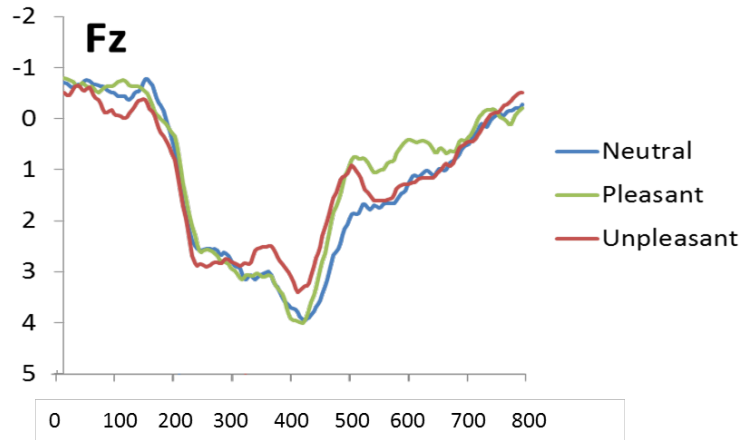


Figure 22. Grand mean waveforms for the pleasant, unpleasant, and neutral conditions at electrode site Fz for the BCI2000, unedited calibration data.

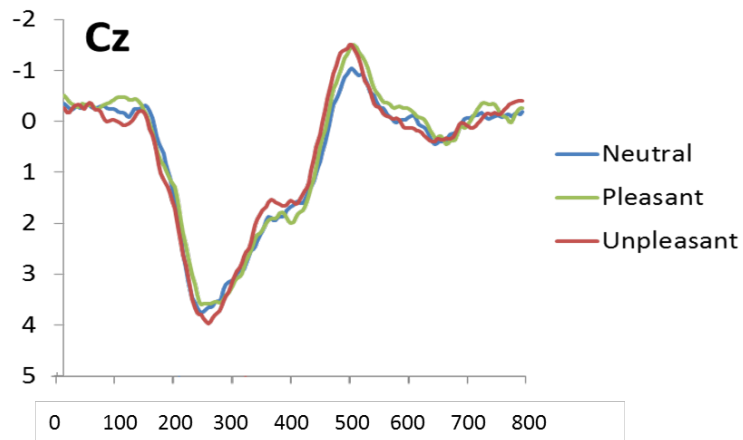


Figure 23. Grand mean waveforms for the pleasant, unpleasant, and neutral conditions at electrode site Cz for the BCI2000, unedited calibration data.

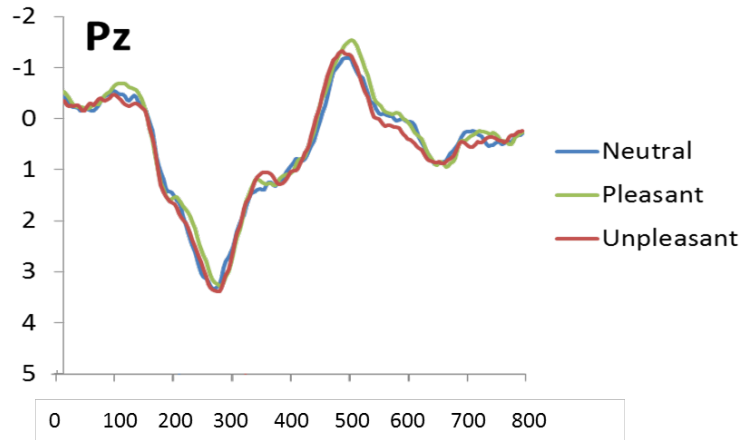


Figure 24. Grand mean waveforms for the pleasant, unpleasant, and neutral conditions at electrode site Pz for the BCI2000, unedited calibration data.

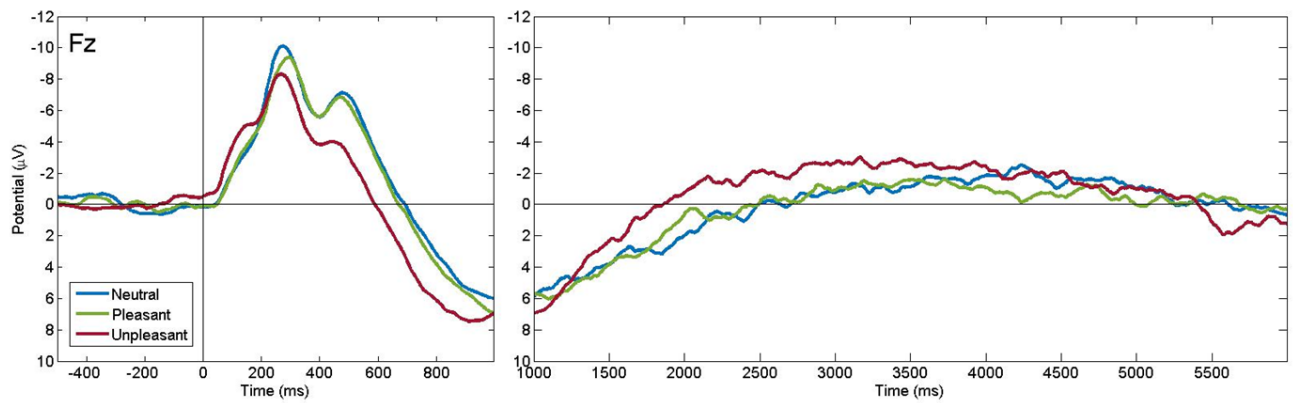


Figure 25. Grand mean waveforms for the pleasant, unpleasant, and neutral conditions at electrode site Fz for the g.Recorder data.

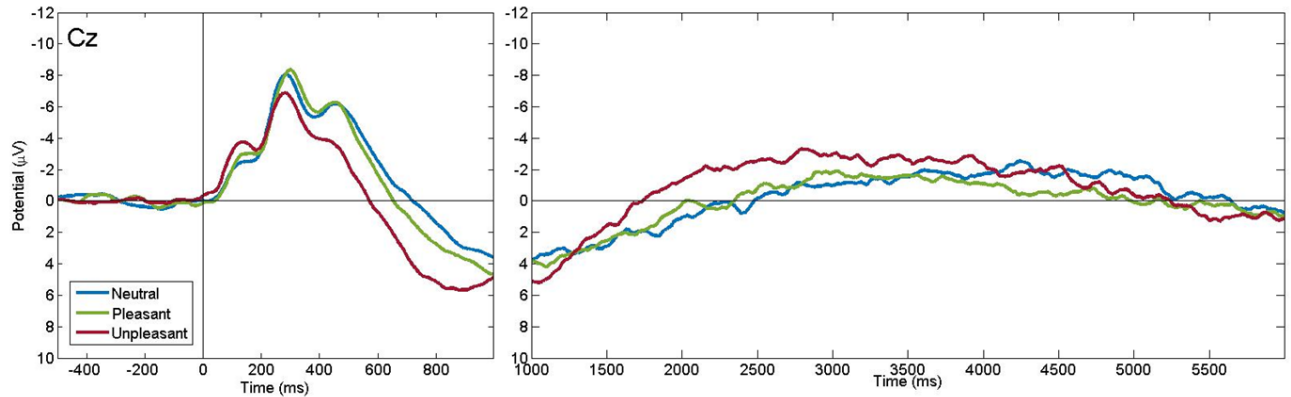


Figure 26. Grand mean waveforms for the pleasant, unpleasant, and neutral conditions at electrode site Cz for the g.Recorder data.

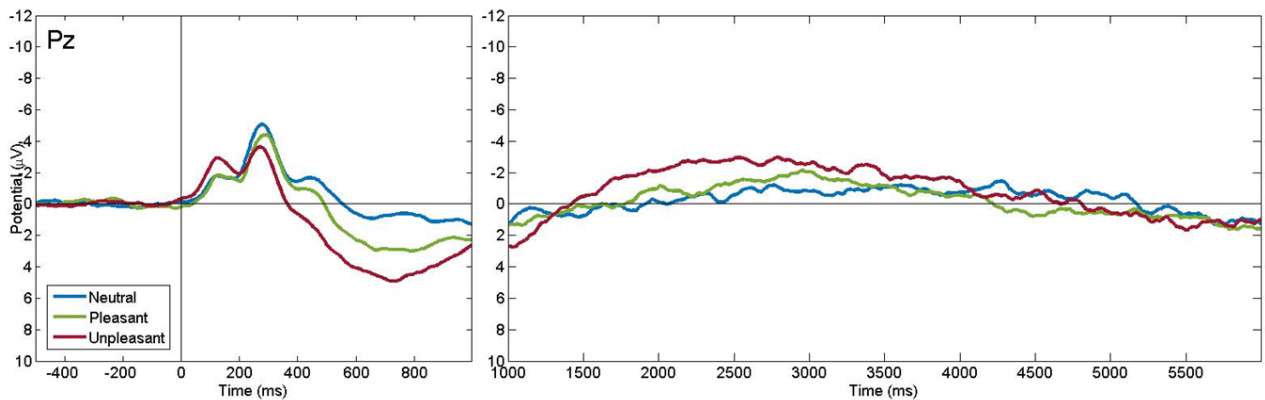


Figure 27. Grand mean waveforms for the pleasant, unpleasant, and neutral conditions at electrode site Pz for the g.Recorder data.

Topography maps were created for the g.Recorder data for each condition at the time point where the peak amplitude for the slow positive voltage change was greatest (Figure 28). This was done in order to visualize the brain activity that was occurring.

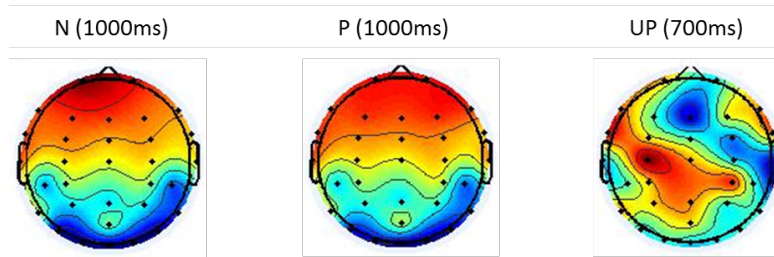


Figure 28. Topography maps for the g.Recorder data for each condition at the peak amplitude for the slow positive voltage change.

Lastly, two one-way ANOVAs were conducted in order to compare the peak amplitudes and latencies at electrode sites Fz, Cz, and Pz for both the BCI2000 unedited calibration data and g.Recorder data. The analysis on the BCI2000 data was done in order to examine differences in the peak amplitudes and latencies for the P300 and N4 components between the three conditions. The analysis on the g.Recorder data looked for differences in peak amplitudes and latencies for the slow positive voltage change. The first analysis, on the BCI2000 data, revealed that there were no significant differences in the peak amplitude ($F(2, 49)=.006, p=.994$) or latency ($F(2, 49)=.265, p=.767$) of the P300 component between conditions. In addition, no significant differences were found in the peak amplitude ($F(2, 49)=.248, p=.780$) or latency ($F(2, 49)=.364, p=.695$) of the N4 component between conditions. The second analysis, conducted on the g.Recorder data, also revealed no significant differences in the peak amplitude ($F(2, 43)=2.065, p=.139$) or latency ($F(2, 43)=2.065, p=.139$) of the slow positive voltage change between conditions.

CHAPTER 6

DISCUSSION

Study 1

Including psychological variables in BCI research has been shown to have the potential to increase the number of potential BCI users, as well as improve the performance of existing users. Study 1 examines the relationship between four of these factors, including motivation, mood, emotion, and depression, and BCI performance. While the impact of some of these factors, including mood (Nijboer et al., 2010) and motivation (Kleih et al., 2011), on BCI performance has been previously examined, no study has examined all of these psychological factors simultaneously. By doing so, the relationship between these four psychological factors and BCI performance should be further clarified.

The first analysis that was done on the data from Study 1 was a principal component analysis. This analysis was conducted in order to determine whether the three outcome variables measuring BCI performance (i.e., accuracy, bitrate, and practical bitrate) could be combined into a single outcome variable. The reason this is desirable is because having a single outcome variable reduces the number of necessary analyses and increases statistical power. The results indicated that a single principal component could be used to combine these three outcome variables and still maintain 91.639% of the variance in the data. This is not surprising since all three outcome variables are related. For example, both bitrate and practical bitrate include accuracy in their calculation formula. Therefore, this single principal component will be used as the measure of BCI performance for the remaining analyses.

In order to determine if any of the four psychological factors are correlated with BCI performance, a one-tailed, bivariate, Pearson correlation was conducted. This analysis revealed

that contrary to the researchers' hypotheses, no significant correlations exist between the psychological factors and BCI performance. Although no previous research has examined the relationship between depression or emotion and BCI performance, there have been studies evaluating the relationship between BCI performance and mood as well as motivation. In a study conducted by Nijboer et al. (2008), positive mood was found to be correlated with high accuracy on a BCI task. Since this is the only study of its kind, it is hard to determine the reason these results were not replicated in the current study. It could be the case that positive mood leads to higher BCI accuracy, but only for some individuals. It is also possible that there was not enough variation among the mood scores to detect a correlation between mood and BCI performance. The current study's participants provided mood scores between 1.7 and 3.0, with possible scores ranging from 1.0 to 5.0. A range of 1.3 out of a possible 4.0 is somewhat restricted. Perhaps future studies should attempt to manipulate the mood of the participant prior to completing a BCI task in order to provide more variation in the data. Unlike mood, the impact of motivation on BCI performance has been examined several times; however, the findings are mixed. Therefore, although it contradicts the researchers' hypothesis, it is not unprecedented that no relationship between motivation and BCI performance was found in the current study. One issue previous researchers have come across is distinguishing between intrinsic (Kleih & Kübler, 2013) and extrinsic (Kleih et al., 2010) motivation. Future studies need to continue to examine the impact of both intrinsic and extrinsic motivation on BCI performance. In addition, motivation appears to be related to several other psychological factors that have an impact on BCI performance. Among these are attention and self-efficacy. Therefore, future researchers should seek to further investigate the individual combined impact of motivation, attention, and self-efficacy on BCI performance.

Depression and emotion have not been previously examined in relation to BCI performance. In the current study, the researchers were unable to obtain a participant population with a wide variation in levels of depressive symptomology, despite using an online survey to screen for participants with high levels of depressive symptomology. The depressive symptomology scores for the current study's participants ranged from 0-26 out of a possible 27; however, upon closer examination it is revealed that the data has a mean of 5.189 and a standard deviation of 5.780. Thus, as a whole, low levels of depressive symptomology were observed. The researchers believe that although no significant relationship was found between depressive symptomology and BCI performance, depression is likely to have a meaningful impact on BCI performance. Future studies should replicate the current study using participants with a wide range of depressive symptomology. Perhaps the participant population could include participants with and without a diagnosis of depression, providing more variation in the data. Only by including severely depressed individuals in such studies can the relationship between depression and BCI performance be revealed.

Based on the current study's findings, it would appear that emotion does not have a significant impact on BCI performance. There seems to be a decent amount of variation in the positive and negative affect scores, so it is unlikely that a lack of variability prevented us from achieving statistical significance. Since Study 2 focuses on investigating the relationship between emotion and BCI performance, it is the researchers' hope that its findings will shed more light on this relationship.

While correlation was used in order to individually evaluate the relationship between each of the four psychological factors and BCI performance, regression was used to determine the total amount of variance in BCI performance that is due to all of the psychological factors

combined. No significant amount of variance in BCI performance due to the psychological factors was found. This further supports the findings from the Pearson correlation that was conducted.

Eight scatterplots were created so that the relationship between each of the psychological factors and P300 peak amplitude could be visually evaluated. By looking at Figure 7, there does not appear to be a relationship between P300 peak amplitude and depression; but again, our participant population lacked variation in their depressive symptomology scores. Figures 10-13 show scatterplots of the four motivation components that were measured using the QCM-BCI. Figure 8 reveals that while the confidence scores were all relatively high, there is not a correlation between confidence and P300 peak amplitude. Although interest and challenge were both consistently high and fear was low in participants, no relationship between either of them and P300 peak amplitude was observed. Figures 14 and 15 show scatterplots of the relationship between the positive and negative affect components of emotion and P300 peak amplitude. No significant correlation was detected. Lastly, Figure 14 shows a scatterplot of the relationship between mood and P300 peak amplitude; again, no relationship is apparent.

While visual examination of the eight scatterplots of the relationships between each of the psychological factors and P300 peak amplitude did not reveal any obvious correlations, a two-tailed, bivariate, Pearson correlation was conducted in order to formally examine these relationships. Interestingly, depression was shown to be significantly correlated with P300 peak amplitude, which is contrary to the researchers' hypothesis. It should be noted, however, that a limitation of the current study is that the dataset lacks a wide variation in depressive symptomology scores. Therefore, these findings may not be accurate and future studies should replicate this study with more variation in depressive symptomology scores.

Although this finding was unexpected, in order to further understand the relationship between depressive symptomology and P300 peak amplitude, participants were placed into one of three groups based on their depressive symptomology score. The first group, “no depression,” consisted of participants who scored between 0 and 4 on the PHQ-9. The second group, “mild depression,” consisted of participants who scored between 5 and 9; while the third group, “moderate to severe depression,” was made up of participants scoring 10+. Once the participants were placed into their groups, a one-way ANOVA was conducted to determine if the three groups differ in P300 peak amplitude. The findings were significant; therefore, post hoc comparisons were conducted in order to determine which of the three groups differed from one another. This analysis revealed that the significant difference in P300 peak amplitude is between the “no depression” and “moderate to severe depression” groups. Again, the “moderate to severe depression” group had higher P300 peak amplitudes than the “no depression” group, which contradicts the researchers’ hypotheses. While these results are convoluted based on the lack of variation in the dataset, it may be the case that the few participants that had high depressive symptomology were also very focused on the task. Considering the participant receiving the highest depressive symptomology score was also the sole participant from the online screening survey to agree to participate in this study, this explanation may be supported. This is because the participant is likely to be highly motivated to perform well and focus on the task since they had already received SONA credit and participating in this study would require them to come to campus and would take an hour and a half of their time. This increase in motivation and/or attention could explain the increase in P300 peak amplitude.

Grand mean waveforms were created for the data at electrode locations Fz, Cz, and Pz (Figures 18-20) so that overall trends in the data could be examined visually. The P300 ERP can

be seen in all three figures; however, it is most prominent at electrode site Pz. In addition, Figure 18 consists of a grand mean waveform at electrode site Pz for all three depressive symptomology groups. This was created in order to visually examine the difference in P300 peak amplitude between the “no depression” and “moderate to severe depression” groups in particular as this difference was found to be significant. By examining this figure, it is clear that there is a large difference between the P300 peak amplitude of these two groups which occurs roughly around 250ms after stimulus presentation.

Study 2

While Study 1 is focused on gaining a better understanding of how a variety of psychological factors are related to BCI performance in general, the purpose of Study 2 is more specific. Study 2 focuses on emotion, which is one of the psychological factors in Study 1 that has not been previously examined by BCI researchers. More specifically, this study sought to elicit pleasant, unpleasant, and neutral emotions in participants to see how each emotion impacted BCI performance. The reason it is important to understand how emotion impacts BCI performance is because BCI users experience a wide range of emotions and they must be able to utilize the BCI to communicate as they experience different emotions.

The first analysis that was conducted on the data from Study 2 was a paired-samples t-test to look for differences between the pre and post PANAS scores in each condition. This analysis was used as a manipulation check in order to ensure the intended emotion was successfully elicited in the participant. It is important to determine whether or not the emotional manipulations were successful in order to continue with the other planned analyses. The results indicated that in the neutral condition, there was a significant decrease in positive affect from pre to post. Although this was not hypothesized, it is not entirely unexpected. The pictures that are

shown to participants in the neutral condition are fairly boring in nature, so as to avoid unintentionally eliciting any pleasant or unpleasant emotions. In addition, participants were required to sit as still as possible while viewing the images in order to obtain clean EEG. Therefore, it is not surprising that participants reported a slight decrease in positive affect following viewing the neutral images. This finding did not impact the planned analyses. Neither of the researcher's hypotheses for the pleasant condition were supported, indicating that the pleasant emotion elicitation was unsuccessful. Therefore, for the remaining analyses, the pleasant and neutral conditions were combined and treated as one neutral condition. In addition, in the unpleasant condition, both of the researchers' hypotheses were supported. More specifically, positive affect decreased significantly from pre to post. Negative affect increased significantly from pre to post.

In order to visually compare the average pleasure and arousal ratings on the SAM survey from the current study's participants as well as the normative data, two line graphs were created. Figure 20 is the line graph of the average pleasure ratings on the SAM scale. This is interesting because there is quite a large difference in the average pleasure rating for the pleasant condition between the two groups. The participants in the normative study had a much higher average pleasure rating for the pleasant condition than the current study's participants. This further supports the finding that the emotional manipulation in the pleasant condition was unsuccessful. It is possible that this is due to the fact that the participant population in the current study consists mainly of college students and they may not be as sensitive to the pleasant images that were used. I suggest that future researchers replicate this study but include a pilot study to find images that college students rate as high on the SAM pleasure survey and use those images in the study. Figure 21 is a line graph of the average arousal ratings of the two groups. Again, there

seem to be large differences in the arousal ratings in that the participants in the normative study had much higher arousal ratings for the pleasant and unpleasant conditions than the current study's participants. As with Study 1, a principal component analysis was conducted in order to determine if the three outcome variables measuring BCI performance (i.e., accuracy, bitrate, and practical bitrate) could be combined into one principal component to be used in future analyses. This analysis also revealed that the three variables could be combined into one based on the finding that one principal component retains 90.434% of the total variance in the dataset.

Using the principal component as the new outcome variable, a paired-samples t-test was conducted to investigate whether there is a statistically significant difference in BCI performance between the neutral and unpleasant conditions. Again, the neutral condition was combined with the pleasant condition to create one neutral condition, based on previous analyses. The results revealed that BCI performance did not significantly differ by condition. Since the pleasant emotion manipulation was unsuccessful, it is not possible to determine the impact of pleasant emotion on BCI performance based on the results of the current study. The findings revealed that neither neutral nor unpleasant emotions impact BCI performance. Although this finding does not support the researchers' hypothesis, it is beneficial to BCI users because they should be able to successfully use their BCI to communicate, regardless of any unpleasant emotions they may be experiencing.

Grand mean waveforms were created for the BCI2000, unedited calibration data for each of the three conditions. Figures 24, 25, and 26 contain the grand mean waveforms at electrode locations Fz, Cz, and Pz, respectively. These waveforms were created in order to provide a visual representation of the peak amplitudes and latencies of the P300 and N4 components for each of the three conditions. For the P300 component, the neutral and pleasant conditions appear to have

higher peak amplitudes than the unpleasant condition with no differences in latency. For the N4 component, it appears the pleasant and unpleasant conditions had higher peak amplitudes than the neutral condition with no differences in latency. These differences are most prominent at electrode site Fz, Figure 22. These differences in peak amplitude between conditions are interesting. The researchers hypothesized that the pleasant and unpleasant conditions would have the highest peak amplitude for both the P300 and N4 components; however, this was only the case for the N4 component.

The same grand mean waveforms were also created for the g.Recorder data; however, instead of using these waveforms to examine the P300 and N4 components, they were used to examine slow positive voltage changes. At electrode location Fz, Figure 25, the pleasant and unpleasant conditions seem to have higher peak amplitudes, with the unpleasant condition also appearing to have a shorter latency. This supports the researchers' hypotheses predicting that the pleasant and unpleasant conditions would have greater peak amplitudes as a result of an increase in arousal and attention. A similar pattern can be seen in Figure 26, the grand mean waveforms at electrode site Cz. However, Figure 27, at electrode site Pz, reveals a slightly different pattern. The latencies of all three conditions have the same latency, with the neutral condition having the smallest peak amplitude, followed by the pleasant condition, with the unpleasant condition having the highest peak amplitude. This also supports the researchers' hypotheses that anticipated this pattern as a result of differences in arousal and attention.

Topography maps were made for the g.Recorder data for the pleasant, unpleasant, and neutral conditions at the time point at which the slow positive voltage change had the highest peak amplitude (Figure 28). These maps allow for the brain activity that was occurring during the BCI task to be visualized. The neutral and pleasant conditions elicited very similar

topographies, and the amplitude peaked at 1000ms in each condition. This supports our finding that we were unable to successfully elicit a pleasant emotion in the participants. The unpleasant condition's topography map reveals a different pattern of brain activity occurring at 700ms with the majority of the activity located at the crown of the head.

Once the researchers had visually inspected the data, two one-way ANOVAs were conducted in order to formally compare the peak amplitudes and latencies at all three electrode sites for both the unedited BCI2000 calibration data and the g.Recorder data. The first one-way ANOVA was done on the BCI2000 data and looked for differences in the peak amplitudes and latencies of the P300 and N4 components between conditions. Contrary to the researchers' hypotheses, none of these analyses yielded statistical significance. The researchers hypothesize that this may be because the pleasant emotion manipulation was not successful. Furthermore, they hypothesize that although the unpleasant manipulation was relatively successful, the images used may not be as arousing for this population. Therefore, future studies should conduct pilot studies in order to choose the images that will be most arousing to the participant population. They could also use other methods of eliciting emotions that may be more salient than an observed image, such as having participants view short videos. The second one-way ANOVA was conducted on the g.Recorder data in order to examine peak amplitudes and latencies of the slow positive voltage change for each of the three conditions. This analysis also did not yield any statistically significant results. The researchers believe this may also be due to the lack of success of the emotional manipulation. Nonetheless, the results were in the predicted direction.

CHAPTER 7

CONCLUSION

The primary focus of the field of BCI has been on improving the system through alterations in stimulus presentation (Townsend et al., 2010) and signal processing techniques (Krusienski et al., 2011). However, without expanding the research to incorporate the end users more through methods such as examining psychological variables, advancements in improving the speed and accuracy of the system will be limited (Kübler et al., 2001). Based on the findings from Study 1, a relationship between the psychological factors that were examined and BCI performance may exist; however, the correlation between them may be smaller than previously expected. Another possible explanation is that our performance measures were not sensitive to the manipulations. Previous research has found promising results that suggest psychological factors such as motivation (Kleih et al., 2011) and mood (Nijboer et al., 2008) can have an impact on BCI performance, if only in some individuals. Perhaps these factors need to be manipulated in order to distinguish differences in BCI performance as a result of these factors. Emotion and depression have not been previously researched with regard to their impact on BCI performance. Therefore, the researchers believe that future research should further examine the impact of these factors on BCI performance by including a clinically depressed population and eliciting a wide range of emotions within their participants.

Study 2 was limited in that the emotional manipulation was unsuccessful in the pleasant condition. Therefore, the pleasant and neutral conditions were combined and treated as a single neutral condition. In addition, the arousal ratings in the present study were much lower for both the pleasant and unpleasant conditions in comparison to the normative data. In order to avoid this problem, future studies should conduct a pilot study in which individuals from the participant

population are shown images so that images that are reported to be the most arousing can be used in the study. This should ensure the emotional manipulations will be successful.

Overall, while neither study provided significant results, previous research has shown psychological factors do impact BCI performance (Nijboer et al., 2010). Therefore, future research should continue to examine psychological factors and their potential impact on BCI performance. If possible, individuals with ALS should be included in future studies in order to understand how psychological factors impact everyday BCI use. Based on the findings of the current study, it appears that emotion does not have an impact on BCI performance. If this is true, it may be beneficial to BCI users as it would mean that they should be able to successfully communicate using the BCI while experiencing a variety of emotions. However, future research should continue to consider emotion as a potential factor that could influence BCI performance. In addition, it is possible that other psychological factors that have not previously been examined could impact BCI performance. The researchers encourage others in the field to continue to search for psychological factors that could impact BCI performance and provide answers towards achieving the ultimate goal of increasing the number of potential BCI users while also increasing the speed and accuracy of BCI systems.

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